Manufacturer Advertising and Retail Prices: An Empirical Investigation*

Current version: June 2017

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Abstract

How do retail prices respond to manufacturer advertising? We use over two years of weekly data for 286 products across eleven product categories to show that retail prices change over and above what is expected after accounting for changes in wholesale prices. This suggests that retailers may behave in a strategic fashion and take advantage of the increased consumer pull when a brand is being advertised. We estimate advertising effects on retail prices that are of sizable magnitude and that vary considerably across products and categories. We propose a number of product and category characteristics that may help explain the way retailers adjust prices in the presence of manufacturer advertising and explore their impact in our data.

Keywords: retailing, advertising, channel coordination

*We are grateful to Frederico Belo, Els Breugelmans, Uli Doraszelski, Elisabeth Honka, Sanjog Misra, Koen Pauwels, and Raphael Thomadsen for their helpful comments and suggestions. We also thank the participants of the 2015 UT Dallas FORMS conference, and seminar participants at ESMT, the University of Frankfurt, Özyeğin University, the University of Minnesota and KU Leuven for their valuable feedback. We specifically thank the discussant Linli Xu for her detailed comments on our paper. Marco Qin provided excellent research assistance. Maria Ana Vitorino gratefully acknowledges support from the Dean's Small Grants Program at the University of Minnesota Carlson School of Management. All errors are our own.

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1 Introduction

Manufacturers and retailers have diverging interests, which may lead to channel conflict and outcomes that are suboptimal. Issues such as the double marginalization problem and the pass-through of trade promotions have been studied extensively (e.g., Jeuland & Shugan 1983, Neslin, Powell & Stone 1995, Tyagi 1999, Moorthy 2005, Besanko, Dubé & Gupta 2005). Far less attention has been devoted to studying the extent to which retailers and manufacturers interests align when demand shifts due to manufacturer advertising. In particular, does advertising affect the way retailers set prices to consumers? And if yes, how? For example, as pointed out in early work by Steiner (1973), retailers may not necessarily want to take advantage of the decreased price sensitivity for a brand as a result of advertising and keep prices low to attract more store traffic. It is also conceivable though, that when there is increased consumer pull for a brand due to manufacturer advertising, the retailer could increase prices as consumers, once in the store, are likely to buy the product they came in for.

In general, the relationship between manufacturer advertising and retail prices is complex and hard to explain on theoretical grounds alone (Bagwell 2007). The relationship is also highly dependent on the specific market setting (Lal & Narasimhan 1996). Yet, because retail prices are the ultimate drivers of demand, understanding how they change during advertising campaigns is essential for accurate sales predictions and assessment of the impact of advertising. Ignoring the effect of advertising on retail prices is likely to lead to an inaccurate assessment of campaign effectiveness (Farris & Albion 1980, Albion & Farris 1987).

To address the question of whether and how retailers adjust prices in response to manufacturer advertising, we conduct a descriptive study across over 200 products in eleven product categories, encompassing both food and non-food items. Unlike previous work, which has only had access to cross-sectional data, i.e., covering a single time period, and has thus focused on comparisons across brands (Farris & Reibstein 1979, Reekie 1979, Albion & Farris 1987), we use a panel data set and can thus better account for the heterogeneity across products. Our approach allows us to get insights on how retailers price individual products over time depending on the level of advertising.

Manufacturers advertise in the hope of stimulating demand and set their prices to retailers, who in turn determine the prices that consumers face. Because manufacturers optimize pricing and advertising jointly (Dorfman & Steiner 1954), wholesale prices are likely to be different in periods when the brand is being advertised. Therefore, to isolate the effect of manufacturer advertising on retail prices and show that retailers price strategically and do not simply pass through the changes in wholesale prices, it is critical to account for the changes in wholesale prices. Fortunately, our data includes a measure of average acquisition cost, which has become an accepted measure of wholesale price (Besanko et al. 2005).[1]

In order to proceed with a minimum set of assumptions, we build on Besanko et al. (2005) and take a reduced-form approach that captures how retail prices depend on wholesale prices and advertising expenditures. Because economic models by their very nature cannot capture all the complexities of retail pricing, recently there has been a renewed interest in descriptive analyses to enrich our understanding of channel issues and specifically of the drivers of retail pricing decisions (Shankar & Bolton 2004, Nijs, Srinivasan & Pauwels 2007). An obvious downside of this approach is that the relationships revealed in the analysis cannot be interpreted in a causal way and thus used for counterfactual analyses.

To our knowledge, this is the first paper to examine empirically the relationship between manufacturer advertising and retail pricing of individual products and to describe the moderators of retailers' pricing response to advertising. There are three elements that make our study unique: (1) access to sales and advertising data across multiple brands and product categories; (2) ability to control for wholesale prices, and (3) panel nature of the data enabling us to consider heterogeneity across products.

We provide evidence that channel coordination issues extend beyond the domain of pricing and trade promotions. Our findings suggest that analyzing the effect of advertising on sales in the channel should also include the effect that advertising

[1] As we outline later in the paper, the measure we have access to encompasses not only wholesale prices but also trade promotions making it very complete.

has on retail prices in order to obtain a complete assessment of the impact of an advertising campaign on consumer demand. Specifically, our results indicate that retailers adjust product prices when the manufacturer advertises the brand over and above any changes in wholesale prices initiated by the manufacturer. There are differences both in the direction of the retail price adjustment and its magnitude across products and categories. We relate these differences to a set of situational factors related to the the market power of both manufactures and retailers and their bargaining position within the channel. In addition, we show that the estimates of wholesale price pass-through rates are also different when the effect of advertising is accounted for because retailers may change prices not only in response to wholesale price changes but also in response to advertising.

The remainder of the paper is organized as follows. In Section 2 we review the related literature and outline how we extend the existing body of knowledge. Sections 3 and 4 introduce the data and our empirical strategy. Section 5 presents the findings of the analysis and discusses the implications for managerial decision-making. Section 6 concludes with limitations and directions for future research.

2 Related Literature

There are two streams of literature on which we build: the theoretical and empirical work on retail pass-through and the research on the relationship between advertising and retail margins. Ours is the first paper to examine empirically the relationship between manufacturer advertising and retail pricing across a large number of products in a variety of categories and describe the determinants of retailers' pricing behavior in the presence of advertising.

A solid body of literature has investigated the relationship between manufacturer wholesale prices (including trade promotions) and retail prices. The central question in that literature is to what extent retailers support manufacturer efforts to stimulate demand by passing the discounts they receive onto the end consumers. Many manufacturers complain that retailers apply about half of the trade dollars to their bottom line rather than to provide lower prices to consumers, while retailers claim that they pass through a high percentage of the trade dollars they receive from manufacturers. Answering the question conclusively has proven rather elusive. Tyagi (2000) shows in a theoretical model that even for a single-product monopolist manufacturer that sells through a monopolist retailer, the pass-through rate depends on the specific properties of the demand function (for a more recent contribution see also Fabinger & Weyl 2013). It is therefore not surprising that applied work in this area offers a variety of theoretical predictions and empirical findings for own-brand and cross-brand pass-through rates (Besanko, Gupta & Jain 1998, Sudhir 2001, Shugan 2001, Moorthy 2005). Besanko et al. (2005) (see also McAlister 2007, Dubé & Gupta 2008) examine a large number of products across several categories and report own-brand pass-through rates of, on average, more than 60%, and cross-brand pass-through rates that are either positive or negative. Pauwels (2007) also finds pass-through rates ranging from 0 to 183 % along with significant cross-brand effects. In the most comprehensive study to date, Nijs, Misra, Anderson, Hansen & Krishnamurthi (2010) investigate how pass-through rates vary across more than 1000 retailers in over 30 states and relate the rates to measures of cost and competition. These authors also find great variability in the pass-through rates that cannot be explained by market structure. We contribute to this literature by showing that channel coordination issues extend beyond the classic retail pass-through and documenting how retailers adjust their prices in view of the changed demand due to manufacturer advertising.

Our research is also related to studies of the relationship between advertising and retail margins, which provide us with some intuition as to the expected effects. For example, it is argued that in the presence of manufacturer advertising, the role of the retailer as demand generator is diminished, and thus their margins suffer. That is, while manufacturers may raise wholesale prices when they advertise, retailers will not necessarily raise their prices (Albion & Farris 1987). Lal & Narasimhan (1996) explore theoretically the impact of manufacturer advertising on wholesale and retail margins. Formalizing an intuitive argument of Steiner (1973, 1978), they provide a set of conditions under which manufacturer advertising can decrease the retail margin while simultaneously increasing the wholesale margin. In this case, retailers earn lower margins on advertised products but higher margins on unadvertised products. We can thus expect to observe not only an effect of advertising on retail prices of the advertised brand but also on rival products. Using a structural model of the laundry market, Chan, Narasimhan & Yoon (2015) investigate how the presence of a strategic retailer affects advertising and pricing competition at the manufacturer level. They show that retailers mitigate pricing competition but intensify advertising competition between manufacturers and that - under the assumptions of their model - when manufacturers compete on advertising in addition to price, retail prices are lower but profits for all players are higher.

In another related paper, Sethuraman & Tellis (2002) examine the implications of information and differentiation theories of advertising on retail price promotions. Their model predicts that if advertising equals information (differentiation) and thus increases (decreases) the price sensitivity of consumers, then categories with higher advertising levels have larger (smaller) discounts than categories with lower advertising levels. Using a cross-section of categories, they find a positive relationship between category-wide aggregate advertising expenditures and the size and frequency of retail price discounts. The obvious difficulty for the empirical analysis is to control for the nature of advertising, which is inherently unobservable. Our empirical analysis does not require us to make any assumptions on the nature of advertising. It also relies entirely on time-series variation for a given product in a given category to identify the impact of manufacturer advertising on retail prices, thus precluding unobserved heterogeneity across brands from biasing the estimates.

3 Data and Variable Operationalization

Data sources. We merge two data sources – a store panel data set providing weekly UPC sales data and a data set with daily advertising expenditures. The sales data come from Dominick's Finer Foods (DFF), the second-largest supermarket chain in Chicago, and covers retail prices, wholesale prices, and promotional activities from 81 stores in 123 weeks. The advertising expenditures data comes from TNS.[2] There are seven different sources of advertising in the TNS data: cable TV, magazines, national newspapers, network TV, spot TV, Sunday magazine, and syndication. We use the total advertising expenditures from all sources and, if advertising expenditures are available at the sub-brand level, we aggregate up to the brand level. The total advertising spend includes both national and Chicago-DMA ads.

Level of analysis. Although the original data are available at the UPC level, analysis of UPC-level data is difficult: there is a large number of UPCs per brand and additionally, the advertising data is mostly available at the brand level. Aggregating the sales and price data all the way up to the brand level presents the challenge of possibly aggregating across UPCs that are uncorrelated in prices. We thus conduct the analysis at the product level, where products are defined by combining UPCs that have the same price level and a very high (larger than 0.85) correlation in their prices (for a similar approach, see e.g., Besanko et al. 2005).

Dominick's practices zone pricing, whereby everyday prices vary across stores in different zones. The data contain an index classifying the 81 stores into 15 pricing zones. Our analysis of the data indicated, consistent with previous research using this data set, that retail prices varied across stores in different zones within a week, while the variation in prices within each zone was very small (see e.g., Besanko et al. 2005). Wholesale prices are identical for all stores within a zone and week. Accordingly, we further aggregate observations across the stores within a pricing zone. Our unit of analysis is thus a product-zone-week.

Product categories and brands selection. There were 17 product categories for which we had both sales and advertising data. We dropped candy, cookies and crackers, because these are very fragmented categories and reliably matching products to the corresponding brands in the advertising data base was extremely hard. Three

[2]Now replaced by Kantar Media's Ad$pender database. Kantar tracks the number of advertisements and advertising expenditures in national media as well as both measures of advertising in local media at the Designated Media Area (DMA) level.

other categories, juices, soups and toothbrushes, were dropped because advertising data was missing for some of the major brands. The final data set includes eleven product categories: five food categories – carbonated soft drinks (CSD), ready-to-eat cereal, frozen dinners (specifically, the healthy/diet brands), oatmeal, and sports drinks; and six non-food categories – bathroom tissue, dish detergents (liquid), laundry detergents (liquid), paper towels,[3] softeners (liquid), and toothpaste. For each category, we include the top national brands (defined in terms of market share) and corresponding products, for which we have advertising data for a sufficient number of weeks. Further, we also include the Dominick's store brand as long as it has a market share greater than 1%. As can be seen from Table 1, the number of brands considered per category varies from three to six, and the number of products varies from seven in sports drinks to 66 in the very fragmented cereals category. Carbonated soft drinks is by far the largest category in terms of sales, followed by cereals and laundry detergent. The categories we consider also vary widely in the share of the store brand - from nonexistent in sports drinks and frozen dinners to 9% in oatmeal and 10% in softeners.

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Insert Table 1 about here

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Prices and advertising measures. Our focal measure, the retail price of a product in a given week and price zone, is constructed by aggregating across UPCs belonging to that product using UPC sales in each store and week as weights.

The DFF data is uniquely suited for our analysis, as it contains information about the profit margin on retail price for each UPC and week. This information is unusual to have together with scanner data and allows us to calculate the wholesale prices (in the same way as in Besanko et al. (2005)). Note that, because the wholesale prices are

[3] We focus on the 1-ct size, which is what consumers typically purchase at supermarket chains like Dominick's.

actually backed out by subtracting the retail margin from the retail price, this means that they effectively reflect the average acquisition cost of items in inventory, which takes into account not only the wholesale prices but also any allowances/payments that are given by the manufacturer to the retailer. This works in our favor because this way, we can focus on the effect of advertising on retail prices while controlling for both wholesale prices and any trade promotions (e.g., off-invoice deals, lump-sum payments) which can be substantial as discussed in Ailawadi & Harlam (2004).

Descriptive statistics of the variables at the brand level are shown in Table 2 for the brands in food categories, and in Table 3 for the brands in non-food categories.[4] In quite a few categories there is a dominant brand - Gatorade and Quaker command 80% and 64% share in sports drinks and oatmeal, respectively. Tide's share in laundry detergents and Bounty's in paper towels are more than three times the next largest rival. There are also a number of categories though with a more even split, such as bathroom tissue, cereals, and dish detergent.

Categories vary considerably in the amounts spent on advertising: cereals and carbonated soft drinks are the most advertised, frozen dinners and oatmeal are the least advertised. The variation across brands within a category is also sizable. Coke's ad spend is about five times that of 7-UP, a similar ratio is observed for Tide and All in laundry detergents. Quaker outspends Nabisco six to one in the oatmeal category. Interestingly, these differences in advertising expenditures are not perfectly correlated with either the brand shares or the retail prices. For example Quaker oatmeal is priced lower than Nabisco and Coke has a slightly lower share than Pepsi despite outspending its rival.

Categories and brands also differ greatly in the degree of promotional activity – carbonated soft drinks, sports drinks, and toothpaste are on promotion over 25% of the time on average, as opposed to cereals, dish detergent, and paper towels, which are rarely on sale.

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Insert Table 2 about here

[4]The split in two tables is done mainly for ease of presentation.

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Factors influencing the effect of advertising on retail prices. We relate the estimated advertising effects as specified in Section 4.1 to a number of product and category characteristics that have been established in the literature as influencing retailer pricing decisions. Table 4 presents descriptive statistics for these factors and outlines their operationalization.

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Insert Table 4 about here

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Brands vary greatly in terms of their share, as was noted above. Their positioning, as reflected in the price premium they command, also exhibits large variation. The price premium variable ranges from 0.68 to 1.60 (not tabulated), which means that some products are sold at much lower/higher prices than competitor products with the same size. Turning to product competition, we see that on average, there are about four competing national products in the same size, with no competition for 17 products, mainly in frozen dinners and oatmeal (but also toothpaste and cereals), and as many as 18 for three products in the highly competitive CSD category (not tabulated). The store brand has a strong presence overall – almost 50% of products compete directly with Dominick's own product. Although we have five food categories and six non-food ones, there are more products in the food categories, about 60% of the total. Category concentration and importance exhibit large variation as well, with category sales over the 123 weeks in the data ranging from 3.6 million dollars for sports drinks to 120 million dollars in CSD, and the share of the top two products in the category from 5.6% in cereals to 53% in sports drinks (not tabulated).

Relationship between retail prices, wholesale prices, and advertising. Examining the data, we see, as may be expected, that retail and wholesale prices of a given brand are closely related. As an example, we show in Figure 1 the weekly retail and wholesale prices for one brand – Charmin bathroom tissue – in pricing zone 2. The graph indicates that wholesale price is a main driver of retail price. Figure 2 shows the weekly retail price for Charmin, along with its promotional intensity and advertising expenditures. Note that promotions are controlled by the retailer, whereas advertising spend is controlled by the manufacturer. The graph also shows that, most of the time, when advertising expenditures increase, so do retail prices. There are, however, exceptions to this pattern (around weeks 25 and 45, for example). In what follows we therefore turn to regression analysis in order to separate out the signal from the noise in the relationship between retail prices and advertising expenditures.

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Insert Figures 1, 2 about here

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4 Model Specification and Estimation

In this section we specify the models we use to describe the relationships in the data. First, we look at how we estimate the effect of advertising on retail prices within products and then we relate the estimated advertising effects to a number of factors that may potentially explain the direction and magnitude of the effects.

4.1 The effect of advertising on retail prices

To obtain the effect of manufacturer advertising on retailer pricing, we proceed analogously to Besanko et al. (2005) and estimate the retail price of product i directly as a function of own and competitive advertising levels, while controlling for own and rivals' wholesale prices.[5] The following equation summarizes our approach:

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\begin{aligned}
\text{RetPrice}_{izt} \;=\;& a_{1i} + a_{2i} \times \text{Adv}_{bt} + a_{3i} \times \text{Othr\_Adv}_{bt} \\
&+ a_{4i} \times \text{Wh\_Price}_{izt} + a_{5i} \times \text{Othr\_WhPrice}_{izt} + a_{6i} \times \text{Promo}_{izt} \\
&+ a_{7i} \times \text{HolidayDummy}_{t} + \text{YearDummies}_{t} \times a_{8i} \\
&+ \text{ZoneDummies}_{z} \times a_{9i} + \epsilon_{izt}, \qquad (1)
\end{aligned}
$$

where the subscript i indexes products, b indexes brands, z indexes pricing zones, and t indexes weeks. RetPrice_{izt} is the retail price of product i in zone z and week t. Wh_Price_{izt} is the own wholesale price, $\text{Othr\_WhPrice}_{izt}$ is the average across rival wholesale prices, Adv_{bt} is the own advertising level, Othr_Adv_{bt} is the average rival advertising level, Promo_{izt} captures the promotions for the product in that week,[6] HolidayDummy_{t}, YearDummies_{t}, and ZoneDummies_{z} are fixed effects for major holidays, for year and for the pricing zones, respectively, and ϵ_{izt} is a mean-zero disturbance. Note that, by construction, advertising levels do not vary across pricing zones, nor across products within a brand. Average retail prices, wholesale prices and rival advertising are all constructed as weighted averages using UPC sales as weights in the case of prices, and brand sales in the case of advertising. To the extent that demographics vary across zones, their impact is automatically controlled for by the zone fixed effects.

The main coefficients of interest in the specification above are a_{2i} and a_{3i} which capture the own and other (i.e., rival) effects of advertising on retail prices, respectively. Also, note that the a_{4i} coefficient captures the pass-through effects of wholesale prices which we will discuss later.

We estimate the model in (1) by OLS and compute standard errors that are robust to heteroskedasticity and autocorrelation. To proceed with a minimum of assumptions, we run the regression separately for each product in each category,

[5] The focus of their paper was on estimating wholesale pass-through, so they do not have advertising in their model.

[6] Similarly to prices, promotional activity is constructed as a weighted average using UPC sales as weights. Promotion, prior to averaging, is defined as a binary variable that indicates whether an UPC is on sale in a given week, store and zone.

leading to 286 regressions. Hence, we do not impose any restrictions on the estimated coefficients across products or across categories. This approach precludes unobserved heterogeneity across products from biasing the estimates.

We choose to estimate product-level – as opposed to product-zone-level – advertising effects in order to obtain more precise estimates. This means that the estimated advertising effects can be interpreted as average effects across zones. To check robustness of our chosen specification, we re-estimated the model and allowed the own advertising coefficient to vary across zones in addition to varying across products (i.e., we estimated this coefficient at the product-zone level). A variance decomposition (ANOVA) analysis revealed that, of the total variation in the estimated own-brand advertising effects, 71.8% occurs between products within categories, 27.8% occurs between categories, and only 0.4% occurs between price zones (not tabulated). Hence, our specification makes sense given the data at hand.

4.2 Explaining differences in advertising effects on retail prices

The above estimation yields product-level estimates of the association between retail prices and advertising. We proceed to investigate the extent to which the variation of the estimated coefficients across products can be explained by the influencing factors outlined in Table 4. The first question is whether the direction of the pricing adjustment in response to advertising, positive or negative, can be explained by these factors. The second question is whether the factors provide intuition for the magnitude of the price adjustment. Note that the effects we obtain are net effects, after we control for any possible impact via the wholesale prices.

We model the probability that the advertising effect (a_{i2}) is positive (versus negative) as:

$$\begin{aligned} \text{logit}(a_{2i} > 0)_i \quad = \quad & b_1 + b_2 \times \text{BrandPower}_i \\ & + b_3 \times \text{Dom\_Competition}_i + b_4 \times \text{NatBr\_Competition}_i \\ & + b_5 \times \text{PricePremium}_i \\ & + b_6 \times \text{Food}_i + b_7 \times \text{Concentration}_i + b_8 \times \text{Importance}_i, \quad (2) \end{aligned}$$

where BrandPower_i denotes the share of the brand to which product i belongs, Dom_Competition_i is an indicator for the presence of a store brand in the same size as product i, $\text{NatBr\_Competition}_i$ is the number of competing national brands of the same size as product i, PricePremium_i is the price premium commanded by the product, Food_i an indicator for whether the product belongs to a food category, and Concentration_i and Importance_i are the share of the top two products and the total sales in the category to which product i belongs, respectively.

The advertising coefficient for each product i, a_{2i}, is estimated with error and since we want observations with higher precision (smaller variance) to carry larger weight, we estimate the logit regressions in (2) using weights for each observation that are proportional to the inverse variance of the parameter estimates.

The estimated advertising effects can be both positive and negative, so in order to explore the relationship between the magnitude of the retailer's response to advertising and the product and category characteristics, we use the absolute value of the estimated coefficient as a dependent variable in our main specification below. The model is given by:

$$\begin{aligned}
|a_{2i}| \quad = \quad & \alpha_1 + \alpha_2 \times \text{BrandPower}_i \\
& +\alpha_3 \times \text{Dom_Competition}_i + \alpha_4 \times \text{NatBr_Competition}_i \\
& +\alpha_5 \times \text{PricePremium}_i + \alpha_6 \times \text{PromFreq}_i \\
& +\alpha_7 \times \text{Food}_i + \alpha_8 \times \text{Concentration}_i + \alpha_9 \times \text{Importance}_i + e_i. \qquad (3)
\end{aligned}$$

To account for estimation error in the dependent variable in (3) we proceed in a similar fashion to our estimation of (2) and use weighted least squares, the weights being the inverse variance of the own-brand advertising coefficients.

5 Results and Discussion

We organize the discussion of our empirical results around the central question about the effect of manufacturer advertising on retail prices. First we look at the product-level estimates from the regressions of retail price on own and rival advertising as specified in equation (1). We address the question or whether and how retailers adjust prices when manufacturers advertise, controlling for wholesale prices and promotions, and we look at whether wholesale pass-through estimates are affected when advertising is taken into account. Next, we investigate whether there are systematic patterns across products and categories in the way the retailer responds to manufacturer advertising using equations (2) and (3).

5.1 The effect of advertising on retail prices

Model fit and face validity. The empirical model specified in equation (1) fits the data well. Across all 286 product-level regressions, the goodness of fit as captured by the R-Squared is 0.72 on average, and the F-tests for the overall fit of the models are highly significant. Our empirical strategy is an extension of Besanko et al. (2005), where we control for the pass-through of wholesale price (which was the main focus of their paper) in order to isolate the effect of advertising on retail prices. We can therefore compare our estimates of the wholesale price effect on retail prices presented in Tables 5 and 6 (columns labeled 'own whsp' and 'cross whsp') to the pass-through rates they report. Our estimates are very much in line with theirs and the estimates in subsequent empirical work (Nijs et al. 2010, Pauwels 2007): 89% of the estimated product-level own wholesale pass-through rates and 66% of the estimated cross-brand pass-through rates are significantly different from zero. About 80% of the pass-through rates are between 50% and 75% and 20% are 76% or higher (not tabulated). These results give us confidence that our regression specifications adequately capture the relationships in the data.

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Own advertising. The model yields estimates of the effect of advertising on the own retail prices of 249 individual products (there are 37 products belonging to the store brand, Dominick's, which does not advertise). After controlling for the changes in wholesale price, promotional activity, and a rich set of fixed effects, we still obtain a large number of significant coefficients. As we can see from the summary in Table 7, about 74% of the estimated own effects (185 out of 249) are significantly different from zero, split between positive (88) and negative (97). What does this result imply? First, it indicates that the retailer behaves in a strategic fashion, as opposed to using a constant-markup policy, as there would be no reaction otherwise given that we control for wholesale prices. Second, our findings suggest that the relationship between wholesale prices and retail prices is a complex one, and that simply looking at the gross effect of wholesale price on retail prices may not be sufficient to paint the complete picture as retail prices may also be adjusted in response to advertising.

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Insert Table 7 about here

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The estimated own effects averaged across products within a brand are reported in Tables 5 and 6 (column labeled 'own ads'). The own advertising effect captures the proportion of a unit ($1,000,000) advertising expenditure change that results in a change in the own retail price. Thus, for example, an advertising effect of 0.50 means an advertising expenditure reduction of $1,000,000 results in a retail price reduction of $0.50. There is substantial variation in the magnitude of the advertising effects across brands (which is reflective of the variation across products) and across categories. For the own effects, the average within-category variation (measured using standard deviations) is 0.12 and the average across-category variation is 0.04

(not tabulated). It is interesting to observe that the effects largest in magnitude occur for smaller brands (Wisk and Cheer in laundry detergents, Scott in paper towels, and Weight Watchers in frozen dinners), whereas the real power brands with large shares in their respective markets like Coke, Pepsi, and Gatorade have very small advertising effects on retail prices. In Section 5.2 we report on a more formal analysis investigating possible determinants of this relationship.

Competitive advertising. Turning our attention to the cross advertising effects, we have a total of 286 products for which cross advertising effects are estimated (249 belonging to national brands and 37 belonging to the store brand). Out of the 286 estimated cross advertising effects, 209 are significantly different from zero (Table 7). In contrast to the own advertising effects, there is a slightly higher number of positive retail price changes in the presence of manufacturer advertising (110 vs. 99). As was the case with the own-brand advertising effects, there is substantial variation in the magnitude of the cross advertising effects across categories and brands as can be seen in Tables 5 and 6 (column labeled ‘cross ads’): the average within-category variation (measured using standard deviations) is 0.08 and the average across-category variation is 0.03 (not tabulated). In most cases where we have included the store brand (Dominick’s) in the analysis, the advertising effect is significantly different from zero for 29 out of its 37 products, suggesting that the retailer changes the retail price of the store brand in response to advertising of the national brands in the category. Table 8 separates the rival effects on national brands from the effects on the Dominick’s brand. We can see that categories with more products tend to have a larger proportion of positive effects on the nationally branded products. In addition, the prices of Dominick’s products tend to increase in the presence of advertising from national brands (19 out of the 29 products that belong to Dominick’s and have significant effects, have positive effects). We return to the effect of the store brand presence on retail price response to advertising in a more systematic fashion in Section 5.2.

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Advertising and wholesale price pass-through In addition to the direct effect of advertising on retail prices (net of wholesale price), we also find that the way the retailer reacts to wholesale price changes may be different when the manufacturer advertises. Comparing a model that includes advertising (as in our model in equation 1) to one that does not (as in Besanko et al. 2005), we find that for 182 (161) out of 286 products, the estimated wholesale pass-through rates are significantly different from each other at the 10% (5%) level. However, the differences in the estimates using the two models seem to be small (see Table 9). The median absolute difference between pass-through rates (among the products with significantly different wholesale pass-through in the two specifications) is 2.3% with an interquartile range of 3.6% (not tabulated). Given that the median wholesale pass-through estimated for the model without (with) advertising is 38.4% (35.8%), this indicates that for most products there is not much difference between using a model with and without advertising to estimate wholesale pass-through. Nevertheless, for a few products (16) the difference in pass-through is greater than 10% indicating that for some products a precise estimate of wholesale pass-through may require taking the effects of advertising into account.

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5.2 Explaining differences in advertising effects on retail prices

In this section, we explain the variation in the retailer's responsiveness to manufacturer's advertising across categories and between products within categories. This analysis is performed by a set of second-stage regressions of the estimated own-brand advertising effects on the brand and product characteristics presented in Table 4.

Note that this analysis is exploratory rather than a test of a priori hypotheses as there is no guidance in the past literature as to what we would expect. Next we discuss the factors used to explain the advertising effects and the results from the estimation of the models (2) and (3).

In Table 10 we show the estimates of the parameters of the models defined by equations (2) and (3), under two different specifications – with and without category fixed effects. Because the store brand Dominick's does not advertise, there are no estimates for the own advertising effects for the 37 Dominick's products. After eliminating these products and three outliers, we are left with 246 observations for the regression. In addition, the variable Price Premium is not defined for all products because some products do not have competitors in the same size, which means that we exclude another 32 products from the regressions.[7]

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Insert Table 10 about here

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Brand power. Brand power is reflective of consumer preferences for a brand and affects both the market share of that brand and its ability to command a price premium. While it is clear that there will be a high correlation between advertising level and retail price across brands depending on their share, it is an empirical question what the relationship will be within a brand. When it comes to wholesale price pass-through, it has been found that larger, more profitable brands receive greater pass-through, possibly due to higher manufacturers' bargaining power (Besanko et al. 2005). Another reason for larger brands to experience price changes more readily is that part of the cost of retail price changes is fixed, so retailers may

[7]As a robustness check we ran a specification with all the products (246) and without the price premium variable and ran a specification with only the selected products (214) and without the price premium variable and the results are comparable across the three sets of regressions. The results are available upon request from the authors.

be more willing to change the prices of large-share brands rather than small-share brands (Dutta, Heide & Bergen 1999).

Larger manufacturers would most likely also have more bargaining power in the channel – powerful brands have more consumer pull (Albion & Farris 1987, Ailawadi, Harlam, César & Trounce 2006) and therefore rely less on the retailer to generate demand. We would expect that the manufacturer has more control over pricing and therefore any retail price adjustment after controlling for wholesale prices would be small. On the other hand, because of the strong consumer pull, when a powerful brand is being advertised, the retailer would have an incentive to raise its price and therefore capture the additional willingness to pay created by advertising. The retailer may, however, also decide to decrease the price if the brand can be seen as a store traffic builder.

We find that the higher the share of a brand, i.e., the more powerful it is, the higher the likelihood that the retailer will increase the retail price when it is being advertised as indicated by the positive coefficient in the logit model (first two columns in Table 10). Our finding can be explained by retailers wanting to harness the pull that was created by the ad campaign. We see, however, that for stronger brands the magnitude of the retail price change is smaller (remaining two columns in Table 10).

Powerful brands usually are priced at a premium. Pauwels (2007) shows that retailer response is higher for expensive brands, likely because of the belief that brands in higher price tiers yields greater promotional effects (Blattberg & Wisniewski 1989) or due to the higher unit margin on expensive brands, which allows more room for decreasing retail prices. We can expect a similar argument to hold when it comes to the response to manufacturer advertising. In our data, the price premium of a product over its competitors has no effect on the direction of retail price adjustment. The magnitude of the retail price change in the presence of advertising, however, is significantly greater when the product commands a price premium over competing brands. When a product is perceived as being one of higher quality, the retailer can potentially gain by increasing its price when there is additional demand created by advertising.

Competition from national and store brands. The competitive landscape a product faces is also likely to affect the likelihood and magnitude of a retailer's price response to manufacturer advertising. When a brand has a larger number of competitors, the retailer will have relatively more power to adjust retail prices to maximize own profits. This is especially true when the retailer carries a store brand rival to the advertised product, as store brands have become a way for retailers to differentiate themselves and thus command higher margins in the channel (Messinger & Narasimhan 1995, Narasimhan & Wilcox 1998). The stronger the store brand, the less vulnerable is the retailer in the respective category. When a national brand that has a direct store brand equivalent is being advertised, the retailer would benefit from increasing the price of the national brand. Consumers loyal to the brand would still buy it and the ones who are more price sensitive may switch to the competing store brand - both actions lead to increased revenue for the retailers. The only reason the retailer may consider either decreasing the price or not changing it at all is the presence of other strong national brands in the category.

Our results show that competition from both national brands and store brands has a significant impact on the relationship between manufacturer advertising and retail prices. Interestingly, the effect on the direction of price adjustment is different for national and store brands (see left two columns in Table 10). If there is more competition from nationally branded products the price changes are more likely to be positive (i.e., when brand A advertises, retail prices for brand A go up). If a product has the store brand as a competitor, the retail price change for that product is more likely to be negative (i.e., brand A advertises, prices for brand A go down). Turning to the magnitude of the price adjustment in response to advertising, we see that the more nationally branded products there are, the larger the adjustment. One possible explanation for this pattern is that if there are many national brands in the category, the store brand (Dominick's) tries to benefit from additional advertising of the brand by increasing prices (and hence margins) for the advertised brand and most of the category (this can be seen from the fact that the cross effects for categories with more products are mostly positive, as reported in Table 8). If there are many national brands in the category, the retailer increases prices for most brands by a little bit. If there are few brands, the effect on each brand is larger (fewer brands to spread out the gain in margins implies larger changes in margins). Now, if the advertised product has store brand competition, then Dominick's does not increase the price for the advertised product as much as a result of advertising. That is, the price increase of a product that is advertised is "dampened" if Dominick's has a competing product. In this case, Dominick's tries to bring additional attention to the advertised category (and hence to its own products) by making sure that prices do not go up as much or even go down.

Category type, concentration and importance. Previous research that has investigated the price-advertising relationship across categories (Albion & Farris 1987, Farris & Reibstein 1979) points to several influencing factors. Some, such as the stage in the product-life cycle, the availability, and the involvement level (i.e., what percentage of a buyer's budget is spent on a product) cannot be investigated in our context, because we only have the typical supermarket categories consisting of mature, widely-distributed fast-moving consumer goods. However, other factors, such as the purchase frequency, competitive environment, and the importance of the category to the retailer have also been found to play a critical role in shaping retailer behavior (Fader & Lodisch 1990, Narasimhan, Neslin & Sen 1996). Categories with higher purchase frequency, such as food categories, are critical for retailers as they are the main store-traffic drivers. They may also be associated with a lower degree of store switching and thus afford more power to the retailer. The empirical question is which of these two forces will prevail and thus affect retailer pricing.

Food categories are typically those with high penetration and high frequency of purchase as the products are perishable, so we would have expected to see an association between the type of product category and the estimated effects of advertising on retail prices. However, the estimated coefficients are not significant.

Turning to the competitive environment, if a category is more concentrated, i.e. a few brands command a large share, then the retailer would likely have less power to adjust prices in response to advertising than in less concentrated categories. High-sales volume categories have a greater impact on store traffic and sales than low-volume categories, and are thus of greater importance to the retailer (Walters 1989). Retailer response to trade promotions has been found to be greater in larger categories (Pauwels 2007) and we would thus expect a similar reaction to manufacturer advertising.

When examining the influence of category concentration and importance, we are unable to find a significant impact on the direction of the retail price adjustment but the regressions with the magnitude of the estimated own advertising effects as dependent variables yield significant parameter estimates for both category concentration and importance. The more concentrated a product category, i.e., the higher the combined share of the top two products, the larger the price change in the presence of advertising. The more important a product category is to the retailer, as measured by its share, the smaller the retail price adjustment in the presence of manufacturer advertising.

A comparison of the results for the regressions with and without category fixed effects reported in Table 10 suggests two things. First, the estimated coefficients for the influencing factors that we include in the analysis are robust to the inclusion of category unobservables. Second, the fact that the R-Squared almost doubles when category fixed effects are included suggests that there is a lot of variation across categories that could be possibly explained with other factors. We leave such investigation for future research.

6 Conclusions

This research aims at providing a description of the retail pricing behavior when manufacturers advertise. While the basic idea that advertising pull should increase channel push has been around for a long time (Farris & Reibstein 1979), there are very few papers studying empirically the effect of advertising on retail prices. In their review of channel interactions Ailawadi, Bradlow, Draganska, Roodekerk, Sudhir, Wilbur & Zhang (2010) pointed to the “understudied leverage of advertising” and our detailed analysis of the advertising effect on the retail prices of 286 products in eleven product categories is a step toward filling this gap in our understanding.

We find that retail price changes are strongly associated with changes in manufacturer advertising. Specifically, the effect of brand advertising on the brand's own retail price is significant for about 75% of products. The retailer, thus, reacts strategically to manufacturer advertising by adjusting the retail price of the advertised product. Importantly, we also find evidence of significant cross-brand effects, indicating that prices of competing products are also adjusted in response to an increase in rivals' advertising in the category. The advertising effects we document are not only significantly different from zero but also rather substantial in magnitude. This finding suggests that when evaluating the effectiveness of advertising marketers should look beyond the – notoriously low – advertising elasticities.

Considering the effect of advertising on retail prices also changes the assessment of the extent of wholesale price pass-through rates. Comparing the estimates of a model that does not include advertising as in Besanko et al. (2005) to our specification that accounts for the advertising effect on retailer behavior, we find that more than half of the pass-through rates are significantly different. Further investigation is needed to determine under what conditions the differences are also of economic significance.

Our analysis reveals that advertising effects on retail prices vary substantially across products and across categories. This variability in the estimated advertising effects can be explained at least partially by a number of category and product characteristics. Our results point to the importance of the power distribution in the channel as well as to the competitive intensity in the product category, suggesting a more complex role of advertising in shaping the channel relationships. Future theoretical work could therefore explore how changing the nature of consumer response or competition would affect the way retail prices react to manufacturer advertising.

Our exploratory analysis of the factors that influence the advertising effects was limited by the data availability. With only eleven product categories, it is very hard to draw generalizable conclusions. Future work should therefore look into including more product categories in order to establish a robust link between product category characteristics and the direction of retail price changes as a response to manufacturer's advertising. Unfortunately, while databases with sales and price data are available across a multitude of regions and product categories, matching advertising data are not as easy to come by, nor are data on wholesale prices. Hopefully this research will provide an impetus for researchers to seek out, and for managers to provide, such data.

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Tables and Figures

Table 1: Overview of product categories included in the analysis

category	sales	# brands	# products	share	DOM
Food categories					
CSD	119,530.40	6	41	0.76	0.05
Cereals	38,601.34	5	66	0.6	0.03
Frozen dinners	16,225.40	3	28	0.71	–
Oatmeal	7,795.18	3	15	0.88	0.09
Sports drinks	3,604.78	3	7	0.89	–
Non-food categories					
Bathroom tissue	18,823.34	5	21	0.82	0.06
Dish detergent	3,893.51	5	18	0.64	0.02
Laundry detergent	22,975.32	5	34	0.63	0.02
Paper towels	7,763.08	5	9	0.71	0.07
Softeners	5,691.16	3	24	0.95	0.1
Toothpaste	5,767.21	4	23	0.63	0.01

Note: This table describes the product categories included in the analysis. *sales* are the total sales in the product category, measured in thousands USD. *# brands* and *# products* are the number of brands and products considered, respectively. *share* is the share of the category that is covered by the brands and products included in the analysis. *DOM* is the share of the store brand (Dominick's). Due to its low share in the frozen dinners category and to its non-existent presence in the sports drinks category, the store brand is not included in the analysis of these categories. Shares are calculated based on total sales in dollars.

Table 2: Shares, advertising expenditures, promotions, and prices by brand. Food product categories.

category	brand	ad spend	share	avg.RP	avg.WP	promos
CSD	Pepsi	178.89	0.30	0.53	0.47	0.70
	Coke	309.31	0.27	0.53	0.47	0.65
	7Up	64.44	0.06	0.70	0.55	0.57
	DOM	0	0.05	0.52	0.34	0.44
	Pepper	142.41	0.04	0.53	0.50	0.60
	Rite	0.16	0.04	0.69	0.60	0.50
Cereals	Kelloggs	491.25	0.21	3.34	2.74	0.21
	General Mills	196.37	0.18	3.61	2.97	0.10
	Post	228.44	0.09	3.16	2.53	0.17
	Quaker	75.76	0.09	3.36	2.69	0.20
	DOM	0	0.03	2.51	1.47	0.28
Dinners	LC	29.02	0.43	2.40	1.60	0.23
	HC	9.28	0.23	2.56	1.62	0.28
	WW	4.67	0.04	1.90	1.16	0.25
Oatmeal	Quaker	48.63	0.64	2.78	2.11	0.09
	Nabisco	9.39	0.15	3.19	2.43	0.09
	DOM	0	0.09	2.25	1.03	0.25
Sports drinks	Gatorade	65.52	0.80	2.66	1.95	0.11
	Allsport	18.82	0.06	1.12	0.76	0.54
	Powerade	23.42	0.04	1.31	0.87	0.27

Note: This table reports a set of descriptive statistics for the brands belonging to food categories included in the analysis. *ad spend* are total advertising expenditures in millions dollars over the period studied. *share* is the share of each brand in each category calculated based on total sales in dollars. *avg.RP*, *avg.WP*, and *promos* are simple averages of brand prices and promotions calculated across weeks and zones. Brand prices for a given week and zone were constructed by aggregating from the UPC level using UPC sales as weights. Promotions, prior to averaging, is defined as a binary variable that indicates whether an UPC is on sale in a given week, store and zone. Only products used in the analysis are considered in these calculations.

Table 3: Shares, advertising expenditures, promotions, and prices by brand. Non-food product categories.

category	brand	ad spend	share	avg.RP	avg.WP	promos
Bathroom tissue	Charmin	50.86	0.19	3.54	2.99	0.11
	Cottonelle	14.36	0.19	3.35	2.88	0.28
	Northern	15.36	0.19	2.50	2.05	0.19
	Scott	0.43	0.19	1.09	0.92	0.22
	DOM	0	0.06	1.94	1.62	0.15
Dish detergent	Palmolive	23.56	0.26	2.09	1.60	0.17
	Dawn	38.48	0.22	2.17	1.75	0.15
	Ivory	16.34	0.07	1.90	1.52	0.04
	Joy	5.85	0.07	1.40	1.06	0.05
	DOM	0	0.02	2.04	1.57	0.07
Laundry detergent	Tide	114.28	0.38	7.47	6.45	0.30
	All	18.92	0.08	5.23	4.20	0.17
	Wisk	38.4	0.08	6.60	5.55	0.32
	Cheer	40.77	0.07	6.94	5.89	0.13
	DOM	0	0.02	4.56	3.20	0.14
Paper towels	Bounty	58.19	0.42	1.41	1.22	0.07
	Viva	1.6	0.12	1.41	1.18	0.21
	DOM	0	0.07	0.65	0.46	0.24
	Brawny	19.8	0.06	1.23	1.02	0.13
	Scott	2.2	0.03	1.37	1.14	0.15
Softeners	Downy	56.15	0.7	5.14	4.13	0.20
	Snuggle	21.22	0.15	4.31	3.45	0.22
	DOM	0	0.10	2.23	1.43	0.15
Toothpaste	Crest	118.58	0.31	2.60	2.15	0.26
	Colgate	105.12	0.21	2.46	2.01	0.23
	Mentadent	103.54	0.10	3.47	2.62	0.37
	DOM	0	0.01	1.67	1.11	0.06

Note: This table reports a set of descriptive statistics for the brands belonging to non-food categories included in the analysis. *ad spend* are total advertising expenditures in millions dollars over the period studied. *share* is the share of each brand in each category calculated based on total sales in dollars. *avg.RP*, *avg.WP*, and *promos* are simple averages of brand prices and promotions calculated across weeks and zones. Brand prices for a given week and zone were constructed by aggregating from the UPC level using UPC sales as weights. Promotions, prior to averaging, is defined as a binary variable that indicates whether an UPC is on sale in a given week, store and zone. Only products used in the analysis are considered in these calculations. In the second left-most column in the table "DOM" stands for Dominick's store brand.

Table 4: Influencing factors of the advertising effects on pricing. Operationalization and Descriptives

Factor	Operationalization	Mean	Std Dev
Product Characteristics			
Brand power	brand share of total sales in category	0.226	0.180
Price premium	ratio of product price over average price of rivals in same size	1.060	0.200
National brand competition	number of national brands in same size	3.825	4.563
Store brand competition	indicator for whether DOM is present in same size	0.484	0.501
Category Characteristics			
Food vs. Nonfood	indicator for whether the category is a food category	0.569	0.496
Concentration	C_2 (combined share of top two products in the category)	0.225	0.122
Importance to retailer	category total sales in millions of dollars	33.208	36.822

Note: This table reports a description of the operationalization and the summary statistics for the variables used to explain the variation in the estimated own advertising effects, calculated across products and categories.

Table 5: Impact of own and rival advertising on retail prices, controlling for wholesale prices (averages across products within each brand). Non-food product categories.

category	brand	own ads	cross ads	own whsp	cross whsp
Bathroom tissue	Charmin	0.061	−0.160	0.602	−0.005
	Cottonelle	−0.064	0.024	0.275	−0.012
	DOM		0.133	0.448	−0.002
	Northern	0.013	−0.072	0.568	−0.006
	Scott	−0.364	−0.024	0.533	−0.001
Dish detergent	Dawn	−0.050	−0.005	0.187	−0.013
	DOM		−0.073	0.112	0.058
	Ivory	0.015	−0.009	−0.307	0.021
	Joy	−0.119	−0.053	0.437	−0.003
	Palmolive	−0.050	−0.024	0.156	0.002
Laundry Detergent	All	0.029	0.048	0.210	−0.015
	Cheer	−0.092	0.007	0.427	−0.028
	DOM		0.012	−0.117	−0.021
	Tide	0.038	−0.017	0.387	0.008
	Wisk	0.091	0.057	0.297	−0.058
Paper towels	Bounty	−0.003	0.037	0.508	0.098
	Brawny	0.013	0.007	0.232	0.058
	Dom		0.017	0.135	−0.032
	Scott	−0.015	−0.006	0.183	−0.096
	Viva	−0.109	0.008	0.344	0.171
Softeners	DOM		0.196	0.934	−0.036
	Downy	0.030	0.032	−0.087	0.000
	Snuggle	0.085	−0.016	0.294	0.000
Toothpaste	Colgate	−0.012	−0.051	0.287	0.012
	Crest	−0.023	−0.005	0.476	0.080
	DOM		0.023	0.514	−0.013
	Mentadent	0.003	−0.039	0.815	0.169

Note: This table reports the results from the product-level OLS regressions described in Section 4 for the products belonging to non-food categories. *own ads* and *cross ads* are simple averages of the coefficients estimated for the variables "own advertising level" and "average rival advertising level" across all products within a brand. *own whsp* and *cross whsp* are simple averages of the coefficients estimated for the variables "own wholesale price" and "average rival wholesale price" across all products within a brand. In the second left-most column in the table "DOM" stands for Dominick's.

Table 6: Impact of own and rival advertising on retail prices, controlling for wholesale prices (averages across products within each brand). Food product categories.

category	brand	own ads	cross ads	own whsp	cross whsp
CSD	7Up	−0.004	−0.007	0.304	−0.066
	Coke	0.001	0.000	0.421	−0.005
	DOM		−0.003	0.785	−0.026
	Pepper	0.000	0.002	0.286	−0.001
	Pepsi	0.001	−0.003	0.301	−0.020
	Rite	0.213	−0.006	0.244	−0.021
Cereals	DOM		0.025	0.604	−0.058
	General Mills	0.002	0.000	0.603	0.017
	Kelloggs	0.007	−0.008	0.443	0.046
	Post	0.024	0.013	0.836	0.076
	Quaker	0.017	0.016	0.584	0.057
Dinners	HC	0.039	0.009	0.243	0.214
	LC	−0.114	0.019	0.603	−0.011
	WW	−0.107	0.088	−0.100	0.477
Oatmeal	DOM		−0.002	*	0.010
	Nabisco	−0.046	0.000	1.914	0.016
	Quaker	0.003	−0.067	−0.315	0.127
Sports Drinks	Allsport	−0.014	−0.009	0.516	0.039
	Gatorade	−0.017	−0.055	0.508	−0.035
	Powerade	0.007	−0.019	0.270	−0.092

*not enough wholesale price variation to estimate own wholesale coefficients for the products that belong to this brand.

Note: This table reports the results from the product-level OLS regressions described in Section 4 for the products belonging to food categories. *own ads* and *cross ads* are simple averages of the coefficients estimated for the variables “own advertising level” and “average rival advertising level” across all products within a brand. *own whsp* and *cross whsp* are simple averages of the coefficients estimated for the variables “own wholesale price” and “average rival wholesale price” across all products within a brand. In the second left-most column in the table “DOM” stands for Dominick’s.

Table 7: Summary of the direction of advertising effects on product retail prices.

	# products		own advertising		rival advertising	
Product category	national	DOM	positive	negative	positive	negative
Bathroom tissue	17	4	8	8	9	9
CSD	34	7	16	7	16	13
Cereals	59	7	25	16	27	19
Frozen dinners	28	0	9	16	14	4
Dish detergent	17	1	2	13	4	12
Laundry	28	6	10	9	12	9
Oatmeal	12	3	3	5	6	7
Paper towels	8	1	3	3	5	1
Softeners	19	5	8	3	11	6
Sports drinks	7	0	2	4	1	4
Toothpaste	20	3	2	13	5	15
Total	249	37	88	97	110	99

Note: This table shows for how many products within each category (out of the total number of products reported in the columns titled *# products*), the coefficients for the variables "own advertising level" and "average rival advertising level" are positive/negative and statistically significantly different from zero (p-value<0.10). Note that the coefficients for the variables "own advertising level" are not estimable for products belonging to the Dominick's store brand given that this brand does not advertise.

Table 8: Breakdown of rival effects for national brands' and store brand's (DOM) products

	National Brands			Store Brand (DOM)		
	# products	rival advertising		# products	rival advertising	
Product category		positive	negative		positive	negative
Bath tissue	17	6	8	4	3	1
CSD	34	15	9	7	1	4
Cereals	59	23	17	7	4	2
Dinners	28	14	4	0	NA	NA
Dish Detergent	17	4	11	1	0	1
Laundry	28	8	8	6	4	1
Oatmeal	12	5	6	3	1	1
Paper	8	4	1	1	1	0
Softeners	19	8	6	5	3	0
Sports Drinks	7	1	4	0	NA	NA
Toothpaste	20	3	15	3	2	0
Total	249	91	89	37	19	10

Note: This table shows the breakdown of the rival effects described on Table 7. In particular it shows for how many products within each category (out of the total number of products reported in the columns titled *# products*), the coefficients for the variables "average rival advertising level" are positive/negative and statistically significantly different from zero (p-value<0.10). Note that no rival effects are estimated for the store brand products in the categories of dinners and sports drinks because the market share for the store brand in these categories is very small (less than 1 %).

Table 9: Comparison of average estimated wholesale price pass-through without and with advertising in the model.

Product category	# products	no advertising	advertising
Bath tissue	21	0.4847	0.4835
CSD	41	0.4416	0.4374
Cereals	66	0.6036	0.5925
Dinners	28	0.4619	0.4592
Dish Detergent	18	0.0634	0.1224
Laundry Detergent	34	0.1441	0.1337
Oatmeal	15	8.5824	8.6068
Paper towels	9	0.4316	0.4231
Softeners	24	1.7906	1.7362
Sport Drinks	7	0.4994	0.4248
Toothpaste	23	0.4203	0.4306

Note: This table compares the wholesale price pass-through for two regression specifications – the one in equation (1) and one that omits the own and rival advertising. A test of whether the coefficients for the variable ownwhp (wholesale price pass-through) are different across the two specifications reveals that for 182 (161) out of 286 products, the coefficients are significantly different from each other at the 10% (5%) level. Mean wholesale pass-through for each category is weighted by the share of each product in the category.

Table 10: Influencing factors of advertising effects on pricing (robust and clustered standard errors in parentheses)

	logit($a_{2i} > 0$)	logit($a_{2i} > 0$)	$\|a_{2i}\|$	$\|a_{2i}\|$
Product Characteristics				
Brand power	13.2658*	18.1582***	−0.0115***	−0.0090***
	(7.7410)	(2.8723)	(0.0035)	(0.0024)
Price premium	−5.9216	−5.8959	0.0016**	0.0017**
	(4.3054)	(4.4300)	(0.0007)	(0.0008)
National brand competition	0.6290***	0.6644***	0.0000**	0.0000***
	(0.1334)	(0.1467)	(0.0000)	(0.0000)
Store brand competition	−3.2953***	−2.6566***	0.0028**	0.0021***
	(1.1549)	(0.5998)	(0.0011)	(0.0005)
Category Characteristics				
Food	−1.4285		0.0028	
	(1.8709)		(0.0039)	
Concentration	−8.4796		0.0282**	
	(8.0669)		(0.0123)	
Importance to retailer	−0.0107		−0.0001***	
	(0.0215)		(0.0000)	
Category Fixed Effects	No	Yes	No	Yes
R-Squared	NA	NA	0.1402	0.4030
N	214	214	214	214

Note: This table reports the results from four different regressions of the product advertising effects a_{2i} (estimated using equation (1)) on product and product characteristics (defined in detail in Table 4). The first two columns correspond to the logit specified in equation (2) (in which the dependent variable takes value 1 if a_{2i} positive and 0 if it's negative) without and with category fixed effects. The last two columns present the results for the model in equation (3) (in which the dependent variable is the absolute value of a_{2i}) without and with category fixed effects. Observation weights inversely proportional to the variance of the dependent variable (advertising effect) are used in all regressions. Standard errors are robust and clustered at the category level (reported in parentheses below coefficient estimates). (***), (**) and (*) denote statistical significance for 1%, 5% and 10% levels, respectively.

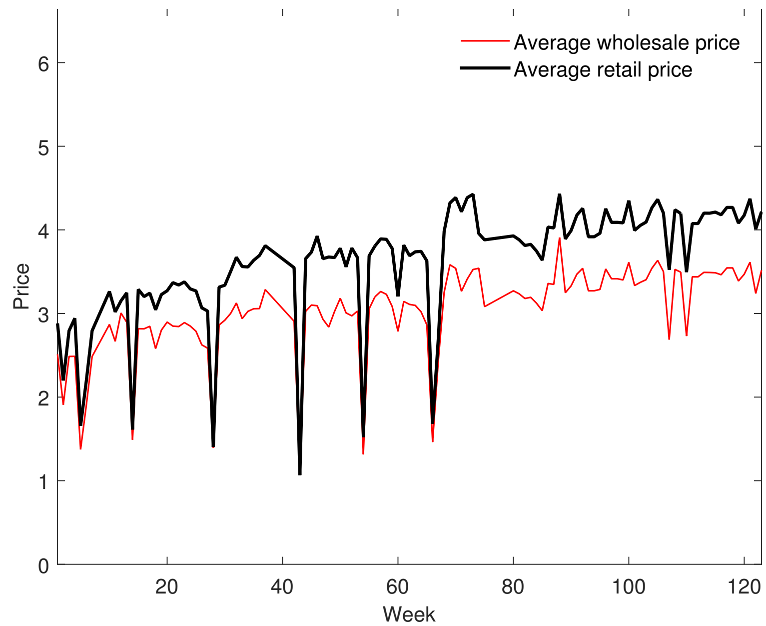

Figure 1: Time series of retail and wholesale prices for Charmin brand of bathroom tissue.

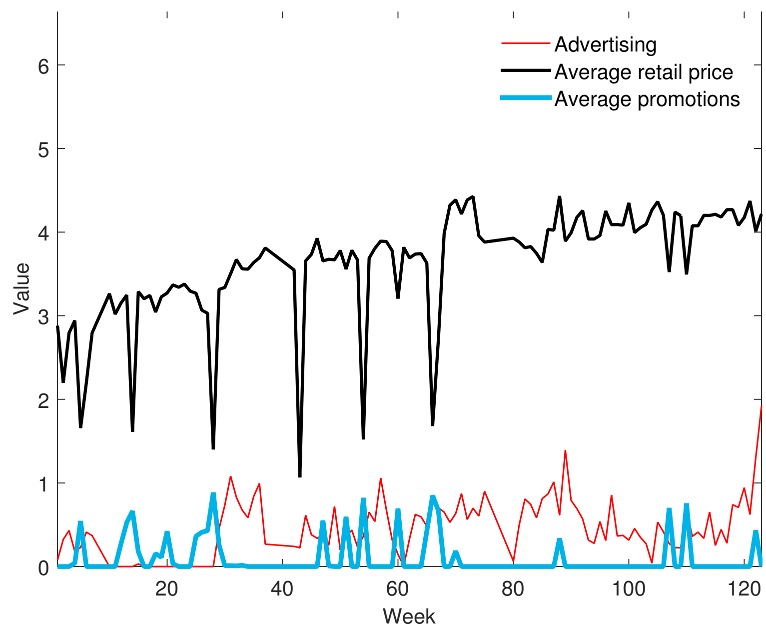

Figure 2: Time series of retail prices, promotions, and advertising for Charmin brand of bathroom tissue.