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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. We decompose the effect of advertising in the channel and highlight an additional 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. The total demand effect of advertising thus comprises the direct effects of advertising on market shares, and 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. We match advertising data for four different categories (both food and non-food) to store-level scanner panel data, which also include information on wholesale prices. Controlling for wholesale prices, we establish in a reduced-form model that the retailer reacts to manufacturer advertising by changing retail prices instead of simply imposing a constant markup on the wholesale price. To further explore the role of the strategic response of the retailer in a systematic fashion and quantify the effects derived in the decomposition, we estimate a discrete-choice model of demand and determine the magnitude of the direct and indirect effects. We find that the indirect effect of advertising through retailer prices is about half the size of the direct effect, and thus substantively affects advertising effectiveness.

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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 the interests of retailers and manufacturers diverge 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 proper 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 thus 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 prices and advertising and retailers react. A notable recent exception is the contribution by Chan, Narasimhan, and Yoon (2017) who develop a dynamic model of advertising and wholesale price competition to study how advertising and wholesale price competition among manufacturers changes if products are sold through a retailer instead of direct to the consumer.

This paper contributes to the literature of the impact of advertising in the channel by answering the question of how retailers' pricing behavior is affected by changes in the level of manufacturer advertising. To answer this question, we start by decomposing the effect of advertising in the channel and highlight an additional 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. The total demand effect of advertising thus comprises the direct effects of advertising on market shares, and 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. This indirect route has not been previously investigated.

Our goal is to show how one can quantify the direct and indirect effects of advertising, so in a next step we move away from the very general formulation of the decomposition to obtain a model we can take to data. We specify a discrete-choice demand model because of its wide applicability and theoretical appeal and derive the retailer's reaction function based on retailer's category profit maximization behavior. Importantly, our decomposition does not require us to take a stance on the nature of vertical interactions in the channel and is consistent with a range of models such as the Vertical Nash or Manufacturer Stackelberg. Even with a relatively parsimonious specification such as ours, determining analytically whether the indirect effect of advertising on sales would be positive or negative is an exceedingly complex task. However, in a stylized version of the model, we are able to show that the direction of the price adjustment for an advertised brand will depend mostly on the market shares, the price sensitivity of consumers and on the retailer markups. This insight drives our choice of product categories to examine in our empirical analysis.

We select two food (cereal and carbonated soft drinks) and two non-food categories (toilet tissue and paper towels) from the Dominick's Finer Foods (DFF) database, which differ in terms of market structure, advertising levels, and retailer markups. We match advertising data to these store-panel data. In addition to the usual sales, prices and promotions information, the DFF data has the advantage of including retailer margins, allowing us to obtain wholesale prices. With the wholesale price data available, we do not need to specify a model of manufacturer competition to back them out as most previous channel research has done (Villas-Boas, 2007; Draganska, Klapper, & Villas-Boas, 2010; Chan et al., 2017).

We start by conducting a reduced-form analysis that does not rely on a specification of demand and demonstrate the existence of a robust effect of advertising on retail prices over and above any adjustment that may have taken place in response to changed wholesale prices. If the retailer were simply following a constant-markup policy, we would not be observing that the retail price changes when the level of advertising changes. Because we are able to control for wholesale prices, we can conclude that the retailer indeed acts in a strategic fashion and adjusts prices 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.

The reduced-form model does not provide any guidance in this regard as it only tells one part of the story, namely how retail prices change with advertising. We thus estimate a random-coefficients demand model, accounting for the endogeneity of both price and advertising, and use our 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.

Our results indicate that the indirect effect of advertising on demand via the strategic price response of the retailer is of non-negligible magnitude, offsetting about half of the direct effect. This finding is stable across product categories, despite the differences in price elasticities, retailer markups, and advertising levels. Therefore, 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. The direction and magnitude of this shift depends on the price elasticity and on the rate of price adjustment on the part of the retailer.

Unlike previous work, which implies that retail prices would always be lowered in the presence of manufacturer advertising (Chan et al., 2017), we show both analytically in a stylized model and empirically in a real-world context that a wider range of reactions is possible. To better understand the drivers behind these different responses, we leverage the estimated structural model and conduct numerical simulations. We find that a higher markup and more price sensitive consumers lead to lower retail prices in response to manufacturer advertising, whereas for low-markup brands the retailers are expected to raise prices when the brand is being advertised. The precise range would vary depending on the context.

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. We show that the typical advertising elasticity calculations would overstate the actual sales response by about twice as much. In the next section, we discuss the key findings in the existing literature on manufacturer advertising and strategic interactions in the channel to set the stage for our empirical contribution.

2. Literature Background

There is a rich theoretical and empirical literature studying the factors affecting consumer demand and brand choice (for an excellent recent review see e.g. Russell, 2014). The two marketing-mix instruments that have been studied the most are price and advertising. Retail prices have been consistently shown to be a key determinant of demand. While researchers disagree on the precise mechanism through which advertising affects demand – information or persuasion – and the best way to assess its effect, there is agreement that advertising also significantly affects consumer decisions regarding which brand to purchase. Channel coordination issues arise because manufacturers have direct control over the amount of advertising in a given period but they do not determine the prices consumers see – they can only affect them indirectly by changing the wholesale prices. Profit-maximizing retailers are then at liberty to decide whether to pass through these changes or not. Fig. 1 depicts these relationships and highlights which ones we study empirically for the first time. Below we briefly review the extant research on the relationships between wholesale and retail prices and the role a retailer may play in moderating the effect of advertising and explain how we contribute to the literature.

2.1. Relationship of Wholesale and Retail Prices

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 & Philip Kotler, 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 the 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 et al., 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 & Desiraju, 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, Misra, Anderson, Hansen, and

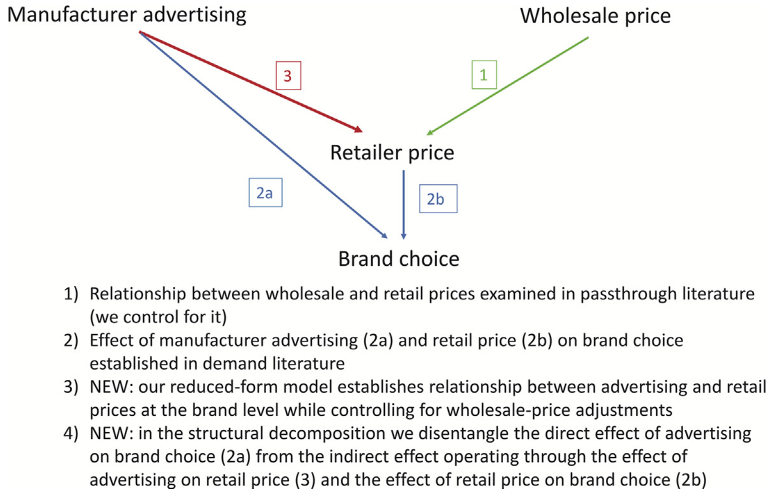

Fig. 1. Structure of our investigation and contribution relative to existing research.

Krishnamurthi (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 problem. While the effect of changes in wholesale prices on retail ones has been studied rather extensively, the effect of advertising on retail prices has received comparatively much less attention in the literature.

2.2. Relationship of advertising and retail prices

Farris and 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 also been devoted to the relationship between advertising and retail margins. For example, Albion and 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 and 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 through which 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 wholesale price, retail prices are lower but profits for all players are higher. However, the question of how changes in the level of brand advertising affect the retail price of the advertised brand and of its rivals is not the subject of their study and remains unanswered.

We contribute to the literature by establishing empirically that retail prices adjust in response to manufacturer advertising and by characterizing the direction and magnitude of this adjustment. Furthermore, because we have access to wholesale prices, we are able to provide direct evidence that the retailer changes prices in response to manufacturer advertising, holding everything else fixed. We are also able to show that a wider range of retailer responses is possible if the relationship between wholesale prices and retail prices is not imposed. Specifically, the reduced-form regressions point to both positive and negative retail price changes in response to changes in the level of manufacturer advertising. In contrast to Chan et al.'s (2017) finding that retail prices decrease when a brand is being advertised, we find also that the retailers may raise prices to "harvest" the pull effect of advertising when we evaluate the indirect effects coming from our structural decomposition.

The remainder of the paper is organized as follows. Section 3 presents the decomposition of the total advertising effect and formulates a discrete-choice model of demand and a retailer reaction function that are needed to quantify the individual components of the decomposition. We describe the data in Section 4. The empirical analysis proceeds in two steps. In Section 5.1 we present a reduced-form analysis to establish the existence of the retailer response to manufacturer advertising. Then, in Section 5.2, we report the results from our demand estimation and calculate the effects obtained from the decomposition of the advertising effect on sales. Section 6 concludes with a discussion of the limitations of our study and directions for future research.

3. Decomposing the Effect of Advertising in the Channel

In this section we show an additional 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. With that purpose, we present a decomposition of the effect of advertising in the channel which shows how, in addition to the direct effects that advertising has on demand, there are 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.

There are J manufacturers setting wholesale prices $w = (w_1, \ldots, w_J)$ and advertising levels $A = (A_1, \ldots, A_J)$ for their brands. Consumers are exposed to advertising and their demand is affected by manufacturers' advertising and by the prices that the retailer sets. Retail prices $p(w, A) = (p_1(w, A), \ldots, p_J(w, A))$ are determined in response to the wholesale prices and consumer demand, which depends on advertising. Because, in the presence of a retailer, retail prices themselves depend on manufacturer advertising, advertising affects consumer demand not only directly but also indirectly through changes in the retail prices that ensue because retailers adjust their strategy in face of the shifted demand.

Formally, the total response of the market share, namely the "induced" demand $S_j(p(w, A), A)$ of brand j to a change in advertising A_j, can be decomposed into three terms:

$$\underbrace{\frac{dS_j(p(w,A),A)}{dA_j}}_{\text{total effect}} = \underbrace{\frac{\partial S_j(p(w,A),A)}{\partial A_j}}_{\text{direct effect}} + \underbrace{\frac{\partial S_j(p(w,A),A)}{\partial p_j}\frac{\partial p_j(w,A)}{\partial A_j}}_{\text{own indirect effect}} + \underbrace{\sum_{k \neq j}\frac{\partial S_j(p(w,A),A)}{\partial p_k}\frac{\partial p_k(w,A)}{\partial A_j}}_{\text{others indirect effect}}. \tag{1}$$

The first term on the right-hand side of Eq. (1) is the sales impact of advertising on demand holding everything else fixed, and the remaining two terms represent the adjustment to the sales impact via 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.

To calculate the effects in this decomposition one needs to estimate consumer demand and to define a retailer reaction function. Estimating demand tells us how the shares vary with changes in advertising, own prices and rival-brand prices, namely $\frac{\partial S_j}{\partial A_j}, \frac{\partial S_j}{\partial p_j}$, and $\frac{\partial S_j}{\partial p_k}$. The derivatives $\frac{\partial p_j}{\partial A_j}$ and $\frac{\partial p_k}{\partial A_j}$ are a rather complex function of the demand parameters and the data, which can be computed from the retailer reaction function. Theoretically, it may be possible to also obtain these derivatives directly, by flexibly regressing prices on advertising and wholesale prices but this approach does not take into account that there may be factors considered by manufacturers when setting advertising levels and wholesale prices that we as researchers do not observe. For this reason, some structure on demand is necessary and below we specify a random coefficients logit model, which has gained wide acceptance in both industry and academia.[1]

The direct effect, $\frac{\partial S_j}{\partial A_j}$, is what is typically used to measure the effectiveness of advertising. Advertising elasticities and other measures are derived based on it. We put ourselves into the shoes of a manufacturer who contemplates how sales would respond if they changed advertising from its equilibrium value. Specifically, we calculate how the induced demand $S(p(w, A), A)$ changes with respect to A, explicitly considering the role of the retailer. Note that if A changes, then $S(p(w, A), A)$ changes for two reasons: directly through demand S and indirectly through the retailer's reaction function $p(w, A)$. In this regard, advertising is very different from the wholesale price. If w changes, there is only an indirect effect of wholesale prices on demand (through the changes in retail prices).[2]

We 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 (calculated considering only the direct effect) to optimize advertising can be misleading.

More specifically, an advertising elasticity is typically obtained by multiplying the direct effect $\frac{\partial S_j}{\partial A_j}$ by $\frac{A_j}{S_j}$. This elasticity is calculated holding everything else constant such as wholesale prices, competitors' advertising, and most importantly retail

[1] We thank an anonymous reviewer for this point.
[2] The model does not specify how w and A are determined. It is typically assumed that there is some equilibrium. In this equilibrium, the values of w and A are functions of parameters, demand shocks, and cost shocks. Accordingly, the value of p is also a function of parameters, demand shocks, and cost shocks. As any one of these changes, so do w and A (and p). This means that w and A will be correlated in equilibrium; it does not mean that A causes w (or the other way around).

prices. In our approach we explicitly incorporate the role of the retailer and quantify how much of change in demand that is induced by the manufacturer's advertising is impacted by the response of the retailer through a strategic change in prices.

To illustrate the calculation of the direct and indirect effects of advertising, we specify below a structural model of demand, which allows us to account explicitly for the presence of unobserved to the researcher factors affecting the way prices and advertising levels are set.

Demand. The utility consumer i derives from purchasing brand $j = 1 \dots J$ in period t and zone z is given by:[3]

$$u_{ijzt} = \alpha_{ij} + \beta_i p_{jzt} + \gamma_i A_{jt} + \kappa D_{jzt} + \xi_{jzt} + \varepsilon_{ijzt}, \tag{2}$$

where α_{ij} are intrinsic brand preferences, p_{jzt} denotes the retail price for brand j in zone z and period t, A_{jt} is the advertising level 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 common demand shock stemming from factors such as shelf space allocation that are unobserved to the researcher. The consumer-specific parameters β_i and γ_i capture the demand response to price and advertising, respectively. We allow for consumer heterogeneity in the valuation of the different options by including random coefficients for the intrinsic brand preferences, price and advertising and set $\alpha_{ij} = \alpha_j + \upsilon_{i\alpha}$, where $\upsilon_{i\alpha} \sim N(0, \Sigma_\alpha), \beta_i = \beta + \upsilon_{i\beta}$, where $\upsilon_{i\beta} \sim N\left(0, \sigma^2_\beta\right)$, and $\gamma_i = \gamma + \upsilon_{i\gamma}$, where $\upsilon_{i\gamma} \sim N\left(0, \sigma^2_\gamma\right)$. These coefficients reflect the variation in the consumers' responsiveness to brands, prices and advertising. In addition we also allow for holiday and zone fixed effects.

Consumers may choose not to purchase any of the brands $j = 1 \dots J$, but instead opt for the outside good, which we define as comprising all the other options in the category. The mean utility of the outside good is normalized to 0, i.e., $u_{i0zt} = \varepsilon_{i0zt}$.

Assuming that ε_{ijzt} is iid extreme-value distributed, the probability that consumer i purchases brand j in zone z and period t is then given by:

$$\Pr_{ijzt} = \frac{\exp\left(\delta_{jzt} + \upsilon_{i\beta} p_{jzt} + \upsilon_{i\gamma} A_{jt}\right)}{1 + \sum_{k=1}^{J} \exp\left(\delta_{kzt} + \upsilon_{i\beta} p_{kzt} + \upsilon_{i\gamma} A_{kt}\right)}, \tag{3}$$

where the mean utility level of brand j in zone z at time t δ_{jzt} is defined as $\alpha_{jzt} + \beta p_{jzt} + \gamma A_{jt} + \kappa D_{jzt} + \xi_{jzt}$. The market shares predicted by the model are obtained by integrating over the individual choice probabilities defined in Eq. (3):

$$S_{jzt}\left(p_{jzt}\left(A_{jt}, w_{jt}\right), A_{jt}\right) = \int \frac{\exp\left(\delta_{jzt} + \upsilon_{i\beta} p_{jzt} + \upsilon_{i\gamma} A_{jt}\right)}{1 + \sum_{k=1}^{J} \exp\left(\delta_{kzt} + \upsilon_{i\beta} p_{kzt} + \upsilon_{i\gamma} A_{kt}\right)} dP(\upsilon_i), \tag{4}$$

with P denoting the heterogeneity distribution function and $\upsilon_i = \left(\upsilon_{i\beta}, \upsilon_{i\gamma}\right)$ the random vector that determines the random coefficients in the logit probabilities. Details on how we estimate demand and calculate the derivatives needed for the advertising decomposition are given in Appendices A and B.

One question that arises when specifying the effect of advertising on consumer demand is that of dynamics. There is a rich tradition in marketing and economics exploring the so-called carryover effect of advertising, namely the phenomenon that past advertising may affect current sales because it can have long-lasting effects on consumer tastes (Nerlove & Arrow, 1962). This effect is typically implemented either through the inclusion of lagged variables or through the construction of an advertising stock (goodwill) variable (see, e.g. Dubé, Hitsch, & Manchanda, 2005). Because our main goal is to demonstrate the decomposition presented in Eq. (1) in a clear manner and because the advertising lags were not significant when included in the demand model, we opted for the more parsimonious specification above.[4]

If manufacturer advertising carries over, then manufacturers will set advertising to dynamically maximize the expected net present value of profit and not just contemporaneous profit. Note that manufacturer price competition is usually modeled as remaining static even if advertising is dynamic (Dubé et al., 2005; Doganoglu & Klapper, 2006; Chan et al., 2017). The retailer would also still set the retail price statically, as there is no carryover effect of retail price. Because – as we explain below – our decomposition depends solely on the retailer's reaction to manufacturer advertising, the above derivations would not change if advertising were dynamic. The decomposition in Eq. (1) would only be affected as far as the values of p, w, and A that enter as inputs into the decomposition would be different in a dynamic equilibrium. In such an equilibrium, manufacturers have an incentive to advertise more because today's advertising stimulates tomorrow's demand. That is, the point at which our decomposition is evaluated – as opposed to the decomposition itself – may change under dynamic advertising.

In addition to the derivatives that are calculated from the demand estimation, to obtain the elements of the decomposition in Eq. (1), we also need the derivatives $\frac{\partial p_j}{\partial A_j}$ and $\frac{\partial p_k}{\partial A_j}$ from the retailer's reaction function, which is presented next.

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

[4] These demand estimation results are available from the authors upon request.

Retailer's reaction function. Given a set of wholesale prices w and advertising levels A, the retailer sets retail prices for all J brands to maximize category profits:

$$\Pi^r = \sum_{j=1}^{J} (p_j - w_j) M S_j(p, A), \tag{5}$$

where M is the market size, and S_j is the market share of brand j as defined in Eq. (4). We drop the time and zone subscripts to simplify notation.

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

$$\frac{\partial \Pi^r}{\partial p_j} = S_j(p, A) + \sum_{l=1}^{J} (p_l - w_l) \frac{\partial S_l(p, A)}{\partial p_j} = 0, \quad j = 1, \ldots, J. \tag{6}$$

Solving the J first-order conditions yields the retailer reaction function $p(w,A) = (p_1(w,A)\ldots)p_J(w,A))$. To determine how retail prices $p(w,A)$ change with the level of manufacturer advertising A, we totally differentiate the retailer first-order conditions for price (6) with respect to advertising to obtain $\frac{\partial p_j}{\partial A_j}$ and $\frac{\partial p_k}{\partial A_j}$. For the complete derivation, please refer to Appendix C.

Note that the derivation of $\frac{\partial p_j}{\partial A_j}$ and $\frac{\partial p_k}{\partial A_j}$ is based solely on demand and the retailer first-order conditions and does not depend on the assumed nature of strategic interactions between manufacturers and retailer (for example, Manufacturer Stackelberg vs. Vertical Nash). It is further independent of the process that determines advertising (static vs. dynamic) but, of course, presumes that advertising is correctly reflected in the specification of demand.

Besides data on retail and wholesale prices and advertising, estimates of demand are the only input needed to calculate the effects of the decomposition defined in Eq. (1). Because we have access to wholesale price data, we do not need to fully specify or estimate the supply side in order to infer wholesale prices. However, for illustration purposes, in Appendix D we specify a complete model of manufacturer competition and derive the equilibrium wholesale prices and advertising. Note that, if A_j changes, then manufacturer j would need to anticipate not only how they will adjust w_j but also how their competitors will adjust their wholesale prices w_{-j} out of equilibrium and possibly their advertising levels A_{-j}.

Because we have no data on prices at competing retailers, we follow the literature in assuming that retailers are local monopolists (Besanko et al., 1998; Sudhir, 2001; Villas-Boas & Zhao, 2005; Che, Sudhir, & Seetharaman, 2007). For the same data, Dominick's Finer Foods, Chintagunta, Dubé, and Singh (2003) report interviewing store managers and conclude that stores compare competitive prices of a sample of half a dozen SKUs, which they deem "more consistent with competition on overall offerings rather than on a category-by-category basis". Consumers typically shop at the retailer closest to them, which gives the retailer some degree of market power (Walters & MacKenzie, 1988; Slade & Margaret, 1995). To the extent that our assumption that retailers are local monopolists is violated, we give too much market power to the retailer. That is, retail margins should be smaller under retail competition. The magnitude of $\frac{\partial p_j}{\partial A_j}$ and $\frac{\partial p_k}{\partial A_j}$ would also change. However, there is no apparent reason to believe that the retailer's reaction would change in a systematic way.

Determining the direction of retail price adjustment. Can something be said regarding the direction in which the retailer is expected to change prices in response to advertising? Farris and Reibstein's (1984) finding that manufacturer advertising may be accompanied by a channel push suggests lower retail prices. Chan et al. (2017) show that, under the assumptions of their model, when manufacturers compete on advertising, retail prices will be lower but this result does not speak to the question of how prices will react to an increase in advertising spend in a given period. We thus turn to the demand model and the retailer's reaction function specified above.

Unfortunately, signing the expression for $\frac{\partial p}{\partial A}$ as defined in Eq. (33) in the appendix is not possible, as there are too many moving parts. While it is clear that the matrix Δ of the second derivatives of profit in Eq. (28) would be negative semidefinite for a profit-maximizing retailer, and conditions for the individual elements of the Ψ matrix in Eq. (31) can be derived, a general determination of the direction of the effect appears out of reach. We start by looking at a simple case with a single brand to obtain intuition as to the drivers of the direction of the effect.

Setting $J = 1$ and dropping brand indices to simplify the notation, we have $\frac{\partial p}{\partial A} = -\frac{\psi}{\delta}$, where δ is $\frac{\partial^2 \Pi^r}{\partial p^2} < 0$. Hence, the sign of retail price adjustment in response to advertising will depend on

$$\psi = \frac{\partial^2 \Pi^r}{\partial p \partial A} = \frac{\partial S}{\partial A} + (p - w)\frac{\partial^2 S}{\partial p \partial A} = \gamma S(1 - S)[1 + \beta(p - w)(1 - 2S)]. \tag{7}$$

Because $\gamma S(1 - S) > 0$ is always true, we can focus on the sign of $1 + \beta(p - w)(1 - 2S)$. We expect this expression to be positive and hence $\frac{\partial p}{\partial A} > 0$ if the price sensitivity is small (in absolute value, recall that β is negative), if the markup is small or if the market share is larger than 1/2 such that the last term becomes negative.

In Section 5.2, we conduct numerical simulations both for the case of $J = 1$ and for the case with two brands (i.e., $J = 2$) to delineate the conditions for the retailer to adjust prices upwards versus downwards. For the empirical analysis, we select several product categories differing along the dimensions identified above, namely price sensitivity, market shares, and markups and investigate the extent to which these factors affect the calculated indirect effects of advertising in a complex setting with multiple competing brands.

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 comprises 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.

Product categories. We included four product categories – two food categories (cereals and carbonated soft drinks) and two non-food ones (toilet tissue and paper towels). We select these categories because they differ in terms of market structure (distribution of market shares), advertising expenditures, and markups and thus allow us to get an idea how the context may affect the retailer's reaction to a change in manufacturer advertising.

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. In each category, we retain all top brands to reach a coverage of at least 70% of total sales.

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.

Retail and wholesale prices. Our focal measures, the retail price and wholesale prices of a brand in a given week and price zone, are 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 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 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 and 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). Moreover, the availability of wholesale prices allows us to quantify the indirect effects of advertising without imposing strong assumptions on the nature of vertical interaction in the channel.

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 demand estimation (details in Section 5.2). For the 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 was sold on a promotion in a given week, store and zone.

Summary statistics. Table 1 reports descriptive statistics of the variables used for the analysis for all brands in the product categories. We observe that, while in the paper towels category we have one dominant brand, Bounty, with approximately 44% share, in the toilet tissue category we have a market with almost even distribution of shares across the top four brands. The cereals and carbonated soft drinks categories are essentially duopolies, with two dominant firms in the respective markets. The advertising expenditures also vary dramatically across categories with the levels in the two food categories being much higher than in the non-food categories but there is also substantial within-category variation. Typically,

Table 1
Descriptive statistics for the brands included in the analysis.

category	brand	share	avg. RP	avg. WP	avg. adspend	promos
Toilet tissue	Charmin	0.212	3.666	3.075	71.602	0.05
		(0.110)	(0.849)	(0.654)	(52.235)	(0.166)
	Cottonelle	0.233	3.45	2.946	25.425	0.096
		(0.114)	(0.807)	(0.660)	(45.603)	(0.161)
	Northern	0.223	2.927	2.405	7.319	0.079
		(0.139)	(0.861)	(0.669)	(13.927)	(0.188)
	Scott	0.178	1.681	1.425	4.319	0.071
		(0.114)	(0.899)	(0.719)	(8.690)	(0.201)
Paper towels	Bounty	0.436	1.409	1.223	99.549	0.041
		(0.095)	(0.096)	(0.070)	(37.673)	(0.172)
	Brawny	0.069	1.247	1.038	19.212	0.034
		(0.045)	(0.115)	(0.096)	(25.457)	(0.128)
	Scott	0.063	1.239	1.016	9.133	0.058
		(0.044)	(0.142)	(0.116)	(29.635)	(0.210)
	Viva	0.127	1.447	1.206	3.345	0.074
		(0.052)	(0.207)	(0.163)	(18.037)	(0.241)
CSD	7Up	0.092	0.591	0.485	71.106	0.276
		(0.083)	(0.192)	(0.143)	(98.270)	(0.344)
	Coke	0.283	0.532	0.475	242.39	0.302
		(0.135)	(0.181)	(0.137)	(130.208)	(0.326)
	Pepper	0.038	0.526	0.499	43.073	0.27
		(0.038)	(0.161)	(0.170)	(35.506)	(0.345)
	Pepsi	0.317	0.537	0.468	134.659	0.286
		(0.167)	(0.174)	(0.130)	(102.799)	(0.331)
Cereals	General Mills	0.316	3.449	2.83	637.558	0.023
		(0.084)	(0.307)	(0.234)	(200.358)	(0.065)
	Kelloggs	0.368	3.358	2.739	966.168	0.052
		(0.094)	(0.338)	(0.272)	(324.145)	(0.105)
	Post	0.128	3.131	2.507	375.389	0.053
		(0.053)	(0.412)	(0.342)	(152.168)	(0.144)
	Quaker	0.092	3.243	2.579	151.832	0.115
		(0.056)	(0.457)	(0.362)	(74.181)	(0.193)

Note: This table reports a set of descriptive statistics for the brands included in the analysis. *adspend* are total advertising expenditures in millions of 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.

the brands with the largest market shares also have the largest advertising spending. Interestingly, in the toilet tissue category, where Cottonelle, Charmin, and Northern have almost equal shares of the market (between 21% and 23%), the expenditures vary from 7.32 million for Northern to 71.6 for Charmin. Based on the reported retail and wholesale prices in Table 1, we can calculate the percentage markup to compare across product categories. Carbonated soft drinks are often used by retailers as loss leaders and this manifests itself in the lowest markups across the analyzed categories, with cereals having the highest retailer markups on average. Carbonated soft drinks also have by far the highest promotional frequency.

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 Fig. 2 the weekly retail and wholesale prices for one brand – Charmin – in pricing zone 2. The graph suggests that the wholesale price is highly correlated with retail price. Fig. 3 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 in Section 5.1. We specify the reaction function of the retailer 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.

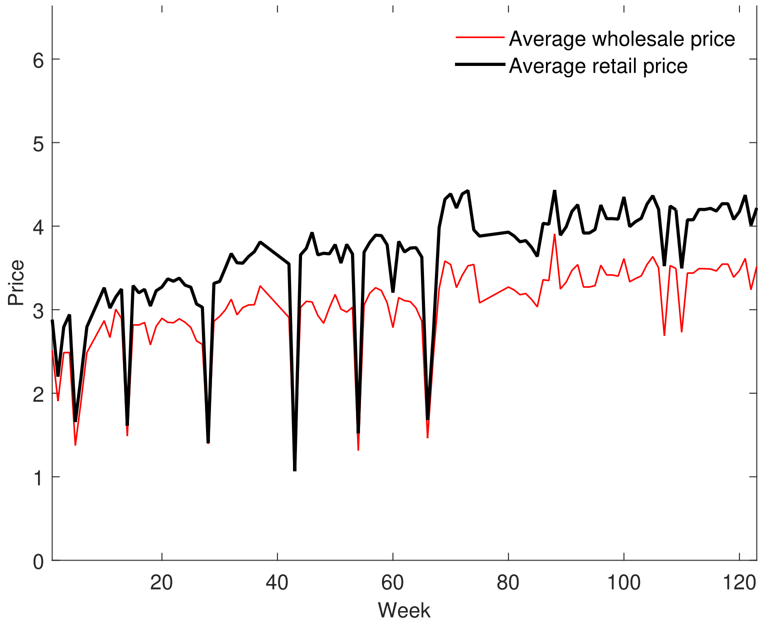

Fig. 2. Time series of retail and wholesale prices for Charmin brand of toilet tissue.

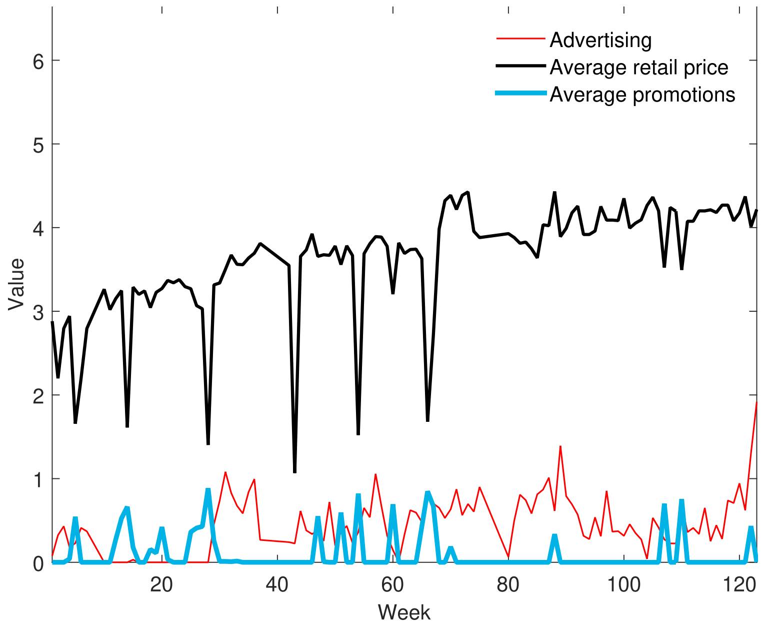

Fig. 3. Time series of retail prices, promotions, and advertising (in millions dollars) for Charmin brand of toilet tissue.

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 in our decomposition (Eq. (1)): (1) the direct effect of manufacturer advertising on sales, (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. Here we use the demand and retailer response functions as defined in Section 3.

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

To obtain the effect of manufacturer advertising on retailer pricing with a minimum of assumptions, we proceed analogously to Besanko et al.'s (2005) study of wholesale price pass-through. 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:

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

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 and competition levels vary across zones, their impact is automatically controlled for by the zone fixed effects. The term ϵ_{jzt} is a mean-zero disturbance.

We assume that ϵ_{jzt} is orthogonal to the included variables and estimate the empirical model in Eq. (8) by OLS. This, in particular, requires that the fixed effects we have included in the model capture any demand factors that the manufacturers observe when setting wholesale prices and advertising but that are unobserved to the researcher. The structural model we estimate and present in Section 5.2 allows us to account for the endogeneity of manufacturer decisions. We 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. Hence, we do not impose any restrictions on the estimated coefficients across brands. 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. 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, more than 70% occurs between brands, hence our specification makes sense given the data at hand.

Model fit and face validity. Table 2 presents the results of the empirical model specified in Eq. (8). Across all brand-level regressions, the goodness of fit as captured by the R^2 is greater than 0.8 for most regressions, and the F-tests for the overall fit of the models are highly significant. All estimated own-brand and cross-brand wholesale price pass-through rates (columns labeled 'Own Whp' and 'Other Whp') are significantly different from zero. The own pass-through rates are also mostly significantly larger than one, which aligns with the findings in Nijs et al. (2010) who report a 1.13 median pass-through of wholesale to retail price.

Own advertising. The model yields estimates of the effect of advertising on own retail prices for each brand in the categories studied (reported in Table 2, column labeled 'Own Ads'). Advertising is measured in millions of dollars. Thus, an advertising effect of 0.50 means an advertising expenditure reduction of $1,000,000 results in a retail price reduction of $0.50. Even after controlling for the changes in wholesale price, promotional activity, and a rich set of fixed effects, we still obtain significant coefficients for 11 out of the 16 brands across the four product categories included in the analysis. The effect is positive for 7 brands, implying that the retailer adjusts prices in the same direction as manufacturer's advertising, and negative for 4 brands, implying that the retailer may lower prices when the manufacturer advertises a brand. Taken together, the estimates indicate 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 no apparent relationship between the product category and the nature of retailer response. The estimated coefficients exhibit much larger variability across brands within a category than across categories. There is also no clear association between the retailer reaction and the average advertising spend for a given brand. While, e.g., the level of advertising of Scott in the toilet tissue category is only roughly 6% of the level of advertising of Charmin and we observe a much larger advertising effect of Scott compared to Charmin, the opposite holds for Post and General Mills in the cereals category: Post has 1/3 of the advertising spending but an order of magnitude larger coefficient. A potential explanation for this is that the effect of advertising on retail price obtained from the reduced-form regression confounds the effect that comes about through changes in demand and the effect of a strategic response through the retailer. In Section 5.2 the structural model will allows us to isolate the role of demand.

Rival advertising. Turning our attention to the cross-advertising effects, we see that 13 out of the 16 estimated coefficients are significantly different from zero. This further reinforces the conclusion that the retailer behaves in a strategic fashion and adjusts retail prices in response to manufacturer's advertising. Most brands across the analyzed categories fea-

Table 2
Impact of own and rival advertising on retail prices, controlling for wholesale prices.

Category	Brand	Own Ads	Other Ads	Own Whp	Other Whp	R^2
Toilet 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)	
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)	
	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)	
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)	
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)	

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. (**) and (*) denote statistical significance for 5% and 10% levels respectively.

ture significant negative retail price changes in the presence of manufacturer advertising, indicating that the retailer lowers the price of these brands if rival brands are more heavily advertised. It does appears that retailer margins would go down for brands whose competitors advertise in the period studied. It is, of course, also possible that there will be relatively increased price sensitivity for the non-advertised brands, and retailers adjust prices accordingly.

One caveat of the reduced-form analysis is that the coefficients estimated from Eq. (8) are complex functions of both demand parameters and the retailer's response to manufacturer advertising. A change in the retail price in response to advertising can happen because there is a change in demand (e.g., price elasticity) or because the retailer adjusts prices in a strategic fashion. Teasing out the exact response, $\frac{\partial p}{\partial A}$, from it therefore is not possible. A further complication arises because the reduced-form regression offers no obvious way to account for demand-side unobservables. We thus complement this model-free evidence with a structural demand model that allows us to separately identify the effects.

5.2. Disentangling the Direct and the Indirect Effects of Advertising

In order to quantify the structural decomposition of the effect of advertising on retail price in Eq. (1), we estimate the demand model defined in Eq. (4). We then use the estimation results to calculate $\frac{\partial S_j}{\partial A_j}, \frac{\partial S_j}{\partial p_j}, \frac{\partial S_j}{\partial p_k}$, and the derivatives $\frac{\partial p_j}{\partial A_j}$ and $\frac{\partial p_k}{\partial A_j}$ from the retailer's reaction function as described in Section 3.

Demand estimation. In the 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, and Vitorino (2017). We measure advertising in units and use the cost of advertisements at the week- and brand-level as instruments. 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.

We follow the algorithm laid out by Berry, Levinsohn, and Pakes (1995) in interacting the structural errors ξ with instrumental variables that control for the possible endogeneity of prices and advertising. Our preliminary checks indicated that the quality of the instruments is 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, for all the product categories. Further, the Kleibergen and Paap rk LM statistic indicates that the instruments adequately identify the models (p-value = 0.000). Details regarding the estimation method are provided in Appendix A.

The results from the demand estimation for our four categories – toilet tissue, paper towels, cereals, and carbonated soft drinks (CSD) are reported in Table 3. First, we note that all signs of the estimated coefficients are as expected. The price effect is significantly negative, and there is a positive effect of advertising on shares for all brand across the four product categories. Promotions also have a significantly positive effect for all categories but paper towels. Turning our attention to the random coefficients, we did not find support for heterogeneity in the response to advertising in any of the product categories, most likely due to the fact that advertising only varies across time within a time period, and not across zones. The estimated standard deviation of the price coefficient is significant for toilet tissue, implying that there is considerable heterogeneity in consumer response to price in this category but it was not significant in the other three product categories we investigated. Similarly, the random coefficients for the brand constants were only significant in the toilet tissue category. It thus appears that the rich set of fixed effects we include in the model captures most of the heterogeneity in demand.

Structural decomposition. Based on the estimated demand parameters, we calculate the direct and indirect effects of advertising that we defined in Eq. (1). To do this, we first compute the individual-level derivatives with respect to price and advertising, integrate over the distribution of γ_i and β_i, and then compute the reaction of retail price to advertising defined in Eq. (33) for each zone and week. Appendix B describes the process in detail.

Table 4 reports the averages of the estimated direct and indirect own effects across all the weeks and zones in the data for all brands and product categories. 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]

What is immediately evident from Table 4 is that, for all brands in all four categories, the total effect is about half the magnitude of the direct effect of advertising. This means that the indirect effect that comes about through the adjustment of retail prices matters. In the simple case without random coefficients and $J = 1$, we can derive that the ratio of direct to indirect effect, given by $-\frac{2+(p-w)\beta(1-2S)}{1+\beta(p-w)(1-2S)}$, would indeed be close to 2 if $(p-w)\beta(1-2S)$ is small.[6] Our empirical analysis demonstrates that this relationship holds also in the more complex setting of multiple brands and consumer heterogeneity. This is especially interesting because the categories we included in the analysis differ greatly in terms of market structure and advertising levels.

To account for the different price and advertising levels and thus obtain comparable measures across product categories, we convert the estimated effects into elasticities which we report in Table 5. To do that, prior to averaging across weeks and zones (and rivals in the case of the indirect other effects) we multiply the effects of advertising on sales (namely, the total, the indirect own, and the indirect other effects) with $\frac{A}{S}$, the price effect (i.e. the terms $\frac{\partial S}{\partial p}$) with $\frac{p}{S}$, and the retailer adjustment (i.e. the terms $\frac{\partial p}{\partial A}$) with $\frac{A}{p}$.

The two leftmost columns in Table 5 enable a direct comparison between the advertising elasticities that are typically used in practice when assessing the impact of advertising on sales and determining optimal advertising spend (column labeled 'direct') and the actual elasticity of 'induced' demand (column labeled 'total'). Typical elasticity calculations rely solely on the calculation of $\frac{\partial S_j}{\partial A_j}\frac{A_j}{S_j}$ which does not take into account the strategic response of the retailer to changes in manufacturer advertising via prices. However, this only captures the direct effect and does not take into account the price response of the retailer to changes in advertising (i.e., the indirect own and other effects), as described in Eq. (1). For the categories we study, accounting for the strategic response of the retailer results in the effect of advertising on shares being about half of that given by traditional elasticities.

The indirect own effect represents the effect of advertising on sales that comes about via the adjustments in retail price. It is negative for all brands in the analysis suggesting 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

[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 $\partial p_j/\partial A_j$.

[6] The direct effect is $\frac{\partial S}{\partial A} = \gamma S(1-S)$ and the indirect effect is $\frac{\partial S}{\partial p}\frac{\partial p}{\partial A} = \beta S(1-S)\left(-\frac{\psi}{\delta}\right)$ where $\psi = \gamma S(1-S)(1+\beta(p-w)(1-2S))$ and $\delta = \frac{\partial^2\pi}{\partial p^2} = 2\frac{\partial S}{\partial p} + (p-w)\frac{\partial^2 S}{\partial p^2} = 2\beta S(1-S) + (p-w)\beta^2 S(1-S)(1-2S)$. Putting terms together, the indirect effect is

$$-\frac{\beta\gamma S^2(1-S)^2(1+\beta(p-w)(1-2S))}{2\beta S(1-S)+(p-w)\beta^2 S(1-S)(1-2S)} = -\frac{\gamma S(1-S)(1+\beta(p-w)(1-2S))}{2+(p-w)\beta(1-2S)}.$$

The ratio of direct to indirect effect is therefore $-\frac{2+(p-w)\beta(1-2S)}{1+\beta(p-w)(1-2S)}$, which would be close to 2 if $(p-w)\beta(1-2S)$ is small.

Table 3
Demand Estimates.

	Toilet tissue	Paper towels	Cereals	CSD
brand1	2.1561**	1.1355**	3.8528**	0.0342
	(0.3448)	(0.2053)	(0.1087)	(0.1873)
brand2	1.1058*	0.0994	3.7917**	0.7980**
	(0.4980)	(0.2358)	(0.1409)	(0.2584)
brand3	1.6244**	0.0492	2.7520**	-0.9859**
	(0.2343)	(0.2453)	(0.0812)	(0.2015)
brand4	0.6041**	1.3137**	2.5530**	1.1350**
	(0.1932)	(0.2562)	(0.0670)	(0.2240)
promotions	1.0914**	-0.0727	0.0944**	0.1572**
	(0.1093)	(0.0455)	(0.0384)	(0.0360)
price	-0.9048**	-1.5785**	-0.8328**	-2.7229**
	(0.0824)	(0.1257)	(0.0160)	(0.2190)
advertising	0.0093**	0.0145**	0.0004**	0.0021**
	(0.0018)	(0.0015)	(0.0001)	(0.0005)
price SD	0.5215**	0.0010	0.0250	0.0233
	(0.1141)	(141.5451)	(4.8104)	(43.0465)
brand1 SD	0.0106			
	(74.1187)			
brand2 SD	2.6681**			
	(0.6908)			
brand3 SD	1.0898**			
	(0.2875)			
brand4 SD	0.0010			
	(84.0094)			
Zone FEs	Yes	Yes	Yes	Yes
Holiday FEs	Yes	Yes	Yes	Yes

Note: This table reports the second-stage estimation results from a nonlinear demand model for the four categories we analyze. Brands are labeled in the same order as in Table 1. The estimation is done at the week-zone level. We use 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 "promotions" 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 5% and 10% levels, respectively.

Table 4
Decomposition of the Advertising Effects.

Brand	Total	Direct	Ind. Own	$\partial S_j/\partial p_j$	$\partial p_j/\partial A_j$	Ind. Other	$\partial S_j/\partial p_k$	$\partial p_k/\partial A_j$
<u>Toilet Tissue</u>								
Charmin	5.4480	10.4960	-5.0960	-10.5186	0.4846	0.0485	2.7545	0.0053
Cottonelle	4.8700	9.6410	-4.8290	-9.6727	0.4993	0.0569	2.4349	0.0071
Northern	5.5090	10.7820	-5.3320	-10.8122	0.4933	0.0595	2.6687	0.0069
Scott	5.1570	10.5950	-5.4910	-10.6265	0.5167	0.0534	2.2049	0.0080
<u>Paper Towels</u>								
Bounty	17.379	34.225	-17.499	-37.37444	0.46742	0.653	5.77733	0.03643
Brawny	4.694	8.952	-4.302	-9.77573	0.43379	0.0447	2.21265	0.0055
Scott	4.349	8.204	-3.893	-8.95949	0.42783	0.0366	2.01666	0.0048
Viva	8.407	15.6	-7.305	-17.03516	0.42577	0.112	3.67807	0.00992
<u>Cereals</u>								
General Mills	0.444	0.867	-0.45	-17.3982	0.0258	0.0267	4.9596	0.0018
Kelloggs	0.473	0.928	-0.488	-18.6310	0.0261	0.0327	5.2462	0.0021
Post	0.232	0.451	-0.225	-9.0460	0.0247	0.0063	2.6622	0.0007
Quaker	0.172	0.332	-0.163	-6.6610	0.0240	0.0038	1.9770	0.0005
<u>CSD</u>								
7Up	0.872	1.635	-0.773	-20.832	0.0347	0.0099	4.748	0.0004
Coke	2.022	3.944	-1.954	-50.252	0.0384	0.0328	9.999	0.0013
Pepper	0.369	0.752	-0.384	-9.575	0.0389	0.0021	2.294	0.0002
Pepsi	2.082	4.03	-1.981	-51.348	0.0379	0.0334	10.079	0.0014

Note: This table reports the decomposition of the total advertising effect into direct effect, indirect-own effect and indirect-other effect. 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 5
Decomposition of the Advertising Effects. Elasticities.

Brand	Total	Direct	Ind. Own	$\partial S_j/\partial p_j$	$\partial p_j/\partial A_j$	Ind. Other	$\partial S_j/\partial p_k$	$\partial p_k/\partial A_j$
Toilet Tissue								
Charmin	0.2515	0.4808	-0.2315	-2.3442	0.0994	0.0017	0.4809	0.0010
Cottonelle	0.0873	0.1716	-0.0853	-2.3764	0.0387	0.0006	0.3652	0.0005
Northern	0.0279	0.0541	-0.0265	-2.2053	0.0165	0.0002	0.3551	0.0002
Scott	0.0179	0.0366	-0.0189	-0.9355	0.0204	0.0001	0.2059	0.0002
Paper Towels								
Bounty	0.3999	0.7874	-0.4022	-1.2535	0.3304	0.0147	0.1850	0.0256
Brawny	0.1381	0.2569	-0.1197	-1.8389	0.0671	0.0012	0.3942	0.0008
Scott	0.0660	0.1197	-0.0541	-1.8394	0.0314	0.0005	0.4164	0.0003
Viva	0.0222	0.0420	-0.0200	-2.0022	0.0111	0.0003	0.4094	0.0002
Cereals								
General Mills	0.0930	0.1814	-0.0936	-1.9841	0.0486	0.0053	0.5345	0.0034
Kelloggs	0.1296	0.2536	-0.1325	-1.7850	0.0772	0.0085	0.4761	0.0061
Post	0.0707	0.1368	-0.0678	-2.2890	0.0304	0.0018	0.6412	0.0009
Quaker	0.0303	0.0576	-0.0278	-2.4712	0.0119	0.0006	0.7124	0.0002
CSD								
7Up	0.0773	0.1367	-0.0598	-1.4897	0.0532	0.0008	0.3118	0.0004
Coke	0.1951	0.3729	-0.1803	-1.0781	0.1923	0.0028	0.1900	0.0058
Pepper	0.0437	0.0883	-0.0447	-1.3888	0.0370	0.0002	0.3016	0.0001
Pepsi	0.1046	0.1972	-0.0939	-1.0480	0.1066	0.0014	0.1691	0.0034

Note: This table reports the decomposition of the total advertising effect into direct effect, indirect-own effect and indirect-other effect, expressed in terms of elasticities to enable the comparison across categories. That is, prior to averaging across weeks and zones (and rivals in the case of the indirect other effects) we multiply the effects of advertising on sales (namely the total, the indirect own, and the indirect other effects) with A/S, the price effect (i.e. the terms $\partial S/\partial p$) with p/S, and the retailer adjustment (i.e. the terms $\partial p/\partial A$) with A/p. Note that the column labeled 'direct' reports what the traditionally calculated advertising elasticity would be, and the column labeled 'total' reports the elasticity taking into account the indirect effect that comes through the adjustment of retail prices. The derivatives with respect to advertising $\partial p_j/\partial A_j$ are multiplied by A_j/p_j and the ones with respect to price $\partial S_j/\partial p_j$ are multiplied by p_j/S_j and then averaged.

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 and compare across brands and product categories, recall that each of the indirect effects has two components – the sales response to retail price and the adjustment of retail prices to advertising. Inspecting the elasticities reported in Table 5, we see that there is considerable heterogeneity in the magnitudes of both price elasticities and in the reaction of the retail price to advertising. The price elasticities are in line with theoretical expectations (smaller than -1) and with previous empirical analyses in these categories (see, e.g., Gordon, Goldfarb, & Li, 2013). On average, the retail price reaction to advertising varies much more within a category than across. Looking at the paper towels category, there is some indication that a dominant position of the brand (in this case Bounty, which has 44% share and more than 4 times the advertising expenditures of its next rival), i.e., a large market share and large adspend are associated with a larger upward price adjustment when this brand advertises. A similar pattern emerges in the carbonated soft drinks category, with Coke and Pepsi featuring much larger adjustments than their smaller competitors with lower ad budgets. Our theoretical investigation of a simpler case reported in Section 3 suggested that the magnitude of the adjustment depends on the retailer markup, with $\frac{\partial p}{\partial A}$ being lower for higher markups (and potentially negative when the price sensitivity is also very high). Among the product categories we investigate, the cereals category has the highest markups and we can see that this category also has the lowest price adjustment, on average. Furthermore, the brands in this category with the highest price elasticity, Post and Quaker, also have a lower magnitude of $\frac{\partial p}{\partial A}$ compared to General Mills and Kelloggs. Again, the reaction is a complex interplay of markup, price sensitivity and shares, so it is not possible to derive a conclusive relationship for each of the factors in isolation. We thus conduct numerical simulations in Section 5.3 below and illustrate in Fig. 4.

As mentioned above, in Table 4 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 the adjustment of retail prices of 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 in the case of the toilet tissue category) 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 6, where the effects for a given brand are presented in the corresponding column. The rows list the brands whose advertising impact is reported. For example, in the toilet tissue category, 38.6% of the indirect effect on Charmin's sales is driven by the brand Cottonelle, 54.2% by the brand Northern, and 7.2% by the Scott brand, respectively. Across categories we see that, even though the patterns of the cross effects are not a perfect reflection of the advertising expenditures, the largest spenders in each category seem to have the largest effect on their rivals' sales.

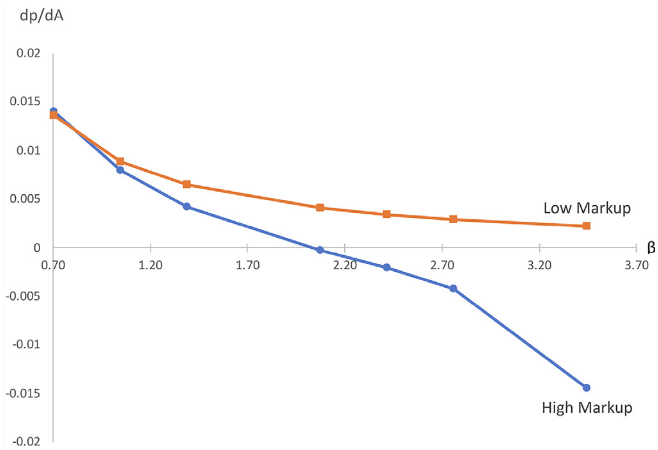

Fig. 4. Retailer reaction to advertising depending on price sensitivity. High versus low markup.

Table 6
Decomposition of the Indirect-Other Advertising Effects.

Toilet Tissue				
	Charmin	Cottonelle	Northern	Scott
Charmin		38.6%	54.2%	7.2%
Cottonelle	54.7%		37.6%	7.7%
Northern	60.4%	30.3%		9.3%
Scott	41.8%	23.7%	34.5%	
Paper Towels				
	Bounty	Brawny	Scott	Viva
Bounty		23.0%	21.6%	55.4%
Brawny	66.9%		10.3%	22.9%
Scott	64.8%	11.4%		23.8%
Viva	75.1%	12.4%	12.5%	
Cereals				
	Genmills	Kelloggs	Post	Quaker
Genmills		61.9%	21.9%	16.2%
Kelloggs	58.8%		23.6%	17.6%
Post	41.0%	46.8%		12.2%
Quaker	40.9%	43.1%	16.0%	
CSD				
	7Up	Coke	Pepper	Pepsi
7Up		46.1%	1.7%	52.2%
Coke	28.0%		2.7%	69.3%
Pepper	16.3%	44.1%		39.6%
Pepsi	36.4%	59.9%	3.6%	

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.

5.3. Direction of the retail price adjustment

We showed in our empirical analysis that a wide range of retailer reactions to manufacturer's advertising is possible if the relationship between wholesale prices and retail prices is not imposed, as in previous studies. Specifically, the reduced-form regressions reported in Section 5.1 point to both positive and negative retail price changes in response to changes in the level of manufacturer advertising. When we evaluate the indirect effects coming from our structural decomposition, we find – in contrast to Chan et al.'s (2017) conclusion that retail prices decrease when a brand is being advertised – that the retailers may raise prices in response to advertising.

Earlier on, in Section 3, we identified price sensitivity, markups, and shares as drivers of the direction of the effect of advertising changes on the retail price and derived the condition that needs to hold for a positive adjustment in the simple case of $J = 1$. In an effort to describe more generally the conditions under which we would expect a positive versus a negative sign of the retail price adjustment, we investigate numerically a range of values for β and $p - w$ for both the case of $J = 1$ and for various competitive scenarios. Naturally, shares will change with β, as will presumably equilibrium prices and wholesale prices. For the numerical illustration, we abstract from the latter.

We start with the average price sensitivity that we estimate and the mean values for p, w, and A that we observe in the data. Shares are computed using these values. We then contrast the retailer reaction $\frac{\partial p}{\partial A}$ in two conditions, a high-markup condition and a low-markup condition for a range of price sensitivities. To see if our intuition for the case of $J = 1$ carries over in a competitive market, we also compute $\frac{\partial p}{\partial A}$ for multiple brands in a market using Eq. (33), whereby we explore markets with only high-markup brands, markets with only low-markup brands, and markets with a mixture of both types. In addition, we vary the levels of advertising. Neither the type of market (single or multiple brands) nor the amount of advertising had a qualitative impact on the direction of the retailer adjustment, so we depict the simplest case of one high-markup brand and one low-markup brand for different values of the price sensitivity parameter β in Fig. 4.

What we see is that, if the markup is low, then the retailer adjustment will be positive irrespective of the level of consumer price sensitivity. If the markup is high, on the other hand, then once the price sensitivity is sufficiently high, the retailer will lower retailer prices in response to manufacturer advertising. That is, when low-markup brands are being advertised, the retailer raises prices to "harvest" the pull effect of advertising. The retailer also responds by raising prices for high-markup brands, when the price sensitivity is sufficiently low. If consumers are very price sensitive, then the retailer lowers the prices of high-markup brands that are being advertised.

In sum, the numerical simulations show that nothing is hard-wired in our model and a variety of outcomes is possible depending on the context. This finding makes it even more remarkable how stable our decomposition is across the four categories we analyzed and suggests that the indirect effect is important more broadly and should be taken into account by manufacturers when deciding their advertising policy.

6. Conclusions

The main questions we set out to answer with this research were whether and how a retailer adjusts prices to end consumers when a brand is being advertised by its manufacturer. Both our reduced-form analysis and the decomposition evaluated using a structural demand model 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 ultimate 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.

One appeal of our approach is its simplicity. Given data on wholesale prices and advertising, we only need a demand estimation and a retailer reaction function $p(w, A)$ to derive the elements of our decomposition and determine the effect of the retailer on the ultimate effect of manufacturer advertising on sales. We assume that the observed wholesale prices and advertising are reflective of an equilibrium and conduct an exercise that is akin to calculating a demand elasticity, extending it to explicitly incorporate the reaction of a strategic retailer. The decomposition can actually be done given any wholesale prices and advertising, no matter how they are determined. The evaluation can be conducted at various alternative values of wholesale prices and advertising to determine sensitivity.

Alas, there is no free lunch, so this simplicity and flexibility come at a cost. Without an assumption on the relationship between wholesale prices and advertising, we cannot say anything about how manufacturers may alter their pricing or advertising strategy when their competitors advertise, or how manufacturers change their wholesale price when they increase or decrease their advertising. One possibility to address this question is to formulate a model, in which manufacturers set wholesale prices after observing advertising levels of all manufacturers in the market. This assumption results in a rather complex model structure, as each manufacturer would need to anticipate not only how they would adjust their own wholesale prices in response to a change in advertising but also how their competitors would adjust their wholesale prices out of equilibrium and possibly their advertising. Since our main goal was to look into the role of the retailer in shaping the ultimate effect of advertising on sales, we preferred to remain agnostic about this relationship and leave it to future research.

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. If data from competing retailers were available, our model and the decomposition could in principle be extended to investigate what the effects would be in this setting. One technical difficulty is that we would have to determine how the entire equilibrium amongst retailers shifts in response to advertising, whereas our assumption of a single retailer allows us to focus on analyzing the retailer's reaction function. We therefore leave this extension to future research.

There is a long tradition in marketing of modeling advertising in a dynamic fashion, considering its long-term effects (for an excellent review, see e.g., Vakratsas & Ambler, 1999). Because we have a short time window in our data and the product categories we analyze are mature, we do not find significant carryover effects and opt for a more parsimonious static model. With a dynamic model of advertising, our decomposition remains the same but would need to be evaluated at different values. It may be a fruitful avenue for future research to repeat our decomposition with other data sets featuring longer time series and hence better suited to investigating dynamic effects of advertising and their impact on consumer demand.

Our analysis across the four different product categories showed remarkable stability of the indirect effect of advertising but also hinted at some potential differences associated with the retailer markups and the price sensitivity in the different markets. Clearly, with only four categories, generalizations are difficult. The empirical work can thus be extended by investigating the effects across a sufficiently large 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.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Estimation of the Demand Model

The unobserved demand shock ξ_{jzt} is derived from decomposing each product's mean utility:

$$\xi_{jzt} = \delta_{jzt} - \alpha_j - \beta p_{jzt} - \gamma A_{jt} - \kappa D_{jzt}, \tag{9}$$

where α_j are intrinsic brand preferences, p_{jzt} is the retail price, and A_{jt} and D_{jzt} are advertising and promotional activity, respectively. The empirical implementation of these variables is as discussed in Section 4.

We employ generalized methods of moments (GMM) to estimate the parameters in demand. The GMM estimator is defined as the product of instrumental variables and the demand error term which is given by the value of the unobserved demand shock ξ_{jzt}. Formally, let $Z = [z_1, \ldots, z_M]$ be a set of instruments such that $E[Z' \cdot \xi(\theta^*)] = 0$, where ξ, a function of the model parameters θ, is the vector of demand error terms. The GMM estimate is then

$$\hat{\theta} = \arg\min_{\theta} \xi(\theta)' Z \widehat{W} Z' \xi(\theta), \tag{10}$$

where $\widehat{W}$ is a consistent estimate of $\left[E\left[Z'\xi\xi'Z\right]\right]^{-1}$.

We use simulation techniques to integrate numerically over the distribution of consumer heterogeneity. For each set of heterogeneity draws we compute ξ by equating the observed market shares to the predicted market shares numerically using the contraction-mapping algorithm provided by BLP. We use the total sales in the category to calculate the market size and hence to infer the share of the inside and outside options but our results are robust to several variations of the market size.

The weight matrix W in Eq. (10) is computed in a two-step procedure. First we set the weight matrix to $(1/n)Z'Z$, where n is the number of observations, and compute an initial estimate of the parameters. Next we use this initial estimate to compute the optimal weight matrix. Standard errors for the estimates are computed using the standard formulas (Hansen, 1982).

Appendix B. Calculation of Derivatives and Effects

This appendix specifies all the individual components that go into the calculation of the effects in the decomposition defined in Eq. (1). We drop the time and zone indices for the sake of parsimony.

The individual probabilities are defined in Eq. (3) and are calculated using the estimated demand parameters. Then, the first derivatives of market shares with respect to prices and advertising are obtained by integrating over the distribution of the households. Specifically,

$$\frac{\partial S_j}{\partial p_j} = \int \beta_i \mathrm{Pr}_{ij}(1 - \mathrm{Pr}_{ij}) dP(\upsilon_i), \tag{11}$$

$$\frac{\partial S_j}{\partial p_k} = -\int \beta_i \mathrm{Pr}_{ij} \mathrm{Pr}_{ik} dP(\upsilon_i),\ j \neq k \tag{12}$$

$$\frac{\partial S_j}{\partial A_j} = \int \gamma_i \mathrm{Pr}_{ij}(1 - \mathrm{Pr}_{ij}) dP(\upsilon_i), \tag{13}$$

$$\frac{\partial S_j}{\partial A_k} = -\int \gamma_i \mathrm{Pr}_{ij} \mathrm{Pr}_{ik} dP(\upsilon_i),\ j \neq k. \tag{14}$$

Similarly, the second derivatives are given by:

$$\frac{\partial^2 S_j}{\partial p_j^2} = \int \beta_i^2 \mathrm{Pr}_{ij}(1-\mathrm{Pr}_{ij})(1-2\mathrm{Pr}_{ij})dP(\upsilon_i), \tag{15}$$

$$\frac{\partial^2 S_j}{\partial p_k^2} = -\int \beta_i^2 \mathrm{Pr}_{ij}\mathrm{Pr}_{ik}(1-2\mathrm{Pr}_{ik})dP(\upsilon_i),\ j \neq k \tag{16}$$

$$\frac{\partial^2 S_j}{\partial p_j \partial p_k} = -\int \beta_i^2 \mathrm{Pr}_{ij}\mathrm{Pr}_{ik}(1-2\mathrm{Pr}_{ij})dP(\upsilon_i),\ j \neq k \tag{17}$$

$$\frac{\partial^2 S_j}{\partial p_k \partial p_l} = \int 2\beta_i^2 \mathrm{Pr}_{ij}\mathrm{Pr}_{ik}\mathrm{Pr}_{il}dP(\upsilon_i),\ j \neq k \neq l, \tag{18}$$

$$\frac{\partial^2 S_j}{\partial p_j \partial A_j} = \int \beta_i \gamma_i \mathrm{Pr}_{ij}(1-\mathrm{Pr}_{ij})(1-2\mathrm{Pr}_{ij})dP(\upsilon_i), \tag{19}$$

$$\frac{\partial^2 S_j}{\partial p_k \partial A_k} = -\int \beta_i \gamma_i \mathrm{Pr}_{ij}\mathrm{Pr}_{ik}(1-2\mathrm{Pr}_{ik})dP(\upsilon_i),\ j \neq k \tag{20}$$

$$\frac{\partial^2 S_j}{\partial p_j \partial A_k} = \int \beta_i \gamma_i \mathrm{Pr}_{ij}\mathrm{Pr}_{ik}(1-2\mathrm{Pr}_{ij})dP(\upsilon_i),\ j \neq k \tag{21}$$

$$\frac{\partial^2 S_j}{\partial p_k \partial A_l} = -2\int \beta_i \gamma_i \mathrm{Pr}_{ij}\mathrm{Pr}_{ik}Pr_{il}dP(\upsilon_i),\ j \neq k \neq l. \tag{22}$$

To calculate the direct and indirect effects of advertising we proceed as follows. Recall that the total response of the market share $S_j(p(w,A),A)$ of brand j to a change in advertising A_j, can be decomposed in three terms:

$$\underbrace{\frac{dS_j(p(w,A),A)}{dA_j}}_{\text{total effect}} = \underbrace{\frac{\partial S_j(p(w,A),A)}{\partial A_j}}_{\text{direct effect}} + \underbrace{\frac{\partial S_j(p(w,A),A)}{\partial p_j}\frac{\partial p_j(w,A)}{\partial A_j}}_{\text{own indirect effect}} + \underbrace{\sum_{k \neq j}\frac{\partial S_j(p(w,A),A)}{\partial p_k}\frac{\partial p_k(w,A)}{\partial A_j}}_{\text{others indirect effect}}. \tag{23}$$

The direct effect, $\frac{\partial S_j}{\partial A_j}$ is simply the first derivative defined above, calculated for each brand and market (week-zone combination).

For the calculation of the indirect effects we need two sets of derivatives, the derivatives of shares with respect to prices, $\frac{\partial S_j}{\partial p_j}$ and $\frac{\partial S_j}{\partial p_k}$, and the derivatives of prices with respect to advertising, $\frac{\partial p_j}{\partial A_j}$ and $\frac{\partial p_k}{\partial A_j}$. The first set is relatively straightforward to calculate by using the first-derivatives formulas above. The derivatives of prices with respect to advertising are in Eq. (33) and require calculating further first and second derivatives as defined above.

Note that, because we have a random coefficients model, for each market (i.e., each week-zone combination) we need to proceed through simulation to calculate each of the first and second derivatives above. This means that, to integrate over the distribution of consumer heterogeneity, we evaluate the expressions inside the integrals above at each draw from the distribution of consumer heterogeneity and then take the average across draws.

Appendix C. Complete Derivations of Retailer Reaction to Advertising Level Change

Given data on wholesale prices, we do not need to make assumptions on the nature of the vertical strategic interaction between multiple manufacturers and the retailer. Given the wholesale prices and the advertising expenditures of the manufacturers, the retailer sets retail prices for all J brands to maximize category profits:

$$\Pi^r = \sum_{j=1}^{J}(p_j - w_j)MS_j(p,A), \tag{24}$$

where w_j is the wholesale price of product j, M is the market size, and $S_j(p,A)$ is the market share of brand j as defined in Eq. (4). We drop the time and zone subscripts to simplify notation.

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

$$\frac{\partial \Pi^r}{\partial p_j} = S_j(p,A) + \sum_{l=1}^{J}(p_l - w_l)\frac{\partial S_l}{\partial p_j} = 0, \quad j = 1,\ldots,J. \tag{25}$$

The above FOCs can be rewritten in matrix notation as:

$$p = w - \nabla^{-1}S, \tag{26}$$

where

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

We now compute how retail prices p change with changes in the level of manufacturer advertising A. Total differentiation of the retailer price first-order conditions with respect to advertising yields expressions for the derivatives $\frac{\partial p_j}{\partial A_k}$, where $j = 1, \ldots, J$ and $k = 1, \ldots, J$:

$$\frac{d\left(\frac{\partial \Pi^r}{\partial p_j}\right)}{dA_k} = \sum_{l=1}^{J} \frac{\partial^2 \Pi^r}{\partial p_j \partial p_l} \frac{\partial p_l}{\partial A_k} + \frac{\partial^2 \Pi^r}{\partial p_j \partial A_k} = 0, \; j = 1, \ldots, J, \; k = 1, \ldots, J. \tag{27}$$

Define

$$\Delta = \begin{bmatrix} \frac{\partial^2 \Pi^r}{\partial p_1 \partial p_1} & \cdots & \frac{\partial^2 \Pi^r}{\partial p_1 \partial p_J} \\ \vdots & \cdots & \vdots \\ \frac{\partial^2 \Pi^r}{\partial p_J \partial p_1} & \cdots & \frac{\partial^2 \Pi^r}{\partial p_J \partial p_J} \end{bmatrix}, \tag{28}$$

where

$$\frac{\partial^2 \Pi^r}{\partial p_j \partial p_j} = 2\frac{\partial S_j}{\partial p_j} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_j^2} \tag{29}$$

and

$$\frac{\partial^2 \Pi^r}{\partial p_j \partial p_k} = \frac{\partial S_j}{\partial p_k} + \frac{\partial S_k}{\partial p_j} + \sum_l (p_l - w_l)\frac{\partial^2 S_l}{\partial p_j \partial p_k}, \, j \neq k. \tag{30}$$

Define

$$\Psi = \begin{bmatrix} \frac{\partial^2 \Pi^r}{\partial p_1 \partial A_1} & \cdots & \frac{\partial^2 \Pi^r}{\partial p_1 \partial A_J} \\ \vdots & \cdots & \vdots \\ \frac{\partial^2 \Pi^r}{\partial p_J \partial A_1} & \cdots & \frac{\partial^2 \Pi^r}{\partial p_J \partial A_J} \end{bmatrix}, \tag{31}$$

where

$$\frac{\partial^2 \Pi^r}{\partial p_j \partial A_k} = \frac{\partial S_j}{\partial A_k} + \sum_{l=1}^{J} (p_l - w_l)\frac{\partial^2 S_l}{\partial p_j \partial A_k}. \tag{32}$$

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

$$\begin{bmatrix} \frac{\partial p_1}{\partial A_1} & \cdots & \frac{\partial p_1}{\partial A_J} \\ \vdots & \cdots & \vdots \\ \frac{\partial p_J}{\partial A_1} & \cdots & \frac{\partial p_J}{\partial A_J} \end{bmatrix} = -\Delta^{-1}\Psi. \tag{33}$$

Appendix D. Illustrative Example of Equilibrium Derivations under Manufacturer Stackelberg

Because we can condition on the available data on wholesale prices, we do not need the full specification of manufacturer behavior to recover wholesale prices to use in the decomposition. For completeness sake though, here we derive the equilibrium for the most commonly used model of channel behavior, the Manufacturer Stackelberg with manufacturers making simultaneous decisions on wholesale prices and advertising (see, e.g., Vilcassim, Kadiyali, & Chintagunta, 1999).

Manufacturers compete with each other à la Bertrand and are Stackelberg leaders vis-a-vis the retailer. They take into account the retailer's reaction function $p(w, A)$ when setting advertising levels and wholesale prices. The objective function of manufacturer j is given by:

$$\Pi_j^m = (w_j - c_j)MS_j(p(w, A), A) - A_j, \tag{34}$$

where c_j is the marginal cost for brand j and A_j are manufacturer j's advertising expenditures.

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

$$\frac{\partial \Pi_j^m}{\partial w_j} = S_j + (w_j - c_j)\sum_{k=1}^{J} \frac{\partial S_j}{\partial p_k}\frac{\partial p_k}{\partial w_j} = 0. \tag{35}$$

The last term in Eq. (35), the change in retail prices in response to changes in wholesale prices, $\frac{\partial p_k}{\partial w_j}$, is derived analogously to $\frac{\partial p_k}{\partial A_j}$ in Appendix C by totally differentiating the retailer FOCs in Eq. (25) with respect to w:

$$\frac{d\left(\frac{\partial \Pi^r}{\partial p_j}\right)}{dw_k} = \sum_{l=1}^{J} \frac{\partial^2 \Pi^r}{\partial p_j \partial p_l}\frac{\partial p_l}{\partial w_k} + \frac{\partial^2 \Pi^r}{\partial p_j \partial w_k} = 0,\ j = 1,\ldots,J,\ k = 1,\ldots,J. \tag{36}$$

Let Δ and ∇ be defined as in Appendix C. We then obtain in matrix form:

$$\begin{bmatrix} \frac{\partial p_1}{\partial w_1} & \cdots & \frac{\partial p_1}{\partial w_J} \\ \vdots & & \\ \frac{\partial p_J}{\partial w_1} & \cdots & \frac{\partial p_J}{\partial w_J} \end{bmatrix} = \Delta^{-1}\nabla. \tag{37}$$

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

$$\frac{\partial \Pi_j^m}{\partial A_j} = (w_j - c_j)M\left(\frac{\partial S_j}{\partial A_j} + \sum_{k=1}^{J} \frac{\partial S_j}{\partial p_k}\frac{\partial p_k}{\partial A_j}\right) - 1 = 0, \tag{38}$$

where $\frac{\partial p_k}{\partial A_j}$ is derived above in Eq. (33) as a function of the demand parameters.

Solving the first-order conditions (35) and (38) yields the equilibrium wholesale prices $(w_1 \ldots w_J)$ and advertising levels $(A_1 \ldots A_J)$. Note that if we had specified that manufacturers first choose advertising and then wholesale prices, then the derivations would include a function $w(A)$ that defines how the equilibrium of the subgame in which wholesale prices are chosen changes with advertising. We follow the literature and avoid this additional complication by stipulating that manufacturers make simultaneous decisions.

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