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Omnichannel marketing: Are cross-channel effects symmetric?

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ABSTRACT

The rapid growth in omnichannel (e.g., Web, call center, sales agent, store) shopping and the need to effectively allocate resources across channels are prompting managers and researchers to better understand cross-channel effects, that is, the effects of marketing efforts in one distribution channel on shopping outcomes in other channels. We develop a broad set of hypotheses about cross-channel effects based on channel richness and influence roles (informative, persuasive). To test the hypotheses, we model the effects (own and cross) of channel marketing efforts on shopping outcomes in different channels through a simultaneous equation system. We estimate these models using data from the auto insurance industry that comprises the exclusive agent, the independent agent, the Web, and the call center channels. Our results offer novel insights. They show that cross-channel effects and elasticities are significant and asymmetric. While the effect of marketing efforts in a channel on shopping outcomes in a dissimilar (with a different primary influence role) channel is positive (e.g., exclusive agent, the Web, and the call center channels are complementary), the magnitudes of the cross-channel effects are asymmetric. Similarly, while the effect of marketing efforts in a channel on shopping outcomes in a similar (with the same primary influence role) channel is negative (e.g., independent agent and exclusive agent channels are substitutional), they are also asymmetric. Exclusive agent efforts have a greater negative effect on the outcomes of independent agent efforts than vice versa. Based on the results, we develop a channel influence vs. influenceability analysis tool for managers to better plan their channel efforts. We also illustrate a resource allocation model that shows substantial incremental profits from the reallocation of marketing efforts based on our model with cross-channel effects relative to a model without cross-channel effects.

1. Introduction

Omnichannel marketing–the practice of simultaneously offering shoppers[1] information, products, services, and support through two or more synchronized distribution channels in a seamless manner–is continuing to grow at a phenomenal rate (Verhoef,

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[1] For expositional use, we use the terms, shopper, consumer, and customer interchangeably throughout the paper.

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Kannan, & Inman, 2015). An overwhelming majority of consumers shop in more than one channel (Sopadjieva, Dholakia, & Benjamin, 2017), and these consumers are more profitable than others (Montaguti, Neslin, & Valentini, 2016). Different distribution channels include the Web, call center, and direct sales force (Neslin & Shankar, 2009). Omnichannel marketing offers organizations greater opportunities to interact with customers through different channels and efficiently use all the channels (Käuferle & Reinartz, 2015; Kumar & Venkatesan, 2005; Montoya-Weiss, Voss, & Grewal, 2003). Omnichannel marketing typically goes beyond multichannel marketing to include coordination of the distribution channels that offer a seamless customer experience.

As channels evolve, cross-channel effects are becoming a significant imperative for omnichannel marketers (Mark, Bulla, Niraj, Bulla, & Scharzwaller, 2019; Watson, Worm, Palmatier, & Ganesan, 2015). Cross-channel effects refer to the effects of marketing efforts in one *distribution* channel or format on shopping outcomes in other channels (Gauri, 2013; Talukdar & Gauri, 2011; The DMA, 2014). The rapid growth in e-commerce and multichannel shopping is significantly altering shopping behavior (Nielsen, 2020) and prompting managers and researchers to better understand cross-channel effects, To effectively allocate resources across distribution channels, managers need to better understand the effects of efforts in different channels on shopping outcomes (e.g., inquiries, quotes, orders, purchases) in other channels.

Cross-channel effects are important in several industries with multiple distribution channels. For example, in the auto insurance industry, State Farm, like other leading brands, uses the exclusive agent, the independent agent, the Web, and the call center channels. In the computing and communication industry, Apple sells through its own stores, independent retailers, the Web, and the call center. In the beverages industry, Starbucks distributes through its own coffee shops, independent stores, the Web, and the call center. In the shoes and accessories industry, Johnston and Murphy sells through its own exclusive outlets, independent department stores, the Web, catalog, and the call center. In each industry, firms need to deeply understand the effects of their efforts in one distribution channel on shopping outcomes in the other channels.

Despite the importance of cross-channel effects in these industries, not much is known about these effects. Prior research on cross-channel effects primarily relates to the effect of the introduction or presence of a channel on sales through other channels (e.g., Wang & Goldfarb, 2017). Breugelmans and Campo (2016) study the effects of price promotions on category purchases in online and store grocery channels. Furthermore, Dinner, Van Heerde, and Neslin (2014) examine the effects of advertising spending in communication channels (traditional, online display, paid search) on click-throughs and subsequent online and offline sales for a clothing retailer.

However, much prior research does not explicitly focus on the effects of *marketing efforts* in one *distribution* channel on shopping outcomes in other distribution channels. In this regard, important research questions are: What are the relative effects of marketing efforts in each distribution channel on shopping outcomes in other distribution channels (cross-channel effects)? Which cross-channel effects are complementary? Which cross-channel effects are substitutional? How do cross-channel effort elasticities compare with own channel effort elasticities?

Cross-channel effects may depend on the channels' relative richness and primary influence roles, which could be informative or persuasive. Some channels may richer offering multiple benefits, whereas others may be leaner with limited benefits. As a result, cross-effects can be complementary, substitutional, or insignificant in nature. Two channels are complementary (substitutional) if efforts in one channel positively (negatively) influence purchases in another channel. In addition, some cross-channel effects can be high or low. A better understanding of the nature, direction, and magnitude of cross-channel effects is critical for researchers and managers from theoretical and practical standpoints, respectively.

To deeply understand cross-channel effects, many firms do not have data on each customer's use of different channels. Although more data on online customer journey are available through advanced Google and Adobe analytics, much data on offline customers' activities are still private and proprietary. Furthermore, privacy regulations, such as general data protection regulation (GDPR) and California consumer privacy act, make it harder to track every customer's data. Thus, many firms cannot always fully track each customer's exact journey (e.g., whether she first visited the Web, called the firm, or contacted an agent). However, firms typically have access to channel level data on variables such as channel efforts and aggregate shopping outcomes in each channel. Therefore, an important question is: how can managers use channel level aggregate data to estimate and infer cross-channel effects?

We address the research questions by first developing a broad set of hypotheses about cross-channel effects. We then formulate a model of cross-channel effects. We estimate the model and the cross-channel effects using channel level aggregate data from the auto insurance industry. Finally, we discuss the results, derive useful theoretical and managerial implications, and illustrate a resource allocation exercise based on our model of cross-channel effects.

Our results offer novel insights, showing cross-channel effects and elasticities are significant and asymmetric. While the effect of marketing efforts in a channel on shopping outcomes in a dissimilar (with a different primary influence role and richness) channel is positive (e.g., exclusive agent, the Web, and the call center channels are complementary), the directions and extent of cross-channel effects are asymmetric. Similarly, while the effect of marketing efforts in a channel on outcomes in a similar (with the same primary influence role) channel is negative (e.g., independent and exclusive agents are substitutional), it can be asymmetric. Exclusive agent efforts have a greater negative effect on independent agents' outcomes than vice versa.

Our research makes important contributions to the omnichannel management literature. First, it offers an approach for researchers and practitioners to develop and estimate a cross-channel effects model using only channel level aggregate data that are more commonly available. Second, it develops broad hypotheses about cross-channel effects based on channel richness and influence roles (informative vs. persuasive), leading to complementary and substitutional cross-effects. Third, it produces several interesting substantive insights regarding asymmetric cross-channel effects. Finally, it offers a useful managerial tool of influence vs. influenceability analysis and a resource allocation model to better allocate resources across channels.

2. Related research

2.1. Web channel on offline channel

The Web channel has significantly reshaped shopping behavior in all the channels (Kannan & Li, 2017; Peterson, Balasubramanian, & Bronnenberg, 1997; Verhoef, Neslin, & Vroomen, 2007). Studies on the addition of Web to existing channels show little or no cannibalization between the channels. Biyalogorsky and Naik (2003) show that online activities do not significantly cannibalize offline sales for compact discs. Pozzi (2013) show that online store increased overall sales with limited effect on offline store sales. In an analysis of catalog and email communications to shoppers, Mark et al. (2019) find that email communication has a positive effect on the frequency of purchases in offline channels.

2.2. Physical store on other channels

Research on the introduction of physical stores on sales in existing channels offers mixed results. Avery, Steenburgh, Deighton, and Caravella (2012) find that when an online retailer adds a physical store, it temporarily cannibalizes the catalog channel, but not the Web, and over the long-run, enhances sales in both the catalog and the Web channels. Similarly, Pauwels and Neslin (2015) show that the introduction of physical stores of a retail firm dampens catalog sales without affecting Web sales, resulting in a net increase in shopping frequency and revenues across channels. Wang and Goldfarb (2017) report that the effect of a new physical store is associated with a decline (spike) in online sales in places where the retailer has a strong (weak) presence. Bell, Gallino, and Moreno (2018) find that eyewear showroom openings increased online and overall sales. Fisher, Gallino, and Xu (2019) report that the opening of a distribution center to reduce delivery time enhanced online sales and spilled over to offline sales.

Some studies suggest that interactions among channels depend on product type. Analyzing data on electronic and physical channels for products of certain quality (new cars) and uncertain quality (used cars), Overby and Jap (2009) find that more transactions involving low (high) quality uncertainty occur in the electronic (physical) channels, suggesting little cross-channel effect for the same product type. Brynjolfsson, Hu, and Rahman (2009) show that the Internet competes fiercely with brick-and-mortar channel for mainstream products, but the effects could be complementary across the Internet, catalog, and store channels for niche products.

2.3. Shopping in one channel on outcomes in other channels

A few studies analyze the effects of shopping in a channel on shopping in other channels. Based on survey responses in six product categories, Verhoef et al. (2007) find significant cross-channel effects within and across shopping tasks such as search. Teerling (2007) also concludes that the role of informational websites on cross-channel shopping behavior may be significant. While these studies examine the effects of shopping across channels, our focus is on the effects of the firm's efforts in each channel on outcomes in the other channels.

2.4. Channel choice

A related research stream focuses on the drivers and consequences of channel choice, switching, use, and offerings, without explicitly addressing cross-channel effects. A firm's channel efforts and customers' channel experience play significant roles in determining customers' channel selection (Ansari, Mela, & Neslin, 2008). Venkatesan, Kumar, and Ravishanker (2007) study the timing of adoption of a new channel by a customer and find differences between the drivers of adoption of second and third channels. The results from these studies suggest that customers' channel choice, channel switching behavior, and price effects are fairly complex and depend on factors such as product category and customer shopping traits. Our research extends these studies by examining the effects of the firm's marketing efforts in each channel on the outcomes in the other channels.

2.5. Communication channels

Another less directly related research stream is on communication channels that play the informative influence role, but our work differs from this stream in important ways. De Haan, Wiesel, and Pauwels (2015), Dinner et al. (2014), Li and Kannan (2014), and Naik and Peters (2009) analyze the effects of efforts in communication or media channels in the earlier stages of the purchase funnel (e.g., search advertising, display/banner advertising) on outcomes in the later stages of the purchase funnel. Similarly, Wiesel, Pauwels, and Arts (2011) examine the effects of communication or media efforts (e.g., email, Adwords, Fax, Flyer). Dinner et al. (2014) estimate the effects of advertising spending in traditional, online display, and online search communication channels on sales in online and offline channels. Mark et al. (2019) find significant effects of catalogs on Web and store purchases. In contrast, we examine the effects of each distribution channel's (e.g., exclusive agent, Web, call center) efforts on shopping outcomes in other distribution channels in advertising's presence. Thus, our research complements this research stream.

Table 1
Review of selected studies related to cross-channel effects.

Study	Cross-channel effect studied	Channels examined	Services studied	Asymmetries explored	Channel management tool included	Control for advertising effects included
Biyalogorsky and Naik (2003)	Online activities on offline sales	Web and store	No	No	No	No
Venkatesan et al. (2007)	Prior channel use on adoption timing of a new channel	Web and store (discount and regular)	No	No	No	No
Verhoef et al. (2007)	Internet search on store purchase	Web and store	No	No	No	No
Brynjolfsson et al. (2009)	Product selection and geography on cross-channel competition	Catalog and Web	No	No	No	No
Avery et al. (2012)	Bricks-and-mortar opening on cross-channel elasticities	Catalog, Web, and store	No	No	No	No
Li and Kannan (2014)	Conversion attribution (communication channels)	Online (e.g., display, search)	No	No	No	No
Dinner et al. (2014)	Advertising spending in communication channels on online and offline sales	Traditional, display, and search ad channels	No	Yes	No	Yes
Pauwels and Neslin (2015)	New physical store opening on revenues in other channels	Catalog, Web, and store	No	No	No	No
Breugelmans and Campo (2016)	Price promotions on online and offline channels	Online and store	No	Yes	No	No
Wang and Goldfarb (2017)	New physical store opening on online sales	Web and store	No	No	No	No
Bell et al. (2018)	New showroom opening on online sales	Web and store	No	No	No	No
Our paper (2020)	Marketing efforts in primarily persuasive channel (exclusive agent, independent agent), primarily informative channel (Web), and balanced channel (Call center) on shopping outcomes in other channels	Web, call center, exclusive agent, and independent agent	Yes	Yes	Yes	Yes

These articles focus on the impact of the presence or addition of one channel on the existing channel(s), the drivers of channel choice, or communication channels. However, most firms have multiple distribution channels and seek to understand the effects of *marketing efforts* in one distribution channel on the outcomes in other channels. Moreover, prior studies do not study cross-channel effects by controlling for the effect of advertising that is influential in many industries such as the insurance industry (Guitart & Hervet, 2017). Furthermore, these studies are mostly about retailers, precluding generalization to service providers, who outnumber retailers. Finally, prior studies do not focus on a managerial cross-channel effort guidance tool. Our study focuses on the cross-channel effects of marketing efforts in each channel on outcomes in other distribution channels after controlling for advertising effects in the same framework. Our empirical application is in the services context and offers a new managerial cross-channel influence-influenceability tool (a channel management tool) and resource allocation insights.

Table 1 presents a review of selected relevant studies in cross-channel effects, including our research. Some research relating to cross-channel effects focuses on firm outcomes when a new purchase channel is added to existing purchase channels. Some studies are about channel choice, while others are on communication channels, which may also play informative roles similar to distribution channels.[2] Some studies (e.g., Ansari et al., 2008) do include email messages. However, much prior research does not control for the effects of rich content advertising such as that in TV and print media–which has a strong impact on consumer outcomes.

3. Hypotheses development

3.1. Cross-channel effects

A firm's efforts in one channel can impact shopping outcomes in another channel (Biyalogorsky & Naik, 2003; Liu, Lobschat, & Verhoef, 2018; Pozzi, 2013). In the following paragraphs, we discuss the effects of marketing efforts in each distribution channel on the shopping outcomes in other channels. Guided by relative richness of channels, the informative versus persuasive communication theory in economics (e.g., Kaldor, 1950; Nelson, 1970, 1974; Stigler, 1961) and psychology (e.g., Petty & Cacioppo, 1986), and the theory of reasoned action (Fishbein, 1980; Fishbein & Ajzen, 1975), we develop hypotheses on cross-channel effects.[3]

Channels differ in communication richness, which refers to the scope to effectively communicate information (Daft & Lengel, 1986). In our context, this richness includes presentation of information, convenience in accessing information, searchability of information, and interactivity between the shopper and the firm. Face-to-face channels are richer than the telephone channel, which

[2] We recognize that research on the 'news' product category has examined cross-effects across print and online formats (e.g., Chen, Hu, & Smith, 2019; Kanuri, Mantrala, & Thorson, 2017). These formats are similar in spirit to channels but fundamentally differ from channels in that shoppers consume the product or service in these channels.

[3] Our extensive discussions with auto insurance executives from our empirical setting also reinforced our arguments.

in turn is richer than written, static channels. In our context, face-to-face such as exclusive and independent agents are richer than call center, which is richer than remote and leaner channels such as catalog and website. Richer and leaner channels add value to shoppers purchasing through different channels through the influence roles that they play.

Each channel also plays two key influence roles in varying degrees to enable shopping behavior: an informative role and a persuasive role (Nelson, 1974; Shrum, Liu, Nespoli, & Lowrey, 2012). Informative communication involves presentation of facts, while persuasive communication entails convincing prospects through a rational appeal, an emotional appeal, or both. These roles add to the richness of each channel. But each channel has a primary influence role that can help us understand and predict the effects of marketing efforts in that channel on shopping outcomes in the other channels. Relative to informativeness, persuasiveness differs more across channels, making it the key differentiator among channels in their impact on shopping outcomes.

Among the channels, the catalog channel and Web channel primarily serve to inform shoppers. These leaner channels primarily allow for presentation of factual information. The Web is richer than the catalog in that it allows retargeting, so it is more persuasive. Mobile app, smart speaker, and kiosk are more informative as well as persuasive than the Web and the catalog. The call center is richer than the Web, catalog, mobile app, smart speaker, kiosk channels. It can provide information but only upon queries from the shopper, making its informative role specific. At the same time, it is interactive, so it can also serve to persuade shoppers. Thus, the call center typically offers a balance of information and persuasion or moderate richness, so we call it a balanced channel. Independent stores and independent agents are richer than the balanced channel. Exclusive stores, exclusive agents, value added resellers, and manufacturers' representatives are also richer than the call center channel. These channels interact with shoppers more than do the other channels. During the interactions, these channels can use rational and emotional appeals to persuade prospects. Thus, these channels' primary influence role is persuasion. Their role goes beyond the call center's persuasive role because these channels allow face-to-face and long interactions with the shopper. A graph depicting the roles, leanness, and richness of the channels relative to one another appears in Fig. 1.

From a customer standpoint, each channel exhibits characteristics that have both benefits and limitations (Avery et al., 2012; Kushwaha & Shankar, 2013). For example, the Web, a primarily informative channel, offers instantaneous access to product information, the ability to search, sort, and compare products, and a low pressure sales environment (Balasubramanian, Raghunathan, & Mahajan, 2005). The electronic channel offers the benefits of convenience and efficacy of information acquisition (Choudhury & Karahanna, 2008). However, it is still lean in that it does not allow physical inspection, demonstration, trial, instantaneous acquisition, or instant gratification. In contrast, the call center channel, with a mix of information and persuasion, is richer, offering personal interactions, authentic answers to questions, and ubiquitous access. At the same time, it does not permit visual inspection and product and price comparisons.

Exclusive sales agents represent a richer channel and are primarily persuasive. They are highly knowledgeable advocates and credible stewards of the firm's products. However, prospective customers may not regard the information obtained from exclusive agents to be entirely objective and may be unable to gather accurate information about competitor brands (Zweifel & Ghermi, 1990). Independent sales agents, who constitute another rich and primarily persuasive channel, offer brand variety and are more unbiased than exclusive agents about the focal firm. However, prospective customers may not expect to get the most accurate information about all the competing brands and may feel that they would be unable to obtain a better deal for a brand than

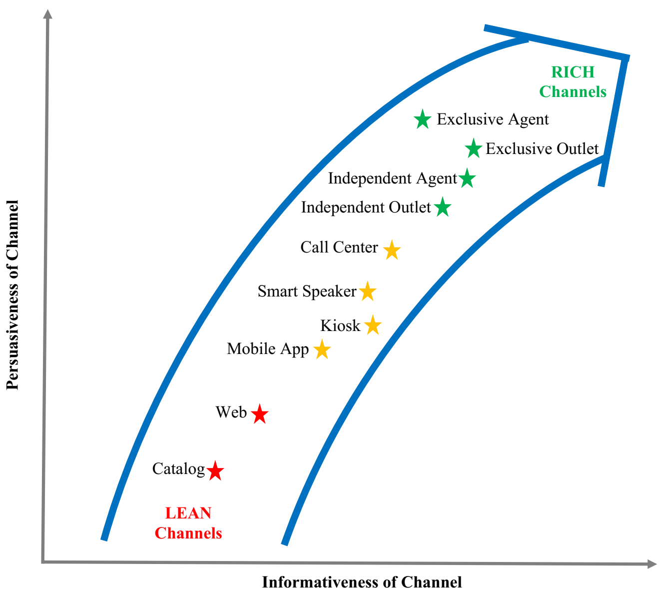

Fig. 1. Classification of distribution channels by their roles. Note: This figure is illustrative and is not drawn to scale. The positions of the channels are relative to one another and not absolute.

they could get from an exclusive agent for that brand (Zweifel & Ghermi, 1990). In addition, customers may perceive both exclusive and independent agents as pushy.

From the firm's viewpoint, these distribution channels are direct or indirect based on the nature of contact and interaction with customers (Sa Vinhas & Anderson, 2005). The Web and the call center are direct channels, allowing the firm to directly interact with customers. In contrast, the exclusive agent and the independent agent channels are indirect channels as the firm relies on these intermediaries to communicate with the customers. This classification loosely maps with the categorization of informative vs. persuasive (Narayanan, Manchanda, & Chintagunta, 2005). Firms use direct channels mainly to exercise an informative role and to some extent a persuasive role. In contrast, firms typically utilize indirect channels to implement a persuasive role.

Another way to classify the channels is as owned versus independent, consistent with dual distribution–a hybrid of vertically integrated and market governance channels (e.g., Srinivasan, 2006). Viewed from this perspective, all the channels in our channel except the independent agent channel are owned channels. The main difference between these two types of channels lies in the extent of the firm's control over marketing efforts. Firms can exercise greater control in their owned channels than in the independent channels. This classification corresponds with our categorization of informative versus persuasive channels in the following way. Firms can use their owned channels to perform either an informative role, a persuasive role, or both. But firms typically utilize independent channels to persuade customers.

The classification of channels in terms of their primary influence role as informative or persuasive is consistent with channel or information richness theory, which is quite fundamental, requiring fewer assumptions. Therefore, we adopt this classification to develop the hypotheses.

To understand the effects of marketing efforts in one channel on shopping outcomes in other channels, we analyze the relative richness and the primary influence roles of the channels. In cases where the channels are dissimilar in richness and if the primary influence roles of two channels are complementary, the benefits of one channel spill over to another channel, producing complementary cross-channel effects. In cases where the richness and primary influence roles of the channels are similar, the limitations of one channel extend to other channels, creating substitutional cross-channel effects. Still in other cases, efforts in any one channel may have only stand-alone effects and not affect outcomes in other channels.

3.2. Complementary cross-channel effects

By combining their richness and primary influence roles, some channels may complement one another. For example, efforts in the lean, primarily informative Web channel can enhance outcomes in other channels such as the call center that serves both informative and persuasive roles. As discussed earlier, the addition of the Web does not cannibalize sales in other channels (Biyalogorsky & Naik, 2003) as it acts an al informative channel for shoppers who may prefer to shop in rich, persuasive channels. Furthermore, trusted websites can direct prospects to make purchases from a more persuasive channel like the call center (Teerling, 2007).

Similarly, call center agents can provide a high level of information and personal service to prospective customers, combining both informative and persuasive roles, empowering shoppers to complete shopping task from a primarily informative channel such as the Web or the catalog. A call center agent can offer a richer human touch to a prospective customer that could increase the likelihood of buying from a primarily informative channel. By personally answering customers' questions, call center agents can enhance customer trust to effect favorable outcomes in informative channels. Shoppers can make decisions in an informative channel based on the intent developed from their interactions with call center agents, consistent with the theory of reasoned action (Fishbein, 1980). After a shopper receives persuasive communication from the balanced channel, she evaluates the arguments over time. If the shopper is convinced, she could minimize the time and effort expended in making her decision by directly going to the lean, primarily informative channel (the Web) and practice self-service. If she goes back to the balanced channel, she would have to wait for an agent to connect and go through social protocols before being able to make her decision. These arguments lead to the following hypotheses.

H1a. Marketing efforts in a primarily informative channel have a positive effect on the shopping outcome in a balanced channel.

H1b. Marketing efforts in a balanced channel have a positive effect on the shopping outcome in a primarily informative channel.

A lean and primarily informative channel such as the Web or the catalog can combine with a rich and primarily persuasive channel such as a brick-and-mortar store or a sales agent to positively influence shopping outcomes in each other's channel. Marketing efforts in a primarily informative channel can direct shoppers to a primarily persuasive channel to complete their task. The phenomenon of research shopping in which a shopper searches for product information on the Web and buys the product at the store is well documented (Verhoef et al., 2007). Indeed, efforts in an online (primarily informative) channel complements outcomes in the direct sales force (primarily persuasive) channel in B2B markets (Lawrence, Crecelius, Scheer, & Patil, 2019). Thus, we expect the effect of marketing efforts in a primarily informative channels like the Web to positively influence outcomes in primarily persuasive channels such as exclusive and independent agents.

A rich and primarily persuasive channel such as the store or the exclusive agent channel can also facilitate positive shopping outcomes in a lean and primarily informative channel. Through extra efforts to accept and handle product returns, stores can assure customers to purchase more on the Web (Mahar, Wright, Bretthauer, & Hill, 2014). Furthermore, in banking, complementary marketing efforts in more persuasive channels such as branches facilitate customer adoption of the Web channel (Campbell & Frei, 2010). Indeed, customers who adopt the outlet store channel increase their purchases on channels such as the Web and the catalog (Soysal & Krishnamurthi, 2016). Similarly, exclusive agents act as strong advocates for the company's brand. Although these agents expend their efforts to consummate shopping outcomes in their own channel, their overall goal is to maximize the probability of prospects buying from the company even if it is in a primarily informative channel. The role of the exclusive and independent agents is similar to that of the stores, branches, and outlet stores in that both these channels perform a persuasive role focused on the company's offerings. This reasoning leads to the next hypotheses.

H2a. Marketing efforts in a primarily informative channel has a positive effect on the shopping outcome in a primarily persuasive channel.

H2b. Marketing efforts in a primarily persuasive channel has a positive effect on the shopping outcome in a primarily informative channel.

We expect channels with a balanced mix of information and persuasion such as the call center to have complementary cross-channel effects on outcomes in richer, primarily persuasive channels. Shoppers touched by call center agents may be well informed about the focal firm's products. If the call center agent provides a high level of service, shoppers may even be inclined toward the firm's products. Such shoppers can consummate their shopping tasks in a richer, primarily persuasive channel like exclusive agent or independent agent.

By the same token, efforts in a richer primarily persuasive channel such as the exclusive agent or the independent agent should also facilitate outcomes in a leaner primarily balanced channel. Exclusive agents and independent agents can move shoppers toward a strong purchase intent for the focal brand. Such shoppers may call the call center and resolve their final questions in an interactive manner and complete their shopping task, consistent with the theory of reasoned action (Fishbein, 1980). Thus, the efforts of primarily persuasive channels can complement outcomes in balanced channels. These arguments lead to the following hypotheses.

H3a. Marketing efforts in a balanced channel have a positive effect on the shopping outcome in a primarily persuasive channel.

H3b. Marketing efforts in a primarily persuasive channel have a positive effect on the shopping outcome in a balanced channel.

3.3. Substitutional cross-channel effects

In contrast, a rich, primarily informative channel when combined with another rich, primarily informative channel may not enhance the effect on the shopping outcomes in the other channel. Shoppers may perceive the marketing efforts in each informative channel as substitutes for obtaining similar information. Similarly, a rich, primarily persuasive channel when combined with another rich, primarily persuasive channel may not have a positive effect on the shopping outcomes in the other channel. In fact, two persuasive channels may be perceived as perfect substitutes by shoppers and may compete with each other for shopper attention.

Channels that are primarily lean, informative (rich, persuasive) may act as substitutes for other primarily informative (persuasive) channels. Prior research offers some evidence for substitution (e.g., Gong, Smith, & Telang, 2015). Customer adoption of the primarily informative Web channel in banking is associated with substitution from other primarily informative channels such as self-service channels (automated teller machines, voice response systems) (Campbell & Frei, 2010). Even in cases where a primarily persuasive channel opens in a location containing another primarily persuasive channel, the cross-channel effect may be substitutional. Indeed, the growth in Web channel sales has come at the expense of the catalog channel, another primarily informative channel (Avery et al., 2012; Pauwels & Neslin, 2015). The channels in these cases are similar in their benefits and limitations, so they serve as substitutes.

The same logic may extend to the effects of marketing efforts in rich and primarily persuasive channels on outcomes in channels with the same primary influence role. Efforts in similar channels can lead to customer perceiving the channels as substitutes because the net benefits in those channels may be similar. Consequently, efforts in one channel may help outcomes in that channel but hurt outcomes in similar channels. Although exclusive and independent agents serve as two primarily persuasive channels in many industries, each channel may independently promote face-to-face human persuasion (Shrum et al., 2012). Consequently, customers perceive these channels as similar in net benefits and treat them as substitutes.

These channels typically compete with each other to get a share of the customers' business. For example, in the auto insurance industry, the compensation of agents is commission based and both exclusive agents and independent agents do not have the incentive to refer a customer to other agents. Therefore, efforts by exclusive agents may hinder shopping outcomes through independent agents and vice versa. The competition between similar channels could also lead to potential conflict (Sa Vinhas & Anderson, 2005). Thus, we predict that these two channels may be more substitutional than complementary. Therefore, we propose the following hypothesis.

H4. Marketing efforts in a channel have a negative effect on the shopping outcome in a similar (with the same primary influence role) channel.

A complete list of all the predicted cross-channel effects appears in Table 2, which shows the directional effects of efforts in each channel on outcomes in other channels. We expect all the complementary (primarily informative, primarily persuasive, balanced) cross-channel effects, except those between the exclusive agent and independent channels, to be positive. Because two

Table 2
Summary of hypotheses/predicted cross-channel effects.

From variable (effect of)	To variable (effect on)	Hypothesis (predicted direction of effect)	Complementary vs. substitutional
Primarily informative channel efforts	Balanced channel quotes	H1a (+)	Complementary
Balanced channel efforts	Primarily informative channel quotes	H1b (+)	Complementary
Primarily informative channel efforts	Primarily persuasive channel quotes	H2a (+)	Complementary
Primarily persuasive channel efforts	Primarily informative channel quotes	H2b (+)	Complementary
Balanced channel efforts	Primarily persuasive channel quotes	H3a (+)	Complementary
Primarily persuasive channel efforts	Balanced channel quotes	H3b (+)	Complementary
Primarily persuasive channel efforts	Primarily persuasive channel quotes	H4 (−)	Substitutional

similar (primarily informative or primarily persuasive) channels often compete for the same business, the efforts of one of these channels will likely negatively influence outcomes in the other channel. The extent to which efforts in each channel will influence outcomes in the other channels is an empirical question we will address in the subsequent sections.

4. Empirical context and data

To test our hypotheses, we analyze data from the automobile insurance industry. A representation of how cross-channel effects occur in this industry appears in Fig. 2. In this context, consumers can ask for an auto insurance brand quote from one of four channels, the exclusive agent, the independent agent, the Web, and the call center channels. A consumer can get information from one channel but obtain a quote or buy a policy from another channel. Thus, the informative and persuasive roles of the

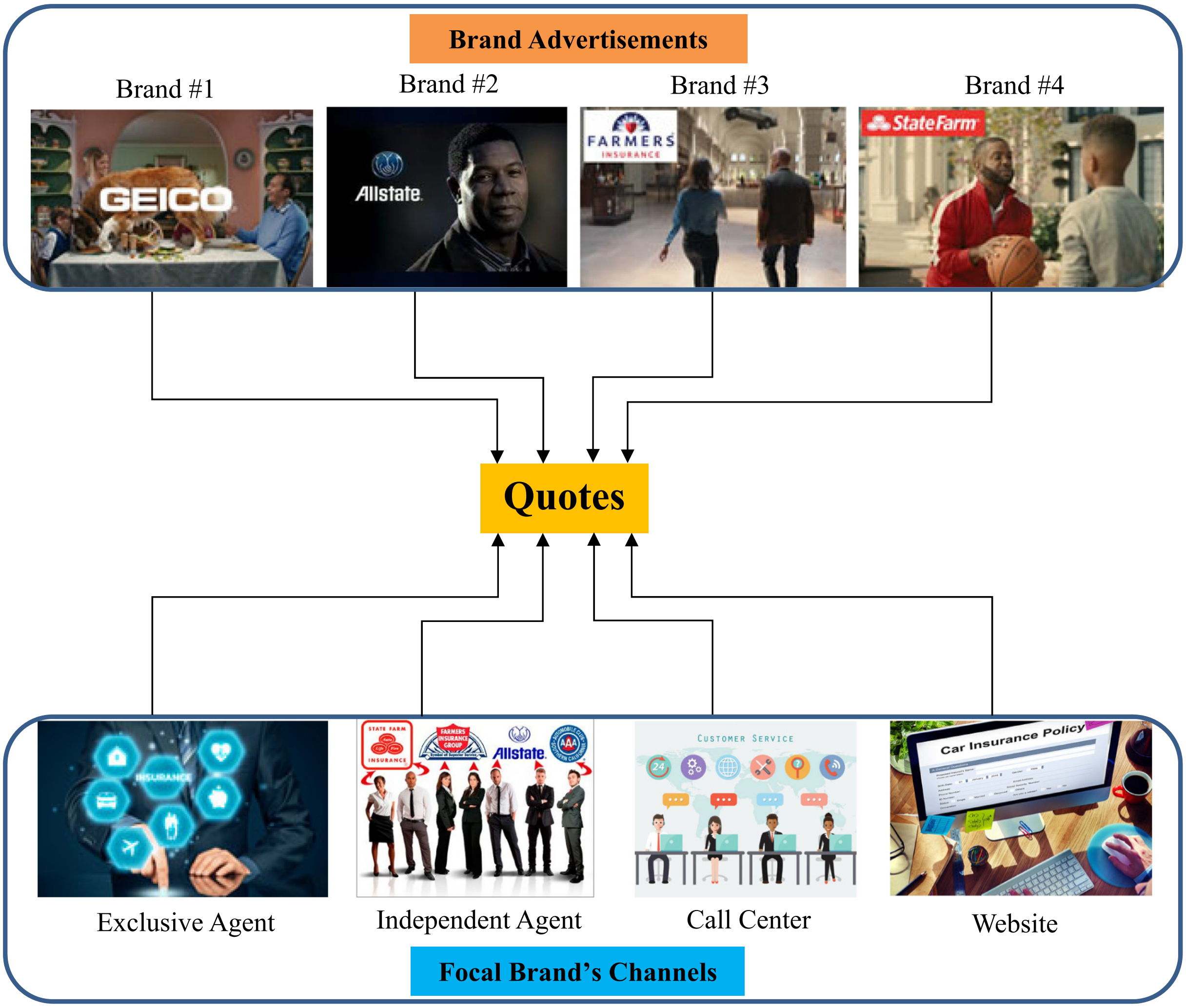

Fig. 2. Cross-channel effects for automotive insurance in the presence of advertising.

distribution channels are important in the channel outcomes. Exclusive agents sell only the focal firm's products. In contrast, independent agents sell products from multiple competitors. In each channel, the key outcome variable is the number of quotes, a big milestone and a forerunner of policies. Unlike in other product categories, a prospect in the auto insurance category needs to provide detailed and confidential personal information to elicit a quote. Therefore, eliciting a quote is a strong signal of purchase intent, and quotes correlate highly with purchases.[4] Quotes and policies are equivalent to sales leads and sales, respectively in most industries. Marketing efforts in each channel impact the outcomes in the same channel as well as in the other channels. Advertising also affects shopping outcomes. All the marketing channel and advertising efforts are mainly directed at increasing quotes.

We collect data on quotes, policies, and channel efforts for the focal brand, one of the largest brands in the industry, for 182 weeks. Because channel effects occur in the presence of advertising, we need to control advertising effects. Therefore, we gathered weekly advertising data for the focal brand from *Adtracker* during the same time frame.[5] The advantages of our dataset are that it offers rich industry-specific information and captures the shopping outcomes in each channel. The operationalization of the variables in the data appears in Table 3.

Table 4 provides summary statistics for the key variables in our model. These summary statistics suggest that the exclusive agent channel is the leading channel for the focal brand, accounting for a majority of the quotes generated, followed by the Web, the call center, and the independent agent channel in that order. The focal brand also has many more exclusive agents than independent agents. This situation is common for the leading brands in the industry. The purpose of this research is to rigorously investigate the cross-channel effects through our models.

Table 5 presents the correlation matrix for the key variables in our data. An analysis of the correlations and collinearity diagnostics suggests that the variance inflation factors do not exceed 10, suggesting that multicollinearity is not an issue in our data.

5. Model formulation and estimation

5.1. Modeling cross-channel effects

To capture the cross-channel effects, we model the number of quotes generated in each channel, that is, quotes by exclusive agents (*EAQ*), quotes by independent agents (*IAQ*), quotes from the Web (*WQ*), and quotes from the call center (*CCQ*) using the following system of equations.[6]

$$EAQ_t = \eta_{10} + \eta_{11}EAQ_{t-1} + \eta_{12}IAQ_{t-1} + \eta_{13}WQ_{t-1} + \eta_{14}CCQ_{t-1} + \eta_{15}EA_t + \eta_{16}IA_t + \eta_{17}WEB_t + \eta_{18}CC_t + \eta_{19}AD_t + \eta_{110}BUSD_t + \eta_{111}UCAR_t + \sum_{j=1}^{3}\eta_{112j}YR_{jt} + \sum_{k=1}^{11}\eta_{113k}MTH_{kt} + \xi^1{}_t \tag{1}$$

$$IAQ_t = \eta_{20} + \eta_{21}EAQ_{t-1} + \eta_{22}IAQ_{t-1} + \eta_{23}WQ_{t-1} + \eta_{24}CCQ_{t-1} + \eta_{25}EA_t + \eta_{26}IA_t + \eta_{27}WEB_t + \eta_{28}CC_t + \eta_{29}AD_t + \eta_{210}BUSD_t + \eta_{211}UCAR_t + \sum_{j=1}^{3}\eta_{212j}YR_{jt} + \sum_{k=1}^{11}\eta_{213k}MTH_{kt} + \xi^2{}_t \tag{2}$$

$$WQ_t = \eta_{30} + \eta_{31}EAQ_{t-1} + \eta_{32}IAQ_{t-1} + \eta_{33}WQ_{t-1} + \eta_{34}CCQ_{t-1} + \eta_{35}EA_t + \eta_{36}IA_t + \eta_{37}WEB_t + \eta_{38}CC_t + \eta_{39}AD_t + \eta_{310}BUSD_t + \eta_{311}UCAR_t + \sum_{j=1}^{3}\eta_{312j}YR_{jt} + \sum_{k=1}^{11}\eta_{313k}MTH_{kt} + \xi^3{}_t \tag{3}$$

$$CCQ_t = \eta_{40} + \eta_{41}EAQ_{t-1} + \eta_{42}IAQ_{t-1} + \eta_{43}WQ_{t-1} + \eta_{44}CCQ_{t-1} + \eta_{45}EA_t + \eta_{46}IA_t + \eta_{47}WEB_t + \eta_{48}CC_t + \eta_{49}AD_t + \eta_{410}BUSD_t + \eta_{411}UCAR_t + \sum_{j=1}^{3}\eta_{412j}YR_{jt} + \sum_{k=1}^{11}\eta_{413k}MTH_{kt} + \xi^4{}_t \tag{4}$$

where *t* is week, *EA* and *IA* are the number of exclusive agents and independent agents, respectively; *WEB* is the number of unique visitors on the website; and *CC* is the number of call center agents. *AD* is the number of advertising impressions. *BUSD* is the number of business days in the week, *UCAR* is the number of used cars registered in the country, and ξ_t^1, ξ_t^2, $\xi_t^3$and $\xi_t^4$are equation-specific random errors.[7] The coefficients η_{15}, η_{26}, η_{37}, and η_{48}capture the own channel effects. In Eq. (1), the coefficientsη_{16}, η_{17},

[4] Indeed, the correlation between quotes and policies is rather high in our data (0.91).

[5] We are unable to disclose the real brand names and the years to preserve confidentiality.

[6] We do not model policies for cross-channel effects because qualification of prospects, the stage before policies are issued, could not be fully performed by the Web and call center channels, so the number of policies issues through the Web was negligible and through the call center was limited. Furthermore, the number quotes is highly correlated with the number of policies in the channels in which they were issued (0.91).

[7] The number of used cars was highly correlated with the number of new cars such that in presence of both, the coefficients are unstable and standard errors are unreliable, so we use the number of used cars (UCAR) to represent all the cars sold during the week.

Table 3
Operationalization of key variables.

Dependent variable	Operationalization
EAQ	Log of number of quotes issued by the focal brand through exclusive agents
IAQ	Log of number of quotes issued by the focal brand through independent agents
WQ	Log of number of quotes issued by the focal brand through website
CCQ	Log of number of quotes issued by the focal brand through call center
Independent variable	Operationalization
EA	Log of number of exclusive agents
IA	Log of number of independent agents
WEB	Log of number of unique visitors to the website
CC	Log of number of call center employees
AD	Log of TV ad impressions by the focal brand
BUSD	Number of business days in the week
UCAR	Used cars registered (in hundred thousands)

Table 4
Summary Statistics of Key Variables.

Variable	Mean	Std. dev.
Number of quotes from exclusive agents (EAQ) [,000]	112.32	18.56
Number of quotes from independent agents (IAQ)	441.95	132.35
Number of quotes from the Web (WQ) [,000]	15.11	7.00
Number of quotes from call center (CCQ) [,000]	8.79	2.87
Number of exclusive agents (EA) [,000]	11.42	0.84
Number of independent agents (IA) [,000]	3.22	0.50
Number of unique Web visitors (WEB) [,000]	292.85	111.62
Number of call center agents/employees (CC) [,000]	1.20	0.11
Focal brand advertising impressions (AD) [,000]	546.56	807.23
Number of business days in the week (BUSD)	4.81	0.39
Used cars registered (UCAR) [,00,000]	0.97	0.27

Note: N = the number of weeks = 182.

Table 5
Correlations among key variables: cross-channel effects.

	Variable	1	2	3	4	5	6	7	8	9	10
1	EAQ										
2	IAQ	−0.22									
3	CCQ	0.59	−0.53								
4	WQ	0.62	−0.53	0.73							
5	EA	0.72	0.32	0.28	0.29						
6	IA	0.66	0.14	0.34	0.40	0.72					
7	WEB	−0.16	0.23	−0.41	0.07	0.04	0.13				
8	CC	0.53	−0.73	0.67	0.87	0.05	0.25	0.03			
9	AD	0.14	0.01	0.04	0.08	0.05	0.16	0.08	0.08		
10	BUSD	0.06	−0.02	0.00	0.03	−0.01	0.02	0.01	0.04	0.03	
11	UCAR	0.47	−0.64	0.50	0.72	0.05	0.19	0.05	0.27	0.46	−0.09

and η_{18}capture the cross-channel effects of the independent agents, the Web and the call center, respectively on the number of quotes from exclusive agents. A similar logic holds for the cross-channel effects in Eq. 2–4. *AD, BUSD,* and *UCAR* are control variables. *YR* and *MTH* represent dummy variables for the year and month, respectively, capturing unobserved fixed effects, j = year, k = month. The coefficients η_{19}, η_{29}, η_{39}, and η_{49} reflect the elasticities of advertising on quotes in each channel.

The numbers of exclusive, independent, and call center agents directly capture the firm's efforts in these channels. However, the firm's efforts in the Web were not directly observable without suitable measures. Nonetheless, the number of unique website visitors (WEB) is a good proxy for the firm's efforts in the Web channel. The extent of efforts in a website is positively associated with number of visits to the website (Dholakia & Rego, 1998). Indeed, there is a high correlation between Web content and traffic to a website (Kalhor & Nikravanshalmani, 2015). Therefore, we use WEB as the measure of the firm's efforts in the Web channel.

To control for state dependence, we include a one period lagged dependent variable in each equation. We also include lagged quotes from each of the other channels. We log transform the dependent, channel effort, and advertising variables, so the coefficients serve as elasticities.

5.2. Endogeneity of key variables

While the focal brand's efforts and outcomes are temporally separated, given the high degree of autocorrelation observed in efforts, we need to account for the potential endogeneity of these efforts in Eqs. (1) through (4). The numbers of exclusive agents (*EA*), independent agents (*IA*), web visitors (*WEB*), call center agents (*CC*), and the focal brand's advertising efforts (*AD*) are endogenous. We use one time period lags for these variables to rule out possible reverse causality. We also use appropriate instruments for each endogenous variable. For each endogenous variable, we select instruments based on both relevance and exclusion restriction.

The number of exclusive agents depends on the wage rate for brokers. If the wage rate is high (low), a firm will hire a fewer (greater) number of agents, satisfying the relevance condition. But the brokers' wage rate is not directly related to the outcome variables. Thus, the exclusion restriction is met. Therefore, we the wage rate for brokers is a good instrument.[8]

Similarly, the number of independent agents depends on the independent service agents' wage rate. As in the case of exclusive agents, the firm will hire fewer (greater) independent agents if this wage rate is higher (lower), meeting the relevance criterion. However, the wage rate of the independent service agents is not directly correlated with the outcome variables. Thus, the exclusion restriction is satisfied and the wage rate of independent service agents is a good instrument for the number of independent agents.

Data on suitable instruments for WEB are generally difficult to obtain. Good instrument candidates such as the number of unique visitors to competitors' website are hard to collect, in particular, at the weekly level. The wage rate of web developers determines the number and quality of web developers to design and run a website. Although web developers' wage rate is correlated with the number of developers (satisfying the relevance condition), it is uncorrelated with the outcome variables. Therefore, the exclusion restriction is satisfied and wage rate of software professionals is a good instrument for the number web development employees.

The wage rate of telemarketers determines the number of telemarketers who would be hired in a call center. Although telemarketers' wage rate is correlated with the number of call center employees (maintaining the relevance condition), it is uncorrelated with the outcome variables. Therefore, the exclusion restriction is satisfied and wage rate of telemarketers is a good instrument for the number of call center employees.

Because competing brands vie for the same customers, the focal brand's advertising will be correlated with the past advertising of its closest competitor brands. Thus, the instrument relevance criterion is met. However, past competitor brand advertising is not directly related with the error terms in Eqs. 1–4 (low correlation of 0.13 to 0.24 in our data), satisfying the exclusion restriction. Thus, for the focal brand's advertising efforts, we use the past advertising impressions of its three closest competitors as good instruments.

To ensure that the results are consistent for different instruments, we also use another set of instruments, the average of the past four weeks of wage rates in a subsequent robustness check.

5.3. Estimation

We estimate Eqs. (1–4) as a simultaneous equation system with correlated errors. Because the values of the outcome variables are large numbers and are log-transformed, they are ratio-scaled and normally distributed.

In Eqs. (1–4), the system of recursive equations, the random error components are likely to be correlated, so to increase the efficiency of the system, we jointly estimate the system and model the correlated errors through a multivariate normal distribution as follows:

$$\begin{bmatrix} \xi^1{}_t \\ \xi^2{}_t \\ \xi^3{}_t \\ \xi^4{}_t \end{bmatrix} \sim MVN\left\{ \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \sum\nolimits_{\xi} \right\} \tag{5}$$

where the equation-specific random errors that are correlated and $\sum_{\xi}$is the unconstrained variance-covariance matrix. Therefore, we estimate the simultaneous equation systems using a seemingly unrelated regression (SUR) procedure, consistent with Mullahy (1997). A single equation estimation would produce consistent estimates, but accounting for covariance in the error structure across equations produces more efficient estimates.

5.4. Validity and strength of instruments

We test the validity and strength of our instrumental variables. The results of the first stage regressions and the fit statistics appear in Table 6. The elasticities of wage rates for brokers, independent agents, and telemarketers from the first stage regression are −0.0228 ($p < 0.05$), −0.0223 ($p < 0.10$), and − 0.4269 ($p < 0.01$), respectively. These results suggest that as wages increase (decrease) the firm exerts less (more) channel efforts. These elasticities are consistent with the mid 80% values reported by

[8] We collected wage rate information from the *Bureau of Labor Statistics* (https://www.bls.gov/oes/tables.htm).

Table 6
Results of tests of instrument validity.

Dependent variable	Endogenous independent variable	Instrument used	Coefficient of instrument	F-stat from first stage regression	Conclusion on the validity of instrument
Quotes from exclusive agents, independent agents, website, and call center	Number of exclusive agents	Wage rate for brokers	−0.0228**	15.28***	We use cost shifter and the wage rates for the professions, as instruments. The cost shifter influences managers' staffing decisions but does not directly influence customers' decisions to obtain quotes or buy policies. Since the system is just-identified, we cannot conduct a Sargan-Hansen over-identification test. The results show that the instruments are valid.
	Number of independent agents	Wage rate for independent service agents	−0.0223*	21.11***	
	Number of unique web visitors	Wage rate for web developers	0.3824**	16.27***	
	Number of call-center agents	Wage rate for telemarketers	−0.4269***	23.18***	
	Advertising impressions	Advertising impressions of three competing brands	1.1555*** −0.5199*** 0.4321***	18.28***	We use Hausman style instruments, i.e., advertising decisions made by competing brands as instruments for the focal brand's advertising. These advertising spending decisions may be directly influenced by common advertising cost shock but not demand shock. The Sargan-Hansen test for over-identifying restriction is insignificant ($p > 0.05$), suggesting the instruments are valid.

For each instrument, F-statistic is well above 10, satisfying Staiger and Stock (1997), Stock and Yogo (2005) tests.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Lichter, Peichl, and Siegloch (2015) in a meta-analysis covering 151 studies. The elasticity of wage rate of web developers and web traffic is positive and significant (0.3824; $p < 0.05$), which could potentially be explained by increase in the popularity of the Web channel in the insurance industry during the data window.

Based on the results from the first stage regression and the relevant Sargan-Hansen test, we can conclude that the instruments are valid. We also test the strength of our instrumental variables through the Staiger and Stock (1997) and Stock and Yogo (2005) tests. The F-statistic in all cases for single instruments is greater than 10, consistent with Staiger and Stock (1997). The F-statistic for the multiple instrument case (focal brand ad) is greater than 13.91, in line with Stock and Yogo (2005). Therefore, we conclude that the instruments are sufficiently strong.

To check how well the instruments control for endogeneity, we examine the correlations between the instruments of marketing efforts and residuals from Eq. (1) through Eq. (4). The correlation between ξ^1 and wage rate of brokers is 0.048 ($p = 0.40$); ξ^2 and wage rate of independent service agents is 0.054 ($p = 0.34$); ξ^3 and wage rate for web developers is 0.032 ($p = 0.57$); and ξ^4 and wage rate for telemarketers is 0.029 ($p = 0.90$). These low and insignificant correlations suggest that these instruments control for endogeneity well.

6. Results and discussion

6.1. Cross-channel effects

The results of the cross-channel appear in Table 7. We discuss the results in the order of the hypotheses. Hypotheses H1a and H1b relate to the cross-channel effects between a lean, primarily informative channel and a balanced channel. Efforts in the Web, a primarily informative channel, has a positive and significant effect (0.1193; $p < 0.05$) on shopping outcome in a balanced channel (quotes through the call center), supporting H1a. However, the reciprocal effect is not significant (0.0620; $p > 0.10$). That is, call center (balanced channel) efforts do not significantly affect quotes through the Web channel (a primarily informative channel), contrary to H1b.

Hypotheses H2a and H2b concern the cross-channel effects between a lean, primarily informative channel and a rich, primary persuasive channel. Consistent with H2a, Web channel (primarily informative channel) efforts has a positive and significant (0.0694; $p < 0.05$) impact on quotes by exclusive agents (primarily persuasive channel). However, Web channel efforts have a negative but insignificant (−0.0129; $p > 0.10$) effect on quotes issues by independent agents (another primarily persuasive channel). But efforts in both the primarily persuasive channels have positive and significant effects on quotes issues by the Web. The effect on quotes in the Web of exclusive agents is 0.185 ($p < 0.10$) and of independent agent is 0.087 ($p < 0.05$).

Hypotheses H3a and H3b are about the cross-channel effects between a balanced channel and rich, primarily persuasive channels. Consistent with hypothesis H3a, the effect of call center (balanced channel) efforts on quotes issues through the exclusive agent (primarily persuasive) channel is positive and significant (0.1127; $p < 0.01$). However, call center efforts have an insignificant effect (0.0246; $p > 0.10$) on quotes through the independent channel, another primarily persuasive channel. By the same token, the effect of efforts in the exclusive agent channel is positive and significant (0.1346; $p < 0.05$) on quotes generated through

Table 7
Results of cross-channel effects model.

	Variable	Quotes from exclusive agents			Quotes from independent agents			Quotes from website			Quotes from call center		
		Coeff	Estimate	S.E.	Coeff	Estimate	S.E.	Coeff	Estimate	S.E.	Coeff	Estimate	S.E.
Lagged channel outcomes	Intercept	η_{10}	10.9126	8.8458	η_{20}	16.4370	12.1781	η_{30}	−6.7578	11.9570	η_{40}	5.6670	7.7718
	Lag EAQ	η_{11}	0.3528***	0.0575	η_{21}	−0.5424***	0.0815	η_{31}	−0.3208***	0.0714	η_{41}	−0.0676	0.0476
	Lag IAQ	η_{12}	−0.1715***	0.0265	η_{22}	0.7641***	0.0370	η_{32}	−0.0988***	0.0342	η_{42}	−0.0196	0.0226
	Lag WQ	η_{13}	−0.0438*	0.0252	η_{23}	−0.0090	0.0348	η_{33}	0.8359***	0.1084	η_{43}	0.0323	0.0220
	Lag CCQ	η_{14}	0.0287	0.0763	η_{24}	−0.0988	0.1062	η_{34}	0.1759*	0.0994	η_{44}	0.7016***	0.0654
Channel efforts	EA	η_{15}	0.3413***	0.1057	η_{25}	−0.0689***	0.0183	η_{35}	0.1847*	0.1081	η_{45}	0.1346**	0.0623
	IA	η_{16}	−0.0353**	0.0150	η_{26}	0.1054**	0.0489	η_{36}	0.0870**	0.0414	η_{46}	−0.0946	0.1305
	WEB	η_{17}	0.0694**	0.0317	η_{27}	−0.0129	0.0120	η_{37}	0.1860*	0.1103	η_{47}	0.1193**	0.0473
	CC	η_{18}	0.1127***	0.0342	η_{28}	0.0246	0.0298	η_{38}	0.0620	0.2817	η_{48}	0.1422**	0.0649
Control variables	AD	η_{19}	0.0077**	0.0037	η_{29}	0.0065**	0.0030	η_{39}	0.0158*	0.0092	η_{49}	0.0089*	0.0050
	BUSD	η_{110}	−0.0139	0.0226	η_{210}	−0.0278	0.0329	η_{310}	0.0727**	0.0261	η_{410}	−0.0028	0.0178
	UCAR	η_{112}	0.1388**	0.0657	η_{212}	0.2185**	0.0910	η_{312}	0.0995	0.0870	η_{412}	−0.0326	0.0569
	Month fixed effects	4 significant			2 significant			3 significant			1 significant		
	Year fixed effects	3 significant			3 significant			3 significant			None significant		

Notes: S.E. = standard error. N = 181.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

the call center channel, lending support to H3b. But again, the efforts in the independent agent channel have an insignificant (−0.0946; $p > 0.10$) effect on quotes generated through the call center channel.

Hypothesis H4 is about cross-channel effect between similar channels. The only two similar channels in our data are both rich, primarily persuasive channels, namely, exclusive agent and independent agent channels. In line with H4, the effect of efforts in the exclusive agent channel on quotes through the independent agent channel is negative and significant (−0.0689; $p < 0.01$). Similarly, the number of independent agents has a significant but smaller negative effect on exclusive agent quotes (−0.0353; $p < 0.05$). Taken together, the results reveal that the effects of efforts in the exclusive agent and independent agent channels on each other are asymmetric.

Thus, in general, efforts in a rich, primarily informative channel, a primarily persuasive channel, and a balanced channel reinforce one another and have complimentary effects on outcomes in one another's channel. However, there are some interesting asymmetries between the channels in these effects. While the effect of efforts in a primarily informative channel on shopping outcomes in a balanced channel is positive, the effect of efforts in a balanced channel on shopping outcomes in a primarily informative channel is insignificant. A possible explanation follows. A shopper typically encounters a leaner, informative channel earlier in the shopping journey. As a result, marketing efforts in such a channel will have positive effects on outcomes in richer, persuasive channels such as the call center and exclusive agent. In contrast, once a shopper moves to a balanced channel such as the call center, efforts in that channel will unlikely move the shopper back to a primarily informative channel for a desired shopping outcome.

Efforts in the rich, primarily persuasive, independent agent channel have some positive and significant effects on shopping outcomes in the other channels, but efforts in the other channels do not have a positive outcome in the independent agent channel. This asymmetry can be explained as follows. Unlike the independent agent channel, the Web, call center, and exclusive agent channels are firm-controlled channels. The efforts in these channels directly benefits the firm. In contrast, because independent agents deal with multiple brands, not all of their efforts are directed toward the focal brand. As a result, the complementary effect of marketing efforts in a dissimilar channel (primarily informative or balanced) is typically weak or insignificant. However, the substitutional effect of a similar channel (another primarily persuasive channel) on the independent agent channel is strong given the focal firm's stakes in its own exclusive agent channel. Given the dedicated sales efforts of exclusive agents, the efforts of independent agents do not make much dent in the number of quotes issued through the exclusive agents.

6.2. Other effects

We now discuss the other effects in the models. The effects of efforts in a channel on outcomes within the same channel are positive and significant; exclusive agents ($p < 0.01$), independent agents ($p < 0.01$), website ($p < 0.10$), and call center ($p < 0.05$). The effects of the control variables are mostly along expected lines. In the model for exclusive agent quotes, the effects of own advertising ($p < 0.05$), lagged quotes through exclusive agents ($p < 0.01$), lagged quotes through call center ($p < 0.10$), lagged quotes from independent agents ($p < 0.01$), and number of used car sales ($p < 0.01$) are significant. In the model of quotes by independent agents, advertising ($p < 0.05$), lagged dependent variable ($p < 0.01$), lagged exclusive agent quotes ($-p < 0.01$), and number of used car sales ($p < 0.01$) all have significant effects. The results of the model for quotes generated through the Web show that advertising ($p < 0.10$), number of business days ($p < 0.05$), lagged Web quotes ($p < 0.01$), and lagged exclusive agent quotes ($p < 0.01$) all have significant effects. The results of the model for number of quotes from the call center show that the effects of lagged dependent variable ($p < 0.01$) and advertising ($p < 0.10$) are significant.

Table 8
Own-channel, cross-channel, and within channel advertising elasticities.

Efforts in	Impact on outcomes in			
	Exclusive agent channel	Independent agent channel	Web channel	Call center channel
Exclusive agent channel	0.342	−0.070	0.186	0.135
Independent agent channel	−0.035	0.110	0.099	−0.086
Web channel	0.073	−0.013	0.206	0.122
Call center channel	0.113	0.025	0.081	0.147
Advertising impressions	0.008	0.007	0.015	0.009

Note: The elasticities are mean values based on 100 bootstrap samples from the quotes model.

6.3. Own and cross-channel elasticities

The magnitudes of own channel and cross-channel elasticities reveal several surprising findings. Table 8 shows the significant own- and cross-channel elasticities and within channel advertising elasticities. The confidence intervals for these elasticities, obtained by bootstrapping given 182 data points, appear in Web Appendix Table A7. With regard to own channel elasticities, we expect primarily persuasive (informative) channels to have the highest (lowest) elasticities, with the balanced channels' elasticities in the middle. While the own elasticity of a rich, primarily persuasive channel, the exclusive agent channel, is the highest (0.342), that of another primarily persuasive channel, the independent agent channel, is the lowest (0.110), contrary to expectations. Moreover, the own elasticity of the Web (0.206), a lean, primarily informative channel, is higher than that of the call center (0.147), a balanced channel. The results suggest that a company's dedicated channels such as exclusive sales agents, website, and call center are much more effective than channels not fully under the firm's control even though the latter may be primarily persuasive channels. The enhanced effectiveness may stem from greater knowledge about the firm's offerings and higher stake in the success of the efforts. The finding that the Web channel's own elasticity is higher than that of the call-center could be attributed to the instant informativeness of the Web and the high user control it offers. Although the call center can personally respond to queries, it also depends on the agent's knowledge and response time.

Many of the cross-elasticities are asymmetric with some of them being counter-intuitive. Some cross-elasticities are insignificant ($p > 0.10$). Among the positive and significant cross-channel elasticities, those of the Web and the call center on exclusive agents are 0.073 and 0.113, respectively, while that of exclusive agents on the Web and the call center are 0.186 and 0.135, respectively. The cross-channel elasticity of the exclusive agent channel on the independent agent channel is more negative (−0.070) than that of the independent channel on the exclusive channel (−0.035). Advertising elasticities within each channel range from 0.008 to 0.015, much smaller than the own and cross-channel elasticities. These differences underscore the importance of cross-channel effects. The dissimilar (similar) channels contribute to complementary (substitutional) cross-channel effects. Although the elasticities are specific to the institutional context and data period, the cross-elasticity comparisons by channel roles are meaningful.

6.4. Robustness checks

To ensure that the results are robust, we performed several alternative analyses. First, we use cost shifters and Hausman style instruments to account for the endogeneity of cross-channel and advertising efforts, respectively. A potential concern with contemporaneous cost shifters like wage rates is that managers may be able to make their effort decisions based only on past values of cost shifters, rendering lagged values of such variables to be more appropriate instruments. As a robustness check, we reestimate our models with averages lagged wage rates as instruments. The results (Web Appendix Table A1) are consistent with those of our main model.

Second, we focus on quotes for our cross-channel model because quote is a key metric that the industry uses analyze at the channel level and because only a limited number of policies were issued in the Web and call center channels. Nevertheless, we did a robustness check of the model with policies as the dependent variable primarily for exclusive and independent agents. The results (Web Appendix Table A2) are substantively similar to those of our proposed model.

Third, to assess the value of estimating cross-channel effects in the presence of advertising, we estimated two alternative models, one without advertising and one with no channel efforts. The results appear in Web Appendix Tables A3 and A4. The fits of these models are inferior to those of the proposed models. Furthermore, the results differ from those of the proposed full models. Thus, these results underscore the importance of including both channel effects and advertising in the model to accurately estimate cross-channel effects on shopping outcomes.

6.5. Model validation

To validate the results from our proposed models, we performed holdout or out-of-sample analyses. We estimated the model on 157 weeks of data and validated it on 25 weeks of holdout sample. The results of these analyses appear in Figs. 3a-3d. These figures show the plots of the actual and predicted values of the dependent variables within and out-of-sample. In Figs. 2a-2d, the predicted outcomes closely track the actual outcomes in both in-sample and out-of-sample with MAPE values of (7.0–9.2)%. In

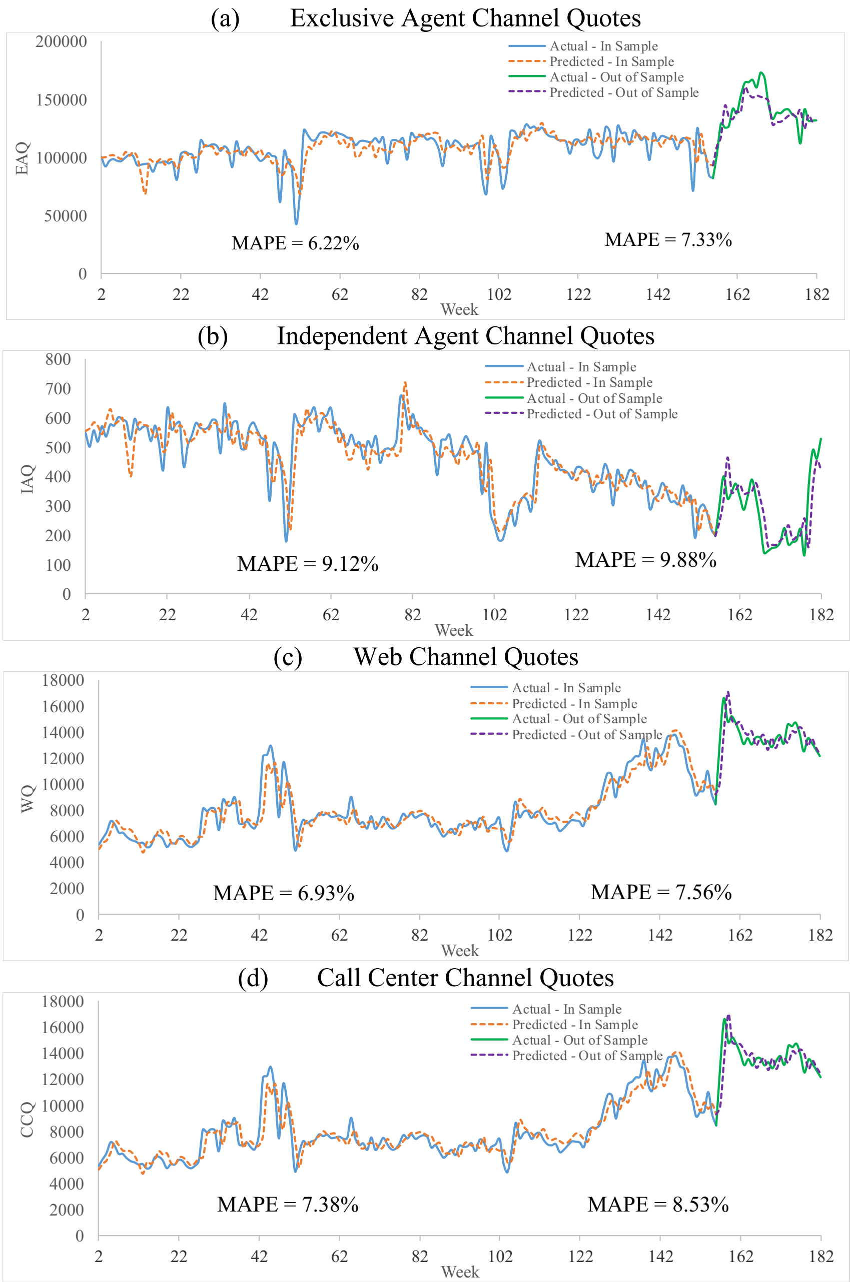

Fig. 3. In-sample and out-of-sample predictive model validation for quotes in each channel. Note: Log transformed variables are re-transformed to the original scale to enhance interpretability.

particular, the out-of-sample fit is the best for the exclusive agent channel that generates the majority of the quotes for the focal brand. Overall, our model validation yields strong fits and predictions both within and out-of-sample. They reinforce the usefulness of the model for descriptive and predictive purposes.

6.6. VAR model

Because we have aggregate data on a number of drivers of channel-specific quotes over time, we could potentially model the outcomes in each channel using vector auto regression (VAR), consistent with Pauwels (2017). We tested the data for stationarity through the augmented Dickey Fuller unit root test (Web Appendix Table A5). The tests reject the null hypothesis of unit root, obviating the need to transform the data. The impulse response functions (IRF) for the four outcome variables and the focal marketing efforts variables together with the total (sum of weekly effects until a steady state) effects appear in Fig. 4. The total effects

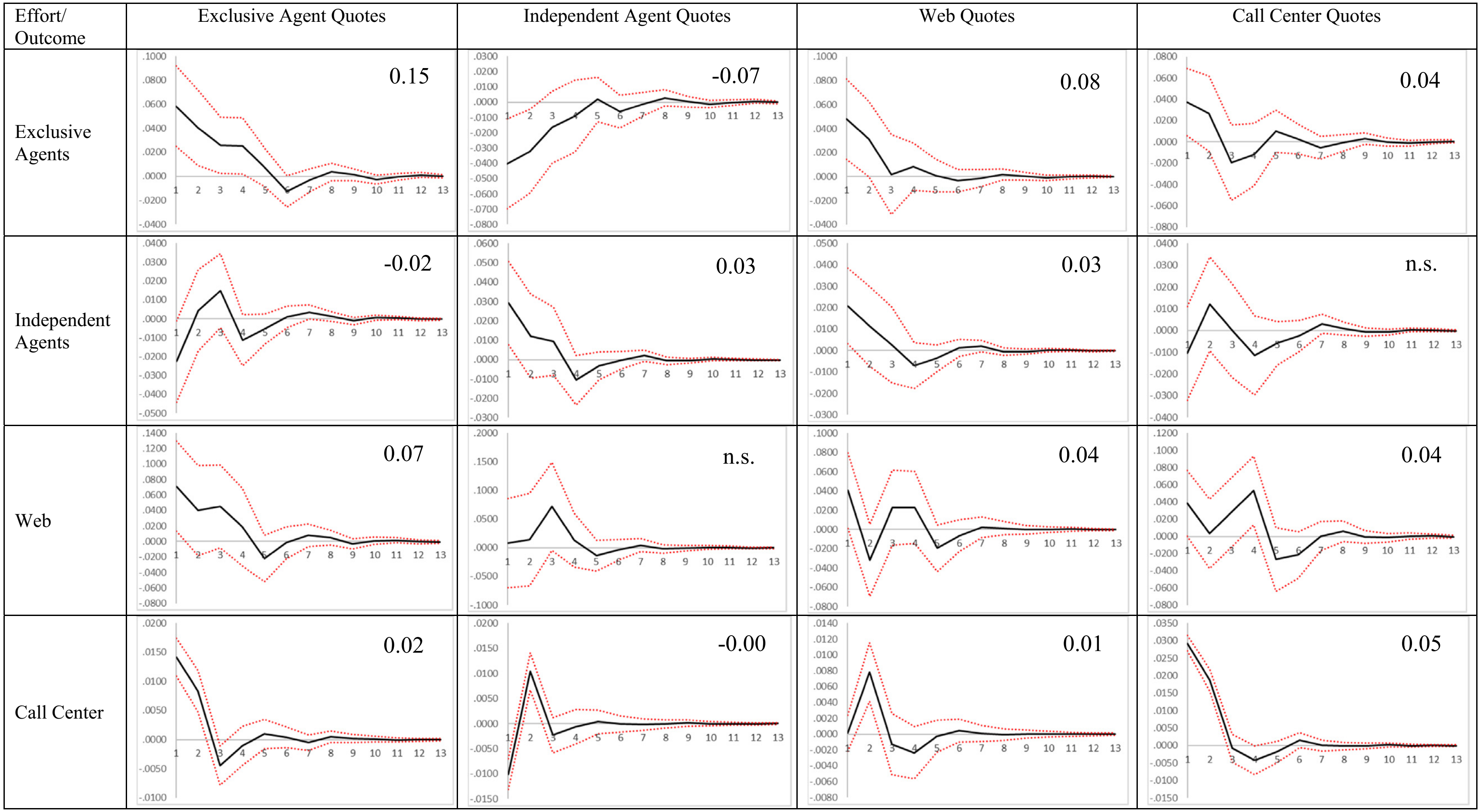

Fig. 4. Impulse response function (IRF) for the effects of marketing efforts in each channel on quotes in each channel. Note: The number in each graph represents the total/net effect of the independent variable on the outcome.

appear reasonable and consistent with the results of our proposed model. Efforts in the exclusive and independent agent channels are counterproductive on outcomes in each other's channel (−0.07 and − 0.02). Web efforts facilitate outcomes from exclusive agents (0.07) and the call center (0.04). Similarly, call center efforts enhance quotes from exclusive agents (0.02) as well as from the Web (0.05). We note that VAR models are typically data intensive and their estimates and impulse response functions may not fully converge to stable values when the number of observations is small. Furthermore, we are testing theory-driven hypotheses. For these reasons, we retain the results from the proposed set of equations that we developed to test the hypotheses.

6.7. Summary of results

To summarize, our results largely support our hypotheses of complementary channel effects among a primarily persuasive channel (exclusive agent), a primarily informative channel (the Web), and a balanced channel (call center). However, cross-channel complementarity is asymmetric in two ways. The first asymmetry is in the direction. In the case of the Web and the call center, Web (call center) efforts have a positive (insignificant) effect on call center (Web) quotes. Likewise, while independent agent efforts have a positive effect on Web quotes, Web efforts do not have a significant effect on quotes through independent agents. The second asymmetry is in the magnitude of complementarity. The call center has a stronger effect on the exclusive agent channel than vice versa. Similarly, Web efforts have a greater positive effect on exclusive agent quotes than vice versa. Exclusive agents have a greater negative effect on independent agent quotes than independent agents have on exclusive agent quotes.

7. Research and managerial implications

Omnichannel management is a burgeoning area for research and practice. Our research on cross-channel effects has critical implications for research and practice.

7.1. Research implications

The test of hypotheses offer new insights on asymmetric cross-channel effects. Our results could lead to a broader theory of channel effects. In such a theory, channel efforts make significant contributions to shopping outcomes through cross-channel effects, extending Brynjolfsson et al. (2009). Importantly, our results could lead to the development of a broader theory of within- and cross-channel effects based on the richness and primary influence role of channels.

Our results have other important research implications. They extend the literature on the effects of one channel on another from just the Web and physical channels context (Bell et al., 2018; Fisher et al., 2019; Wang & Goldfarb, 2017) to an omnichannel context comprising rich, persuasive as well as lean, informative channels. They also extend Avery et al. (2012), Pauwels and Neslin (2015), and Pozzi, 2013 from cannibalization between store and catalog or online channels to competition within rich, persuasive channels such as independent and exclusive agents. Our work complements Dinner et al.'s (2014) work about the effect of spending in advertising channels on sales to the effects of marketing efforts in each distribution channel on outcomes in the other distribution channels. It also extends Breugelmans and Campo's (2016) research on cross-channel promotions in a grocery setting and Mark et al.'s (2019) work on the effects of catalogs on other channels to cross-channel effects of marketing efforts in the services context. Our research presents evidence for both substitutional and complementary cross-channel effects. Our findings could spawn additional research into a comprehensive theory of why some channels are complementary and some channels are substitutional.

Our research also offers scope for the development of a theory about the relative magnitudes of channel effects on shopping outcomes. We find that within each channel, advertising elasticities are lower than those of channel elasticities, including cross-channel elasticities. This result suggests that within a distribution channel such as the independent agent channel and the exclusive agent channel, the role of the communication vehicle such as advertising may be muted. These findings provide a fertile ground for the development of a more nuanced theory on the roles of the communication and distribution channels and the interplay between the two channel types in effecting purchases, extending Dinner et al. (2014) and Li and Kannan (2014).

The surprising finding that a rich, primarily persuasive independent agent channel positively affects quotes in a lean, primarily informative Web channel without a reciprocating effect poses intriguing theoretical possibilities. When independent agents inform shoppers about alternative brands, some shoppers may visit their websites and indicate their interest in those brands. Some of these shoppers may view the brands' websites as more accurate and perhaps unbiased sources of a brand's information than that provided by independent agents, who might be perceived as promoting slanted information on brands better aligned with their compensation. This opens up the role of channel credibility in additionally explaining asymmetric cross-channel effects.

7.2. Managerial implications

The results offer valuable implications for managerial practice. First, managers should use a rich, primarily persuasive channel such as the exclusive agent, a lean, primarily informative channel such as the Web, and a balanced channel such as the call center in a coordinated way. Such cross-channel integration is critical to firm's growth (Cao & Li, 2015). Because exclusive agents have the highest own elasticity as well as high cross-elasticity on the call center, firms should allocate more efforts to exclusive agents. Moreover, the Web has the second highest own elasticity and high levels of cross-channel elasticities on exclusive agents and the call center. Therefore, enhancing website capability to offer better information, navigation, visibility, and direct fulfillment is critical. Furthermore, because the call center has high own elasticity and high cross-elasticity on exclusive agents, investing in the call center is also advantageous. Thus, allocating more resources to dissimilar channels with varying richness–such as the exclusive agent, the Web, and the call center–reinforces these channels in a synergistic manner. The findings have broad implications in other contexts. Consumer packaged goods and durables firms should invest in own stores, own websites and call centers to provide a seamless omnichannel experience to the customer and benefit from positive cross-channel effects.

Second, the result that the rich, primarily persuasive channels, the exclusive and the independent agent channels are substitutional and asymmetric offers practical guidelines. In general, firms may not desire too much competition between exclusive and independent agents lest that leads to price erosion and service variance across the agents. However, because marketing efforts in at least one of these two channels have a negative effect on the other, firms will have to act creatively. To boost overall impact, managers may want to minimize cannibalization between these two agencies by redefining their roles and incentives. They could use independent agents more for reaching new shoppers or for new product launches, and exclusive agents more to develop deep relationships and repeat purchases for core products. Because exclusive agents have a stronger negative effect on independent agent quotes than vice versa, managers could reexamine the nature and magnitude of incentives to align these channels together. Again, we can extend this result broadly to other contexts and suggest that firms should distribute their products judiciously between exclusive outlets and independent stores and align margins or commission levels for these channels based on the cross-channel elasticities.

Third, by understanding this nuanced effect of advertising relative to channel effects, capitalize on cross-channel effects, within each channel, managers should assign fewer resources to advertising than to channel efforts.

Finally, from the cross-channel elasticities, managers can derive greater actionable insights by using an important tool, namely, a graph of influence and influenceability of the different channels. Managers can compute influence and influenceability as follows.

$$INCE_c = \sum_{i=1}^{C-1} e_{ci} \tag{6}$$

$$INTY_c = \sum_{i=1}^{C-1} e_{ic} \tag{7}$$

where $INCE_c$ is influence of channel c, C is the total number of channels, e_{ci} is the elasticity of efforts in channel c on outcome in channel i, and $INTY_c$ is the influenceability of channel c, and e_{ci} is the elasticity of efforts in channel i on outcome in channel c. The influence and influenceability graph for our data appears in Fig. 5. The Web has the highest total influence on the other channels. In contrast, the exclusive agent is influenced most by the other channels but has the least positive influence on the other channels. The call center channel is in the middle with regard to both influence and influenceability. Finally, the independent agent channel has a negative overall influence on the other channels and is also influenced lowest by other channels.

Managers can use the results from this graph together with own channel elasticities to prioritize the relative importance of each channel for marketing efforts. Managers can see that the exclusive agent channel is most valuable because it has the highest own channel elasticity as well as the highest influenceability. They may find the Web channel to be important because it has the second highest own channel elasticity and the highest influence on the other channels. Managers can also appreciate the call center's value with moderate levels of own elasticity, influence and influenceability. Contrary to the efforts expended in it, the independent agent channel has the least own elasticity and cross-channel influence and influenceability. Therefore, managers should deemphasize this channel. By determining the relative importance of each channel through this graph, managers can better coordinate the levels of efforts in each channel.

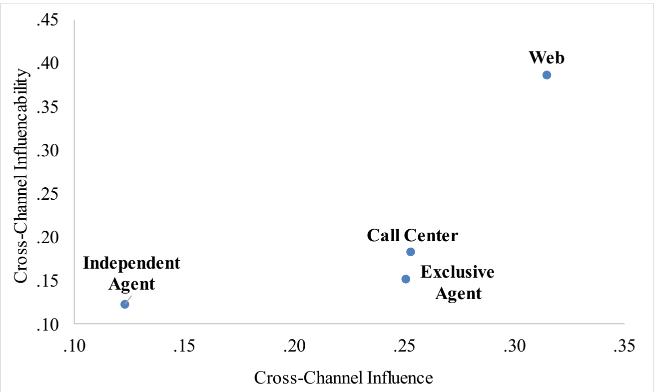

Fig. 5. Cross-channel influence-influenceability chart. Note: The numbers on the axes represent elasticities.

Table 9
Reallocation of marketing efforts across channels.

Marketing spending	Without cross-channel effects					With cross-channel effects				
	Profit change	Allocation across channels				Profit change	Allocation across channels			
		Exclusive agent	Independent agent	Web	Call center		Exclusive agent	Independent agent	Web	Call center
20% less with reallocation	7.91%	94.19%	4.34%	1.08%	0.40%	24.95%	72.28%	2.52%	17.69%	7.51%
10% less with reallocation	9.19%	94.49%	4.21%	0.96%	0.35%	29.12%	73.20%	2.24%	17.88%	6.67%
Current level (no reallocation)	0.00%	68.07%	20.16%	8.61%	3.16%	0.00%	68.07%	20.16%	8.61%	3.16%
Current level with reallocation	10.08%	94.73%	4.09%	0.86%	0.32%	32.63%	75.63%	2.02%	16.35%	6.01%
10% more with reallocation	10.65%	94.94%	3.99%	0.78%	0.29%	35.49%	77.84%	1.83%	14.86%	5.46%
20% more with reallocation	10.94%	95.12%	3.90%	0.72%	0.26%	37.81%	79.69%	1.68%	13.62%	5.01%

7.3. Resource allocation exercise

We illustrate the managerial usefulness of our model through a resource allocation exercise. We recognize that closed form optimal marketing efforts based on the estimated model is tedious to derive. Therefore, we use numerical analysis to compute the optimal levels of marketing efforts using the estimated own- and cross-elasticities, the levels of other variables, and the unit costs of efforts in each channel. The results appear in Table 9. They show the allocation percentages across the channels at different levels of marketing spending or budget relative to the actual marketing expenditures. These budget levels are akin to different spending scenarios proposed by Dinner et al. (2014). The table also reveals the profit differentials for different marketing spending levels relative to the actual marketing spending. To highlight the value of our cross-channel effects model, the table displays resource allocation outputs based on two models: model without cross-channel effects and with cross-channel effects (see Web Appendix Table A6).

The profit levels for resource allocation based on the model with cross-channel effects are consistently higher than those for the model without cross-channel effects for all marketing budget levels. Although the profit from optimization based on a model without cross-channel effects is greater than the firm's actual profit (10.02% more), the profit from optimization based on our model with cross-channel effects is much greater (32.63% more). The incremental profits from our model is highest (37.81% more) when the marketing budget expands by 20%.

The optimal reallocation of marketing budget across the channels reveals interesting insights. The firm's actual channel allocation mix was 68.07% for exclusive agents, 20.16% for independent agents, 8.61% for the Web, and 3.16% for call center. A reallocation based on optimization through a model without cross-channel effects produces an optimal channel mix of 94.73% for exclusive agents, 2.02% for independent agents, 0.86% for the Web, and 0.32% the call center. These numbers suggest a significant shift in resource allocation from the independent agent, the Web, and the call center channels toward exclusive agents mainly because the exclusive agents have the highest own elasticity. However, a reallocation based on our proposed model with cross-channel effects suggests a channel mix of for 75.63% for exclusive agents, 2.02% for independent agents, 16.35% for the Web, and 6.01% for call center. These results suggest that the firm needs to move substantially away from exclusive and independent agents toward the Web and call center. These results are consistent with the influence-influenceability matrix. The cross-channel effects of a primarily informative channel and a balanced channel on primarily persuasive channels explain the shift in allocation. Without considering these cross-channel effects, the firm overspent on primarily persuasive exclusive and independent agents.

These findings based on cross-channel effects are consistent with the general trend in channel allocation. Across industries, there is a growing shift in allocation of resources toward leaner and more efficient channels such as the Web channel. Banks have moved more toward the Web and mobile channels. So have most retailers, in particular, post Covid-19. Service organizations are reallocating toward leaner and balanced channels. Theoretically, the allocation findings suggest a trade-off between maximizing the high own elasticities of rich, persuasive channels and leveraging the high cross-channel elasticities of lean, informative and balanced channels.

8. Limitations, future research, and conclusions

Our research has limitations that future research could address. First, our models do not include competitor channel efforts because data on competitor brands were unavailable. With competitor data, a more complete model of own and competitor channel efforts could be developed.

Second, channel roles may vary across categories and stages in customer journey. Future research could examine cross-channel effects for categories in which the catalog channel and industrial channels are relevant, extending Käuferle and Reinartz (2015). With disaggregate data, future work could explore differential channel roles in customer journey and customer relationship management across channels, furthering Verhoef et al. (2010).

Third, with data on prices, promotions and customer satisfaction, a more comprehensive model of shopping outcomes can be developed. Online and offline prices can differ (Ancarani & Shankar, 2004) and may result in differential cross-channel effects. Furthermore, offline satisfaction can affect online purchases for services (Montoya-Weiss et al., 2003).

Fourth, our study could be extended to examine cross-channel integration (Cao & Li, 2015). Fifth, our model is at the channel level as data at the consumer level are difficult to obtain. With shopper level data, we could analyze the mechanisms behind cross-channel effects.

Finally, cross-channel effects could be studied in conjunction with cross-buying as the drivers and consequences could be somewhat similar (Kumar, George, & Pancras, 2008).

In conclusion, we sought answers to important questions relating to the growing phenomenon of cross-channel effects. Our research offers fresh insights. It shows that cross-channel effects are significant and asymmetric. While channels with dissimilar primary influence roles (e.g., the exclusive agent, the Web and the call center channels) are complementary, the direction and magnitude of the cross-channel effects are asymmetric. Likewise, while channels with similar primary influence roles (e.g., the independent agent and exclusive agent channels) are substitutional or competitive, their cross-channel effects are also asymmetric. Within each channel, own channel elasticity is greater than advertising elasticity. The findings offer important implications for theory and practice with regard to allocation of channel efforts across channels.

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Appendix A. Supplementary data

Supplementary analyses to this article can be found online at https://doi.org/10.1016/j.ijresmar.2020.09.001.

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