Decomposing the Effect of Advertising: What Happens in the Retail Channel?*

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Abstract

The diverging interests of manufacturers and retailers famously give rise to the double marginalization problem but have consequences far beyond pricing. Advertising is another marketing instrument that is under the control of the manufacturer but its ultimate effect on consumer demand also depends on retailers' pricing decisions. Using a data set covering 11 products categories and 38 brands, we establish that the retailer acts strategically in response to manufacturer advertising by changing retail prices instead of following a simple constant-markup policy. To further explore the role of the strategic response of the retailer in a systematic fashion, we employ a theoretical model of channel interactions in price and advertising, and analytically decompose the effect that a change in advertising by the manufacturer will have on consumer demand. The decomposition highlights the difference between the direct effect of advertising on demand, which underlies measures such as advertising elasticities, and the indirect effect that comes about because the retailer adjusts prices in response to the demand shift caused by advertising. To illustrate this decomposition, we estimate a discrete-choice model of demand for one of the product categories in our data and determine the magnitude of the direct and indirect effects. We find that the indirect effect of advertising through retailer prices is of sizable magnitude and thus substantively affects the assessment of advertising effectiveness.

Keywords: retailing, advertising, channel coordination

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 pioneering work by Steiner (1973, 1978, 1993), 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). This 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).

Our goal is to broaden the issue of channel coordination to advertising and examine whether and how the retailer reacts strategically by in-store price setting to manufacturer advertising. Most extant research, as Ailawadi et al. (2010) point out, has shied away from modeling the impact of advertising within the distribution channel because of the relative difficulty of implementing a multi-stage game where manufacturers set both wholesale price and advertising and retailers react. A notable recent exception is the contribution by Chan, Narasimhan & Yoon (2017) who develop a dynamic model of advertising and wholesale price competition, and show how the presence of a retailer leads to increased advertising spending but softer price competition. We complement their study by specifically focusing on the ways in which the retailer may adjust retail prices when a brand is being advertised.

To examine how advertising effectiveness may change in the presence of a strategic, category-profit maximizing retailer, we formulate a structural model of demand and supply, where consumers select a product that maximizes their utility, manufacturers compete by setting wholesale prices and advertising, and retailers determine the retail price to the end consumer (Sudhir 2001, Chintagunta, Dubé & Singh 2003, Chan et al. 2017). We highlight an alternative route through which advertising affects sales, namely via the changes in the retail price that a strategic retailer makes in response to changes in demand following manufacturer advertising. Our model allows us to decompose analytically the total demand effect of advertising into the direct effects of advertising on market shares, and into the indirect effects coming through adjustments that the retailer makes to the in-store prices of all the brands in a given product category in response to the shifted demand due to advertising.

For our empirical investigation we match advertising data to store-panel data from the Dominick's Finer Foods data, containing information on retail prices, wholesale prices, and manufacturer advertising over a period of 123 weeks. First, we provide reduced-form evidence for the effect of advertising on retail prices, controlling for any adjustments in the wholesale prices. As we show in our model derivations, the reduced-form we take to the data represents the retailer's reaction function in the vertical channel game without imposing any restrictions on the nature of demand or the nature of strategic interactions between the channel participants. In addition, the reduced-form analysis allows us to investigate a broader set of categories than a structural model (for a similar argument, see e.g. Besanko et al. 2005). Our findings suggest that the retailer acts in a strategic fashion and adjusts prices in response to manufacturer advertising to maximize its own profits. To properly assess the impact of their advertising, manufacturers should thus understand how this strategic price adjustment affects consumer demand for their brands.

Therefore, in a next step, we use our structural decomposition of the effect of advertising on sales to quantify both the part of the effect that is driven directly by changes in demand (direct effect) and the part that results from changes in retail prices (indirect effect) in response to manufacturers' advertising. This decomposition allows us to assess the importance of the retailer's reaction to advertising. We estimate a discrete-choice demand model for the bathroom tissue category while accounting not just for the commonly addressed potential price endogeneity but also for advertising endogeneity. We use the demand estimates to evaluate the direct and indirect effects given by our structural model and find that the indirect effect of advertising on demand via the strategic price response of the retailer is statistically significant and of non-negligible magnitude. This finding suggests that using advertising elasticities alone for the assessment of campaign effectiveness may be insufficient as advertising elasticities only capture one part of the total effect of advertising on consumer demand. Consumer demand may also shift due to the changes in retail prices in the presence of advertising.

To our knowledge, this is the first paper to examine empirically the relationship between manufacturer advertising and retail pricing at the brand level and to directly quantify the impact of retailer's price adjustments on manufacturer advertising effectiveness. There are three data elements that enable us to add novel insights to the extant literature on the role of advertising in the channel: (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 allowing us to consider heterogeneity across brands and not rely on cross-sectional variation for identification.

The remainder of the paper is organized as follows. We briefly review the related literature in Section 2. Section 3 presents the structural model and the decomposition of the total advertising effect. We describe the data in Section 4. In Section 5.1 we present the reduced-form analysis of 11 product categories and, in Section 5.2, we illustrate the quantification of the structural decomposition of the advertising effect on sales using one of the product categories in our data. Section 6 concludes with a discussion of the limitations of our study and directions for future research.

2 Related Literature

The early channel literature is predominantly theoretical in nature and has focused on pricing and mechanisms for channel coordination to avoid the double marginalization problem (for an excellent overview, see e.g., Lilien, Kotler & Moorthy 1995). In the past decades, empirical work in this area has also flourished but the focus on pricing issues has remained. Most notably, the purported shifting power in the channel has become a central topic. Researchers have examined to what extent there is evidence that retailers indeed receive more than their fair share of channel profits (Farris & Ailawadi 1992, Messinger & Narasimhan 1995). A number of studies has looked at the effect of private labels (store brands) in this rise of pricing power of the retailers (see, e.g., Chintagunta, Bonfrer & Song 2002). The final word is still out regarding whether the higher power of the retailers is necessarily bad for manufacturers – it is not a zero-sum game (Draganska, Klapper & Villas-Boas 2010).

Another area of potential conflict between manufacturers and retailers are trade promotions. The central question here is to what extent retailers support manufacturer efforts to stimulate demand by passing the discounts they receive to consumers. Many manufacturers complain that retailers apply about half of the trade dollars to their bottom line rather than providing 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 of trade promotions 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, McShane, Chen, Anderson & Simester 2016). 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. McShane et al. (2016) focus solely on deviations from regular prices (thus excluding promoted prices) and find that pass-through generally exceeds 100%. In the most comprehensive study to date, Nijs et al. (2010) investigate how pass-through rates vary across more than 1000 retailers in over 30 states and relate the pass-through 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.

It seems undisputed that advertising affects consumer demand (even though the extent to which it does and its exact mechanism are still contentious matters) and thus researchers have long posited that retailers are expected to react to the changed demand. Farris & Reibstein (1984) proposed early on that advertising pull increases channel push because retailers are more likely to stock and display prominently products that are being advertised, thus magnifying the impact of manufacturer advertising on sales. A substantial amount of research has been also devoted to the relationship between advertising and retail margins. For example, Albion & Farris (1987) argue that, in the presence of manufacturer advertising, the role of the retailer as demand generator is diminished, and thus the retailer's margins suffer. That is, while manufacturers may raise wholesale prices when they advertise, retailers will not necessarily raise their prices. 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 build on this literature by documenting how retailers adjust their prices in view of the changed demand due to manufacturer advertising and also by decomposing the total effect of advertising to highlight the indirect way that manufacturer campaigns can affect sales via the reaction of the retailer.

Most closely related to our paper, Chan et al. (2017) develop a structural model of the laundry detergent category to investigate how the presence of a strategic retailer affects advertising and price competition at the manufacturer level. They show that retailers mitigate price 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. Because the emphasis of their research is on advertising competition, they opt for a dynamic model that sacrifices analytical tractability. In this paper, we focus explicitly on solving the model so that we can decompose the total effect of advertising on demand and show which part of the advertising effect is affected by the pricing behavior of the retailer. Another way in which our research complements their contribution is that we have access to wholesale prices, and are thus able to provide additional direct evidence across several product categories that the retailer changes prices in response to manufacturer advertising, holding everything else fixed.

3 A Model of Advertising in the Channel

Here we develop a structural model of demand and supply which takes into account the strategic interaction between the manufacturer and the retailer in the distribution channel. In the model, manufacturer advertising acts as a demand shifter. We use the commonly accepted Manufacturer Stackelberg model (see, e.g., Sudhir 2001, Che, Sudhir & Seetharaman 2007) to describe the vertical strategic interaction between multiple manufacturers and the retailer. The manufacturers act as Stackelberg leaders and sell their brands through a common retailer. The retailer observes the wholesale prices and the advertising expenditures of the manufacturers and then sets retail prices for all brands to maximize category profits. The manufacturers choose wholesale prices and advertising expenditures to maximize the profits of their own brands. The horizontal strategic interaction between the manufacturers is represented as Bertrand competition, where manufacturers compete in wholesale prices and advertising levels. The equilibrium concept is sub-game perfect Nash equilibrium. We keep the model as simple as possible in order to maintain analytical tractability while maintaining a minimum of assumptions.

Our model allows us to decompose the total demand effect of advertising into the direct effect of advertising on sales (or, alternatively, market shares), and into the indirect effects coming through adjustments that the retailer makes to the in-store prices in response to the shifted demand due to advertising. While the model developed below is tightly specified in order to derive the decomposition of the total demand effect of advertising, we show that one can abstract from many of the assumptions we make and derive a more general retailer reaction function that underlies our reduced-form empirical analysis.

3.1 Demand

We formulate a discrete-choice model of demand (Besanko et al. 1998, Sudhir 2001). The utility consumer i derives from purchasing brand $j = 1 \dots J$ in period t and zone z[1] is given by:

$$u_{ijzt} = \alpha_{jz} - \beta p_{jzt} + \gamma A_{jt} + \kappa D_{jzt} + \xi_{jzt} + \varepsilon_{ijzt}, \tag{1}$$

where p_{jzt} denotes the retail price for brand j in zone z and period t; A_{jt} is the consumer advertising exposure levels for brand j in period t, D_{jzt} denotes promotional activity for brand j in zone z and period t, and ξ_{jzt} is a demand shock stemming from factors such as shelf space allocation that are unobserved to the researcher. The parameters β and γ capture the demand response to price and advertising, respectively.

We allow consumers to not purchase any of the brands $j = 1 \dots J$ but instead opt for the outside good, which comprises all the other options in the category. The mean utility of the outside good is normalized to 0, i.e.,

$$u_{i0zt} = \varepsilon_{i0zt}.$$

[1] As we explain in Section 4, Dominick's Finer Food practices zone pricing and, therefore, the appropriate level of analysis is a zone and not a store.

Assuming that ε_{ijtz} is iid extreme-value distributed, we obtain the familiar logit expression for the market shares:

$$S_{jzt} = \frac{\exp(\alpha_{jz} - \beta p_{jzt} + \gamma A_{jt} + \kappa D_{jzt} + \xi_{jzt})}{1 + \sum_{k=1}^{J} \exp(\alpha_{kz} - \beta p_{kzt} + \gamma A_{kt} + \kappa D_{kzt} + \xi_{kzt})}. \tag{2}$$

3.2 Retailer

Given our assumed game structure, i.e., Manufacturer Stackelberg, we solve for the subgame perfect Nash equilibrium via backward induction. That is, we start by determining the optimal response of the Stackelberg follower, the retailer.[2] The retailer sets retail prices for all J brands to maximize category profits:

$$\Pi^r = \sum_{j=1}^{J} (p_j - w_j) M S_j = 0, \tag{3}$$

where w_j is the wholesale price of product j, M is the market size, and S_j is the market share of brand j as defined in equation (2).

The first-order conditions (FOCs) for prices (divided by M) are given by

$$\frac{\partial \Pi^r}{\partial p_j} = S_j + \sum_{l=1}^{J} (p_l - w_l) \frac{\partial S_l}{\partial p_j}, \quad j = 1, \ldots, J. \tag{4}$$

The above FOCs can be rewritten in matrix notation as:

$$p = w - \nabla^{-1} S,$$

where

$$\nabla = \begin{bmatrix} \frac{\partial S_1}{\partial p_1} & \frac{\partial S_2}{\partial p_1} & \cdots & \frac{\partial S_J}{\partial p_1} \\ \frac{\partial S_1}{\partial p_2} & \cdots & \cdots & \frac{\partial S_J}{\partial p_2} \\ \vdots & & & \\ \frac{\partial S_1}{\partial p_J} & \cdots & \cdots & \frac{\partial S_J}{\partial p_J} \end{bmatrix}, \quad p = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_J \end{bmatrix}, \quad w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_J \end{bmatrix}, \quad S = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_J \end{bmatrix}.$$

[2] We drop the time and zone subscripts to simplify notation.

The retailer's first-order conditions define the retail price p as a function of wholesale prices, w, and manufacturer advertising, A. This function $p = f(w, A)$ is the retailer's reaction function in our model of the distribution channel. In Section 5.1, we estimate directly this function to assess how the retailer responds to wholesale prices and manufacturer advertising. Note that, while we have derived the retailer's reaction function in the context of a specific model, it arises in many other models as well. In particular, the exact same function arises in an alternative game in which the manufacturer chooses w and A sequentially rather than simultaneously (as per the standard model we use) and also if we assume that the retailer and the manufacturers make decisions simultaneously instead of having the manufacturers act as Stackelberg leaders. The existence of the retailer's reaction function (but not its particular functional form) is similarly not tied to our logit demand model nor to the way we assume advertising affects demand. For example, we may alternatively assume that advertising is informative and affects consumers' choice sets rather than the utility the consumer derives from purchasing the products. We thus view estimating the retailer's reaction function in Section 5.1 as providing model-free evidence on whether and how retailers adjust prices in response to manufacturer advertising.

Returning to our analytical model, we now compute how p changes with w, and with A, respectively, as these are key measures given our research question of how retailers react to manufacturer advertising. To obtain $\frac{\partial p}{\partial w}$, we totally differentiate the retailer first-order conditions (4) with respect to w.

$$\frac{d(\frac{\partial \Pi^r}{\partial p_j})}{dw_k} = \sum_{l=1}^{J} \frac{\partial^2 \Pi^r}{\partial p_j \partial p_l} \frac{\partial p_l}{\partial w_k} + \frac{\partial^2 \Pi^r}{\partial p_j \partial w_k} = 0, \ j = 1, \ldots, J, \ k = 1, \ldots, J.$$

Let

$$\Delta = \begin{bmatrix} \frac{\partial^2 \Pi^r}{\partial p_1 \partial p_1} & \cdots & \frac{\partial^2 \Pi^r}{\partial p_1 \partial p_J} \\ \vdots & \cdots & \vdots \\ \frac{\partial^2 \Pi^r}{\partial p_J \partial p_1} & \cdots & \frac{\partial^2 \Pi^r}{\partial p_J \partial p_J} \end{bmatrix},$$

where

$$\frac{\partial^2 \Pi^r}{\partial p_j \partial p_j} = 2\frac{\partial S_j}{\partial p_j} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_j^2}$$

and

$$\frac{\partial^2 \Pi^r}{\partial p_j \partial p_k} = \frac{\partial S_j}{\partial p_k} + \frac{\partial S_k}{\partial p_j} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_j \partial p_k},\ j \neq k.$$

After some algebra, we obtain:

$$\begin{bmatrix} \frac{\partial p_1}{\partial w_1} & \dots & \frac{\partial p_1}{\partial w_J} \\ \vdots & & \\ \frac{\partial p_J}{\partial w_1} & \dots & \frac{\partial p_J}{\partial w_J} \end{bmatrix} = \Delta^{-1}\nabla. \tag{5}$$

Note that all of the expressions in the above matrices can be evaluated using solely demand parameters.

Turning our attention to the effect of advertising on prices, total differentiation of the retailer price first-order conditions with respect to advertising yields expressions for $\frac{\partial p}{\partial A}$:

$$\frac{d(\frac{\partial \Pi^r}{\partial p_j})}{dA_k} = \sum_{l=1}^{J} \frac{\partial^2 \Pi^r}{\partial p_j \partial p_l}\frac{\partial p_l}{\partial A_k} + \frac{\partial^2 \Pi^r}{\partial p_j \partial A_k} = 0,\ j = 1, \dots, J,\ k = 1, \dots, J,$$

where

$$\frac{\partial^2 \Pi^r}{\partial p_j \partial A_k} = \frac{\partial S_j}{\partial A_k} + \sum_{l=1}^{J} (p_l - w_l)\frac{\partial^2 S_l}{\partial p_j \partial A_k}.$$

If we define

$$\Psi = \begin{bmatrix} \frac{\partial^2 \Pi^r}{\partial p_1 \partial A_1} & \dots & \frac{\partial^2 \Pi^r}{\partial p_1 \partial A_J} \\ \vdots & \dots & \vdots \\ \frac{\partial^2 \Pi^r}{\partial p_J \partial A_1} & \dots & \frac{\partial^2 \Pi^r}{\partial p_J \partial A_J} \end{bmatrix} = \begin{bmatrix} \frac{\partial S_1}{\partial A_1} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_1 \partial A_1} & \dots & \frac{\partial S_1}{\partial A_J} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_1 \partial A_J} \\ \vdots & \dots & \vdots \\ \frac{\partial S_J}{\partial A_1} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_J \partial A_1} & \dots & \frac{\partial S_J}{\partial A_J} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_J \partial A_J} \end{bmatrix},$$

then we can write out the expression for the change in retail prices in response to changes in advertising in matrix form as:

$$\begin{bmatrix} \frac{dp_1}{dA_1} & \cdots & \frac{dp_1}{dA_J} \\ \vdots & \cdots & \vdots \\ \frac{dp_J}{dA_1} & \cdots & \frac{dp_J}{dA_J} \end{bmatrix} = -\Delta^{-1}\Psi. \tag{6}$$

Now that we have defined the reaction function of the retailer, we examine the behavior of the manufacturers.

3.3 Manufacturers

Manufacturers compete with each other à la Bertrand and are Stackelberg leaders. That is, they take into account the retailer's reaction function when setting advertising levels and wholesale prices. The objective function of manufacturer j is given by:

$$\Pi_j^m = (w_j - c_j)MS_j - f(A_j), \tag{7}$$

where c_j is the marginal cost for brand j and $f(A_j)$ is a function that maps advertising for brand j onto the manufacturer's advertising expenditures.

The first-order condition with respect to wholesale price (after dividing by M) is

$$\frac{d\Pi_j^m}{dw_j} = S_j + (w_j - c_j)\frac{dS_j}{dw_j} = 0,$$

where

$$\frac{dS_j}{dw_j} = \sum_{k=1}^{J} \frac{\partial S_j}{\partial p_k}\frac{\partial p_k}{\partial w_j}. \tag{8}$$

The last term in equation (8), the change in retail prices in response to changes in wholesale prices, $\frac{\partial p_k}{\partial w_j}$, is derived above in equation (5) as a function of the demand parameters.

The first-order condition with respect to advertising is given by

$$\frac{d\Pi_j^m}{dA_j} = (w_j - c_j)M\frac{dS_j}{dA_j} - f'(A_j) = 0.$$

In the next section, we take a closer look at the total response of sales to a change in advertising, $\frac{dS_j}{dA_j}$, in order to explicitly show how the retailer's strategic behavior ultimately affects sales.

3.4 Decomposition of the Effect of Advertising

The focus of our investigation is on the reaction of the retailer to manufacturer advertising. We can use our theoretical structural model of demand and supply to quantify the importance of the adjustments to prices that the retailer makes when a brand is being advertised. To do so, we decompose the total response of market shares to a change in advertising $\frac{dS_j}{dA_j}$ into the three terms in the following expression:

$$\frac{dS_j}{dA_j} = \underbrace{\frac{\partial S_j}{\partial A_j}}_{\text{direct effect}} + \underbrace{\frac{\partial S_j}{\partial p_j}\frac{\partial p_j}{\partial A_j}}_{\text{own indirect effect}} + \underbrace{\sum_{k \neq j} \frac{\partial S_j}{\partial p_k}\frac{\partial p_k}{\partial A_j}}_{\text{others indirect effect}} . \qquad (9)$$

Note that estimating demand yields $\frac{\partial S_j}{\partial A_j}$, $\frac{\partial S_j}{\partial p_j}$, and $\frac{\partial S_j}{\partial p_k}$ as simple functions of the estimated coefficients and the market shares. The derivative $\frac{\partial p}{\partial A}$ is a rather complex function of the demand parameters and the data, which can be computed as shown in equation (6). The first term in the right-hand side of equation (9) is the sales impact of advertising on demand holding everything else fixed, and the remaining two terms represent the adjustment to the sales impact based on the retailer's reaction function. Specifically, the second term (labeled "own indirect effect") refers to the impact on the sales of the focal brand that results from the change in the retailer's price of the focal brand due to the focal brand's advertising. Depending on the sign of $\frac{\partial p_j}{\partial A_j}$, the retailer's reaction either reinforces or dampens the effect of manufacturer advertising on sales. In the latter case, it would appear that the retailer "harvests" the pull effect of advertising. The third term (labeled "others indirect effect") captures the effect on sales of the focal brand via the adjustment the retailer makes to the prices of competing brands in response to advertising of the focal brand.

The direct effect, $\frac{\partial S_j}{\partial A_j}$, is what is typically used to measure the effectiveness of advertising – it is given by the advertising coefficient γ in equation (1), after having estimated demand, multiplied by $S_j(1 - S_j)$. Advertising elasticities and other measures are derived based on it. We will show that the indirect effects, namely the effect that stems from changes in the retail price of the focal brand, $\frac{\partial S_j}{\partial p_j}\frac{\partial p_j}{\partial A_j}$, and the indirect effect that comes about because of changes in the rival prices when the focal brand advertises can also be important when assessing the overall impact of advertising on demand. That is, in the presence of a strategic retailer, considering only advertising elasticities to optimize advertising can be misleading.

4 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 data. 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 data come from 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. There are seven different sources of advertising in the Kantar 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 activity 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. We thus aggregate the sales data to the brand level. Furthermore, 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 confirmed, 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 and analyze the data at the brand-zone-week level.

Product categories and brands selection. There are 17 product categories for which we have both sales and advertising data. We drop candy, cookies and crackers, because these are very fragmented categories and reliably matching products to the corresponding brands in the advertising data base would be extremely hard to do. Three other categories, juices, soups and toothbrushes, are dropped because advertising data is 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), for which we have advertising data for a sufficient number of weeks. Further, we include the Dominick's private label brand in those categories for which its presence represents more than 5% of sales. The number of brands considered per category varies from three to six, and they cover from 60% of the total market share for fragmented product categories such as cereal to 90% and higher for more concentrated product categories such as oatmeal, sports drinks and softeners.

Retail and wholesale prices. Our focal measure, the retail price of a brand in a given week and price zone, is constructed by aggregating across UPCs belonging to that brand using UPC-level 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

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

to have together with scanner data; indeed, and as discussed above in Section 2, it was not available to Chan et al. (2017) for their analysis. Having profit margins allows us to calculate wholesale prices (in the same way as in Besanko et al. 2005). Note that, because the wholesale prices are 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 any trade promotions (e.g., off-invoice deals, lump-sum payments) that are given by the manufacturer to the retailer and that can be substantial as discussed in Ailawadi & Harlam (2004). Having wholesale prices is important for our purposes because we can analyze descriptively the strategic response of the retailer to advertising by measuring how retail prices vary with advertising while controlling for changes in wholesale pricing (and, at the same time, any trade promotions). Further, the wholesale prices can be also of use as instrumental variables to address potential price endogeneity concerns in demand estimation.

Advertising measure. Our data reports both advertising units and advertising expenditures in different media across weeks and brands. Units (also called placements) are simply the number of advertisements placed. There is no weighting (based on spot length, size, etc.). Using units as a measure has the advantage that we can back out the cost of advertising and use it as an instrument to correct for endogeneity in our structural estimation (details in Section 5.2). For our reduced-form analysis we use advertising expenditures because it makes the interpretation of the effects easier.

Promotions. Although they are not the main focus of our investigation, promotions affect sales and we therefore control for them in our analysis. Our promotional activity measure at the brand level 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.

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Insert Tables 1, 2 about here

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Descriptive statistics of the variables used for the analysis are shown in Table 1 for the brands in food categories and in Table 2 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 is also a number of categories 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 as can be seen in Tables 1 and 2. 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 and for Quaker and Nabisco 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. For the most part, brands with a larger spending in advertising are also the ones that purchase more ad units. Note however that the relationship between ad spending and ad units is not perfect. This reflects the fact that some advertising markets and types of advertising are more expensive than others.

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Insert Figures 1, 2 about here

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

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 suggests that wholesale price is highly correlated with 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 shows that, most of the time, for this brand, when advertising expenditures increase, so do retail prices. There are, however, exceptions to this pattern (around weeks 25 and 45, for example). In Section 5.1 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.

5 Empirical Analysis

We proceed in two steps in our empirical analysis. We start by examining the relationship between retail prices and advertising in a reduced-form fashion. As pointed out in Section 3, the first-order conditions for the retailer profit-maximization problem define retail prices as a function of wholesale prices and advertising. In Section 5.1 we specify this reaction function in a general form, without restrictions on either the demand function or the manufacturers' pricing conduct. The analysis reveals a significant relationship between manufacturer advertising and retailer prices, after taking into account any possible effect of wholesale prices.

Next, to better understand how advertising affects retail prices and, ultimately, sales, we quantify the three constituent parts of the advertising effect on sales derived from our structural model (equation 9): (1) the direct effect, (2) the indirect effect through adjustment of the retail price of the focal brand, and (3) the indirect effect through adjustment of the prices of the rival brands in response to advertising of the focal brand.

5.1 Reduced-Form Assessment of the Relationship Between Advertising and Retail Prices

To obtain the effect of manufacturer advertising on retailer pricing across a large number of brands and product categories, we proceed analogously to Besanko et al.'s (2005) study of wholesale price pass-through. More specifically, we estimate the retail price of brand j directly as a function of own and rivals' competitive advertising levels, while controlling for own and rivals' wholesale prices:

$$\begin{aligned}\text{RetPrice}_{jzt} = \; & a_{1j} + a_{2j} \times \text{Adv}_{jt} + a_{3j} \times \text{Othr\_Adv}_{jt} \\ & + a_{4j} \times \text{Wh\_Price}_{jzt} + a_{5j} \times \text{Othr\_WhPrice}_{jzt} + a_{6i} \times \text{Promo}_{jzt} \\ & + a_{7j} \times \text{HolidayDummies} + a_{8j} \times \text{YearDummies} \\ & + a_{9j} \times \text{ZoneDummies} + \epsilon_{jzt}, \end{aligned} \tag{10}$$

where the subscript j indexes brands, z indexes pricing zones, and t indexes weeks. RetPrice_{jzt} is the retail price of brand j in zone z and week t. Wh_Price_{jzt} is the own wholesale price, $\text{Othr\_WhPrice}_{jzt}$ is the average across rival wholesale prices, Adv_{jt} is the own advertising level, Othr_Adv_{jt} is the average rival advertising level, and Promo_{jzt} captures the promotions for the brand in that week. To capture shifts in demand across time and guard against endogeneity concerns, we include a rich set of fixed effects. HolidayDummies, YearDummies, and ZoneDummies are fixed effects for major holidays, for years and for the pricing zones, respectively. To the extent that demographics vary across zones, their impact is automatically controlled for by the zone fixed effects. ϵ_{jzt} is a mean-zero disturbance.

We estimate the empirical model in equation (10) 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 brand in each category, leading to 41 regressions. Hence, we do not impose any restrictions on the estimated coefficients across brands or across categories. This approach precludes unobserved heterogeneity across brands from biasing the estimates.

The main coefficients of interest in the specification above are a_{2j} and a_{3j}, which capture the own and other (i.e., rival) effects of advertising on retail prices, respectively. These terms are loosely related to the indirect effects of advertising in the decomposition in equation (9), with the caveat that the decomposition captures the effect of own advertising on sales via the adjustment of own and competitors' prices whereas the coefficients in this model represent the effects of own and rival advertising on the retail price of the focal brand. The a_{4j} coefficient captures the pass-through rates of wholesale prices which have been the focus of earlier research (Besanko et al. 2005, Nijs et al. 2010).

We choose to estimate brand-level – as opposed to brand-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 the 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 brands (i.e., we estimated this coefficient at the brand-zone level). A variance decomposition (ANOVA) analysis revealed that, of the total variation in the estimated own-brand advertising effects, 71.8% occurs between brands within categories, 27.8% occurs between categories, and only 0.4% occurs between price zones. Hence, our specification makes sense given the data at hand.

Model fit and face validity. The empirical model specified in equation (10) fits the data well. Across all 41 brand-level regressions, the goodness of fit as captured by the R^2 is 0.72 on average, and the F-tests for the overall fit of the models are highly significant.

As noted above, the estimates of the wholesale price effect on retail prices presented in Tables 3 and 4 (columns labeled 'Own Whp' and 'Other Whp') represent wholesale pass-through rates. All estimated own-brand pass-through rates are significantly different from zero and 73% of the estimated cross-brand pass-through rates are significantly different from zero (at the 5% level.) All but six pass-through rates are also significantly different from one, with six smaller and the remaining 29 larger. These estimates are in line with the results in Besanko et al. (2005) and the estimates in subsequent empirical work (Nijs et al. 2010, Pauwels 2007). In particular, the clustering around one we observe is consistent with the most recent report in Nijs et al. (2010) of a 1.06 mean and 1.13 median pass-through of wholesale to retail price.

Own advertising. The estimated own effects by brand are reported in Tables 3 and 4 (column labeled 'Own Ads'). 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.

The model yields estimates of the effect of advertising on the own retail prices of 38 brands in the 11 product categories (there is no effect for the store brand Dominick's, as it 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. About 71% of the estimated own effects (27 out of 38) are significantly different from zero, split between positive (13) and negative (14). First, this result 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. There is substantial variation in the magnitude of the advertising effects across brands 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 0.09 (not tabulated). Note also that the positive sign of the estimated own effect of advertising for the Charmin brand is consistent with the pattern in Figure 2 (discussed in Section 4), namely that the retailer seems to adjust prices in the same direction as the manufacturer's advertising.

Rival advertising. Turning our attention to the cross advertising effects, we have a total of 41 brands for which cross-advertising effects are estimated (38 national brands and 3 store brands). Out of the 41 estimated cross advertising effects, 30 are significantly different from zero. Of those, in contrast to the own advertising effects, most indicate a significant negative retail price changes in the presence of manufacturer advertising (21 out of 30). 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 3 and 4 (column labeled 'Other Ads'): the average within-category variation (measured using standard deviations) is 0.06 and the average across-category variation is 0.03 (not tabulated).

5.2 Structural Decomposition of the Effect of Advertising

In order to illustrate the structural decomposition of the effect of advertising in equation (9) we focus on the bathroom tissue category because the four brands represented have a significant share of the market. Further, in this category, the store brand (Dominick's) is not a significant player which makes the analysis more precise given that the store brand does not do brand-specific advertising.

We estimate an aggregate nonlinear demand model as defined in equation (2) using the transformation suggested by Berry (1994) to obtain a linear estimation equation:

$$\ln(s_{jzt}) - \ln(s_{0zt}) = \alpha_{jzt} - \beta p_{jzt} + \gamma A_{jt} + \kappa D_{jzt} + \xi_{jzt}, \tag{11}$$

where s_{jzt} is the observed share of brand j in zone z and week t, and s_{ozt} is the corresponding share for the outside option. We include brand, zone and holiday dummies (α_{jzt}), retail price (p_{jzt}), advertising (A_{jt}), and promotional activity at the brand-week level (D_{jzt}) as independent variables. We use the total sales in the category to calculate the market size and hence to infer the share of the outside option but our results are robust to several variations of the market size.

In our demand estimation, in addition to accounting for the endogeneity of the pricing variable, as is common in the literature, we also address the potential endogeneity of the advertising variable. As instruments for retail prices we use wholesale prices (for an excellent explanation of the rationale, please refer to Chintagunta et al. 2003). To instrument for advertising we employ a similar strategy to Honka, Hortaçsu & Vitorino (2017) and use the cost of advertisements at the week- and brand-level. Advertising costs act as an exogenous shifter of advertising placement decisions because they are likely to be correlated with advertising intensity but uncorrelated with latent consumer utility. Average advertising costs are calculated for each type of media by using total advertising expenditures and units for each week and media type. Because different brands have different allocations of advertising units across media, we calculate an average advertising cost per brand and week (weighted by the share allocated to each media type). This means that advertising costs are not just week- but also brand-specific.

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Insert Table 5 about here

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The results from the nonlinear demand model estimation are reported in Table 5.

Looking at Table 5, we note that all signs of the estimated coefficients are as expected. The price effects are negative, and – consistent with theory – the estimated effect when using instrumental variables is larger compared to OLS. Similarly, we see that the positive effect of advertising is attenuated when ignoring the endogeneity of this marketing instrument, and the obtained effect is much stronger when instruments are used. Promotions also have a strong positive effect on shares, as expected. The quality of the instruments seems to be good. The F-statistics of the identifying instruments in the first-stage estimation have p-values of 0.000 for both the price and the advertising regressions. Further, the Kleibergen and Paap rk LM statistic indicates that the instruments adequately identify the model (p-value=0.000).

Based on the estimated demand parameters, we calculate the direct and indirect effects of advertising that we defined in equation (9). The direct effect is obtained as $\frac{\partial S_j}{\partial A_j} = \gamma S_j(1-S_j)$, and the indirect effects are obtained by multiplying the derivatives with respect to price $\frac{\partial S_j}{\partial p_j} = -\beta S_j(1-S_j)$ and $\frac{\partial S_j}{\partial p_k} = \beta S_j S_k$, respectively, with the corresponding derivative of price with respect to advertising calculated from equation (6).

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Insert Table 6 about here

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Table 6 reports the averages of the estimated direct and indirect own effects across all the weeks and zones in the data. Note that the indirect other effects are averaged not just across weeks and zones but also across rival brands. The averages of each of the two individual components of the indirect other effects ($\partial S_j/\partial p_k$ and $\partial p_k/\partial A_j$) are calculated by first taking the average of the derivatives across all rivals of a given brand in a given week and zone and then taking the average across weeks and zones.[5]

We obtained standard errors (not tabulated) for the advertising effects in Table 6 via bootstrapping. Specifically, we used the known joint distribution of the estimated demand coefficients to generate 100 samples of simulated demand parameters. Then, we calculated new predicted shares using the original data and each of the new sets of demand parameters. Finally, using each of the new 100 sets of predicted shares and simulated demand parameters, we re-calculated all the derivatives needed for the calculations of the effects and the resulting total and partial effects. All the effects in Table 6 are significant at the 1% level.

What is immediately evident from Table 6 is that, for all brands, the total effect is about half the magnitude of the direct effect of advertising which means that the indirect effect that comes about through the adjustment of retail prices matters. Our results thus imply that advertising elasticities (which correspond to the direct effect multiplied by A_j/p_j) may not be sufficient to fully understand the effect of advertising on sales. For example, according to the demand estimation, the direct effect of Charmin's advertising on its shares is 19.722×10^{-4}. This value corresponds to an advertising elasticity of 0.7107 and is usually what manufacturers focus on when assessing the impact of advertising on sales and determining optimal advertising spend. However, as can be seen from the effects reported in Table 6, the actual effect (which we call total effect) of Charmin's advertising on its share is actually about 50% smaller (i.e., 10.165×10^{-4}) once we account for the strategic response of the retailer to changes in Charmin's advertising, i.e., for the indirect effects. Given

[5] Note that, in the table, the product of each of the individual components of the indirect effects does not match exactly the value for the indirect effects because the average of a product is not the same as the product of two averages. For example, the average of the indirect own effects (given by $\partial S_j/\partial p_j \times \partial p_j/\partial A_j$) is not the same as the product of the individual averages of $\partial S_j/\partial p_j$ and $\partial p_j/\partial A_j$.

the sign and relatively large magnitude of the indirect-own effect (-9.737×10^{-4}) it appears that the retailers 'harvest' the pull effect of advertising and manufacturers get less bang for their advertising dollars than they would if the retailers would not react. The indirect effect on other retail prices is small; retail price adjustments of rival brands are an order of magnitude less important than retail price adjustment of the focal brand.

To investigate further how the indirect effects come about, recall that each of the indirect effects has two components – the sales response to retail price and the adjustment of retail prices to advertising.

Let us look again at the reported effects for Charmin as an example. The price sensitivity ($\partial S_j/\partial p_j$) we estimate is -6.676×10^{-2}, implying a price elasticity of -1.28 , which is on the lower side but very much in line with the average elasticity of -0.92 reported for this category by Gordon, Goldfarb & Li (2013). The cross-effect of price on sales ($\partial S_j/\partial p_k$) is – unsurprisingly – much smaller, 1.790×10^{-2}. Looking at the effect of advertising on price ($\partial p_j/\partial A_j$) we see that it is substantial (1.446×10^{-2} for Charmin); further it is positive, indicating that the retailer adjusts prices in the same direction as the Charmin's advertising. Interestingly, these results are consistent with the pattern suggested by Figure 2 (discussed in Section 4). The effect of Charmin's advertising on rival prices ($\partial p_k/\partial A_j$) is much smaller ($0.03 \times 10^{-2}$) which, in combination with the small cross price effect on sales ($\partial S_j/\partial p_k$), yields an indirect other effect that is an order of magnitude smaller than the own indirect effect. This means that the retailer reacts much more strongly by changing the price of the advertised brand than by adjusting the prices of rival brands.

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Insert Table 7 about here

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As mentioned above, in Table 6 we average the indirect other effects not just across weeks and zones but also across rival brands. While this average provides an overall sense of the magnitude of all indirect other effects, it does not convey how each of the rival brands contributes to the indirect effect of a given brand. To understand the contribution of each individual rival brand we therefore first calculate the average of each cross indirect other effect (for example, the effect that the brand Cottonelle has on the brand Charmin) across all weeks and zones and then use those averages to calculate the contribution in percentage terms of each rival brand to the overall indirect other effect. The results of this analysis are reported in Table 7, where the effects for a given brand are presented in the corresponding column. For example, 43% of the indirect effect on Charmin's sales that results from the adjustment the retailer makes to the prices of competing brands in response to Charmin's advertising is driven by the brand Cottonelle, 42% by the brand Northern, and 15% by the Scott brand, respectively. Interestingly, the largest spender in the category, Charmin, has in most cases the largest effect on its rivals' prices but the patterns of the cross effects are not a perfect reflection of the advertising expenditures. Cottonelle has about a quarter of Charmin's advertising units, yet the retailer makes adjustment to the prices of other brands ($\partial p_k / \partial A_j$, not tabulated) of roughly the same magnitude when Cottonelle advertises.

6 Conclusions

The main questions we set out to answer with this research were whether and how a retailer adjusts prices to end consumers in the presence of manufacturer advertising. We develop a model of channel interactions in both pricing and advertising that we take to the data in two ways. First, we estimate a general reduced-form reaction function that requires minimal assumptions and allows for the analysis across multiple product categories. Then we delve deeper into the proposed mechanism by deriving a decomposition of the advertising effect from a structural model of demand and supply.

Both the reduced-form and the structural analyses point to the strategic nature of the retailer's conduct as opposed to one that relies on a simple constant-markup policy. Our findings indicate that a category-profit-maximizing retailer adjusts prices to end consumers, thus affecting the short-term advertising effect on sales. We conclude that, when assessing the effect of advertising on sales, looking only at the advertising elasticities may not paint an adequate picture of the total impact of advertising, as advertising elasticities ignore the sizable indirect effect that comes about due to the strategic adjustment of the retail prices.

Our results suggest a more complex role of advertising in shaping the channel relationships that merits further exploration. One important limitation to the current study is the lack of data on retail competition. As suggested in previous work (Farris & Albion 1980), advertising can lead to increased competition among retailers, which would most likely lead to lower prices. Our model and the decomposition can be applied in a straightforward fashion to investigate what the effects would be in this setting.

Earlier research had also highlighted the effect advertising would have on distribution (Farris & Reibstein 1979). Building a more complex model than the current one to study the interaction of pricing and distribution decisions in the presence of manufacturer advertising would certainly enrich our understanding of the channel and how retailers react to shifted consumer demand for an advertised brand.

The empirical work can also be extended by investigating the effects across a larger number of product categories to allow for establishing 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: Shares, advertising, promotions, and prices by brand. Food product categories.

category	brand	ad spend	ad units	share	avg.RP	avg.WP	promos
CSD	7Up	64.44	8,746	0.06	0.70	0.55	0.57
	Coke	309.31	29,814	0.27	0.53	0.47	0.65
	Pepper	142.41	5,298	0.04	0.53	0.50	0.60
	Pepsi	178.89	16,563	0.30	0.53	0.47	0.70
	Rite	0.16	4	0.04	0.69	0.60	0.50
Cereals	General Mills	196.37	60,568	0.18	3.61	2.97	0.10
	Kelloggs	491.25	91,786	0.21	3.34	2.74	0.21
	Post	228.44	35,662	0.09	3.16	2.53	0.17
	Quaker	75.76	14,424	0.09	3.36	2.69	0.20
Dinners	HC	9.28	733	0.23	2.56	1.62	0.28
	LC	29.02	6,354	0.43	2.40	1.60	0.23
	WW	4.67	832	0.04	1.90	1.16	0.25
Oatmeal	DOM	0	0	0.09	2.25	1.03	0.25
	Nabisco	9.39	1,553	0.15	3.19	2.43	0.09
	Quaker	48.63	8,925	0.64	2.78	2.11	0.09
Sports drinks	Allsport	18.82	2,977	0.06	1.12	0.76	0.54
	Gatorade	65.52	4,822	0.80	2.66	1.95	0.11
	Powerade	23.42	2,465	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 of dollars over the period studied. *ad units* are total advertising units 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. In the second left-most column in the table "DOM" stands for Dominick's store brand.

Table 2: Shares, advertising, promotions, and prices by brand. Non-food product categories.

category	brand	ad spend	ad units	share	avg.RP	avg.WP	promos
Bathroom tissue	Charmin	50.86	8,091	0.19	3.54	2.99	0.11
	Cottonelle	14.36	2,873	0.19	3.35	2.88	0.28
	Northern	15.36	827	0.19	2.50	2.05	0.19
	Scott	0.43	488	0.19	1.09	0.92	0.22
Dish detergent	Dawn	38.48	9,321	0.22	2.17	1.75	0.15
	Ivory	16.34	3,008	0.07	1.90	1.52	0.04
	Joy	5.85	2,378	0.07	1.40	1.06	0.05
	Palmolive	23.56	9,529	0.26	2.09	1.60	0.17
Laundry detergent	All	18.92	3,163	0.08	5.23	4.20	0.17
	Cheer	40.77	6,442	0.07	6.94	5.89	0.13
	Tide	114.28	24,008	0.38	7.47	6.45	0.30
	Wisk	38.40	6,613	0.08	6.60	5.55	0.32
Paper towels	Bounty	58.19	11,249	0.42	1.41	1.22	0.07
	Brawny	19.80	2,171	0.06	1.23	1.02	0.13
	DOM	0	0	0.07	0.65	0.46	0.24
	Scott	2.20	1,032	0.03	1.37	1.14	0.15
	Viva	1.60	378	0.12	1.41	1.18	0.21
Softeners	DOM	0	0	0.10	2.23	1.43	0.15
	Downy	56.15	17,158	0.7	5.14	4.13	0.20
	Snuggle	21.22	4,988	0.15	4.31	3.45	0.22
Toothpaste	Colgate	105.12	16,410	0.21	2.46	2.01	0.23
	Crest	118.58	19,673	0.31	2.60	2.15	0.26
	Mentadent	103.54	17,915	0.10	3.47	2.62	0.37

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. *ad units* are total advertising units 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. In the second left-most column in the table "DOM" stands for Dominick's store brand.

Table 3: Impact of own and rival advertising on retail prices, controlling for wholesale prices. Food product categories.

Category	Brand	Own Ads	Other Ads	Own Whp	Other Whp	R^2
CSD	7UP	0.003	-0.002*	1.176**	-0.038	0.823
		(0.003)	(0.001)	(0.016)	(0.025)	
	Coke	0.001**	-0.005**	1.104**	-0.057**	0.832
		(0.000)	(0.001)	(0.023)	(0.020)	
	Pepper	-0.005**	0.010**	0.797**	0.092**	0.720
		(0.002)	(0.002)	(0.020)	(0.035)	
	Pepsi	-0.001	-0.003**	1.228**	-0.091**	0.837
		(0.001)	(0.000)	(0.022)	(0.014)	
	Rite	0.596**	-0.002	0.710**	-0.198**	0.712
		(0.081)	(0.002)	(0.016)	(0.026)	
Cereals	General Mills	0.006**	-0.034**	1.188**	-0.080**	0.862
		(0.003)	(0.003)	(0.027)	(0.016)	
	Kelloggs	-0.016**	-0.016**	1.079**	-0.094**	0.758
		(0.003)	(0.005)	(0.035)	(0.023)	
	Post	0.020**	-0.020**	1.095**	0.024	0.923
		(0.003)	(0.004)	(0.013)	(0.017)	
	Quaker	-0.026*	-0.003	1.101**	-0.140**	0.828
		(0.015)	(0.006)	(0.025)	(0.029)	
Dinners	HC	0.133**	-0.004	1.290**	-0.044	0.506
		(0.014)	(0.012)	(0.051)	(0.037)	
	LC	-0.116**	-0.097**	1.261**	-0.332**	0.665
		(0.017)	(0.044)	(0.055)	(0.037)	
	WW	-0.017	0.043**	0.457**	0.287**	0.354
		(0.025)	(0.011)	(0.048)	(0.038)	
Oatmeal	DOM	NA	-0.031**	1.851**	-0.011	0.592
			(0.011)	(0.085)	(0.016)	
	Nabisco	-0.177**	-0.016**	1.055**	-0.009	0.811
		(0.032)	(0.005)	(0.039)	(0.009)	
	Quaker	0.017	-0.129**	0.996**	-0.183**	0.840
		(0.011)	(0.026)	(0.031)	(0.024)	
Sports drinks	Allsport	-0.001	-0.007*	1.246**	0.059**	0.709
		(0.008)	(0.004)	(0.028)	(0.008)	
	Gatorade	-0.124**	-0.098**	1.213**	0.082**	0.851
		(0.009)	(0.016)	(0.015)	(0.032)	
	Powerade	-0.038**	-0.014**	1.095**	-0.120**	0.850
		(0.008)	(0.007)	(0.029)	(0.017)	

Note: This table reports the results from the product-level regressions described in Section 5.1. The variable "Own Ads“" is measured in millions of dollars. Promotional activity is also included as a control but not displayed here. In the second left-most column in the table "DOM" stands for Dominick's. The effect of "Own Ads" is not estimated for each of the DOM brand because DOM does not advertise at the brand-level. (**) and (*) denote statistical significance for 5% and 10% levels respectively

Table 4: Impact of own and rival advertising on retail prices, controlling for wholesale prices. Non-food product categories.

Category	Brand	Own Ads	Other Ads	Own Whp	Other Whp	R^2
Bathroom tissue	Charmin	0.043**	0.058**	1.220**	0.014**	0.979
		(0.008)	(0.023)	(0.008)	(0.005)	
	Cottonelle	0.029	-0.087**	1.166**	0.047**	0.960
		(0.021)	(0.030)	(0.008)	(0.009)	
	Northern	-0.067**	-0.130**	1.288**	-0.019**	0.968
		(0.014)	(0.022)	(0.008)	(0.006)	
	Scott	0.633**	0.019	1.215**	0.007*	0.993
		(0.206)	(0.012)	(0.005)	(0.004)	
Dish detergent	Dawn	-0.091**	0.150**	1.229**	-0.001	0.892
		(0.015)	(0.027)	(0.018)	(0.014)	
	Ivory	-0.047**	0.048**	1.434**	0.036**	0.950
		(0.007)	(0.011)	(0.013)	(0.008)	
	Joy	-0.118**	-0.034**	1.345**	0.006	0.979
		(0.012)	(0.009)	(0.007)	(0.005)	
	Palmolive	-0.101**	-0.013	1.066**	-0.061**	0.827
		(0.021)	(0.020)	(0.021)	(0.015)	
Laundry detergent	All	0.260**	0.129**	1.196**	-0.148**	0.731
		(0.054)	(0.026)	(0.021)	(0.015)	
	Cheer	-0.200**	0.027	1.145**	-0.020**	0.897
		(0.027)	(0.017)	(0.012)	(0.010)	
	Tide	0.008	-0.146	1.028**	-0.043	0.328
		(0.038)	(0.151)	(0.209)	(0.034)	
	Wisk	-0.017	-0.033	0.940**	-0.101**	0.713
		(0.041)	(0.030)	(0.020)	(0.020)	
Paper towels	Bounty	-0.001	-0.036*	1.049**	0.047**	0.807
		(0.003)	(0.019)	(0.024)	(0.009)	
	Brawny	0.037**	-0.011**	1.044**	0.032**	0.817
		(0.007)	(0.005)	(0.018)	(0.016)	
	DOM	NA	0.014	0.387**	-0.108**	0.424
			(0.008)	(0.048)	(0.021)	
	Scott	0.069**	0.020**	1.125**	-0.088**	0.840
		(0.011)	(0.006)	(0.012)	(0.015)	
	Viva	-0.176**	0.006	0.929**	0.499**	0.764
		(0.045)	(0.009)	(0.029)	(0.034)	
Softeners	DOM	NA	0.190**	1.020**	-0.062**	0.628
			(0.022)	(0.039)	(0.016)	
	Downy	0.075**	0.006	1.095**	-0.023**	0.848
		(0.016)	(0.034)	(0.021)	(0.010)	
	Snuggle	0.198**	-0.102**	1.119**	-0.028	0.897
		(0.022)	(0.022)	(0.014)	(0.018)	
Toothpaste	Colgate	0.004	-0.130**	0.943**	-0.129**	0.431
		(0.006)	(0.010)	(0.042)	(0.025)	
	Crest	-0.004	-0.019**	1.065**	0.026	0.659
		(0.007)	(0.006)	(0.035)	(0.024)	
	Mentadent	0.022**	-0.049**	1.265**	0.232**	0.923
		(0.005)	(0.008)	(0.019)	(0.029)	

Note: This table reports the results from the brand-level regressions described in Section 5.1. The variable "Own Ads“" is measured in millions of dollars. Promotional activity is also included as a control but not displayed here. In the second left-most column in the table "DOM" stands for Dominick's. The effect of "Own Ads" is not estimated for each of the DOM brand because DOM does not advertise at the brand-level. (**) and (*) denote statistical significance for 5% and 10% levels respectively.

Table 5: Demand Estimates

	OLS	IV
Charmin	1.519***	0.914***
	(0.052)	(0.105)
Cottonelle	1.518***	1.438***
	(0.050)	(0.057)
Northern	1.274***	1.374***
	(0.048)	(0.055)
Scott	0.651***	0.699***
	(0.036)	(0.043)
Price	−0.349***	−0.422***
	(0.012)	(0.017)
Advertising	0.001***	0.012***
	(0.000)	(0.002)
Promo	0.508***	0.711***
	(0.049)	(0.060)
Zone FEs	Yes	Yes
Holi FEs	Yes	Yes
N	6780	6780

Note: This table reports the second-stage estimation results from a nonlinear demand model for the Bathroom Tissue Category. The estimation is done at the week-zone level. Model (OLS) does not address for potential endogeneity while Model (IV) uses wholesale prices as instruments for prices and advertising costs as instruments for advertising intensity. The variable "Advertising" corresponds to advertising intensity and is measured in units. The variable "Promo" for a given week and zone was constructed by aggregating from the UPC level to the brand 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. Standard errors are reported in parentheses under the coefficient estimates. (***) and (**) denote statistical significance for 1% and 5% levels, respectively.

Table 6: Decomposition of the Advertising Effects

	Charmin	Cottonelle	Northern	Scott
Total Effect	10.165	10.425	10.152	8.549
Direct Effect	19.722	20.494	19.855	17.446
Indirect Own Effect	−9.737	−10.292	−9.863	−9.033
$\partial S_j/\partial p_j$	−6.676	−6.937	−6.721	−5.905
$\partial p_j/\partial A_j$	1.446	1.472	1.459	1.524
Indirect Other Effect	0.179	0.223	0.159	0.136
$\partial S_j/\partial p_k$	1.790	1.835	1.806	1.593
$\partial p_k/\partial A_j$	0.030	0.036	0.028	0.027

Note: This table reports the decomposition of the total advertising effect into direct effect, indirect-own effect and indirect-other effect. The total, direct and indirect effects reported are all statistically significant at the 1% level. The direct effect is obtained as $\frac{\partial S_j}{\partial A_j} = \gamma S_j(1 - S_j)$, the indirect effects are obtained by multiplying the derivatives with respect to price $\frac{\partial S_j}{\partial p_j} = -\beta S_j(1 - S_j)$ and $\frac{\partial S_j}{\partial p_k} = \beta S_j S_k$, respectively, with the corresponding derivative of price with respect to advertising ($\partial p/\partial A$) calculated from equation (6). The effects reported are averages of the estimated direct and indirect own effects across all the weeks and zones in the data. Further, the indirect other effects are averaged across weeks and zones and also across rival brands. The averages of each of the individual components of the indirect other effects are calculated by first taking the average of the derivatives across all rivals of a given brand in a given week and zone and then taking the average across weeks and zones. Note that the product of each of the individual components of the indirect effects does not match exactly the value for the indirect effects because the average of a product is not the same as the product of two averages. For example, the average of the indirect own effects (given by $\partial S_j/\partial p_j \times \partial p_j/\partial A_j$) is not the same as the product of the individual averages of $\partial S_j/\partial p_j$ and $\partial p_j/\partial A_j$. The average effects in the table have been multiplied by 10^4, and their individual effect components ($\partial S/\partial p$ and $\partial p/\partial A$) by 10^2, for reporting purposes.

Table 7: Decomposition of the Indirect-Other Advertising Effects

	Charmin	Cottonelle	Northern	Scott
Charmin		48%	47%	34%
Cottonelle	43%		41%	31%
Northern	42%	36%		35%
Scott	15%	15%	12%	

Note: This table reports the contribution of each individual rival brand for the indirect other effect of a given brand in percentage terms. The reported percentages are obtained by first calculating the average of each cross indirect-other effect (for example, the effect that the brand Cottonelle has on the brand Charmin) across all weeks and zones and then by dividing each of those average cross-brand effects by the average of the total indirect-other effect. Each cell reports the contribution of the brand in the corresponding row to the total indirect effect of the brand in the corresponding column. For example, 43% of the indirect effect on Charmin's sales that results from the adjustment the retailer makes to the prices of competing brands in response to Charmin's advertising is driven by the brand Cottonelle, 42% by the brand Northern, and 15% by the Scott brand.

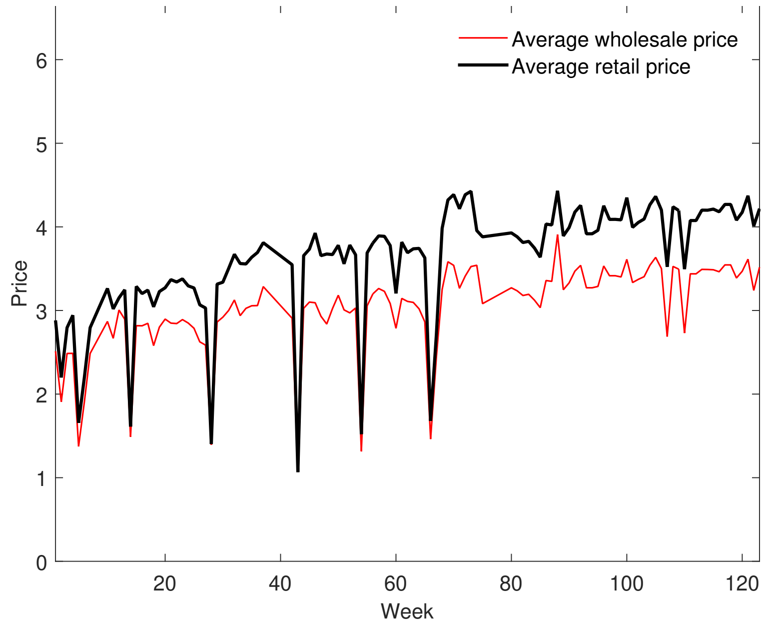

Figure 1: Time series of retail and wholesale prices for Charmin brand of bathroom tissue.

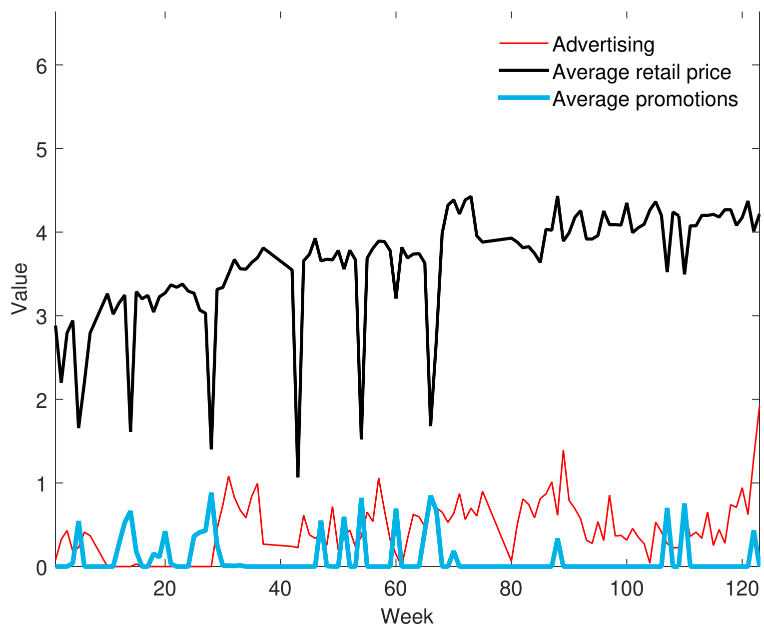

Figure 2: Time series of retail prices, promotions, and advertising (in millions dollars) for Charmin brand of bathroom tissue.