The Impact of Advertising Along the Conversion Funnel*

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We assemble a unique data-set which combines information on advertising with path-tracking data on consumers' movement within a supermarket as well as purchase information. Using this novel information on consumer behavior prior to a purchase, we trace out how advertising impacts consumer behavior along their path-to-purchase. Surprisingly, we find that advertising has no significant effect on the number of consumers visiting a particular product category. The null effect is precisely estimated and even at the upper end of the confidence interval, a one standard deviation shift in advertising increases category traffic by only 1.3%. On the other hand, we do find that advertising significantly impacts consumers at the lower end of the conversion funnel by increasing sales conditional on visiting the category. A one standard deviation change in advertising (evaluated at the point estimate) increases category-level sales significantly by 11%. We further decompose the impact in sales and find that the increase is driven by consumers buying multiple products within the category. The number of consumers purchasing in the category is not affected. Consistent with the absence of an effect on category traffic and the nature of the sales increase, we find no evidence of spillover effects of advertising between categories which are stocked in the proximity of each other in the store. We do however find spillovers between non-advertised products within the same category. Finally, we propose a simple model that ties the findings together and analyzes the potential mechanisms underlying the observed patterns.

Keywords: Advertising, Conversion Funnel, Spillovers, Path-tracking Data

1 Introduction

When allocating advertising spending, marketers care at what stage of the conversion funnel advertising has the largest impact on consumers. In a brick-and-mortar store context, advertisers need to know: does advertising bring consumers to the store, does it increase traffic to specific parts of the store, does it increase engagement with the advertised category, and finally, does advertising increase product sales? Understanding whether advertising influences sales as well as which parts of the conversion funnel are affected is relevant for managers in assessing the overall impact of their advertising efforts. If advertising a specific product brings additional consumers to the store, it is likely that those additional consumers also purchase other (non-advertised) products in the store. If instead, advertising is most effective at the lower part of the conversion funnel and increases purchases by consumers that would have visited the category even in the absence of the ad, then the impact of advertising will be more narrow and confined to the category or even only the specific product being advertised.

Despite the practical relevance of decomposing the conversion funnel, there is relatively little empirical evidence on this issue, most likely due to a lack of appropriate data. Marketing researchers have traditionally only been able to observe consumer purchases and hence most of the advertising literature focuses on analyzing the impact of advertising on sales, but does not explore the different stages of the conversion process. In this paper, we make use of a novel data set which allows us to observe consumer behavior in a brick-and-mortar store at a greater level of detail. Specifically, we use a data set of consumer "path-tracking" information obtained from radio-frequency identification (RFID) tags which are attached to consumers' shopping carts. This data allows us to track precisely which path the consumer took through the store as well as where she was located in the store at each point in time. Combined with data on product locations, this allows us to measure whether a consumer visited a particular product category and at what time during her trip she made the visit. For the same set of consumers, we also observe purchases as well as the advertising activity they are exposed to across a large set of categories. Using all these pieces of data together, allows us to investigate the impact of advertising onto parts of the consumer decision process that are typically not observed.

More specifically, the research questions we address in this paper are the following. First, we analyze at what stage of the conversion process advertising has the largest impact on consumers. Second, we analyze the consequences of this decomposition in terms of advertising spill-over effects. To answer the first question, we make use of the path-tracking data on consumers' movement within the store and analyze whether the number of consumers visiting a particular category as well as the timing of their visit are affected by advertising. We then analyze the impact of advertising on purchase behavior conditional on visiting the category. To answer the second question, we analyze spillover effects across categories which stocked in vicinity to each other in the store as well as between individual products within each category.

Our paper establishes several key findings. First, we investigate *whether advertising drives foot-traffic* to the advertised categories in the store. We implement this analysis by regressing the number of consumers passing a specific category on a given day on the number of advertised products in that category while controlling for category fixed effects and other marketing activity. Surprisingly, we find that feature advertising *does not* increase traffic towards featured categories. The null effect is precisely estimated and, even at the upper bound of the confidence interval, a one standard deviation shift in the number of advertised products increases daily category traffic by only 1.3 percent. These results show that any possible increase in sales must be driven by an effect of advertising on purchase behavior conditional on visiting the category.

Second, we analyze *whether and how advertising affects purchases.* We find that the number of advertised products has a significant impact on category sales and leads to a 12 percent increase in purchase quantity. When decomposing the effect, we find that the increase in sales originates almost entirely from one specific margin of adjustment. We find that the number of consumers purchasing in the category is not significantly affected by advertising, but instead the quantity purchased per consumer is the primary driver of the sales increase. Furthermore, we also find that the increase in sales is driven by consumers purchasing a larger number of different products from the same category rather than multiple units of the same product. Together with the results from the traffic data, this sales decomposition paints a detailed picture along which margins advertising is able to affect consumer behavior. We find that advertising does have a significant impact, both in a statistical and economic sense, on the final outcome variable of interest, quantity sold. However, along the conversion funnel, advertising is ineffective at various stages of the process. Neither does it impact traffic patterns, nor does it convert a higher number of consumer to buying in the category. Instead, the overall advertising effect is primarily driven by consumers purchasing more variety within the category.

Third, we investigate advertising spill-over effects both within categories (between different products) as well as across categories that are stocked in proximity to each other in the store. We implement the latter type of analysis based on a detailed map of the store that allows us to define the location as well as the set of nearby products for each category. Consistent with the null effect on traffic, we find no evidence that advertising in a specific category increases purchases in other nearby product categories. However, within categories we do find evidence for advertising spillovers between individual products, which is consistent with the finding of consumers buying more variety in response to advertising. Specifically, we find that when advertising a specific product, both its own sales and sales of other products in the same category increase. Furthermore, the impact of advertising on other products in the same category is substantial and the total category-level impact of advertising is three-times as large as the effect on the advertised product itself. Therefore, based on both findings, we argue that spillovers from advertising exists, are quantitatively important and and should be taken into account by managers when making decisions about advertising. Our results imply that advertising can be used to promote the category as a whole, rather than just the individual product being featured. At the same time, advertising is not effective in promoting the entire store because spillovers only occur within the confines of a specific category and do not extend beyond it.

Our paper contributes to several strands of literature. First, it extends the work using data on consumers' within-store movement, such as Hui et al. (2009a) who document shoppers deviations from the most efficient path through the store or Jain et al. (2014) who analyze the impact of consumers interaction with a sales representative on their in-store behavior. Also within this literature, Seiler and Pinna (2016) estimate the benefits from search in terms of price saving from longer in-store search. Hui et al. (2013a) and Hui et al. (2013b) both analyze unplanned shopping behavior using video-tracking and RFID tracking technology respectively. To the best of our knowledge, none of the prior papers in this literature combined advertising data with data on consumers' movement within the store. In fact, only Jain et al. (2014) investigate the impact of a marketing intervention, in their case the interaction with a sales person, onto consumer behavior. As we argue in this paper, understanding how marketing activity affects consumers' path-to-purchase can yield important new insights and we see this paper as a first foray into this research area.

Apart from path- or video-tracking studies in a brick-and-mortar store context, another application of similar methods is from online browsing data. A wide range of papers have investigated consumer search behavior in this realm (see for example Kim et al. (2010), De Los Santos et al. (2012), Chen and Yao (2016)), but mostly focus on estimating the primitives of the search process such as consumer search costs and preferences. The impact of advertising and other marketing tools is not typically the focus of the analysis. However, the type of analysis we conduct in this paper can also be applied to an online context, which would be an interesting area for future research. We conjecture that certain patterns we find in the physical store setting of our paper might look very different in an online context due to the fact that navigating through a brick-and-mortar store is more costly and less flexible than online browsing.

A second stream of literature that we aim to contribute towards is the nascent literature on measuring advertising spillovers. Sahni (2016) shows that advertising spillover do exists and are quantitatively important in the context of online advertising and characterizes between what type of companies they occur. Lewis and Nguyen (2014) show spillovers across competing firms in online search behavior (following an ad exposure). Anderson and Simester (2013) show that spillovers exist for products sold by catalog and they are most prevalent in categories with higher switching costs. Shapiro (2015) estimates spillovers in the context of pharmaceutical advertising. In their study of promotional email coupons, Sahni et al. (2016) find that these coupons are effective at increasing revenue on the webpage, but find that the majority of the effect is due from spillovers to other product to which the coupon does not apply and even other categories. In contrast, in this paper we find spillovers to be relatively confined to a specific product category and they do not spillover to other categories in the store. Similar to Anderson and Simester (2013) and Sahni (2016), we thus characterize the nature of spillover, in our case as a function of store geography. We are furthermore able to analyze the antecedents of spillover effects (or the absence of such effects) by analyzing consumers' movement in the store. This is similar to the analysis of both browsing as well as purchase behavior in Sahni (2016).

Third, our paper also relates to the stream of studies on the effects of marketing mix on shopping behavior. Kumar and Leone (1988) use store level scanner data of diapers to show that price promotion is the most effective marketing tool driving sales, followed by feature advertising and display. There is significant within-store substitution for the promoted products but ambiguous effect for across-store substitution. Walters (1991) and Walters and MacKenzie (1988) advance the literature by considering the spillover effect of promotions on non-promoted products. They find that there is significant within-category substitution effect but only limited support to the "loss-leader" story (i.e., the promotion boosts overall store sales even though the promoted products suffer a loss). Using more detailed individual level data, Bodapati and Srinivasan (2006) investigate the effect of feature advertising and find that only a small percentage (10%) of consumers respond to such a tool. In comparison to previous studies, our paper is able to focus closer on the shopping funnel owning to the detailed individual level path and purchase data.

Finally, we contribute to the literature on measuring advertising effects more broadly (see the summary in Bagwell (2007) for instance). However, we differ from most of the prior literature by focusing not only on the impact of advertising on purchases, but also on consumers movement through the store. Furthermore, we provide a decomposition of the sales effect of advertising into an impact on the number of consumers purchasing as well as the variety and quantity purchased per consumer. While this analysis does not leverage the path-tracking data, our paper is to the best of our knowledge the first to provide such a decomposition.[1]

The remainder of the paper is structure as follows. In Section 2, we present the data and descriptive statistics. In Sections 3.1 and 3.2, we analyze the impact of advertising on traffic and sales respectively. In Section 4, we discuss identification and provide a set of robustness checks. Sections 5 and 6 investigate spillovers effects and present some additional results, respectively . Section 7 discusses the possible underlying mechanism that is consistent with our empirical findings, using a simple and intuitive model. Section 8 concludes.

2 Data and Descriptive Statistics

Our data comes from two sources. First, we obtained data from a large store in Northern California that belongs to a major supermarket chain.[2] For this store, we observe individual-level purchases as well as data on the path a consumer took through the store for a subset of shopping trips over a period of 26 days.[3] In terms of the purchase data, we have information on all consumers that visited the store during a six-week window that comprises the 26 days for which we also observe the path data. For each shopping trip, we observe the full basket of products as well as the price paid for each item. Furthermore, we are able to link the path data to the corresponding purchase

[1] We note that this type of decomposition has been conducted frequently in the literature on estimating price elasticities and the decomposition of price elasticities into an incidence, brand choice and quantity elasticity. However, no such decomposition was typically implemented in studies of advertising effectiveness.

[2] We are not able to disclose the identity of the supermarket. The store has a fairly typical format with a trading area of about 45,000 square-feet and a product range of 30,000 UPCs.

[3] The days in the path data are 8/24/2006 - 8/29/2006 and 9/7/2006 - 9/26/2006.

baskets from the sales data.[4] Finally, we have detailed information on the location at which each UPC is stocked in the store. We then complement this data with a second piece of data containing information on feature advertising from the IRI data set (see Bronnenberg et al. (2008)).

Below, we provide more details on the path data as well as how the feature advertising and path data are merged together to form the final data set. The purchase data is similar in structure to any supermarket scanner data set and we hence do not provide any additional discussion regarding that particular part of the data.

2.1 Path Data

We record the paths consumers took when walking through the store using RFID tags that are attached to their shopping carts and baskets (see Sorensen (2003) and Hui et al. (2009b)). Each RFID tag emits a signal about every four seconds that is received by a set of antennas throughout the store. Based on the signal, triangulation from multiple antennas is used to pinpoint the consumer's precise location. The consumer's location is then assigned to a particular point on a grid of so-called "traffic points," which is overlaid onto the store map and which are about four feet apart from each other, thus allowing for a fairly granular tracking of the consumer. For every path, we observe a sequence of consecutive traffic points with a time stamp associated with each point.[5] We also note that, not all shopping carts and baskets in the store are equipped with RFID tags and we therefore only observe path data for a subset of about 7% of all store visits. We use the path data to derive two key variables: the daily number of consumers visiting a particular product category and the timing of consumers' visits to each category.

In order to compute both variables, we first match the grid of traffic points to product locations that are in the vicinity of the consumer from a given traffic point.[6] This provides a mapping of UPCs to traffic points that a given consumer might visit during a particular shopping trip. For our final set of 21 categories (see Section 2.2 below for more details on how we select the categories), we find the locations of all relevant UPCs and the traffic points associated with the set of products belonging to each category. For each shopping trip, we consider the consumer to have visited a category if during her trip she was located on a certain number of traffic points associated with a specific category. In our baseline definition of a visit, we require a trip to cross at least three traffic points pertaining to the category.[7] We also compute how far into the trip the consumer walked past a specific category by calculating the time elapsed since the beginning of the trip to the point at which the consumer is first located on a traffic point associated with the category.

Figure 1 illustrates the definition of both variables for a specific trip (indicated by the dashed line) and category. The figure depicts an illustrative aisle of the supermarket which stocks the

[4] In section (A) of the appendix, we provide details on how the two pieces of data are combined.

[5] If a consumer moves further than to an adjacent traffic point between signals, the movement over traffic points in between the signals is interpolated. As the signal is emitted at a high frequency little interpolation is necessary for most trips.

[6] The data provide the linkage between traffic and product points. Most product locations are associated with two or three traffic points.

[7] Our results are not sensitive to this assumption and we provide robustness checks using different visit definitions.

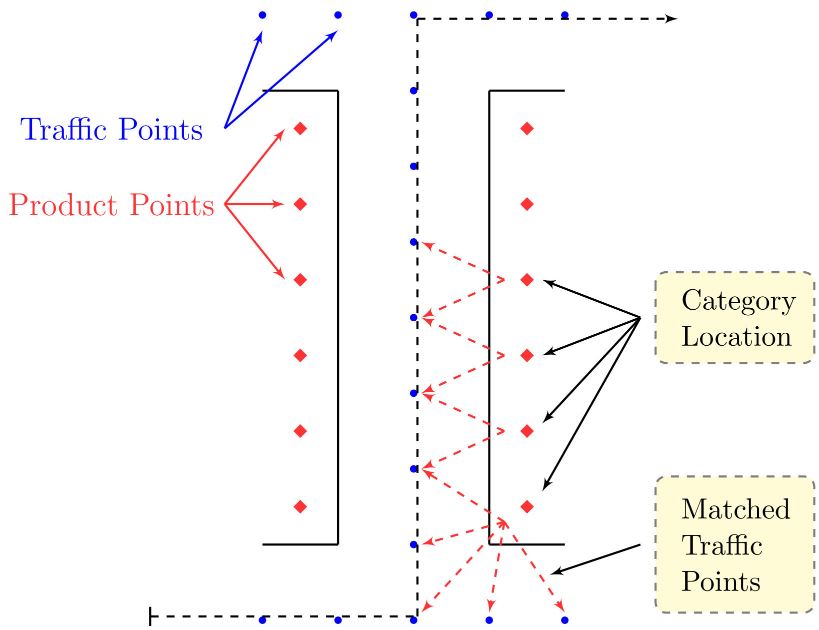

Figure 1: **Category Visit Definition.** The picture illustrates a consumer traversing an aisle. Consumer location within the aisle is recorded on a grid of traffic points. Products are located at specific locations on the shelf, which are coded up as a grid of product points. Product points are matched to nearby traffic points, allowing us to measure whether and when a consumer visisted the category. The dashed black line denotes the consumer's path when traversing the aisle.

focal category on the lower right-hand side of the aisle. A series of traffic points inside the aisle, as well as at the lower end are considered to be in the vicinity of the category and are used to identify whether the consumer visited the category. In this case, the consumer passed six traffic points associated with the category and we hence define his trip as a visit to the focal category. To compute the time of the category visit, we retrieve the time stamp when the consumer is first located on one of the relevant traffic points (in this case the lowermost traffic point inside the aisle) and calculate the time elapsed since the start of her trip.

In the case of both category visits and visit timing, we mostly use the variables aggregated to the category/day level in our empirical analysis. For the case of category visits, we calculate the total number of consumers visiting the specific category each day. In order to capture visit timing, we compute the average number of minutes elapsed since the beginning of the trips for each category/day pair.

2.2 Feature Advertising Data

We supplement the purchase and path data with additional information on feature advertising activity, which we obtain from the IRI data set. The store-level IRI data set contains purchase information, feature advertising at the product/store/day-level, as well as information on price and product displays. We only make use of the IRI data in a limited way in order to complement our main data set with the relevant feature advertising information that is missing from the path-tracking data.

Unfortunately, the store for which we have the path data is not itself contained in the IRI data, which only contains a sample of stores. However, for the purpose of obtaining information on feature advertising, this is not particularly problematic because stores of the same chain located in the same local market use the identical feature advertising.[8] We are hence able to infer the relevant feature advertising information from several stores of the same chain that are located in the same market (in this case Northern California) and are contained in the IRI data set.[9] We then add this feature advertising information for each UPC/day combination to our path-tracking data set. We note that, while most of our analysis is conducted at the daily level, feature advertising only changes at weekly intervals. Our final data set covers four weeks and hence contains four sets of featured products per category.

We also use the IRI data to compute a proxy for product displays at the path data store. Product displays, in contrast to feature advertising, are typically store specific and hence we cannot simply infer product displays from other stores of the same chain. We nevertheless compute a proxy for product displays by calculating the fraction of stores of the same chain that displayed the product in a given week, which we interpret as a display probability for the specific product at our focal store. To the extent that stores feature similar products, for instance due to a manufacturer's merchandising spending, this proxy will allow us to capture the likelihood of a specific product being featured.

2.3 The Final Data Set: Merging and Category Selection

Our final data set comprises 1,200 products in 21 categories across 26 days. The IRI data set constraints our data set in terms of categories, whereas the path-tracking data limits the time horizon. IRI contains information on 30 categories, but some of those contain very few products that are rarely purchased and other categories are never featured and thus do not provide relevant variation for our analysis. We therefore end up with 21 categories in our final data.

The primary location of these categories within the store are displayed in Figure 2. As the figure shows, the categories in our data are fairly spread out in terms of their location and they also cover a broad set of category "types" such as food and household items, storable and perishable items etc. The one major omission from the set of categories is fresh food such as produce or fresh meat which is missing from the set of categories provided in IRI and hence not part of our analysis. We also note that many categories are stocked in several different parts of the store with a "primary" location in an aisle in the center section of the store as well as additional "secondary" locations in the open areas to the left and right of the primary aisle, as well as on top of the aisles, opposite the

[8] Feature advertising is usually implemented at the market level because this allows the chain to only provide one advertising leaflet for the entire market.

[9] In order to merge the IRI data, we use a unique data set that allows us to match the anonymized store-ids in the IRI data to the actual name of the store. This data was necessary in order to merge the feature information with the store in the path data. Typically, such data is not available to researchers.

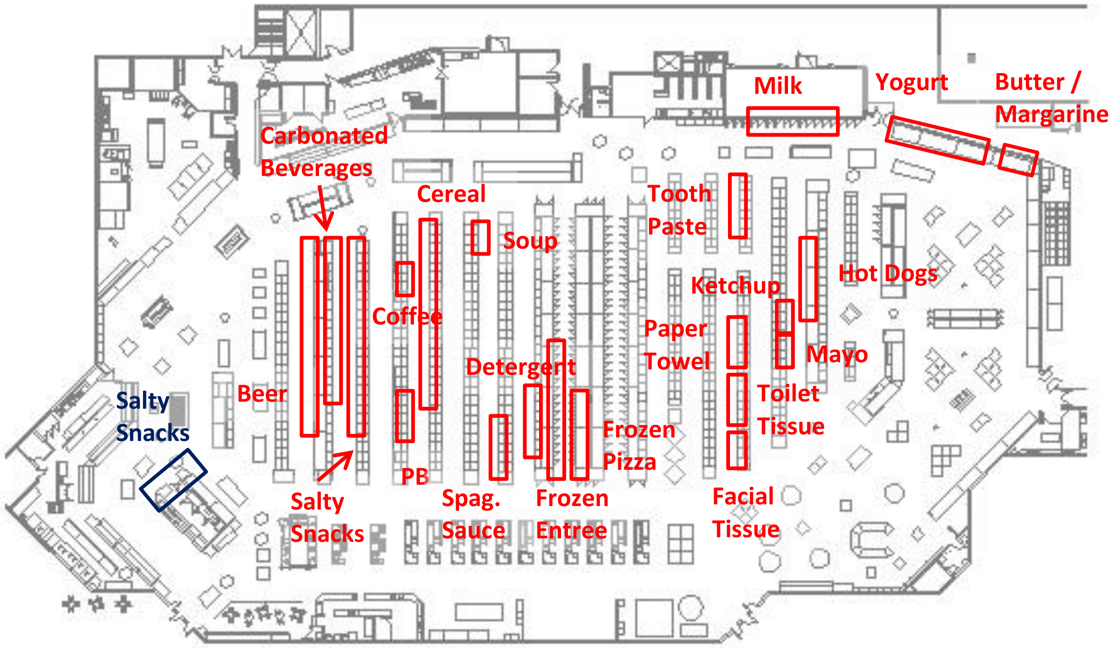

Figure 2: **Store map with Category Locations.** Primary location for all 21 categories are depicted in red. An illustrative secondary location for the salty snacks category is depicted in blue.

entry/exit of the store. The map in Figure 2 only depicts all primary locations and an illustrative secondary location for the salty snacks category in the open area in the left part of the store.

2.4 Descriptive Statistics

We start by providing an overview of the traffic and sales pattern across the categories in our data. The first two columns of Table 1 report the total daily category traffic as well as the share of traffic relative to the total number of consumers visiting the store. For simplicity of exposition, the 21 categories are ordered in descending order by their traffic share. We find that there is substantial heterogeneity across categories in terms of the amount of traffic they are exposed to, ranging from over 90 percent for carbonated beverages to below 10 percent for butter and margarine. There are hence some parts of the store that are rarely visited, whereas other product locations are are passed by a large fraction of consumers.

Columns (1) and (2) are based on all product locations of each category in the store, i.e. both the primary location in the aisle as well as any secondary locations. Because secondary locations tend to receive generally more traffic, presumably because they are used to reach other parts of the store, we also provide an alternative definition of traffic based on primary locations only. Unsurprisingly, traffic numbers are generally lower, but still vary substantially across the different categories. Also, for some categories the difference between total traffic and primary location traffic is large and the gap can be up to 70 percentage points in the case of carbonated beverages. Due to

	Traffic	Traffic Share	Traffic (Primary Location Only)	Traffic Share (Primary Location)	# Cons. Purchasing	Total Quantity	# UPCs	# Feat.
Carbonated Bev.	4,866	97.4	1,392	27.8	431	349	108	16.8
Salty Snacks	4,429	88.6	1,237	24.7	405	322	129	18.8
Beer	4,321	86.5	654	13.1	145	135	67	6.0
Soup	3,582	71.7	1,695	33.9	273	115	79	13.3
Spaghetti Sauce	3,534	70.7	1,630	32.6	101	73	43	5.1
Detergent	2,985	59.7	1,052	21.1	36	34	21	3.4
Milk	2,950	59.0	1,062	21.2	199	152	44	4.6
Mustard / Ketchup	2,616	52.3	685	13.7	50	46	17	0.3
Toothpaste	2,427	48.6	1,022	20.4	28	27	18	0.5
Cereal	2,229	44.6	2,045	40.9	485	319	130	32.0
Frozen Dinner	2,188	43.8	1,305	26.1	455	166	201	66.2
Yogurt	1,988	39.8	1,266	25.3	940	341	143	26.2
Coffee	1,783	35.7	1,783	35.7	46	37	21	1.5
Hot Dog	1,631	32.6	1,548	31.0	60	47	21	2.4
Frozen Pizza	1,359	27.2	1,217	24.4	95	60	44	7.1
Paper Towels	1,123	22.5	1,123	22.5	66	62	16	0.8
Toilet Tissue	1,095	21.9	928	18.6	78	72	15	1.1
Facial Tissue	948	19.0	584	11.7	67	43	13	1.6
Peanut Butter	850	17.0	850	17.0	29	28	17	0.5
Mayonnaise	562	11.2	562	11.2	81	76	20	0.5
Butter / Marg.	165	3.3	165	3.3	145	118	33	1.0

Table 1: **Traffic, Sales and Feature Advertising Across Categories.**

these pronounced differences, we later analyze traffic flows separately for primary and secondary locations. Furthermore, we note that primary locations are typically signposted with the names of the categories stocked in the specific aisle and hence visits to those locations are likely to be more indicative of consumers explicitly seeking out the category.

We also report category level sales as well as the share of purchases relative to total category traffic (based on all locations).[10] Also at this level we find large heterogeneity in sales levels as well as conversion rates of visiting consumers (captured by the traffic count) to sales. Finally, we report the number of UPCs in each category and the average number of featured products. On average about 10 to 20 percent of UPCs are featured on any given day within a category.

[10] We define "Sales" as the number of consumer purchasing in the category, rather than the total quantity purchased in order to make the sales number comparable to the traffic count (both are in units of consumers).

3 Decomposing the Impact of Advertising

3.1 Category Traffic

We start by analyzing the impact of feature advertising onto category traffic. As noted earlier, this part of the conversion funnel has typically not been analyzed because researchers were lacking information on consumers' movement within the store. The path-tracking data provides us with a unique opportunity to unpack the effect of advertising by analyzing this "upper level" of the conversion funnel. To the best of our knowledge, this is the first paper to provide such an analysis.

Our empirical strategy is to regress daily category traffic onto the number of featured products within that category, as well as category and day fixed effects, and controls for other marketing activity. Standard errors are clustered at the category level. Formally, we estimate the following regression:

$$Traffic_{ct} = \alpha \times FeatureNum_{ct} + X'_{ct}\beta + \delta_c + \theta_t + \varepsilon_{ct} \tag{1}$$

where $Traffic_{ct}$ denotes category traffic, i.e. the number of consumers visiting category c on day t. $FeatureNum_{ct}$ denote the number of featured UPCs in category c on day t. X_{ct} denotes a vector of other (time-varying) marketing variables. Specifically, we include the number of promoted items in the category, the average category-level price[11] and a proxy for the number of displayed items (see Section 2.2). δ_c and θ_t denote category and day fixed effects, respectively. ε_{ct} is the regression error term.[12]

Our baseline specification defines a category visit as a trip that passes at least three traffic points which are associated with the category and is based on all product locations of the category. Column (1) of Table 2 reports the results from this regression. Interestingly, we find that the number of features has *no* statistically significant impact on category traffic and is in fact very close to zero in a statistical sense with a p-value of 0.707. Furthermore, the coefficient on the number of features is not only insignificant, but also small in magnitude. Featuring one additional product leads to 0.631 additional consumers visiting the category. Relative to an average of 2,270 daily category visits, this effect is very small.

To further illustrate the magnitude of the effect, consider a one standard deviation increase in the number-of-features variable, which is equal to 8 additional products being featured.[13] Such an increase in the feature advertising variable leads to about 5 additional visitors (0.631*8), a 0.22

[11]The price information is obtained from the purchase data. A promotion is defined as a reduction of at least 15 percent relative to the base-price. The average price level is computed as the average (unweighted) price of all products in the category and capture promotional price fluctuation over time in a more continuous fashion (relative to the number-of-promotions variable).

[12]We would not expect price to be an important control in the traffic regression, because product prices are usually not known to the consumer before reaching the shelf. We nevertheless maintain the number of promotions and average price as control variables in the traffic regression, to make the regression as comparable as possible with the later regression of sales onto feature advertising and other marketing variables (where the price control is more important).

[13]We compute the standard deviation of features *within* categories, by regressing the feature variable onto category fixed effect and then calculating the standard deviation of the residuals from this regression.

	All Locations			Only Primary Category Locations		
Dependent Variable	(1) # Cat. Visits	(2) # Cat. Visits	(3) # Cat. Visits	(4) # Cat. Visits	(5) # Cat. Visits	(6) # Cat. Visits
Category Visit Definition	$\geq$ 3 Traffic Points Visited	$\geq$ 5 Traffic Points Visited	$\geq$ 7 Traffic Points Visited	$\geq$ 3 Traffic Points Visited	$\geq$ 5 Traffic Points Visited	$\geq$ 7 Traffic Points Visited
Mean	2,270	1,589	1,124	1,133	743	533
S.D.	1,397	1,239	1,100	532	448	425
# Features	0.631	-0.428	-0.295	-0.148	-0.105	-0.250
	(1.654)	(1.029)	(1.005)	(0.963)	(0.969)	(1.059)
Category FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Marketing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	546	546	546	546	546	546
Categories	21	21	21	21	21	21
Days	26	26	26	26	26	26

Table 2: **The Impact of Advertising on Category Traffic.** Marketing controls are the number of promoted items in the category, the average category-level price and a proxy for the number of displayed items.

percent increase (100*5/2270). Even evaluated at the upper bound of the 95 percent confidence interval (i.e., two standard deviations above the point estimate), the effect magnitude is still small. Specifically, a one standard deviation increase in the number of features will lead to 31 additional visitors, a mere 1.3 percent increase in the number of visits. A final way to assess the relevance of the effect in terms of magnitude is to compare it to the effect of feature advertising onto sales, which we present later. When running the equivalent regression to the one above, but using category sales as the dependent variable, we find a statistically significant increase in sales of 11 percent. Therefore the effect of feature advertising on sales (evaluated at the point estimate) is an order of magnitude larger than its effect onto traffic (evaluated at the upper bound of the confidence interval).

In order to probe the robustness of the null result regarding the impact of features onto traffic, we run several additional specifications. We first implement a set of regressions which use different definitions of category traffic. Instead of assuming that a consumers visited a category when her path passed at least 3 traffic points, we consider several more conservative definitions, which require the consumer to pass a larger number of associated traffic points. Column (2) and (3) of Table 2 report the results from two regressions which base the category definition on at least 5 and 7 traffic points respectively.[14] Results are similar to our baseline specification. The point estimates are close

[14]For categories that have fewer than 5 or 7 traffic points associated with them, a visit was defined as a consumer

to zero and in fact slightly negative and the standard errors are smaller relative to the baseline specification reported in column (1). We also run a further set of regressions using between 1 and 15 traffic points as the basis for the category traffic definition. Across all 15 specifications, the effect is consistently statistically insignificant with an average (minimum) p-value of 0.841 (0.616) and small in magnitude.

In a second set of robustness checks, we narrow the category definition down to only the primary location of the each category. As described in Section (2.4), many categories are stocked at different points in the store. Typically, there is a primary location either in an aisle or at the back wall of the store (for perishable items) and further locations in the open areas of the stores. While the primary locations usually stocks a larger variety of products, the secondary locations often experience higher traffic volume. Furthermore, if consumers who see a feature ad are explicitly seeking out the featured category, we might expect an effect on traffic to show up mostly for the primary locations because those are typically labeled and signposted with the category names. We therefore construct traffic measures using only the primary location of each product for the 3, 5 and 7 traffic point definitions used previously. The results from those three regressions are reported in columns (4) to (6) of Table 2 and again show a clear null effect with point estimates and standard errors that are of similar magnitude as the estimates in the first three columns.

Furthermore, due to the store lay-out, some categories may have generally higher traffic than others. As the first column in Table 1 shows, this is particularly true for the traffic definition based on all location. For instance, over 90 percent of consumer walk through parts of the store where carbonated beverages are stocked. When products in such a high traffic category are featured, the marginal effect on traffic could potentially be small because of the already high level of baseline traffic. To address the concern that the small effect in high traffic categories is driving the overall null effect, we re-estimate the baseline specification in column one, but exclude categories with high traffic volume. When we exclude categories with more than 80 percent or 60 percent average traffic volume, we again find that the effect is small and insignificant.[15]

Finally, we also investigate an alternative measure of category traffic which is based on the total number of minutes that consumers spent on traffic points belonging to the category (on a given day) and again find a small and insignificant coefficient estimate.[16]

We conclude that across a wide variety of alternative specifications, the impact of advertising on category traffic is statistically insignificant and small in magnitude. Consequently, advertising does not seem to be able to attract an economically meaningful number of additional consumers to areas of the store where the specific categories are stocked.

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passing all relevant traffic points.

[15]The coefficient (standard error) is 2.652 (4.521) when using an 80 percent cut-off and -1.223 (3.963) based on a 60 percent cut-off.

[16]Based on all category locations, the coefficient (standard error) in the specification is equal to 3.722 (4.746). This again constitutes a small effect relative to the average number of daily category-visit-minutes of 1,741.

3.2 Category Sales

In this section, we estimate the effect of feature advertising on sales. The objective of this analysis is two-fold. First, we aim to establish whether advertising has any impact on purchases and how the magnitude of the effect compares to the null effect on traffic. Second, we decompose the effect of advertising onto purchases into different adjustment margins. Specifically, we analyze to what extent the increase in sales originates from a larger number of consumers purchasing in the category or from individual consumers purchasing a larger quantity of either the same product or of different products from the same category. Together with the results on consumer traffic presented in the previous section, this allows us to paint a detailed picture of the way in which advertising affects the consumer's decision making process. Furthermore, the decomposition of the effect allows us to better understand the behavioral mechanism underlying the response to advertising and hence has direct managerial implications.

We start by implementing the following regression:

$$Sales_{ct} = \alpha \times FeatureNum_{ct} + X'_{ct}\beta + \delta_c + \theta_t + \varepsilon_{ct} \tag{2}$$

where $Sales_{ct}$ denotes a measure of product purchases in category c on day t. $FeatureNum_{ct}$ denote the number of featured UPCs in category c on day t. X_{ct} denotes a vector of other (time-varying) marketing variables. δ_c and θ_t denote category and day fixed effects, respectively. ε_{ct} is the regression error term. The specification is hence identical to the one used for analyzing category traffic, but now we use sales instead of traffic as the dependent variable. We note that we "re-use" the same notation for the regression coefficients used for the traffic regression in the interest of simplicity.

In order to decompose the effect of advertising into the different margins, we use three different measures of purchase outcomes. First, we compute a simple count of the number of consumers purchasing within the category. We then expand this metric to also capture consumers buying different products (UPCs) from the same category as well as consumer purchasing multiple units of the same product. In order to separately capture both dimensions, we first compute the number of consumer/UPC pairs but ignore multi-unit purchases of the same UPC by the same consumer. In a final step, we also include multi-unit purchases by using total quantity purchased in the category as the dependent variable. To illustrate the decomposition is a simple way, consider a consumer that purchased 2 units of product A and 1 unit of product B in the same category. We code this purchase bundle as one consumer, two consumer/UPC pairs and three units of total quantity purchased in the category.

We start by reporting the results from a regression using the count of consumers as the dependent variable in column (1) of Table 3. We find that the estimated effect is insignificant, which complements our earlier finding regarding the null effect of features on category traffic. Not only are there no additional consumers visiting the category due to advertising, but for those consumers whose shopping paths overlap with the category, advertising also does not convert them into pur-

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	# Cons. Purchasing	# Cons./ UPC-pairs	Quantity	Quantity (From Single-Product Trips)	Quantity (From Multi-Product Trips)
Mean	124.8	166.3	200.7	117.9	82.7
S.D.	123.3	196.8	255.7	111.3	187.1
# Features	0.425	2.797**	3.562**	-0.324	3.886**
	(0.331)	(1.226)	(1.544)	(0.339)	(1.615)
Category FEs	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes
Marketing Controls	Yes	Yes	Yes	Yes	Yes
Observations	546	546	546	546	546
Categories	21	21	21	21	21
Days	26	26	26	26	26

Table 3: **The Impact of Adverting on Purchases.**

chasing in the category. Next, we analyze the impact of advertising on the number of consumer-UPC pairs sold within a category on a given day. The results from the regression are reported in column (2) of Table 3 and show that features significantly increase the number of consumer/UPCs pairs. Together with the null result from the first column, this implies that advertising leads to the same number of consumers buying a larger number of different products within the category. Finally, we also include multi-unit purchases into our outcome variable by using the total number of purchases as the dependent variable.[17] The results are reported in column (3) of Table 3. The coefficient is significant and one additional featured product in the category leads to an 3.6 additional units sold. To better assess this magnitude, consider an increase of 8 units in the number of products featured (a one standard deviation shift). Such an increase leads to an 28.5 additional units sold (3.562*8), a 11 percent increase (3.562*8/256). This effect is large in magnitude and in particular much larger than the corresponding increase in traffic. As reported in the previous section, an additional 8 product being featured increases traffic by only 5 category visitors or 0.22 percent.

Taken together, columns (1) to (3) show that feature advertising enhances sales by increasing the order size of consumers who are *already* buying, rather than the overall likelihood of purchase across consumers. Furthermore, the increase in order size originates from consumer buying multiple products rather than several units of the same product. We therefore conclude that the increased sales come from people buying a higher level of variety, instead of just more units of the same

[17]The data contains outliers for the quantity purchased. Some consumers are recorded as having bought up to 80 units of the same UPC. We therefore cap quantity at four units at the consumer/UPC level (the 99th percentile of the quantity distribution). When using uncapped quantity as the dependent variable we obtain a point estimate (standard error) of 1.503 (1.043). The quantity outliers lead to a drastic increase in the standard error relative to the result in column (3), although the point estimate is similar.

product. To provide further support for the increase in variety being the primary driver of the advertising effect, we proceed to decompose the quantity increase documented in column (3) into purchase quantity that originates from single product purchases and quantity purchased that originate from multi-unit purchases. Results from those "split-regressions" are reported in columns (4) and (5), which show that the effect of advertising is entirely driven by an increase in multi-unit purchases whereas the number of single unit purchases is unaffected.

One explanation for the patterns documented above is that consumers are very habitual in terms of their shopping paths and feature advertising is hence not capable of altering traffic patterns. Instead, consumers might be aware of a featured item (from seeing the advertising before entering store) when walking through an aisle they would have passed through anyway. The awareness of the feature might thus make them more likely to purchase without altering their shopping path. Such a mechanism through which feature advertising works is in line with the memory and fluency theory extensively studies in the literature. It suggests that, after a consumer being exposed to some earlier advertisement, the implicit memory of the consumer about the product will boost the likelihood of purchase at a later time, even without her consciously memorizing the details about the ads (e.g., Keller (1987), Lee (2002), and Angela Y. Lee (2004)).

4 Identification and Robustness Checks

We do not have access to random variation in advertising[18] and thus the identification of the impact of feature advertising on traffic, sales and other outcomes relies on variation in marketing activity within categories over time. This leaves two possible factors that cause bias in our estimates. First, different forms of marketing activity might be correlated over time and second, advertising could be correlated with time-varying demand shocks (e.g. turkey is more likely to be advertised around Thanksgiving).

A priori, we think both issues are unlikely to be a concern in our setting. We control for other marketing activity in all of our regressions. Furthermore, our data covers only a short time window and does not contain major holidays or other special events and hence the scope for demand fluctuations over time is limited. Finally, both possible confounds would tend to overstate sales effects because advertising is most likely positively correlated with demand shocks and other marketing activity. It is however less clear how either of the two channels can spuriously generate a null effect on category traffic and a positive effect on sales. Nevertheless, we turn to further investigate both issues in a battery of robustness checks below.

4.1 Time-Varying Demand Shocks

One possible issue in our context could be the fact that within categories, demand varies over time in a way that is correlated with the intensity of feature advertising. In order to control

[18] Although randomized field experiments have gained in prominence, they are mostly confined to online markets. To the best of our knowledge, no advertising experiment has been implemented in a brick-and-mortar setting like ours.

for such demand shocks in a flexible way, we would ideally want to include category/time-period specific dummies in the regression. However, the unit of observation in our data is a category/day combination and hence we are not able to control for demand fluctuations at such a granular level.

To circumvent this shortcoming of our main data-set, we use additional data for multiple stores from the IRI data (for the same set of categories and over the same time period). The advantage of the IRI data lies in the fact that we have sales and marketing information for a large set of stores (rather than just the one store used in the main regressions)[19]. This allows us to control for marketing activity, while at the same time being able to back out category-specific time-trends that are common across store. Specifically, we run the following regression, which bears similarity to our baseline regression framework:

$$Sales_{jct} = \alpha \times FeatureNum_{jct} + X'_{jct}\beta + \xi_{ct} + \varepsilon_{cjt}$$

where j denotes a specific store, c denotes the category and t denotes a week (IRI reports data at the weekly, rather than daily level). $Sales_{jct}$, $FeatureNum_{jct}$ and X_{jct} are defined as before, but are store-specific now. X_{jct} contains the number of promoted products, average price and the number of products on display.[20] Due to the fact we have jct-level data, we can allow for category-week specific demand shocks ξ_{ct}. Having recovered those demand shocks from the IRI data, we then include the fitted values of demand shocks $\hat{\xi}_{ct}$ into our baseline regression for the focal store.[21]

We report results with the demand shock as additional control variable for both the traffic and the sales regressions in columns (3) and (4) of Table 4 which replicate column (1) of Table 2 and column (3) of Table 3 respectively. For easier comparison we also provide these baseline results for the impact on traffic and in sales in column (1) and (2) of Table 4. The impact on the feature advertising coefficient across in both regressions is minimal and the null result for traffic as well as the positive and significant effect on sales are robust to the inclusion of this additional variable. Furthermore, the market-level demand shocks are positive, but statistically insignificant. We note that, despite the insignificance, the sales regression coefficient on the demand shock is not significantly different from 1, which is the value we would expect to see if our focal store is subject to the same common demand fluctuations as the other stores used to impute the demand shocks.[22] While we only report one traffic and sales-based regression respectively, results are similar when controlling for demand shocks using any of the other specifications reported in Tables 2 and 3.

This robustness check deals with the issue of time-varying demand shocks as long as those shocks are common across stores, such as high demand for turkey at thanksgiving. While we think this is

[19] We re-iterate that the main regressions are based on data from only one store because the path-tracking data was only collected for one store.

[20] We note that in our main data, the display information is noisy, because we infer it from other stores of the same chain. This is not the case here, the IRI dataset contains the exact display information for the stores used in this regression.

[21] We use only a subset of comparable stores from IRI. Specifically, we select all stores in California that belong to one of four major chains. Our focal store is also located in the same geographical area and belong to one of the four chains.

[22] Because the across-store regression is estimated at the weekly level, we divide the demand shock values by 7 in order to make them comparable to the daily sales values used in the baseline regression.

likely to be a reasonable assumption, this robustness test is not able to deal with store/category-specific demand shock. The fact that we use IRI data from similar stores in the same geographical market lends further support to the assumption of common demand patterns.

4.2 Correlation in Marketing Activity

A second issue could arise from a correlation of feature advertising with other marketing activity, namely price promotions and product displays. We note that we control for both price and displays in our main regression and in terms of price controls include both the average category price level and the number of promoted items as control variables. As a first additional test, we more rigorously control for other marketing activity in a non-linear fashion. Specifically, we include second- and third-order for all three marketing control variables. Doing so, we find that the coefficient on the number of featured items remain insignificant in the traffic regression and significant and positive in the sales regressions. For instance, when regression total category quantity on feature advertising and controls, we find a coefficient (standard error) of 3.23 (1.19) when including higher order controls versus 3.56 (1.54) in the corresponding main regression (see column (3) of Table 3).

The most problematic element regarding our attempt to control for other marketing activity is the display variable. As mentioned in Section 2.2, we do not observe display information for the focal store. We therefore approximate display information by calculating the weekly fraction of stores that display a specific product in stores of the same chain in the same local market (Northern California). The product-specific fraction of displays is then added up across products within a category to yield the number-of-displayed-products proxy-variable for each category. This is a somewhat crude proxy for displays and we hence run a set of robustness checks here.

First, to assess the possible impact of correlated displays on our estimates, it is useful to consider a few basic descriptive statistics on the usage of displays. Among all three observed marketing activities, i.e. promotions, feature advertising and displays, the latter is the least frequently used. Across all products used in the IRI sample in the previous section, the fraction of product/week combinations during which each marketing tool is used is as follows: promotions (40%), feature ads (16%), displays (8%). Furthermore, the correlation between the different marketing tools is not particularly high. The correlation of feature ads and displays is equal to 0.15 and only 0.10 after controlling for category fixed effects.[23] Therefore, the potential for display mis-measurement to bias our estimated effect of feature advertising onto sales and traffic is not particularly large.

Nevertheless, we implement a set of additional regressions to assess possible effects from the imperfect display control variable on our regressions. One thing to note is that the impact of displays onto the traffic and sales regression might be different. In case of the sales regression, one might worry that when controlling imperfectly for displays, the effect of features might be overestimated. In the case of the traffic regression, the direction of the bias is less clear. It is conceivable that displays occur in other parts of the stores rather than the typical location of

[23] To control for category fixed effects, we regress feature and display dummies respectively onto category fixed effects and then analyze the correlation between the residuals from both regressions.

the category. End-of-aisle displays are the most prominent example of this. Therefore, we might record fewer consumers walking past a specific category because they are able to pick the product up elsewhere. This specific mechanism could therefore lead to a bias towards zero in the traffic regression and an upward bias in the sales regression. We implement two tests below to address this issue.

First, we note that the sales variable used in our estimation is based on product "pick-ups" that are recorded in the path-tracking data. In other words, we are only recording the sale of a product if the product appears in the consumer's checkout basket *and* the consumer walked through the aisle where the product is stocked. Therefore, if displays divert consumers away from aisles, because consumers pick up the product elsewhere, this should bias both the traffic and sales results towards zero. Hence the divergence of traffic and sales effects cannot originate from this mechanism.

We nevertheless further probe our data to test whether displays do led to more purchases from temporary locations rather than the main category locations. We can implement such a test by computing for each category/day-pair the number of purchased products (from the checkout data) as well as the number of items picked up from the main category locations. The latter is obtained from the path-data and requires the consumer to visit the category. If displays divert traffic and sales from the typical category locations, we would expect the number of purchases relative to pickups to increase as a function of displays. We test this by regressing the ratio of purchases to pickups onto features, displays and other control variables (following the specification used in our baseline regression). We run this regression using the ratio of both primary location and all location pick-ups relative to total purchases. We find that in both cases the display proxy variable (not reported in the table) has no significant effect on the purchase ratio and the feature advertising (which might be correlated with unobserved display variation) has a positive and marginally significant effect in one of the two specification. However, the significant effect is small in magnitude and the sign effect is positive, i.e. features led to more pick-ups relative to total purchases, whereas the display correlation would imply a negative effect. Hence these regressions provide evidence against displays diverting traffic away from permanent locations. If anything, it seems that displays lead to more pick-ups relative to total purchases, which might be due to the majority of displays being located close to the category's permanent location (i.e. within the same aisle). However, the magnitude of the effect is quite small.[24]

In a second test, we confine our analysis to perishable products, which cannot be moved to different locations such as end-of-aisle placements due to the need for these products to be stored in refrigerators. We re-run the main traffic and sales regressions based on the 6 categories containing perishable products only[25] and find that the results are robust to using this sub-sample of categories. Results for both traffic and sales regressions are reported in columns (5) and (6) of Table 4. As for the previous robustness checks, we only report one traffic and sales-based regression respectively.

[24]The standard deviation of the pick-up/purchase ratio (based on all locations) is 0.524 and hence a one standard deviation shift in the number of features (8 additional products), leads to an increase of 4 percent of a standard deviation (0.003*8/0.524).

[25]The 6 perishable categories are frozen entrees, frozen pizza, milk, yogurt, butter / margarine and hot dogs.

	Baseline		*Demand Shock Control*		*Only Perishable Categories*		*Pickup/Purchase Ratio*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	# Category Visits	Quantity Purchased	# Category Visits	Quantity Purchased	# Category Visits	Quantity Purchased	Pickup to Purchase Ratio (Prim. Loc.)	Pickup to Purchase Ratio (All Loc.)
Category Visit Definition	All Locations $\geq$3 Traffic Points Visited	n/a	All Locations $\geq$3 Traffic Points Visited	n/a	All Locations $\geq$3 Traffic Points Visited	n/a	n/a	n/a
# Features	0.631	3.562**	0.965	3.718**	-0.998	5.255***	0.001	0.003**
	(1.654)	(1.544)	(1.594)	(1.415)	(1.261)	(1.044)	(0.002)	(0.001)
Imputed Demand Shock			1.106	0.517				
			(0.694)	(0.544)				
Category FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Marketing Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	546	546	546	546	156	156	546	546
Categories	21	21	21	21	6	6	21	21
Days	26	26	26	26	26	26	26	26

Table 4: **Robustness Checks.**

However, results are similar when controlling for demand shocks using any of the other specifications reported in Tables 2 and 3. Taken together the set of tests described above helps us rule out any bias in our estimates stemming from imprecise measurement of product displays.

5 Spillover Effects

We next explore two different types of spillovers that feature advertising can potentially generate. First, we explore whether categories that are stocked nearby featured categories are affected by advertising in the focal category. This analysis makes use of the detailed information on product locations within the store that we have access to. To the best of our knowledge such "micro-geographic" spillovers within a store have not previously been explored because data on store layout and product locations has not typically been available to researchers. Second, to further explore the impact of feature advertising for a specific product on the category as a whole, we explore whether advertising leads to category expansion, brand substitution or potentially even positive spillover effects between products. We first turn to spillovers between categories which are stocked close to each other.

5.1 Cross-Category Spillovers

Two unique aspects of our data are that we observe both consumers' movement through the store and product locations. In this section, we leverage the second part of the data in order to explore whether feature advertising has any effect beyond the focal category and specifically, whether nearby categories are positively or negatively affected by feature advertising. Based on our previous finding that the number of consumers visiting a specific category is not affected by advertising, we conjecture that a spillover effect onto adjacent categories not likely to occur. However, it is conceivable that the change in purchase behavior that we do measure within the category does alter behavior on the remainder of the consumer's trip and hence nearby categories could be affected. We therefore proceed to investigate cross-category spillovers empirically.

Our analysis proceeds in a similar fashion as the analysis of sales within the category (see equation 2), but for the fact that we substitute sales of nearby products for sales within the category as the dependent variable. Apart from the change in the dependent variable, we employ the same regression framework as earlier and control for category and day fixed effect and a set of marketing controls. In order to define which product are stocked nearby the set of 21 categories for which we observe advertising, we first find all locations at which products of a particular category are stocked. Based on these set of coordinates for each category, we then find all *other* product locations that are within a certain distance of any product point belonging to the category.

Our baseline specification uses all category locations and defines vicinity as a 15 feet radius around each product location. In other words, for say the beer category, we find all locations at which beer is stocked and then draw a 15 feet radius around each location and find all possible locations within this radius at which other products might be stocked. We note that we make sure

	Cross-Category Spillovers			*Within-Category Spillovers*	
	(1)	(2)	(3)	(4)	(5)
Dependent Variable	# Purchases	# Purchases	# Purchases	# Purchases	# Purchases
Definition of Nearby Products	≤15 Feet All Loc.	≤10 Feet All Loc.	≤10 Feet Primary Loc.	n/a	n/a
Mean	1407	676	203	1.99	1.99
S.D.	1125	592	137	6.11	6.11
# Features	-2.800	-1.200	-0.467		
	(1.732)	(1.191)	(0.596)		
Feature Dummy				0.502***	0.421***
				(0.148)	(0.144)
Fraction of Other Products Featured					0.933**
					(0.446)
Category FEs	Yes	Yes	Yes	No	No
Product FEs	No	No	No	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes
Marketing Controls	Yes	Yes	Yes	Yes	Yes
Observations	546	546	546	31,200	31,200
Products	n/a	n/a	n/a	1,200	1,200
Categories	21	21	21	21	21
Days	26	26	26	26	26

Table 5: **Spillover Effects Across and Within Categories.**

that vicinity is only defined in open spaces of the store, i.e. we do not consider adjacent aisles within 15 feet as nearby locations because these are separated by a wall. Having defined nearby locations, we find all products that are stocked at these locations and compute the cumulative daily sales volume across all products. We hence end up with a count of sales of nearby products at the daily level for all 21 categories.

The results using the baseline definition are reported in column (1) of Table 5. We find a negative, but insignificant effect which is consistent with our prior that cross-category spillover effects are unlikely to occur. Evaluated at the point estimate, the estimated effect corresponds to a 1.6 percent decrease in sales and the 95 percent confidence intervals ranges from a 3.5 percent decrease to a 0.3 percent increase. We note that relative to the traffic regressions, our estimates our somewhat noisier. Nevertheless, the range of effect within the confidence interval are economically relatively small and we can rule out large positive effects.

We also probe the robustness of our results to alternative definitions of nearby categories. We first narrow the radius to 10 feet and then also employ a definition that is based only on the primary locations of each category rather than all product locations (again using a 10 feet radius). Results from both specifications are reported in columns (2) and (3) of Table 5 and show negative and insignificant effects. Finally, we also run a set of regressions that distinguish nearby products by their relationship with the focal category. Specifically, we divide nearby products into substitutes, complements and unrelated products and run regressions separately for each type. Consistently across all three product types, we find small, negative and insignificant effects.[26]

In summary our results show that, if anything, there are small negative spillover effect and feature advertising in a given category causes lower sales in nearby categories.[27] The effects are however statistically insignificant and economically small relative to the effect on sales within the focal category. We hence conclude that advertising decisions for individual categories can be taken in isolation without a need to coordinate such decisions across categories.

5.2 Within-Category Spillovers

We next proceed to analyze the response to feature advertising at the individual product level. We have already seen that features lead to higher sales at the category level in Table 3. However, the impact of features on purchases of individual products could be larger, because part of the increase in product sales might be due to consumers substituting away from competitor products in the same category. Or inversely, advertising might lead to spillover effects onto other products within the category that are not themselves advertised.

In order to capture both category expansion as well as brand substitution and spillover effects within one unified regression framework, we propose the following linear regression equation

$$Sales_{jt} = \alpha_1 Feature_{jt} + \alpha_2 \frac{Feature_{-jt}}{N_{c_j} - 1} + Z'_{jt}\beta + \gamma_j + \vartheta_t + e_{jt}, \tag{3}$$

where $Feature_{jt}$ is a dummy variable which is equal to one if product j is featured on day t. $Feature_{-jt}$ denotes the number of products featured in category c_j that product j belongs to, but excludes product j itself. The variable therefore represents the number of *other* products featured in the same category. Dividing by $(N_{c_j} - 1)$, the number of other products in the category, yields the fraction of other products featured. Z'_{jt} denotes other marketing controls and contains the same variables as previous regressions, but all includes an analogue to the $Feature_{-jt}/(N_{c_j} - 1)$ term for each of the marketing variables. γ_j and ϑ_t denote product and day fixed effects and e_{jt} is the error term. Standard errors are clustered at the product level.

To see why the formulation above is useful for analyzing brand substitution, spillover and category expansion effects, consider the predicted change in sales when product j is featured. At

[26] We also note that the majority of nearby products belongs to unrelated categories (88 percent) and only a small subset of products are either substitutes or complements of the focal category.

[27] While previous literature has proposed that price promotion may be used as "loss leader" to boost overall store sales (e.g., Rajiv Lal (1994)), the empirical evidence is mixed. Some studies support the "loss-leader" model (e.g., Chevalier et al. (2003)), others show otherwise (e.g., Nevo and Hatzitaskos (2006) and Bayot and Caminade (2015)). Our finding cannot confirm the loss-leader model, at least it shows that for the promotion at a focal category does not spread out to others.

the individual product level, the change in sales is given by

$$E(\triangle Sales_{jt}|\triangle Feature_{jt} = 1) = \alpha_1.$$

We can similarly compute the predicted change for other products in the same category. For any competitor product in the same category, $Feature_{-jt}$ increases by one unit and hence the predicted change is equal to $\alpha_2/(N_{c_j} - 1)$. Because there are $(N_{c_j} - 1)$ other products, the predicted change aggregated to the category-level is given by

$$E(\sum_{k \in c_j} \triangle Sales_{kt}|\triangle Feature_{jt} = 1) = \alpha_1 + (N_{c_j} - 1)\frac{\alpha_2}{(N_{c_j} - 1)} = \alpha_1 + \alpha_2.$$

In terms of magnitude, we would expect $\alpha_2 \geq -\alpha_1$. In the case of $\alpha_2 = -\alpha_1$, there is no category expansion effect and the increase in sales for any product is generated entirely from substitution away from other products in the same category. If $\alpha_2 = 0$, there is no brand substitution and the entire increase in product-level sales translates into the category growing by the same amount. Finally, the case of $\alpha_2 > 0$ represents a positive spillover effect and hence the category-level increase is larger than the product-level effect and advertising helps boost sales even for non-advertised products.

We present results from the regression outlined above in Table 5. For ease of exposition, we first present results from a regression that omits the variable capturing advertising of other products within the same category in column (4). Unsurprisingly, we find that feature advertising has a positive effect on product-level sales. In column (5) of Table 5, we report results for the full specification outlined above. We find that both the coefficient on the feature dummy as well as the coefficient on the fraction of other products featured are positive and statistically significant. Furthermore, although less precisely estimated, α_2 is roughly twice as large as the own-advertising effect represented by α_1, suggesting that there are substantial spillover effects within the category.

6 Additional Results

Before proceeding to the analysis of the underlying mechanism, we provide additional results on two further outcomes. First, we investigate the impact of advertising on the timing of category visits and second, we analyze whether the amount of time spent in front of the category is influenced by advertising. Both outcomes have not previously been observable, but can be tracked here based on the path-tracking data. Both aspects allows us to paint a more complete picture of the impact of advertising and the findings will turn out to be useful when we analyze the possible channels through which advertising can affect consumer behavior along the conversion funnel. We present a more detailed analysis with regards to both issues in Sections B and 123 of the appendix and provide only a summary of the key results here.

We first turn to the timing of category visit. One possible impact that feature advertising might have, is to make the consumer visit a particular category earlier. This type of effect seems likely if the featured product becomes part of the consumer's set of planned purchases on the specific trip and those planned purchases happen earlier on the trip. In order to systematically explore the timing of category visits, we compute for each shopping trip, the point in time at which the consumer is for the first time walking past a specific product category. We then regress the average time since the start of the trip at which a specific category was visited on the number of featured products in a particular category (as well as the usual set of control variables). We implement this analysis using time elapsed before visiting the category, as well as the fraction of fraction of shopping time elapsed and find the advertising has a small and insignificant effect. This precise null results is robust to measuring visit to primary versus all locations as well measuring visit timing only for consumer that purchased in the category. We hence conclude that feature advertising does not impact when consumers visit a specific category, which provides some evidence against advertising leading to categories being "top-of-mind" (possibly due to the consumer explicitly noting specific products on her shopping list) and therefore being visited earlier.

Second, we ...

7 Analysis of Mechanism: A Simple Model of Advertising Impact

In this section we outline a simple model outlining the possible channels through which advertising could conceivably influence category traffic, category purchase, and individual product purchases (as well as other outcomes that we measured earlier in the paper). Our analysis captures some elements commonly used in models of advertising impact such as a distinction between impact of advertising on the specific product being advertised versus the category it belongs to. However, we amend our model framework in two ways. First, we consider the possibility for advertising to either change consumers' purchase intentions directly (for instance because the consumer puts the advertised product on her shopping list) or by building memory regarding the advertised product. The distinguishing feature between the two is the fact that memory can only be retrieved by the consumer through some external stimulus that reminds the consumer of the ad.

Importantly, when thinking about the impact of advertising exposure in the case of feature advertising, we need to consider the fact that reading a feature advertising leaflet is a very conscious choice and hence certain types of consumer will select into reading feature advertising. We capture this idea by allowing the exposure of consumer i to an ad for product j to be determined by the following expression:

$$AdExp_{ij} = \alpha_0 + \alpha_1 CatIntent_{ic,t-1} + \alpha_2 ProductIntent_{ij,t-1} + \varepsilon_{ij}^{Ad}$$

Where $AdExp_{ij}$ denotes whether the consumer saw the ad for product j. $CatIntent_{ic,t-1}$ denotes the consumer intention to purchase in the specific category c that product j belongs to, which arises from consumption needs such as having run out of detergent. $ProductIntent_{ij,t-1}$ denotes the purchase intention for a specific product and ε_{ij}^{Ad} is a residual term that captures all other reasons for a consumer to become exposed to the ad. Note that we use a $(t-1)$ subscript on the two purchase intention variables, to denote that these variables refer to the consumer pre-ad-exposure, and the purchase intention might change due to the advertising.

To capture the impact of advertising on consumer choices such as traffic and purchases, we first consider a set of intermediate measure that are influenced by advertising. First, advertising might influence the consumer's purchase intention at the category or product level. I.e. after seeing the ad, the consumer might make a mental note to purchase from the specific category or even a specific product that was advertised. We denote purchase intent after ad exposure by $CatIntent_{ij}$ and $ProductIntent_{ij}$ (note that the $(t-1)$ subscript is dropped here). Furthermore, we consider the possibility that the ad registers with the consumer without her taking an immediate and conscious action. We denote such a memory effect at the category- and product-level respectively as $CatMemory_{ij}$ and $ProductMemory_{ij}$.

Finally, we relate the four measures (where applicable) to the three stages of the conversion funnel we observe: category visit ($Visit_{ic}$), category purchase incidence ($Purchase_{ic}$) and product choice ($Purchase_{ij}$).

$$\begin{aligned}
Visit_{ic} &= \beta_0 + \beta_1 CatIntent_{ic} + \beta_2 CatMemory_{ic} + \varepsilon_{ic}^{Visit} \\
Purchase_{ic}|Visit_{ic} &= \gamma_0 + \gamma_1 CatIntent_{ic} + \gamma_2 CatMemory_{ic} + \varepsilon_{ic}^{Purchase} \\
Purchase_{ij}|Purchase_{ic} &= \delta_0 + \delta_1 CatIntent_{ic} + \delta_2 ProductIntent_{ij} + \\
&\quad + \delta_3 CatMemory_{ic} + \delta_4 ProductMemory_{ij} + \varepsilon_{ij}^{Visit}
\end{aligned}$$

The error terms in each line capture all other factors predicting the respective action, all other terms were defined above.

We can now relate the expressions above to the effects (or absence of effects) documents earlier in the paper. First, we find that neither the number of consumer visiting the category or purchasing in the category changes as a function of advertising, or formally (for the case of category visits):

$$\beta_1 \frac{\partial CatIntent_{ic}}{\partial AdExp_{ic}} + \beta_2 \frac{\partial MemoryIntent_{ic}}{\partial AdExp_{ic}} = 0$$

It seems plausible that $\beta_1 > 0$ because consumer needing to buy a specific category will be more likely to visit it. And hence it follows that advertising exposure does not affect purchase intent at the category level, i.e. $\partial CatIntent_{ic} / \partial AdExp_{ic} = 0$. The case is less clear for the memory effect. It could be the case that the derivative of memory with respect to advertising is zero or alternatively, it could be the case that memory is built, but not retrieved when entering the store and deciding which categories to visit, i.e., $\beta_2 = 0$.[28]

A similar reasoning applies to the case of category purchase incidence. It seems likely that $\gamma_1 > 0$ and hence this provides another piece of evidence that category purchase intentions are not altered by advertising. Again, the case for the memory effect is less clear. When visiting

[28]We note that it is unlikely that any of the four terms in the equation are negative and hence both terms of the sum need be equal to zero.

the category it is possible that memory of the ad exposure is triggered. Hence the null effect is consistent with either no impact of advertising on memory or no memory retrieval when walking past the category.

Finally, with regards to the individual product-level regressions we find that both advertised products as well as non-advertised products in the same category benefit from advertising and therefore:

$$\frac{\partial Purchase_{ij}}{\partial AdExp_{ij}} > 0\,, \quad \frac{\partial Purchase_{i,-j}}{\partial AdExp_{ij}} > 0$$

where the second expression denotes the spillover onto other products in the category. Inspecting the third equation above (and taking as given that advertising does not impact category purchase intention), the effect on advertised products could originate from purchase intent regarding the product (holding constant category purchase intent). I.e. the consumer already wanted to purchase in the category and the ad led him to switch a product he would purchased in the absence of the ad to the advertised product. Alternatively the effect could be explained by a memory effect at either the product or category level. I.e. when engaging with the category, the consumer is reminded of seeing an ad for the category / the specific product and that leads her to purchase the advertised product.

A crucial piece is the fact that non-advertised products also benefit. If all the effect was coming from product specific constructs, then we would expect to see substitution between brands and hence non-advertised product would experience a decrease in sales. Hence, the source of the spillover has to originate from the category-level memory effect, i.e. the consumer is reminded of advertising for the category (rather than just the specific product) and this leads to more purchases even for non-advertised products. We cannot rule out that there are product-specific effects, either through memory or purchase extent, but in terms of driving sales of non-advertised product the category-level memory seems to dominate the possible sales decrease from product-specific substitution effects.

Two key findings emerge from the analysis based on this simple framework. First, we are able to establish that the intention to purchase in the category is not influenced by advertising. This could be partly explained by the fact that consumer that pay attention to feature advertising in a specific category do so because they are already planning to purchase in the category and hence $CatIntent_{ic}$ does not increase relative to its pre-exposure state $CatIntent_{ic,t-1}$. A further piece of evidence in support of this is the fact that one might expect a category with higher purchase intent to be visited earlier in the trip. We do find this not to be the case as demonstrated in Section 123. Second, we find support for the notion that advertising builds memory that is (at least partly) specific to the entire category rather than the individual product. The main piece of evidence in this regard is the presence of spillover effects within categories. Interestingly, we see no increase in the number of consumers purchasing in the category and hence it appears that the memory effect is not triggered when walking past the category, but only when engaging with the category. Specifically, consumer that do decide to buy in the category when the category is advertised more strongly tend to purchase larger quantities of products.

Our conclusions with regards to memory or purchase intention effects that are specific to individual products are less clear-cut. We cannot rule out the presence of such effects which increase sales of advertised products at the expense of other products in the category. However, the fact that advertising leads to higher sales for non-advertised products within the same category shows that the memory effect at the category level outweighs any potential product substitution effects. Overall, we see the patterns in our data as evidence for more subtle advertising effects that are triggered. by repeated exposures and engagement with product-related advertising or the products themselves. We also note that there is some parallel to our findings in the findings on online advertising. For instance 123 and 123 find that advertising increases product sales, however frequently consumers that eventually purchase the product do not immediately click on the ad when it is delivered, but rather they arrive later at the seller's webpage and purchase. Similarly in our setting, consumer do not directly appear to take any action to purchase the advertised product, but exposed consumer are more likely to eventually convert when arriving at the shelf for other reasons.

8 Conclusion

In this paper, we leveraged a new data set that combines advertising information with path-tracking data of consumers' movements in a brick-and-mortar store. We use this unique data set to shed light on different steps in the conversion process that had typically been unobserved. While advertising does have a significant impact on total quantity sold, we find advertising to be entirely ineffective at various stages of the process. Neither does it impact traffic patterns, nor does it convert a higher number of consumer to buying in the category. Instead, the overall advertising effect is mostly driven by consumers purchasing more variety within the category.

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A Appendix: Linking Sales and Path Data

One of the important features of our data set is the linkage of sales to trip records. As part of the RFID tracking process, the data report when the consumer arrives at the checkout. Independently, the sales data also have a time stamp for each shopper's transaction at the checkout. Comparing the time stamp of a particular path with the sales data allows us to define a set of "candidate" checkout product baskets that occurred at a similar point in time.[29] Matching which trip goes with which specific transaction involves considering the physical location (i.e., longitude = x and latitude = y relative to the store map) of all the UPCs in each candidate basket. Based on how many of those locations lay on the path we are trying to match, a score is created for the baskets and the highest-scoring one is matched to the path.[30] The matches do not necessarily yield a perfect score, because consumers might occasionally leave the cart and pick up an item. Therefore, we might not see the path of the consumer going past a specific item, even if the item was in her matched purchase basket. In this case, no information on search time will be available for the particular item.

B The Impact of Feature Advertising on Visit Timing

Having established that the fraction of consumers visiting a particular category is not influenced by feature advertising in Section 3.1, we further explore whether advertising alters the consumer's path through the store in more subtle ways. One possible impact that feature advertising might have, is to make the consumer visit a particular category earlier. This type of effect seems likely if the featured product becomes part of the consumer's set of planned purchases on the specific trip and those planned purchases happen earlier on the trip.

In order to systematically explore the timing of category visits, we compute for each shopping trip, the point in time at which the consumer is for the first time walking past a specific product category. We then compute the average time since the start of the trip at which a specific category was visited at the day/category level.[31] We first regress the time of the visit (measured in minutes since the start of the trip) and fraction of total shopping time elapsed on the number of featured products in a particular category. Both regressions include category and day fixed effects and marketing controls and hence mirror the traffic regression in equation (1).

[29] The path data time stamp that records the arrival at the checkout can be noisy because the consumer will be stationary when standing in line at the cashier. Therefore, checkout baskets within a certain time window after the consumer became stationary in the check-out area qualify as possible matches.

[30] The data provider did not disclose the precise algorithm to us.

[31] We can only define visit timing for consumers that actually pass the category at all during their trip. The day/category average therefore represent the average visit time for the subset of consumers that visit the specific category.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Minutes Elapsed Since Start of the Trip	Fraction of Time Elapsed (0 to 100)	Minutes Elapsed Since Start of the Trip	Fraction of Time Elapsed (0 to 100)	Minutes Elapsed Since Start of the Trip	Fraction of Time Elapsed (0 to 100)
Variable Definition	All Locations	All Locations	Primary Location	Primary Location	Conditional on Purchase	Conditional on Purchase
# Features	0.002 (0.002)	0.006 (0.005)	0.005 (0.003)	0.010* (0.006)	-0.014 (0.017)	0.030 (0.057)
Category FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Marketing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	546	546	546	546	546	546
Categories	21	21	21	21	21	21
Days	26	26	26	26	26	26

Table 6: **The Impact of Advertising on Visit Timing.**

We start by implementing the analysis based on all product locations for each category. In other words we define visit timing as the point in time at which a consumer first passes any location in the store associated with the particular category. The results using both minutes elapsed and fraction of shopping time elapsed are reported in columns (1) and (2) of Table 6. Columns (3) and (4) replicate the same regressions, but base the visit timing only on the primary locations of each category. Across all four specifications, we find effects of feature advertising that are consistently small in magnitude and mostly insignificant. Take for example the results in column (1). According to the (insignificant) point estimates, a one standard deviation increase in the number of features (8 additional features) in a particular category delays the visit to the category by 0.016 minutes (i.e. about 4 seconds) or shifts the visit timing back by 0.05 percentage points relative to the total duration spent in the store.[32] Even the marginally significant effect in column (4), although statistically different from zero, is still similarly small in magnitude and does not constitute an economically meaningful shift in the timing of the category visit.

Finally, it is possible that advertising only affects a small set of consumers who are planning to purchase within the category due to the feature ad. When analyzing the visit timing of all consumers in the store, a significant effect on this small group of consumers might be masked by the unaltered behavior of the majority of visitors to the store. We hence isolate the group of consumer which are most likely to be affected and compute the average time of a category visit

[32]We also ran the same set of regression based on distance walked before reaching a specific category (rather than time elapsed) and found similarly small and insignificant results.

(on each day) based only on consumers that are observed to purchase in the specific category. The results from regressions based on this measure of visit timing are reported in columns (5) and (6) of Table 6. Even though the estimates are slightly noisier than the specifications presented in the first four columns, we again find a null effect of feature advertising on visit timing and the confidence intervals do not contain effect sizes that are economically meaningful.[33]

We hence conclude that feature advertising does not impact when consumers visit a specific category. Together with the previously established fact that the number of consumers visiting a particular category is not affected by feature advertising, this establishes that consumers' path are relatively rigid in the sense that feature advertising does not attract more consumers to the category location nor does it alter the timing of the visit.

[33]The confidence interval for columns (5) and (6) respectively are equal to [-0.050,0.021] minutes and [-0.089,0.149] percentage points.