Marketing Letters
https://doi.org/10.1007/s11002-021-09592-6

Investigating cross-media effects in a multichannel marketing environment: the role of email, catalog, television, and radio

Karthik Sridhar[1] · **Ashish Kumar**[2] · **Ram Bezawada**[1]

Accepted: 29 July 2021 Published online: 19 August 2021

Abstract
We empirically examine the cross-media effects of personalized and mass media on consumers' purchase incidence in a multichannel shopping environment. We capture the cross-media effect as the combined impact of two distinct marketing communications on consumers' purchase behavior. Our data consists of individual-level transaction data and information on consumers' exposure to multiple marketing media consisting of personalized (catalog and email) and mass (television and radio) media. We find that personalized (mass) media are more influential in driving consumers' online (offline) purchases in a multichannel shopping environment. Our analysis of cross-media effects reveals synergistic (attenuating) effects between media components *across* (*within*) personalized and mass media. Furthermore, our examination of media elasticities demonstrates that discounting such cross-media effects between personalized and mass media components can bias a firm's assessment of the effectiveness of media components in a multichannel-multimedia marketing environment. Results from our model can help marketing managers in the optimal planning of integrated marketing communication in a multichannel-multimedia shopping environment.

Keywords Multichannel · Cross-media · Email · Catalog · Television · Radio

✉ Ashish Kumar
ashish.kumar@rmit.edu.au

Karthik Sridhar
karthik.sridhar@baruch.cuny.edu

Ram Bezawada
ram.bezawada@baruch.cuny.edu

1 Allen G. Aaronson Department of Marketing and International Business, Zicklin School of Business, Baruch College-The City University of New York, New York, NY, USA

2 School of Economics, Finance and Marketing, College of Business and Law, RMIT University, Melbourne, Australia

1 Introduction

In the USA, digital surpassed traditional/mass ad spending for the first time in 2019 (eMarketer, 2019). According to eMarketer (2021), out of the $60 billion advertising expenditure recorded in the retail industry, 6.5% went to radio, 14% was spent on catalog and magazine advertising, 27% on TV, and 48% on internet/mobile advertising. About 19% of a firm's marketing budget is allocated for email marketing initiatives (eConsultancy, 2019). Nevertheless, traditional media (such as television) are still relevant as they create a synergy with personalized/one-to-one media (Naik & Raman, 2003). As part of their integrated marketing communication strategy, firms employ a mix of multimedia marketing communications to directly or indirectly influence consumers' shopping behavior by informing and reminding them about product offerings (Keller, 2001). Firms disburse marketing communications through a combination of personalized marketing media outlets (e.g., emails, paid search ads, catalogs) and mass/traditional media outlets (e.g., television, radio). A multimedia mix strategy creates new challenges for marketing managers to optimize their limited marketing budget by leveraging the strengths of constituent communication outlets (Voorveld et al., 2011). Thus, it becomes critical for marketers to understand how messages across multiple marketing media outlets interact and influence consumer behavior to optimally target consumers.

While extant literature has investigated the impact of personalized media on multichannel shopping behavior, it has fallen short in examining the effect of such media in the presence of mass media, and in understanding the interaction/cross-media effects between the constituent media outlets constituting personalized and mass media. In a multichannel-multimedia marketing environment, firms need to understand the role of individual marketing communication outlets and their impact on consumers' shopping behavior to optimize their marketing communication programs. Furthermore, the effectiveness of direct and cross-media effects can vary across online and offline channels in such an environment creating added challenges in structuring a multichannel-multimedia marketing program. This study addresses the above issues by evaluating the effectiveness of multiple personalized and mass marketing media outlets in a multichannel shopping environment while accounting for direct and cross-media effects.

We develop an econometric model to disentangle the direct and cross-media effects of four marketing media vehicles/outlets—email, catalog, television, and radio—on consumer's purchase incidence in a multichannel setting. Emails and catalogs constitute a firm's personalized media, while television and radio belong to the firm's mass media. Our model uses the copula method to account for the endogeneity emanating from consumer self-selection and the firm's selective targeting prevalent in personalized marketing communications through email and catalog. We estimate our empirical model at the consumer level by combining a unique scanner panel data capturing consumers' purchases with the firm's marketing communication databases. We also account for the effects of the other marketing components of price and sales promotion. We provide interesting insights on the interaction between personalized and mass media components in influencing consumer shopping behavior across channels.

Our empirical analysis suggests that in a multichannel shopping environment like ours, while both personalized and mass media components significantly impact consumers' purchase incidence across both online and offline channels, personalized marketing media—email and catalog—are relatively more influential than mass media—television and radio—in driving online purchases. Again, in our context, mass media are relatively more effective for offline purchases. Interestingly in our multimedia mix, assessment of cross-media effects indicates synergies between media components *across* personalized and mass media while revealing attenuating effects between media components *within* personalized and mass media. We also demonstrate that discounting such cross-media effects between personalized and mass media components can bias a firm's assessment of the effectiveness of media components in a multichannel-multimedia marketing environment such as ours.

2 Related literature

Early studies in this field explored the effects of a firm's multichannel strategy on firm profitability (Venkatesan et al., 2007), consumer spending (Kushwaha & Shankar, 2013), and consumer channel adoption (Chintagunta et al., 2012). Recently, studies have shifted towards investigating the effectiveness of media components on consumer shopping behavior across online and offline channels (Batra & Keller, 2016). To that end, studies explore the significance of catalog, email, digital advertising, and traditional advertising in a multichannel environment (Dinner et al., 2014; Danaher et al., 2020). Studies have also documented the varying effects of consumers' price sensitivity (Chu et al., 2008), price dispersion (Brynjolfsson & Smith, 2000), search cost (Chintagunta et al., 2012), and price promotions (Arce-Urriza et al., 2017) across channels. Insights from these studies reveal that managing multiple media in a multichannel shopping environment is challenging due to consumers' channel migration.

However, extant literature has primarily investigated the impact of either personalized media (Danaher et al., 2020; Zantedeschi et al., 2017) or traditional media (Naik & Raman, 2003) on the multichannel shopping environment. Firms with multichannel marketing strategies often adopt marketing media strategies involving both personalized and mass media. Investigating one type of media in the absence of the other can lead to sub-optimal media attributions. Naik and Raman (2003) highlight the importance of understanding cross-media interactions ignored in recent studies (e.g., Danaher et al., 2020). Furthermore, investigations of multimedia effects on multichannel shopping shirk from providing insights on actual purchase behavior (e.g., Naik and Peters (2009) study impact of digital ads and mass media on website visits and offline visits devoid of actual purchase). Thus, analyzing the direct and cross-media effects of both personalized and mass media on consumer purchase behavior in a multichannel shopping environment is managerially relevant for better media attribution.

While recent studies (Danaher et al., 2020) examine the overall effect of multimedia components on multichannel shopping behavior, we, through our study, disentangle this overall effect of a media component on multichannel shopping as emanating due to its direct impact and interaction with other media components used by the firm. While prior studies focused on investigations about one media type (for instance, personalized media consisting of paid search, catalog and email by Danaher et al. 2020), our research broadens such an examination using media components belonging to a firm's personalized and mass media strategy. By doing so, we expand on our current understanding of this topic by studying the influence of cross-media effects of not only components within media categories but also across personalized and mass media.

3 Model

We follow the standard random utility framework to model consumers' purchase incidence decisions for a given multichannel retailer (Chu et al., 2008). Let U_{ht}^{c} be the latent utility of household h's decision to buy at time t from the channel $c \in$ {Online, Offline}, which we model as follows:

$$\begin{aligned} U_{ht}^{c} = \alpha_h^c &+ \underbrace{\beta_{1h}^{c}\mathrm{Price}_{ht}^{c} + \beta_{2h}^{c}\mathrm{Promotion}_{ht}^{c}}_{\text{Marketing mix}} \\ &+ \underbrace{\theta_{1h}^{c}\mathrm{Email}_{ht} + \theta_{2h}^{c}\mathrm{Catalog}_{ht} + \theta_{3h}^{c}\mathrm{Television}_{ht} + \theta_{4h}^{c}\mathrm{Radio}_{ht})}_{\text{Direct media effects}} \\ &+ \nu_{1h}^{c}\mathrm{Television}_{ht} \times \mathrm{Radio}_{ht} \\ &+ \mathrm{Catalog}_{ht} \times (\nu_{2h}^{c}\mathrm{Television}_{ht} + \nu_{3h}^{c}\mathrm{Radio}_{ht}) \\ &+ \underbrace{\mathrm{Email}_{ht} \times (\nu_{4h}^{c}\mathrm{Catalog}_{ht} + \nu_{5h}^{c}\mathrm{Television}_{ht} + \nu_{6h}^{c}\mathrm{Radio}_{ht})}_{\text{Cross-media effects}} \\ &+ \boldsymbol{\mu}_h^c\mathbf{Holiday}_t + \epsilon_{ht}^{c}, \end{aligned} \tag{1}$$

where α_h^c is household h's intrinsic purchase preference for channel c, β_{1h}^{c} and β_{2h}^{c} are consumers' price and promotion sensitivities for channel c respectively, $\theta_{1h}^{c} - \theta_{4h}^{c}$ capture the direct media effects of email, catalog, television, and radio in channel c, $\nu_{1h}^{c} - \nu_{6h}^{c}$ capture the cross-media effects in channel c, and $\boldsymbol{\mu}_h^c$ captures the effects of various holidays on channel c. We specify no purchase occasion as $U_{ht}^{0} = \epsilon_{ht}^{0}$. Furthermore, we specify $\begin{pmatrix} \epsilon_{ht}^{Online} - \epsilon_{ht}^{0} \\ \epsilon_{ht}^{Offline} - \epsilon_{ht}^{0} \end{pmatrix} \sim MVN\left[0, \begin{pmatrix} 1 & \rho\sigma_2 \\ \rho\sigma_2 & \sigma_2^2 \end{pmatrix}\right]$, which gives us a multinomial probit framework for channel incidence.

In Eq. 1, Email_{ht} and $\mathrm{Catalog}_{ht}$ are personalized media, and $\mathrm{Television}_{ht}$ and Radio_{ht} are mass media used by the firm. Firms tend to increase mass media communications during holidays and special occasions critical to the business. In Eq. 1, we control for such firm actions by including a vector of holiday dummies, $\mathbf{Holiday_t}$, constituting federal holidays and special occasions. On the other hand, the firm targets personalized media to specific consumers who are more likely to purchase (Danaher et al., 2020). Such an approach by the firm makes these variables endogenous (e.g., omitted variable bias) in our model. Moreover, the permission-based nature, i.e., consumer's preference to receive these communications from these media components,, presents self-selection bias in the model. We account for these endogeneity issues by using the copula method. Following (Park & Gupta, 2012), we use copula function, C, to construct the joint density function, F, of endogenous regressors in the model, Email_{ht} and Catalog_{ht}, and the error term, $\boldsymbol{\epsilon}_{\mathbf{ht}}^{\mathbf{c}}$, as follows:

$$F(\text{Email}_{ht}, \text{Catalog}_{ht}, \boldsymbol{\epsilon}_{ht}^{c}) = C(M_{\text{Email}}(\text{Email}_{ht}), M_{\text{Catalog}}(\text{Catalog}_{ht}), M_{\text{Online}}(\epsilon_{ht}^{Online}), M_{\text{Offline}}(\epsilon_{ht}^{Offline}); \Pi), \quad (2)$$

where $M(.)$ is the marginal distribution function, and Π captures the degree of dependence among the endogenous regressors. We utilize the Gaussian copula as it is widely used in various marketing applications (Danaher & Smith, 2011). Using the Gaussian copula, we can specify the endogenous variables and the error terms to be distributed $N(0, \Sigma)$. Following Park and Gupta (2012), we can derive the joint density function under the Gaussian copula assumption (2) as follows:

$$F(\text{Email}_{ht}, \text{Catalog}_{ht}, \boldsymbol{\epsilon}_{ht}^{c}) = C(M_{\text{Email}}(\text{Email}_{ht}), M_{\text{Catalog}}(\text{Catalog}_{ht}), M_{\text{Online}}(\epsilon_{ht}^{Online}), M_{\text{Offline}}(\epsilon_{ht}^{Offline}); \Pi) = \int_{-\infty}^{\Phi^{-1}(U_{\text{Email}})} \int_{-\infty}^{\Phi^{-1}(U_{\text{Catalog}})} \int_{-\infty}^{\Phi^{-1}(U_{\epsilon Online})} \int_{-\infty}^{\Phi^{-1}(U_{\epsilon Offline})} \frac{e^{-\frac{1}{2}t'\Theta^{-1}t}}{2\pi}, \quad (3)$$

where U_{Email}, $U_{Catalog}$, $U_{\epsilon Online}$, and $U_{\epsilon Offline}$ are the probability integral transformations for $M_{\text{Email}}(Email_{ht})$, $M_{\text{Catalog}}(Catalog_{ht})$, $M_{\text{Online}}(\epsilon_{ht}^{Online})$, and $M_{\text{Offline}}(\epsilon_{ht}^{Offline})$, respectively. This estimation method (which is similar to the control function approach by Petrin & Train 2010) provides consistent parameter estimates by accounting for the correlation between the endogenous regressors and the error, $\boldsymbol{\epsilon}_{ht}^{c}$. Such a copula based method has been applied in marketing to address the endogeneity issue of marketing mix variables (Danaher & Smith, 2011).

4 Data

Our dataset comes from a nationally recognized leading retailer of liquor products in the state of New York. As a part of the multichannel strategy, it sells its products through offline (brick and mortar store) and online (retailer website) channels. As per the laws in New York, liquor products are sold only in (privately owned) approved specialty stores (for example, they cannot be sold in supermarkets). Since the focal retailer is the dominant player in the region, it attracts a loyal clientele. Another essential feature of online orders is that the retailer cannot ship the order outside the state. Thus, shopping at either the physical store or online represents a viable option for consumers in our sample. They chose one or the other based on their preferences- this feature makes it particularly attractive to disentangle the effects of multiple marketing media across online and offline channels.

As a part of the multimedia mix strategy, the retailer adopts multiple marketing media consisting of mass media components such as television and radio and personalized marketing media components such as email and catalog. In addition, the dataset also has information on the retailers' marketing mix, price and sales promotion. We use data spanning over two and a half years, a total of 135 weeks, from January 2010 to July 2012. The retailer's promotion week is the same as the calendar week, i.e., the same prices and sales promotions are in effect from Monday to Sunday. Different kinds of promotions are run weekly. Given the above, we operationalize our price, sales promotion and communication mix variables weekly. We combine the scanner panel dataset consisting of household purchase histories[1] with other databases on email marketing, catalog mailing, television, and radio advertising.

Since we specify a completely heterogeneous model, we select those households in our sample with a minimum of two purchases.[2] To effectively assess the parameters for direct and cross-media effects, we further select households that consumed at least one personalized media during the study period. This yields 4,181 households from which we randomly select 500 households to estimate our empirical model. Following this approach, our framework abstracts away from customer acquisitions and focuses on customer retention. We now describe the operationalization of the variables used in the model.

Email Emails are part of personalized media used by the retailer. We have a detailed database on the retailer's email marketing activities which tracks individual-level responses to retailer emails. For a given week, we operationalize this variable as the total number of emails opened by the consumer.

Catalog Catalogs are personalized physical booklets sent periodically by the retailer to its consumers. These catalogs contain detailed information on products, prices, and a calendar of tasting/sampling and educational programs. For a given week, we operationalize this variable as the total number of catalogs sent to the consumer.

Television For television ads, we have information on the gross rating points (GRP) of the television programs in which the retailer's ads were featured. To operationalize this variable, we use the sum total of GRPs of all the television programs broadcast during a week where the retailer's ads were featured and weigh it by program length. The retailer's standard television advertisement length of 30 s is used as the basis for weighting. Thus, the television ads of 60 s receive twice the weight, and 15 s get half the weight. Since we lack more detailed information on viewership habits, we assume all households in our database are exposed to television ads.

Radio Radio ads are featured during radio programs such as talk shows, bulletins, game shows and infomercials. We have information on GRP ratings of the radio programs in which the retailer's ads were featured. This variable is operationalized similar to television ads. Note that a standard radio ad is 60 s long.

[1]The retailer has a consumer relationship management (CRM) system using loyalty card program

[2]In this dataset, we find that about 88.74% of consumers purchase at least twice.

We operationalize these media components, $Media \in$ {Email, Catalog, Television, Radio} as media stock, $MedStock_t$, variable. Following Tellis and Weiss (1995) and Dinner et al. (2014), we define $MedStock_t$ variable as: $MedStock_t = \delta Media_t + (1 - \delta) MedStock_{t-1}$, where $\delta \in (0, 1)$ is decay parameter which we estimate in our model.

Price and sales promotion We operationalize price variables as $/ml for each household on each shopping trip. For the price variable, we compute the per-unit price for each SKU and share-weight it using the SKU market share using constant weights (Pauwels & Srinivasan, 2004). We use the net price, i.e., price net of all discounts, to compute the price variable. Note that if a consumer purchases from a channel, we use the consumer's net price. We employ the share-weighted method to compute the price variable for the channel in which the purchase is not recorded. We operationalize the sales promotion variable (akin to promotional breadth used in literature) as the number of SKUs bought by the consumer on sale divided by the total items bought in the shopping trip. For the channel not used by the consumer, we operationalize it as the number of SKUs on sale divided by the total number of items in the channel.

Holiday **Holiday** is a vector of binary variables for federal holidays and special occasions critical to wine sales. It includes dummy variables for New Year's Day, Presidents Day, Memorial Day, Independence Day, Labor Day, Columbus Day, Veteran's Day, Thanksgiving Day, Christmas, Valentine's Day, Easter and Mother's Day. We set the variable as 1 for weeks preceding the holiday/special occasion and 0 otherwise. For Thanksgiving, we set the variable 1 for both the preceding and following week.

We present the data descriptive in Table 1. Among personalized media, firms target consumers more frequently using emails (1–2 emails per week) as opposed to catalogs (3–4 catalogs per year). Consumers are more exposed to retailers' television

Table 1 Data summary

Variable	Mean	Standard deviation
Marketing media		
Email (# of emails opened per week)	1.57	1.45
Catalog (# of catalog sent per week)	0.07	0.01
Television (weighted GRP per week)	72.13	69.34
Radio (weighted GRP per week)	27.29	11.17
Marketing mix		
Price ($/ml)	0.02	0.01
Promotion breadth (%)	0.37	0.15
Purchase incidences		
Total purchase incidences	14567	
Holiday purchase incidences	21.62%	

ads (72.13 GRP) than radio ads (27.29 GRP). The unit price of the alcohol products is \$0.02/ml, and 37% of products are bought on promotion per week.

5 Results

We estimate our model using Bayesian techniques and Markov Chain Monte Carlo (MCMC) methods with 60,000 iterations while incorporating a purpose-built Gibbs sampler. The last 10,000 are utilized to calculate parameter posterior means and precise standard errors upon ensuring convergence. We use the draws to assess contrasts between parameter estimates, where applicable. To reduce the computational burden, we use the grid search method to obtain the optimum values for our δ parameters. We present the estimates in Table 2.

Table 2 Estimation results

	Parameter estimates	
	online	*Offline*
Price (β_1^c)	−6.3015*** (2.1787)	−7.0451*** (2.6642)
Promotion (β_2^c)	1.2334*** (0.4593)	0.8673** (0.3493)
Email (θ_1^c)	0.8989*** (0.0983)	0.2117** (0.1019)
Catalog (θ_2^c)	0.4760*** (0.0449)	0.3163*** (0.0495)
Television (θ_3^c)	0.1135*** (0.0301)	0.3403*** (0.0482)
Radio (θ_4^c)	0.0581*** (0.0115)	0.2165*** (0.0464)
Television × radio (ν_1^c)	−0.0885** (0.0432)	−0.1802** (0.0904)
Catalog × television (ν_2^c)	0.0237* (0.0130)	0.3769* (0.2136)
Catalog × radio (ν_3^c)	0.1840 (0.1289)	0.2830 (0.3331)
Email × catalog (ν_4^c)	−0.3683*** (0.1336)	−0.1899* (0.1107)
Email × television (ν_5^c)	0.2051* (0.1047)	0.0579** (0.0231)
Email × radio (ν_6^c)	0.0020 (0.1188)	0.0031 (0.1145)
Holiday[1] ($\boldsymbol{\mu}^c$)	-	-
Intercept (α^c)	−2.3898** (1.0864)	0.2151*** (0.0492)
Email decay (δ_{Email})	0.4916*** (0.0291)	
Catalog decay ($\delta_{Catalog}$)	0.3854** (0.1732)	
Television decay ($\delta_{Television}$)	0.8702** (0.3422)	
Radio decay (δ_{Radio})	0.5819*** (0.1928)	

Note: *p¡0.10, **p¡0.05, ***p¡0.01: these significances indicate that 90%, 95%, and 99% confidence intervals exclude zero, respectively. Posterior standard errors are in brackets

[1] For the sake of parsimony we do not report all parameter estimates for variables in the **Holiday**$_t$ vector. Both online and offline purchases are influenced prominently by Valentine's Day (0.8321*** Online; 1.4712*** Offline) and Mother's Day (0.7212** Online; 1.2711** Offline). Multichannel purchase is least influenced by Labor Day (−0.7721* Online; −1.0153** Offline) and Columbus Day (−0.8919* Online; −1.1919* Offline)

5.1 Effects of price and sales promotion

Results reveal that marketing mix, price and promotion, are the main drivers of consumers' purchase incidence in a multichannel environment. Consistent with prior studies (Chu et al., 2008) consumers are less price-sensitive online ($\beta_1^{Online} = -6.30$) than in offline channel ($\beta_1^{Offline} = -7.05$). This can be attributed to lower search costs for online channels. Conversely, consumers are more promotion sensitive online ($\beta_2^{Online} = 1.23$) than in offline ($\beta_2^{Offline} = 0.87$) channel.

5.2 Effects of media

5.2.1 Direct media effects

In our multimedia-multichannel environment, the direct effects of personalized media (i.e., email and catalog) on online channel incidence are more than mass media's effects (i.e., television and radio). In the offline channel, television and catalog directly impact incidence, followed by radio and email. Comparing the direct effects across channels, we observe that personalized media influences incidence online more than offline.[3] In contrast, mass media such as television influences offline more than online channel incidence. The differential influence of radio across channels is not significant.[4] Thus, in our multichannel shopping environment, the direct impact of personalized media is more effective in stimulating online shopping behavior. The direct effect of mass media has a more significant effect on offline shopping behavior.

Additionally, by assessing the decay parameters ($\boldsymbol{\delta}$), we find that for personalized communications, the overall influence on consumer shopping behavior in the current period (t) stems primarily from communications in the prior ($t - 1$) period. In contrast, for mass media, the effect of media communications in the current period is more than that of the past period.

5.2.2 Cross-media effects

Our results reveal some very interesting cross-media effects. We observe that the cross-media influence of similar components within a marketing media category on consumers' purchase incidence in a multichannel shopping environment to be negative. Specifically, email-catalog interaction ($\nu_4^{Online} = -0.3683$, p¡0.01; $\nu_4^{Offline} = -0.1889$, p¡0.1) and television-radio interaction ($\nu_1^{Online} = -0.0885$, p¡0.05; $\nu_1^{Offline} = -0.1802$, p¡0.05) negatively impact channel incidence. We surmise that the marketing content for media communications within personalized media and within mass media respectively tend to be similar. In other words, there might exist an overlap in products marketed using personalized media through email and catalog at a particular time. Similarly, the messages relayed through mass media

[3] β_{Email}^{Online} - $\beta_{Email}^{Offline}$ = 0.6872, p¡0.01; $\beta_{Catalog}^{Online}$ - $\beta_{Catalog}^{Offline}$ = 0.1597, p¡0.01

[4] $\beta_{Television}^{Online}$ - $\beta_{Television}^{Offline}$ = -0.2268, p¡0.01; β_{Radio}^{Online} - $\beta_{Radio}^{Offline}$ = −0.1584, n.s.

components in a particular period tend to be comparable. Continued exposure to similar messages can affect the consumer's information processing capacity, leading to cognitive overload (Malhotra et al., 1982). Such an overload can lead to delays and even postponement in decision making (Mitchell et al., 2005), which we observe as attenuating effects of media components on purchase intentions. Interestingly, in our context, the cognitive overload at the individual level in personalized media exists at the aggregate level through mass media exposure.

On the other hand, cross-media effects emanating from the mixing of personalized and mass media types tend to accentuate or reinforce constituent media effects in our case. Email-television interaction positively impacts both online and offline channel incidence ($\nu_5^{Online} = 0.2051$, p¡0.1; $\nu_5^{Offline} = 0.0579$, p¡0.05). Similarly, catalog-television interaction positively impacts online and offline channel incidence ($\nu_2^{Online} = 0.0237$, p¡0.1; $\nu_2^{Offline} = 0.3769$, p¡0.10). Marketing communication disbursed through television ads has been found to influence consumers' online activities, such as brand search and site visits (Du et al., 2019). Thus, television ads can accentuate consumer purchase incidence across channels in conjunction with personalized media such as emails and catalogs. The interaction effects between personalized and mass media types highlight the importance of strategically integrating different marketing media types for marketing communication disbursement in a multichannel shopping environment such as ours. Additionally, and in contrast with prior findings (e.g., Danaher et al. 2020), we observe patterns of influence of mass media in the presence of personalized media and vice-versa on shopping behavior. Insights about cross-media effects between personalized and mass media components on consumer purchase behavior across channels are also unique to our study.

6 Discussions

We assess the overall impact of our retailer's marketing mix by computing elasticities (with and without media interaction effects) for online and offline purchases (Table 3).[5] Price and sales promotion are the main drivers of consumers' purchase behavior in our multichannel shopping environment. Expectedly, consumers are more price (promotion) conscious while purchasing in the offline (online) channel as opposed to the online (offline) channel (Chu et al., 2008). Similar to recent findings (Zantedeschi et al., 2017; Danaher et al., 2020), we observe that the overall impact of email (0.0628) and catalog (0.0468) on online shopping is high. Additionally, television's impact on online purchases is relevant (0.0219).

Interestingly, in our research context, television (0.0707) and catalog (0.0573) dominantly impact purchases in the offline channel when compared to email (0.019)

[5] We employ simulation techniques (e.g., Allenby and Lenk 1994) for computing the elasticities. We use parameter estimates to compute base channel incidence probabilities and the change in channel incidence probabilities due to a 5%, 10%, 15%, and 20% bump respectively for each independent variable. These are then averaged to obtain the final elasticies and corresponding standard error. Since media component disbursement frequencies are different—emails can be sent daily while catalogs are sent less frequently, managers should interpret the media effectiveness accordingly.

Table 3 Marketing mix and media elasticities[1]

Variables	With cross-media effects		Without cross-media effects	
	Online	*Offline*	*Online*	*Offline*
Price	−1.4169***	−2.3880**	−1.4171**	−2.3886***
	(0.4118)	(0.9841)	(0.6163)	(0.8736)
Promotion	0.1893***	0.1130**	0.1899***	0.1133***
	(0.0529)	(0.0467)	(0.0599)	(0.0248)
Email	0.0628***	0.0190**	0.0611***	0.0091*
	(0.0075)	(0.0087)	(0.0184)	(0.0052)
Catalog	0.0468***	0.0573***	0.0408*	0.0418***
	(0.0053)	(0.0060)	(0.0232)	(0.0049)
Television	0.0219***	0.0707*	0.0258***	0.0716**
	(0.0029)	(0.0382)	(0.0026)	(0.0293)
Radio	0.0071	0.0180**	0.0159*	0.0186**
	(0.0725)	(0.0076)	(0.0084)	(0.0083)

[1] Standard errors are in parenthesis

***p¡0.01, **p¡0.05, *p¡0.10

Elasticities with (without) cross-media effects consider (neglect) the interaction effects of marketing media

and radio (0.018). This is in sharp contrast to findings by Danaher et al. (2020), where they find that email (0.043) and catalog (0.031) dominate in-store purchases. It is important to note that Danaher et al. (2020) study personalized media impacts devoid of mass media presence. By investigating the effect of personalized media types in the presence of prominent mass media used by retail firms in the marketplace in our study, we indicate that the impact of email in driving in-store sales can be overstated and that of catalogs understated in prior literature. However, we do not entirely discount the use of email for offline purchases because of the low cost associated with this media. Moreover, by comparing the elasticities from our model to ones computed without cross-media effects, we find that discounting cross-media effects leads to understating the overall impact of personalized media and overstating the impact of mass media on both online and offline shopping behavior.

Furthermore, disentangling the overall impact of media components into their own effects and cross-media effects in this study enables us to provide marketing managers with better insights. Recent studies have advocated for optimal consumer exposure to emails, catalogs and paid search ads individually. With attenuating cross-media effects stemming from possible cognitive overloads in consumers, we recommend that managers make optimal assessments across all of the firm's constituent personalized media and mass media components simultaneously. If managers increase consumer exposure to emails, they should take the necessary steps to decrease consumer exposure to other personalized media. In other words, an increase in budget allocation for emails warrants a simultaneous decrease in the budget for catalogs. Unlike recent studies, we still find that mass media such as television and radio are still relevant for firms and in the presence of personalized media accentuate preference for online and offline channels—albeit such influence is relatively higher for offline channel. Since television synergistically interacts with personalized media, increased exposure to television ads can improve the effectiveness of personalized communications. Managers are better served in increasing budget allocation for television to increase the impact of personalized media (Naik & Raman, 2003). Overall, it is essential for retailers to not rely on the same type of marketing media to engage with their consumers in multichannel shopping environments similar to ours. Mixing different types of marketing media has additional benefits, as our results suggest.

7 Conclusion

In this study, we capture the cross-media effects of email, catalog, television, and radio in a multichannel shopping environment. The empirical results show the significance of cross-media effects in influencing consumers' shopping behavior. There are limitations to this study. We assume that television and radio exposure is equivalent for all the consumers in a time period. While we control for seasonal increases in television and radio ad exposures by using holiday variables as controls, future research can address this issue using sophisticated empirical methodologies. Better data on TV and radio exposures can be used to address endogeneity issues. Moreover, we do not account for the quality of the media content and its impact on multichannel shopping. Future studies can extend our framework using field experiments in a multi-retail environment to obtain causal findings.

Declarations

Author contribution All authors contributed equally.

Availability of data and material The study uses data from a third party that precludes from making data publicly available due to the non-disclosure agreement signed with the firm.

Code availability Not applicable (The study uses open-source R programming language).

Declarations

Competing interests The authors declare no competing interests.

References

Allenby, G. M., & Lenk, P. J. (1994). Modeling household purchase behavior with logistic normal regression. *Journal of the American Statistical Association*, *89*(428), 1218–1231.

Arce-Urriza, M., Cebollada, J., & Tarira, M. F. (2017). The effect of price promotions on consumer shopping behavior across online and offline channels: Differences between frequent and non-frequent shoppers. *Information Systems and e-Business Management*, *15*(1), 69–87.

Batra, R., & Keller, K. L. (2016). Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing*, *80*(6), 122–145.
Brynjolfsson, E., & Smith, M. D. (2000). Frictionless commerce? a comparison of internet and conventional retailers. *Management science*, *46*(4), 563–585.
Chintagunta, P. K., Chu, J., & Cebollada, J. (2012). Quantifying transaction costs in online/offline grocery channel choice. *Marketing Science*, *31*(1), 96–114.
Chu, J., Chintagunta, P., & Cebollada, J. (2008). Research note-a comparison of within-household price sensitivity across online and offline channels. *Marketing Science*, *27*(2), 283–299.
Danaher, P. J., Danaher, T. S., Smith, M. S., & Loaiza-Maya, R. (2020). Advertising effectiveness for multiple retailer-brands in a multimedia and multichannel environment. *Journal of Marketing Research*, *57*(3), 445–467.
Danaher, P. J., & Smith, M. S. (2011). Modeling multivariate distributions using copulas: Applications in marketing. *Marketing Science*, *30*(1), 4–21.
Dinner, I. M., Heerde Van, H. J., & Neslin, S. A. (2014). Driving online and offline sales: The cross-channel effects of traditional, online display, and paid search advertising. *Journal of marketing research*, *51*(5), 527–545.
Du, R. Y., Xu, L., & Wilbur, K. C. (2019). Immediate responses of online brand search and price search to tv ads. *Journal of Marketing*, *83*(4), 81–100.
eConsultancy (2019). 2019 email marketing industry census. Last accessed on July 2021, https://econsultancy.com/reports/email-census/.
eMarketer (2019). Us digital ad spending will surpass traditional in 2019. Last accessed on July 2020, https://www.emarketer.com/content/us-digital-ad-spending-will-surpass-traditional-in-2019.
eMarketer (2021). Us digital ad spending 2021. Last accessed on July 2021, https://www.emarketer.com/content/us-digital-ad-spending-2021.
Keller, K. L. (2001). Mastering the marketing communications mix: Micro and macro perspectives on integrated marketing communication programs.
Kushwaha, T., & Shankar, V. (2013). Are multichannel customers really more valuable? the moderating role of product category characteristics. *Journal of Marketing*, *77*(4), 67–85.
Malhotra, N. K., Jain, A. K., & Lagakos, S. W. (1982). The information overload controversy: an alternative viewpoint. *Journal of Marketing*, *46*(2), 27–37.
Mitchell, V.-W., Walsh, G., & Yamin, M. (2005). Towards a conceptual model of consumer confusion. *ACR North American Advances*.
Naik, P. A., & Peters, K. (2009). A hierarchical marketing communications model of online and offline media synergies. *Journal of Interactive Marketing*, *23*(4), 288–299.
Naik, P. A., & Raman, K. (2003). Understanding the impact of synergy in multimedia communications. *Journal of Marketing Research*, *40*(4), 375–388.
Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science*, *31*(4), 567–586.
Pauwels, K., & Srinivasan, S. (2004). Who benefits from store brand entry? *Marketing Science*, *23*(3), 364–390.
Petrin, A., & Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research*, *47*(1), 3–13.
Tellis, G. J., & Weiss, D. L. (1995). Does tv advertising really affect sales? the role of measures, models, and data aggregation. *Journal of Advertising*, *24*(3), 1–12.
Venkatesan, R., Kumar, V., & Ravishanker, N. (2007). Multichannel shopping: Causes and consequences. *Journal of Marketing*, *71*(2), 114–132.
Voorveld, H. A., Neijens, P. C., & Smit, E. G. (2011). Opening the black box: Understanding cross-media effects. *Journal of Marketing Communications*, *17*(02), 69–85.
Zantedeschi, D., Feit, E. M., & Bradlow, E. T. (2017). Measuring multichannel advertising response. *Management Science*, *63*(8), 2706–2728.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.