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ORIGINAL EMPIRICAL RESEARCH

In pursuit of an effective B2B digital marketing strategy in an emerging market

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Abstract

In business markets, firms operating in developing economies deal with burgeoning use of the internet, new electronic purchase methods, and a wide range of social media and online sales platforms. However, marketers are unclear about the pattern of influence of firm-initiated (i.e., paid media, owned media, and digital inbound marketing) and market-initiated (i.e., earned social media and organic search) digital communications on B2B sales and customer acquisition. We develop and test a model of digital echoverse in an emerging market B2B context, using vector autoregressive modeling to analyze a unique 132-week dataset from a Brazilian hub firm operating in the marketplace. We find empirical evidence supporting our conceptual framework in emerging markets. Underscoring the importance of a market development approach for emerging markets, the findings show that owned media and digital inbound marketing play a bigger role in influencing customer acquisition. Impressions generated through earned social media complement owned media, but not paid media. These insights highlight the notion that while sources of digital echoverse may remain the same across countries, its components exert a particular pattern of influence in an emerging market context. This is expected to encourage managers to rethink their digital strategies for B2B customer acquisition and sales enhancement while operating in emerging markets.

Keywords Digital echoverse · Digital B2B · Digital media elasticities · Emerging markets · Vector autoregression · Inbound marketing · Paid media · Owned media · Earned social media · Sales · Customer acquisition

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Marketers are increasingly shifting their attention and investments from "traditional advertising" to new forms of "social and digital marketing" (De Vries et al. 2017). This shift is even more dramatic in emerging markets because the rise in social media usage and online advertising is the fastest in these markets. Moreover, B2B e-business is outgrowing B2C due to the mobile usage of B2B applications (Agnihotri et al. 2016). As noted by Levine et al. (2001), if customer conversations are treated as "products," the strategy to market such products has to take the context (B2B vs. B2C; developed vs. emerging economy) into consideration (Lilien 2016; Sheth 2011). Scholars have questioned whether insights generated from extensive research on developed markets can be applied in emerging markets due to their disparateness in terms of market size, cultural norms, legal system, and political ties (Grewal et al. 2015).

Notably, contemporary marketing literature examines B2C digital marketing, with its focus on brand building and consumer journey, involving purchase and post-purchase activities in the context of both developed (e.g., Colicev et al. 2018; Dinner et al. 2014; Kumar et al. 2017; Li and Kannan 2014;

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Stephen and Galak 2012) and emerging economies (e.g., Kumar et al. 2017). Conversely, literature on B2B digital marketing, with its focus on lead segmentation and subscriber engagement, is limited to the developed economy context (e.g., Bruce, Foutz & Kolsarici 2012; Fang et al. 2015; Villanueva et al. 2008) (see Fig. 1 for a comprehensive review). Hence, there exists a B2B "knowledge gap" that calls for systematic investigation of different digital marketing strategies in an emerging economy context (Atsmon et al. 2012; Lilien 2016; Mele et al. 2015).

In this study, we provide a comprehensive treatment of the varied digital media platforms and analyze its effects on new sales and customer acquisitions in business markets from one emerging economy, Brazil. Since B2B e-commerce operations in emerging economies like Brazil and India are complex and challenging, digital marketers utilize the services of a "hub." A hub is a digital intermediary/firm that connects online resellers/virtual stores (e.g., Dafiti.com shoes store) to marketplaces (e.g., Amazon, Netshoes, etc.). The hub provides end-to-end expert services including catalogue management, seller panel management, marketplace interfacing, account management, international business, etc. Companies like MicroAd in Indonesia and Brand Hawkers in India are examples of such hub services. The hub invests in paid media, owned media and digital inbound marketing, seeking to increase new sales with online resellers/virtual stores.

We apply and extend the "echoverse" concept to our research setting. The echoverse system represents the "entire communication environment in which a brand/firm operates, with actors contributing and being influenced by each other's actions" (Hewett et al. 2016, p. 1). In our study, we specifically focus on a firm's *digital echoverse* that involves various firm-initiated as well as market-initiated digital communications. Our categorization of different digital media communications is based on their origination and control characteristics. On one hand, firm-initiated communication is proffered through owned media (controlled by the firm; e.g., the company website), paid media (bought by the firm; e.g., sponsored advertising) and digital inbound marketing (the firm's investment in digital content creation; e.g., blogs, whitepapers, webinars, etc.). Market-initiated digital communications, on the other hand, are represented by earned social media (not controlled or bought by the firm; e.g., likes, shares and comments on social media outlets) and organic search (website visits originating from a click on search engines, which, thereby, provide free traffic to the company website) (Li and Kannan 2014). Since business outcomes such as sales are considered a critical source within an echoverse (Hewett et al. 2016), we include business customer acquisition and new sales as components of business outcomes.

Bearing in mind the nuances of B2B exchanges and the unique context of emerging markets, we examine the effects of digital media on business outcomes. Specifically, our proposed framework (Fig. 2) aims to address the following questions involving the strength, nature and asymmetries of a B2B firm's digital echoverse in an emerging market context: (1) To what extent do firm-initiated and market-initiated digital communications and business outcomes affect each other? (2)

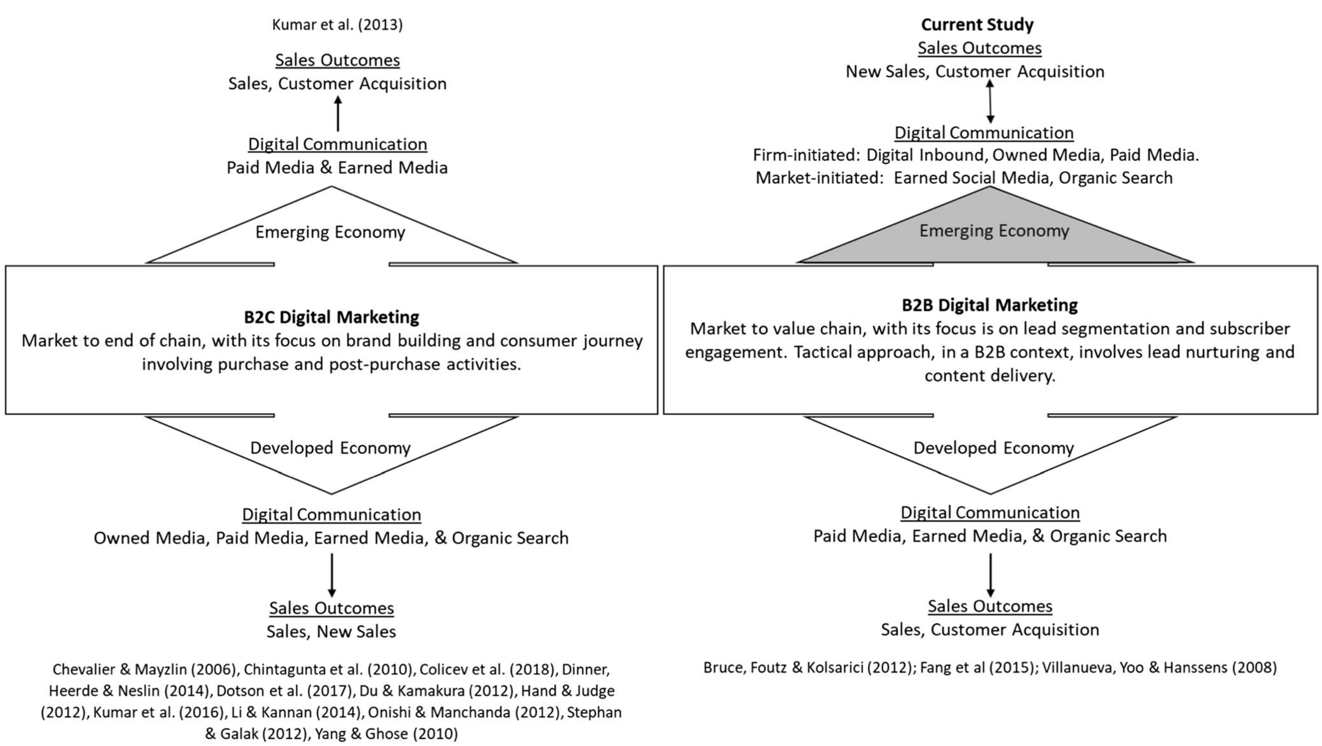
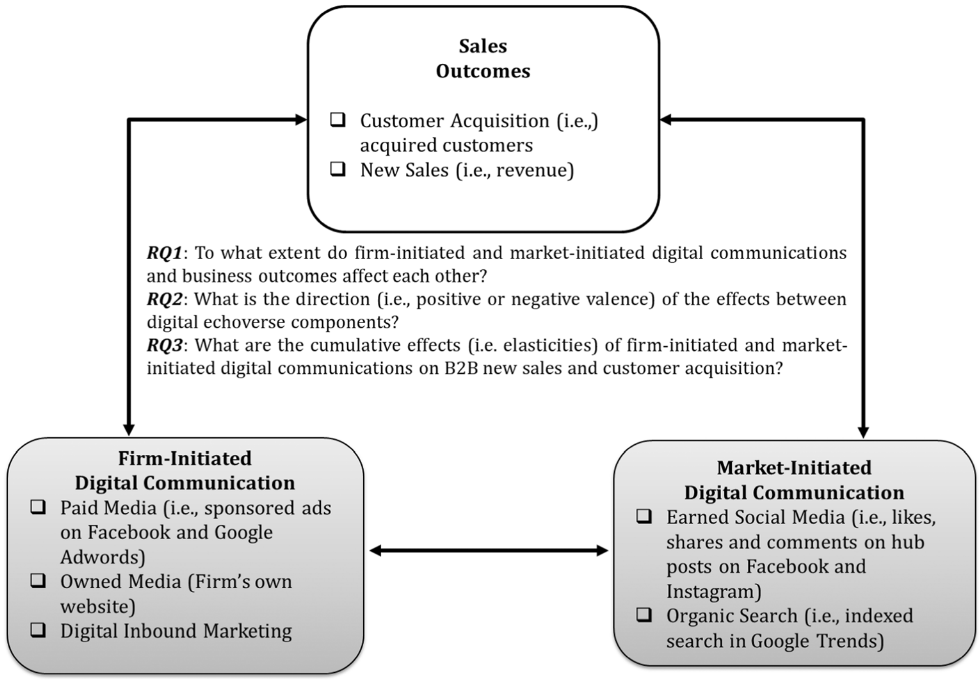


Fig. 1 Review of digital marketing strategy literature and research gap

Fig. 2 Conceptual O-I-E-O framework and research questions



Notes: A B2B firm's *digital echoverse* in an emerging market is represented by three sources (in boldface) and seven components.

What is the direction (i.e., positive or negative valence) of the effects between digital echoverse components? (3) What are the cumulative effects (i.e., elasticities) of firm-initiated and market-initiated digital communications on B2B new sales and customer acquisition?

Using data from an online hub in Brazil, we develop a vector autoregressive model with exogenous variables (VARX) of digital media types and business outcome measures (new B2B sales and B2B customer acquisition). The dataset spans almost three years of weekly information, including specific time series information such as seasonal effects and structural breaks for sales and marketing investments. The findings contribute to the existing literature in several ways. Most importantly, the results provide evidence of a digital echoverse in emerging markets; *owned-inbound-earned-organic search* (O-I-E-O), in that order of magnitude,[1] had cyclical and reciprocal effects on new B2B sales and customer acquisition. Specifically, an impulse of 1% shock on owned media and digital inbound marketing produces an average impact of .26% and .02% on customer acquisition, respectively. These findings are relevant because managers can integrate different media investments, comparing their effects to different business outcomes. Second, while developed markets exhibit, on an average, long-run advertising elasticities of .24, the new sales elasticity for digital inbound marketing is .38 and for owned media is .47 in Brazil, an emerging market. These results suggest that digital inbound marketing is a new and effective form of marketing for increasing sales in emerging markets by shaping customers' expectations through relevant and helpful content. Our results reinforce Sheth's (2011) argument about the importance of a market development strategy in shaping customer expectations for improving business outcomes in emerging markets. Third, a period-by-period analysis of owned media and digital inbound marketing unveils a positive pattern of media elasticities that emerge after the third period and become increasingly higher and persistent after the fourth period, supporting the echoverse theoretical model (Hewett et al. 2016).

The different "actors" of the digital echoverse architecture contribute in several ways: owned media is a form of "response" from customers that opens contacts with firms using their website after being influenced by media investments based on customized content, personal interactivity, and engagement (digital inbound marketing). Additionally, the importance of digital inbound marketing of a B2B company endorses the penetration and the increasingly positive response of strategies like these in an emerging economy. The results are corroborated by the forecast error variance decompositions (Pauwels 2017), highlighting the importance of firm-initiated digital communications. With respect to market-initiated communication, both earned media and organic search have positive influence on B2B sales and new customer acquisition. Finally, our findings reveal that both firm-initiated and market-initiated digital communications explain customer acquisition, which, in turn, influences new sales and cyclically increases digital inbound marketing and paid media.

[1] We note that O-I-E-O ordering does not imply directionality. We thank an anonymous reviewer for this point.

Next, we highlight the nuances of emerging economies relevant for a B2B digital marketing strategy.

Theoretical background and research questions

Digital marketing in B2B markets

Digital marketing toolkits are well suited for business marketers as they (1) aim at value chain intermediaries, (2) develop value propositions that focus on economic value, and (3) deal with fewer customers of larger individual transactions (Lilien 2016). As business customers are content-driven and technically savvy, they are comfortable in engaging via digital channels. Their attention towards digital resources and inclination to involve social media into the buying process have initiated the discussion on digital marketing strategies for B2B markets (Ancillai et al. 2019). Most of the business customers (over 80%) participating in an industry survey report that social content has influenced their purchasing journeys (Minsky and Quesenberry, 2016). As recurring revenue generation through contractual agreements is critical in B2B markets, enabling and sustaining customer engagement through digital media to secure sales every week, month, quarter and year is important.

Scholarly research focusing on digital marketing in the B2B context is nascent and offers narrow insight into the phenomenon. Contemporary studies, although very few, have begun incorporating the differences between B2B and B2C markets when examining the effects of digital media platforms (Agnihotri et al. 2017). For example, Swani et al. (2014), while analyzing the Twitter communication of Fortune 500 companies, suggest that “marketers in B2B and B2C settings exhibit significant differences in their branding and selling strategies; their use of message appeals; and the use of cues, links and hashtags to support information searches” (p. 873).

B2B digital marketing strategy differs from the strategy adopted by B2C digital marketing, primarily, in terms of focus and approach. In business markets, the focus is essentially on marketing to value chain (Lilien 2016), with attention towards lead segmentation, content delivery and subscriber engagement (Järvinen and Taiminen 2016). On the other hand, in a B2C context, digital marketing strategy is focused on brand building and end-consumer journey, involving purchase and post-purchase activities (Kannan and Li 2017). Finally, the rapid developments/research in digital marketing in business markets have almost exclusively focused on firms operating in developed markets. Hence, scholars have highlighted the need for research in B2B digital marketing in developing economies (Grewal et al. 2015).

Emerging economy context

Grewal et al. (2015) outline the key distinguishing features of business markets in emerging economies relative to developed economies: (1) the relative size and nature of government versus business buying, (2) the under-developed legal system in emerging markets, (3) the non-contractual and extensive webs of business relationships, (4) the extent to which business relationships affect a firm’s ability to perform in an emerging economy, and (5) the major influence of political ties on business processes in emerging economies. Hence, we expect the different channels of digital marketing communications—firm-initiated or market-initiated—to have varied impact on customer acquisition and B2B sales for the firms operating in developed and emerging economies. With proliferation of the use of internet among much of the population across the globe, the adoption of high standard digital marketing techniques has become the need of the hour for both developed and emerging economies. However, the difference in the rate of internet usage between the developed and developing nations can significantly impact the firms’ adoption of such B2B digital strategies (Alavi 2016). According to a recent Forrester Research, the demand for e-business in markets such as Europe and North America, where internet usage is high, has increased by double in just the last five years. However, since internet infrastructure in other developing countries continues to be poor and challenging (66% in Brazil, 52% in China and 35% in India), while B2B digital marketing thrives in the developed economies, the proportion of customers (B2B/B2C) using different interactive online services in emerging economies is less compared to the overall population.

The B2B digital landscape in emerging economies is often characterized by low levels of customer usage and frequency, high offline buying activities (Gilfoil 2012) and few B2B platforms for e-commerce (Alavi 2016). The upside for marketers is the high growth opportunity due to rapidly increasing adoption rates of digital media in emerging economies (Jobs 2012; Pedada et al. 2019). However, firms operating in developing countries face more challenges in e-business than marketers in the developed nations due to a host of factors such as low PC penetration, lower internet usage rate and a culture averse to credit/e-commerce transactions (Sheth 2011). Furthermore, an additional challenge for these firms is the rampant customer heterogeneity in terms of segments, purchase, and post-purchase behavior (Alavi 2016). Compared with developed market firms, social CRM is more important for firms operating in emerging market as customers’ expectations, and their desire to engage and be acknowledged digitally is increasing steadily. Due to the recent evolution of technology, users in BRIC countries, unlike their western counterparts, demonstrate a more balanced use of different social platforms (Gilfoil 2012). B2B buyers and sellers in emerging economies prefer marketing through owned media (such as websites) than their counterparts in developed economies who rely more on earned or organic media, which include social networking services like Facebook (Piskorski and Mecall 2010). Piskorski and Mecall (2010) have argued that users from countries like China and India are more engaged with the use of social media, i.e., customers tweet, microblog, share video content at least twice as many times as users in developed countries do. Word-of-mouth (WOM) is also becoming a major driver of customers' brand/product choice due to the growing culture of social validation in emerging economies.

In emerging economies, B2B digital marketing is outgrowing B2C e-business due to increasing mobile phone usage of B2B applications. Social media helps firms to better communicate with and respond to business clients, and thereby firms are resorting to inbound digital marketing with an aim to attract, engage, and delight buyers (Agnihotri et al. 2016). This allows the firms to develop a valuable relationship with the clients, resulting in generating a positive impact on the firms' businesses as well as their potential customers.

B2B digital marketing echoverse in an emerging economy

Hewett et al. (2016) were the first to coin the term *echoverse* in a B2C context. According to their research, it refers to the total communication environment involving firms/brands and their customers and how messages across varied channels (i.e., corporate communications, news media, and user-generated social media) interact with each other as feedback loops, termed the echoverse. Firms initiate the process through advertising, press release, etc.; customers react to it through online WOM and social media. Subsequently, firms respond to the customers' reactions on social media, thereby leading to the formation of a loop. Hence, an ideal setting would comprise traditional ad-spends, corporate communications, press releases, and digital communications (Atsmon et al. 2012; Berthon et al. 2012). However, in our study, we have a sharper focus on the "digital echoverse" in a B2B context.

Digital echoverse is often characterized as the combination of a company's website along with its social media presence (Holliman and Rowley 2014). We extend the echoverse idea to business markets through comprehensive investigation of varied digital channels that are firm-initiated and market-initiated. Furthermore, unlike Hewett et al.'s (2016) study that uses data from very large corporations like Wells Fargo and Bank of America, our research studies the data from a small and medium digital intermediary in Brazil called the *hub*. This firm uses only digital channels for all kind of communication and marketing activities. Hence, we believe that our data setting is the right fit for our study.

We posit that, in the digital marketing context, a firm would contribute to a digital echoverse through various firm-initiated digital communications, such as paid media, owned media, earned social media, and digital inbound marketing. Actors outside the domain of the firm, such as business customers and other companies, would also contribute to the firm's echoverse through market-initiated digital communication like organic search and earned social media (Hewett et al. 2016). We argue that sources of the digital echoverse may remain same across countries; however, components belonging to such sources may be different in diverse market contexts. For example, technological advancements, such as the average bandwidth and speed of internet, make certain types of media platforms more (or less) useful than others in different countries. Political systems and government attitudes too impact the acceptance of a digital media platform in a country (e.g., the Chinese government's ban on Facebook). LinkedIn attracts high interest among B2B customers in India, while interest in Facebook and Instagram is high in Brazil (Carro 2018).

We believe that answers to these research questions would help us in developing an effective digital marketing strategy. The overall idea behind a successful B2B digital marketing program in an emerging economy such as Brazil is to draw the business customers towards the company by positioning it as an attractive target for the customer to search for. As reviewed earlier, given the diminishing influence of outbound marketing, digital media platforms are providing opportunities to engage customers. It is, however, critical for effective digital marketing strategy that managers do not treat different media platforms in silos. Instead, managers should visualize different digital marketing tools and channels as parts of a digital echoverse (Hanna et al. 2011). Next, we discuss in detail the different components of digital communications and explain their relevance and use in the B2B emerging market context.

Digital communication components

Paid media In the marketing literature, paid media has been defined as a type of media within a firm's social media ecosystem that must be paid for, such as sponsored advertising (e.g., Hanna et al. 201). Aligning with the literature, we define paid media as weekly investment on online paid media search, such as sponsored advertising on Facebook and Google AdWords (Dinner et al. 2014; Stephen and Galak 2012; Hanna et al. 2011).

In the digital marketing context, paid media is a highly profitable approach since its cost is low when managers evaluate its "conversion" into sales (Dinner et al. 2014). Previous research suggests positive effects of paid media on firm outcomes. In Alibaba marketplace, Fang et al. (2015) find that paid media influences click-through rates and sales. The success of paid media on firm outcomes depends on the ad position (Ghose and Yang 2009), keyword positioning into a search engine (Rutz and Trusov 2011), costs of drawing customers (Yao and Mela 2011), the effective use of long-tail keywords (Bucklin et al. 2010), and search impressions/click-through-rates (Dinner et al. 2014). Building upon the literature, we explore the association between sponsored ads on Facebook and Google AdWords, and new B2B sales/customer acquisition.

Owned media In the literature, owned media is referred to as website visits that represent a customer activity metric (Srinivasan et al. 2016). Websites are primarily owned and managed by the firm and provide a platform for customers to initiate contact with a focal firm. In our study, we present owned media as the sum of weekly contacts initiated by potential clients via the firm's (i.e., hub) website through the option "I want to be a company customer." In owned media, the hub firm does not pay outsiders to create/promote digital content (Hanna et al. 2011). We argue that owned media could influence new sales and sales repetition as different and updated content can positively influence buyer intention (Stephen and Galak 2012). On their websites, firms attract customers through press releases, videos, and podcasts. Such media activities are increasingly utilized by buyers operating in emerging economies (Jobs 2012). Hence, digital marketers are paying equal attention to owned media alongside paid media activities (Alavi 2016).

Digital inbound marketing Digital inbound marketing reflects marketing strategies where potential customers are voluntarily attracted to a company's website (Halligan and Shah 2009). This approach is based on customized content, personal interactivity and engagement to provide organic search (Dinner et al. 2014; Kumar et al. 2017; Opreana and Vinerean 2015). As hub firms in emerging economies are new in creating marketplaces, customers need to acquire information for decision making based on blogs, social media platforms, and other sources. Accordingly, we define digital inbound marketing as hub firm's weekly investment in inbound marketing operationalized via a third-party agency.

The focus of digital inbound marketing is to find potential leads by matching their needs with specific content in order to transform them into active clients (Schultz 2016). Adopting this digital strategy, firms can suggest products and services based on buyers' activity, experience, interaction, and profile (Steenburgh et al. 2011). In suggesting products and services with more accuracy, firms could be more effective and efficient in terms of prospecting potential customers and generating sales and profits (Lusch and Vargo 2009). Our assumption about digital inbound marketing is based on customized and accurate content marketing. Inbound marketing generates customer engagement and is more effective in transforming potential leads into effective customers. Further, in emerging economies, customers increasingly desire to be engaged digitally and be acknowledged rapidly (Alavi 2016). This provides an opportunity to create elaborate and customized digital content via websites, blogs, whitepapers, etc. Therefore, digital marketers in emergent economies carefully design digital content with relevant information, keywords, and meta tags (information about the structure of the webpage) so that B2B buyers' search queries lead them to the firm's webpage.

Earned social media Earned social media is the media activity that customers, companies, and other agents produce in social media environment.[2] The firm has very little or, in most cases, no control over the creation and dissemination of this type of digital content. Empirical models of marketing phenomena in digital contexts usually characterize earned social media as user-generated activities such as likes, shares, and comments (Tirunillai and Tellis 2012; De Vries et al. 2017). Accordingly, we define earned social media as the sum of likes, shares, and comments on hub posts in social media (i.e., Facebook and Instagram) at a given time.

Information from a social source has been considered more influential "in shifting customers' opinions and, ultimately, triggering purchasing behavior" (Stephen and Galak 2012, p. 3). The influence of this piece of information occurs because business customers tend to believe their friends and, therefore, can become admirers and subsequently loyal customers of these companies. Interestingly, there has also been discussion related to the asymmetric interplay of earned social media, paid media and market outcomes. For example, Onishi and Manchanda (2012) suggest that paid media incentivizes earned media prior to the product launch. However, it becomes less impactful during the post-launch period. Moreover, suggesting a cyclical effect, the authors argued that market outcomes, in turn, impact blogging quantity. Such complex interplay may be more visible in emerging markets as customers in these markets differ from their developed market counterparts in more than one manner. As discussed previously, in emerging economies, customers utilize social media platforms at least twice as often as users from developed economies (Gilfoil 2012; Piskorski and Mecall 2010). Given such large and growing number of users in emerging economies, their likes, shares, comments, etc. on social media platforms impact customer purchase decisions and sales (Atsmon et al. 2012).

[2] Notably, social media environment varies between countries. For example, LinkedIn, a widely used social media platform for B2B marketers in the U.S. (154 million users), is still growing in our emerging market context, i.e., Brazil (35 million users). LinkedIn was launched in Brazil in 2010. In terms of utilization, 43% of LinkedIn's traffic comes in from the U.S. alone. On the other hand, in terms of Facebook membership, the U.S. is the only developed country in the top five list (the rest are India, Brazil, Indonesia, and Mexico). Also, Brazil is the third country in the world based on number of Instagram users (U.S. =120 million, India = 75 million, and Brazil =69 million; Statista 2019).

Organic search Both organic and paid search characterize "the visits originated from a click on search engines, such as Google, Bing and Yahoo." However, organic search provides "free traffic to the firm's website," while paid search involves "a fee per click for the firm" (Li and Kannan 2014, p. 46). By knowing specific and most commonly searched terms, firms can utilize the information for posting precise content to generate traffic. Organic search engine marketing can be divided into two classes: (1) pay for performance, i.e., distinguishability through sponsored links and banners, and (2) organic search engine optimization. In this study, we focus on organic search engine optimization, considering that organic links are better than sponsored links from the customer's viewpoint. Specifically, Google Trend is treated as a form of organic search because it assists in predicting the future by the volume of queries that customers generate (Dotson et al. 2017). The hub firm involved in the study uses Google Trend to predict search activity of customers based on search index of keywords related to the subject. An important objective is to understand the use of Google Trend as a potential predictor of both customer acquisition and new sales simultaneously.

Our assumption on market-initiated organic search is based on literature that suggests search engine as a predictor of firm outcomes (Du and Kamakura 2012). Based on previous research in an emerging market, namely Chile, Google Trend influenced the decision making of automobile sale (Carrière-Swallow and Labbé 2013). Berman and Katona's (2013) study shows that for the organic ranking of a website to be improved by search engine optimization, it is necessary that the quality of content of the website exhibits a strong positive correlation with what customers value. Therefore, we argue that a positive level of organic search engine optimization can enhance the quality of the search engine's ranking system, thus satisfying its visitors.

Methodology

Data and sources

Since our framework presents multiple directional pathways among different variables, we develop a vector autoregressive model. We implicitly assume that all variables are endogenous in the system, resembling the echoverse model developed by Hewett et al. (2016) and the brand-building model proposed by De Vries et al. (2017). Both models have originated from developed markets such as the U.S. and Europe. Prior studies have followed this intuition in estimating marketing performance using paid or social media decision variables (Colicev et al. 2018). Multivariate time series models like VARX are used in marketing research to assess interrelationships among marketing decision and performance variables, as well as to identify both contemporaneous and persistent effects (Kim and Hanssens 2017).

The empirical data is sourced from an online hub firm, which exclusively operates in one country, Brazil, in the digital context. This Brazilian hub firm is a digital sales management service provider, which mediates the interests of virtual retailers (e.g., online resellers) and specific marketplaces (e.g., Wal-Mart, Amazon, Carrefour, Netshoes, Extra, Ponto Frio, Casas Bahia, Dafiti, Kanui, Americanas.com, Mercado Livre, Submarino). Together, these marketplaces receive more than 70 million of online visits per month and e-commerce in Brazil is expected to generate approximately R$ 50 billion in revenues. Specifically, the hub focuses on managing and supervising sales from online resellers to marketplaces and end customers who make purchases online directly from these virtual retailers. Online resellers offer a different mix of product categories such as shoes, clothing, luggage, furniture, computers, accessories, etc. Marketplaces are real online shopping malls of different major retail brands. The hub firm does not utilize offline or other traditional advertising mediums such as TV or print media. Given our focus on a digital echoverse, the hub firm's business model fits our research context well.

Dataset The sample consists of weekly data. The data refers to the hub's investments on paid media and inbound marketing. Earned social media is media 'earned' through Facebook and Instagram. Organic search is provided by search queries on Google while owned media is the initiated contacts on the hub's website. The longitudinal data spans 132 weeks, from July 2014 to January 2017.

B2B outcome variables New B2B sales and customer acquisition are the two marketing response measures. According to Katsikeas et al. (2016, p. 8), "performance measures relating to customer behavior have been dominated by retention, with only recent attention focusing on acquisition." New B2B sales represent the sum of weekly new sales for acquired B2B customers, which are new online resellers/virtual retailers classified as "clients" by the hub. Hence, the variable "new sales" records only the first month of payment of a contract that had been just signed between the hub and a given retailer. This outcome variable is inside the firm value dimension (Kannan and Li 2017) for digital businesses. Data on new B2B sales were extracted remotely from Pipedrive data through customer data management software. B2B customer acquisition is the total number of online virtual resellers acquired weekly and it represents new B2B customers that the hub is acquiring (Katsikeas et al. 2016). Information on this variable was also extracted from the customer data management software.

Earned social media is the weekly number of impressions of the focal firm's messages on Facebook and Instagram. It is based on likes, comments and spontaneous shares of messages about the hub media (De Vries et al. 2017). Likes, comments and shares are classified as earned social media because the company does not directly generate them (Stephen and Galak 2012), but they express feelings or affective components of attitude in digital environments (Srinivasan et al. 2016). For measuring earned social media, we used Facebook audience insights (which evaluate audiences and aggregate information about geography, demographics, the hub total page likes, and purchase behavior) and Instamizer app (which evaluates audiences from multiple posts on Instagram). LinkedIn profile, a usual communication strategy in the B2B context, was not implemented by the company during the period of analysis, as the hub firm launched its LinkedIn profile in March 2016. In the Brazilian emerging market, firm and consumer usage of social media is largely concentrated on Facebook and Instagram (Carro 2018).

Paid media is the total weekly investments on search advertising. The Brazilian hub pays for services, such as Google AdWords and sponsored posts on Facebook, as a strategy to develop click-throughs to convert search actions into sales (Dinner et al. 2014).

Owned media refers to the activities in the media channels created by the hub, such as websites or blogs, which are under the hub's direct control. Owned media captures initiated-contacts (e.g., leads) on the website (Dinner et al. 2014; Stephen and Galak 2012).

Digital inbound marketing is the weekly investment on organic tactics based on interactivity and engagement, leading to organic search (Opreana and Vinerean 2015). The hub works with only one third-party agency for its digital inbound marketing on a weekly fee basis. The agency implements the digital inbound marketing campaign on behalf of the firm for a budget. We treat such investments as a proxy for digital inbound marketing.

Organic search is the weekly average percentage of search-queries for the hub's name on Google, provided by Google Trends. It is a variable that represents individual clicking on non-advertised results by search engines (Haan et al. 2016). Table 1 presents variables, definitions and references used in operationalizing the variables in our study.

The weekly average of new B2B sales is R$ 2049.23, ranging from R$ 0.00 (on weeks where there were no new signed contracts between the hub and its clients) to R$ 16,691.00. The average of customer acquisition (new clients) is 6.98. Earned social media registers a weekly average of 49.23, representing the average sum of likes, shares and comments on posts on Facebook and Instagram. On average, 41.39 firms initiate contact with the hub through the website. Advertising-specific variables unveil the hub's average weekly spending, R$ 148.64 on paid search and R$ 874.75 on inbound marketing.

Table 1 Variable operationalization and importance in extant marketing literature

Variable	Definition	Background	References
1. New B2B Sales	Weekly sum of payments regarding the first month contracts between the hub and its B2B customers	Sales is a firm value dimension in the context of digital marketing (Kannan and Li 2017)	Kannan and Li (2017); Katsikeas et al. (2016); Rust et al., (2004)
2. B2B customer acquisition	Sum of weekly acquired customers	Acquisition is an element of the customer value dimension, (Kannan and Li 2017) and is an important customer behavior variable (Katsikeas et al. 2016)	De Vries et al. (2017); Trusov et al. (2009)
3. Owned media	Sum of weekly contacts initiated by potential clients via the website through the option "I want to be a company customer"	Website visits are owned media which represent a customer activity metric (Srinivasan et al. 2016)	Dinner et al. (2014); Srinivasan et al. (2016)
4. Earned social media	Sum of likes, shares, and comments on hub posts in social media (Facebook and Instagram) in time *t*	Firm to consumer impressions generate activities from consumers (De Vries et al. 2017) becoming a form of earned media (Stephen and Galak 2012) for a given firm	Kumar et al. (2017); Srinivasan et al. (2016); Stephen and Galak (2012); De Vries et al. (2017)
5. Digital Inbound marketing	Weekly investment in inbound marketing operationalized via a third-party agency. This means that the firm pays for digital inbound marketing	Inbound marketing is based on customized content, personal interactivity and engagement to provide organic search	Dinner et al. (2014); Kumar & Gupta (2016); Opreana and Vinerean (2015)
6. Paid media	Weekly investment on online paid media search, such as sponsored ads on Facebook and Google AdWords	Paid search advertising is a strategy developed to increase click-throughs, and then conversions into sales	Dinner et al. (2014); Stephen and Galak (2012); Hanna et al. (2011)
7. Organic Search	Interest in the hub signalized by an indexed search in Google Trends. The terms used are 'hub' and 'marketplace'	Indexed search is a leading online activity and an underlying component of the sales funnel progression	Haan et al. (2016); Dotson et al. (2017)

Model and analysis

The theoretical model includes seven variables that refer to the environment of digital media communication. Our empirical approach depicts a marketing system where marketing inputs and responses are all endogenous. That is, marketing performance is explained by itself in past time (*t*-n) and by the lag of other variables (Hanssens and Parsons 1993). Similar approaches have been used in testing media effects of companies in developed economies (De Vries et al. 2017; Haan et al. 2016; Kim and Hanssens 2017; Kumar et al. 2017; Srinivasan et al. 2016; Stephen and Galak 2012), and we extend the same approach to an emerging market.

Similar to prior studies that analyze the interrelationships between marketing in the context of digital businesses and performance (De Vries et al. 2017; Kumar et al. 2017), we employ a double logarithmic transformation (ln-ln) to all model variables. The model uses a similar notation to the one used by De Vries et al. (2017), as their VARX weekly model also controls for a time trend and seasonal components (weekly dummies). Hence, the constant terms (α) and a deterministic time trend (δ_t) were included for all endogenous variables. We added a small constant (+1) to the original values of the variables before applying the logarithmic transformation.

In some of the first periods (weeks), we identified irregular shifts (breaks) for sales and marketing investments. The presence of structural breaks "biases the results of the unit-root tests in favor of finding unit roots" (Bronnenberg et al. 2000, p. 24). To account for this particularity, we included a dummy term for structural breaks for all the time series. The breakpoint identification for attributing the dummy variable was given after applying the routine used in Zivot and Andrews (1992) to all the endogenous variables. We additionally employed a test for identifying multiple breaks in all series (Clemente et al. 1998), since unknown structural breaks are a relatively common scenario in marketing VAR models (Pauwels 2018). We also applied other routines and tests using Pauwels (2017, 2018) framework for modeling time-series relations in marketing. These are fully described in model specification subsection. The full system of the VARX model is presented in Eq. 1:

New B2B Sales	=	B2BS
B2B Customer Acquisition	=	B2BCA
Earned Social Media	=	ESM
Paid Media	=	PM
Owned Media	=	OM
Digital Inbound Marketing	=	DIM
Organic Search	=	OS

$$
\begin{bmatrix} \ln(\mathrm{B2BS}) \\ \ln(\mathrm{B2BCA}) \\ \ln(\mathrm{ESM}) \\ \ln(\mathrm{PM}) \\ \ln(\mathrm{OM}) \\ \ln(\mathrm{DIM}) \\ \ln(\mathrm{OS}) \end{bmatrix} = \begin{bmatrix} \alpha_{\mathrm{B2BS}} \\ \alpha_{\mathrm{B2BCA}} \\ \alpha_{\mathrm{ESM}} \\ \alpha_{\mathrm{PM}} \\ \alpha_{\mathrm{OM}} \\ \alpha_{\mathrm{DIM}} \\ \alpha_{\mathrm{OS}} \end{bmatrix} + \begin{bmatrix} \delta_{\mathrm{t,B2BS}} \\ \delta_{\mathrm{t,B2BCA}} \\ \delta_{\mathrm{t,ESM}} \\ \delta_{\mathrm{t,PM}} \\ \delta_{\mathrm{t,OM}} \\ \delta_{\mathrm{t,DIM}} \\ \delta_{\mathrm{t,OS}} \end{bmatrix} + \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} & \theta_{1,4} & \theta_{1,5} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \theta_{7,1} & \theta_{7,2} & \theta_{7,3} & \theta_{7,4} & \theta_{7,5} \end{bmatrix} \times \begin{bmatrix} \mathrm{X}_{1,\mathrm{t}} \\ \mathrm{X}_{2,\mathrm{t}} \\ \mathrm{X}_{3,\mathrm{t}} \\ \mathrm{X}_{4,\mathrm{t}} \\ \mathrm{X}_{5,\mathrm{t}} \end{bmatrix}
+ \sum_{\mathrm{j}=4}^{\mathrm{J}} \begin{bmatrix} \Phi^{\mathrm{j}}_{1,1} & \cdots & \Phi^{\mathrm{j}}_{1,7} \\ \vdots & \ddots & \vdots \\ \Phi^{\mathrm{j}}_{7,1} & \cdots & \Phi^{\mathrm{j}}_{7,7} \end{bmatrix} \begin{bmatrix} \ln(\mathrm{B2BS}_{\mathrm{t-j}}) \\ \ln(\mathrm{B2BCA}_{\mathrm{t-j}}) \\ \ln(\mathrm{ESM}_{\mathrm{t-j}}) \\ \ln(\mathrm{PM}_{\mathrm{t-j}}) \\ \ln(\mathrm{OM}_{\mathrm{t-j}}) \\ \ln(\mathrm{DIM}_{\mathrm{t-j}}) \\ \ln(\mathrm{OS}_{\mathrm{t-j}}) \end{bmatrix} + \begin{bmatrix} \varepsilon_{\mathrm{t,B2BS}} \\ \varepsilon_{\mathrm{t,B2BCA}} \\ \varepsilon_{\mathrm{t,ESM}} \\ \varepsilon_{\mathrm{t,PM}} \\ \varepsilon_{\mathrm{t,OM}} \\ \varepsilon_{\mathrm{t,DIM}} \\ \varepsilon_{\mathrm{t,OS}} \end{bmatrix} \tag{1}
$$

Equation 1 uses a similar notation that was used in De Vries et al. (2017), where *t* indicates the week and *j* indicates the number of lags included in the model (four, after conducting a test for lag order selection and the Lagrange-multiplier test for autocorrelation of the fitted VARX model; Appendix 1, Table 8). The parameters $\Phi^{\mathrm{j}}_{\mathrm{i,i}}$ reflect direct (diagonal) and indirect (off-diagonal) effects among the variables in the system. As we mentioned earlier, in addition to the constant terms (α), we included a deterministic time trend (δ) for all variables (De Vries et al. 2017). Finally, we controlled for the structural breaks presence (X_1 equals 1) according to Zivot and Andrews' (1992) breakpoint identification and included additional controls for seasonal effects (X_2 through X_5 for week 1 through week 4) similar to Pauwels et al. (2004). The vector of errors ε_t is the main component of our analysis, as we conducted all possible orderings (5040) among the endogenous variables after Cholesky decomposition of the error terms (De Vries et al., 2017), founding on the argument that prior theory does not suggest a clear causal ordering (Pauwels, 2018). The estimation of 5040 VARs with different orderings also reproduces the possible nature of media decisions in emerging markets (i.e., simultaneity), while providing the average effects (elasticities) of the decision variables.

Model specification

For model specification, we follow the methodological procedures used in assessing the interrelationships between media variables and marketing performance (Pauwels 2018; Trusov et al. 2009; De Vries et al. 2017). The objective of this comprehensive routine is to guarantee a stable VARX capable of explaining more than one variable (Pauwels 2017). The initial methodological step comprises simply testing for endogeneity among marketing variables using bidirectional Granger causality tests (Trusov et al. 2009). See step 1 in Table 2.

In step 2 (Table 2), we analyze the presence of a unit root in model variables. In checking for a unit root, we resorted first to a structural break test, as suggested in Zivot and Andrews (1992), because we found irregular patterns on some variables by visual inspection. We use hypothesis testing to check if a given variable has a unit root with a structural break, in both intercept and trend (Lumsdaine and Papell 1997).

Table 2 Overview of methodological steps, descriptions and specific aspects

Methodological step	Description	Specific aspects
1. Analysis of endogeneity among marketing variables (Hewett et al. 2016; Pauwels 2017; Trusov et al. 2009; De Vries et al. 2017)	Granger causality tests the temporal causality in each pair of variables	Test against four lags as data is weekly. The objective of this initial step is to identify the presence of endogeneity among model variables (Trusov et al. 2009). We report minimum p values across four lags. Results are depicted on Table 7.
2. Unit root tests (Kwiatkowski et al. 1992; Pauwels 2017; Srinivasan et al. 2010; Trusov et al. 2009; Zivot and Andrews 1992)	Assuming a structural break in both the intercept and trend (Zivot and Andrews 1992) or multiple structural breaks (Clemente et al. 1998) in the series.	According to Zivot and Andrews (1992), breaks are endogenous in the system (e.g. our data spans a nascent firm with irregular sales and marketing inputs in first weeks). Additionally, we conducted the two versions of Clemente et al. (1998) unit root tests in different transformations of the model variables (Bronnenberg et al. 2000), in levels and logs, to assess structural breaks (Table 3). Then, we used Zivot and Andrews (1992) and Clemente et al. (1998) routines (Table 7). We found only stationary variables and no cointegration tests were necessary.
3. Generating Cumulative Impulse Response Functions after estimating a VARX model (Evans and Wells 1983; Pauwels et al. 2004; Pauwels 2018; De Vries et al. 2017)	We used Cholesky decomposition of the error terms after continuously change the ordering among endogenous variables in the VAR system.	This procedure (5040 VARX possible orderings) enables the possibility to compute and compare the average relative effectiveness (De Vries et al. 2017) among different types of media, their average effect (grand mean) and period-by-period cumulative elasticities (Table 5). The Cholesky decomposition solves the problem of contemporaneous correlation between the elements of the error vector (Evans and Wells 1983)
4. Comparison with alternative models (Srinivasan et al. 2016; Trusov et al. 2009; De Vries et al. 2017)	We compared the estimated model with alternative models.	We compare our model against multiplicative models using single dependent variables (New B2B Sales or B2B Customer Acquisition) (Table 6) and models based on means, random walks and autoregression of the endogenous variables (Table 10, Appendix 3). Our model was superior in all tests.
5. Conducting in-sample forecasts with the estimated VAR (Hewett et al. 2016)	We used 70% of the data as estimation sample and the remainder as validation sample.	We conducted this approach using a 50-steps ahead forecast of New B2B Sales and B2B Customer Acquisition (Fig. 5, a-d)

Since the possible presence of structural breaks might potentially distort unit root tests (Bronnenberg et al. 2000), and "variables can display a wide variety of structural breaks of unknown number, duration and form" (Becker et al. 2006, p. 381), we test the presence of multiple structural breaks, verifying the presence of gradual shifts in their means. We reproduced methodological procedures to verify double mean shifts (Baum et al. 1999) on model single time series applying the two versions of Clemente et al. (1998) unit root test (Baum et al. 1999). Appendix 2 (Table 9) shows the complete details of the additive outlier and the innovation outlier routines on all model variables in levels and logs, using a similar procedure employed in Bronnenberg et al. (2000). Table 3 details the statistics and conclusion of unit root tests for all model variables.

Table 3 Unit root and structural breaks routines on model variables in natural logs

Variable	Additive outlier (AO) routine[1]			Innovation outlier (IO) routine[2]			Final interpretation
	1st break (t)	2nd break (t)	(rho – 1)[3] (t)	1st break (t)	2nd break (t)	(rho – 1) (t)	
Ln(New B2B Sales)	3.63***	1.24	−8.27***	4.42***	0.34	−11.15***	Stationary with a structural break
Ln(B2B customer acquisition)	3.79***	6.37***	−6.80***	3.92***	4.54***	−10.20***	Stationary with multiple breaks
Ln(Owned media)	−2.95***	5.89***	−4.22	−6.12***	7.15***	−7.18***	Stationary with multiple breaks
Ln(Earned social media)	−6.32***	−6.93***	−2.88	2.16	−2.22**	−3.25	Stationary with multiple breaks
Ln(Inbound marketing)	31.15***	7.47***	−1.49	24.25***	12.57***	−24.25***	Stationary with multiple breaks
Ln(Paid media)	37.44***	−6.35***	−3.41	21.00***	−12.93***	−20.79***	Stationary with multiple breaks
Ln(Organic search)	3.87***	1.93*	−7.05***	3.39***	2.83**	−9.61***	Stationary with multiple breaks

*** p value < .01; ** p value < .05; * p value < .10

[1] The additive outlier (AO) routine captures a sudden mean of a given series. T-statistics for structural breaks significances are displayed on the 1st and 2nd 'break' columns

[2] The innovation outlier (IO) routine allows for a gradual shift in the mean of a series. T-statistics for structural breaks significances are displayed on the 1st and 2nd 'break' columns

[3] Results for the Clemente et al. (1998) unit root hypotheses in all series, in logs. Alternative hypothesis is that the series is stationary with breaks. Critical value is −5.49 (5%) to all of them

Model output

We generate cumulative impulse response functions after estimating the VARX model (see step 3 in Table 2). To do this, we perform Cholesky decomposition of the error terms after the estimation. However, we continuously change the ordering among endogenous variables in the VAR system. The 5040 VARX possible orderings enable us to compute and compare the average relative effectiveness (De Vries et al. 2017) among different types of media, their average effect, and eventually, period-by-period cumulative elasticities. The Cholesky decomposition for estimations solves the problem of contemporaneous correlation between the elements of the error vector (Evans and Wells 1983) and works similarly as a conceptual experiment. This methodological approach compares the time profile of the effect of hypothetical shocks on endogenous variables with a baseline profile that involves the expected values of endogenous variables in the absence of those shocks (Kim and Hanssens 2017).

Final methodological decisions include comparing the estimation model with alternative models and conducting in-sample forecasts to assess general performance (see step 4 in Table 2). We first compare our VARX estimation with other time series models based on means, random walks and (univariate) autoregressions of endogenous variables (Appendix 3, Table 10) (Dekimpe and Hanssens 1995; De Vries et al. 2017; Trusov et al. 2009). In generating forecasts, we select 70% of the data as estimation sample and the remainder as validation sample (Hewett et al. 2016) and use the 50-step-ahead forecast of the two main response variables—new B2B sales and B2B customer acquisition (Fig. 5).

Next, we compare the elasticities generated from the impulse-response functions of the VARX against two multiplicative models using the response variables (New B2B Sales and B2B Customer Acquisition) as the main dependent variables of these models.[3] In the empirical development of these models, we deal with potential endogeneity that can arise as the result of strategic behavior from managers using different media strategies. Elasticities obtained from our VARX model are more reliable than those shown in the alternative rival models.

Results

Cumulative elasticities

Figure 3 shows the relationships between echoverse components resulting from Granger causality tests. Table 4 presents the average cumulative elasticities of different digital media formats on the two main response variables, computed after a simulation of the 5040 VARX possible orderings. We use different orderings to assess the sensitivity of the elasticities in accordance with Dekimpe and Hanssens (1995). These elasticities accumulate significant effects with t-statistics greater than 1 in absolute value after a decomposition of the error terms (De Vries et al. 2017). According to the results, investments in media, in general, produce more concrete results on new B2B sales as compared to customer acquisition. New B2B sales elasticity for owned media is .47, while customer acquisition elasticity for the same variable is .26. Similarly, new B2B sales elasticity for inbound marketing is .38, while customer acquisition elasticity for the same is .02. These two media variables—owned media and inbound marketing—are responsible for the largest effects on the two response variables.

In addition, results show that earned social media sales elasticity is .06 for new B2B sales and − .05 for customer acquisition. Similarly, organic search sales elasticity is .06 for new B2B sales and − .03 for customer acquisition. Our results corroborate the observation that marketing decisions may exhibit paradoxical effects on financial (sales) and behavioral (acquisitions) measures (Hanssens and Pauwels 2016). This is because despite practitioners implicitly assuming positive correlations among marketing performance measures, empirical experience shows trade-offs between different measures of performance (Katsikeas et al. 2016).

At least two new B2B sales average elasticities found in our research (for owned media and inbound marketing) are higher and different from the average current-period advertising elasticity of .12 reported by Sethuraman et al. (2011) and that of .09 computed by Henningsen et al. (2011). Results based on data from developed markets are even more different when considering B2B customer acquisition. De Vries found elasticities of .20 for traditional advertising and .10 for Firm-to-consumer impressions (Facebook likes, comments, and shares). In our empirical approach, only owned media (.26) and inbound marketing (.02) produce an average positive effect on this response variable. However, in the long run some effects revert to a positive influence, for example, new B2B sales elasticity for earned social media starts increasing after the second week.

Finally, we find evidence for cyclical effects of digital media and performance outcomes using Granger causality tests (Fig. 3 and Table 7). Owned media has a bi-directional effect on earned media, and similarly, inbound marketing has bi-directional effect on organic search. As noted earlier, owned and inbound are the two-firm initiated digital mediums that have the strongest effects on both business outcomes. Additionally, we find support for a digital echoverse wherein both firm- and market-initiated digital media have bi-directional effects on each other and on performance metrics, which subsequently have an effect on the digital media investments in a cyclical fashion. This is a powerful finding as it clearly showcases the interplay of different media and the cyclical feedback effects on key B2B performance outcomes

[3] We thank the reviewer for suggesting the estimation of alternative multiplicative models.

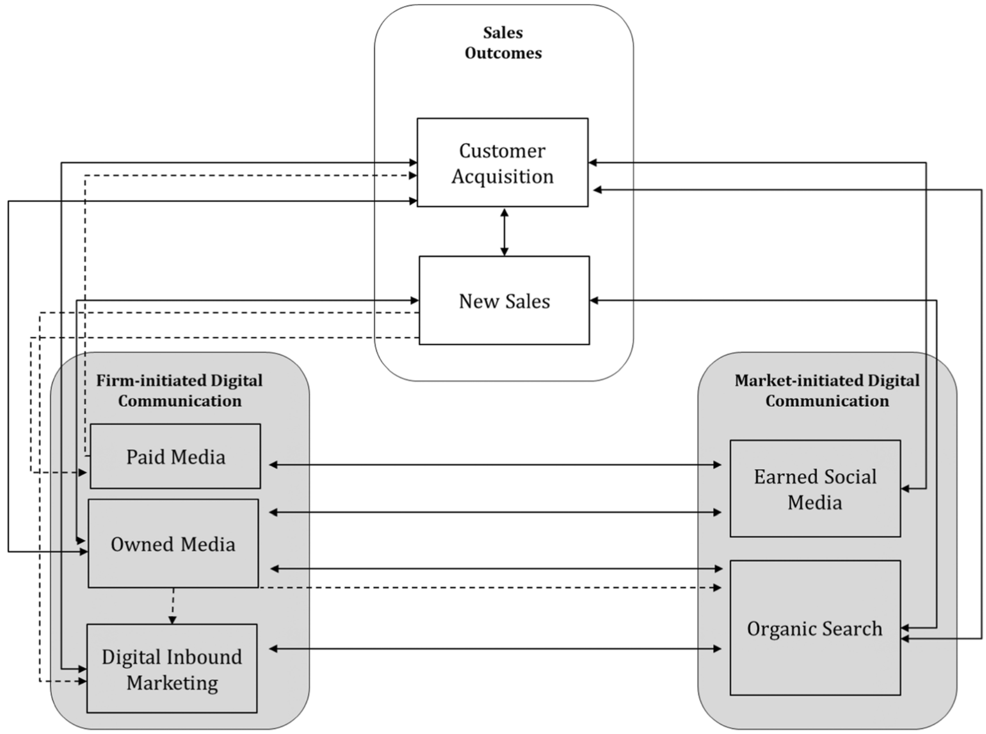


Fig. 3 Modeling O-I-E-O framework resulted from Granger causality tests. *Note*. Solid arrows indicate bidirectional causality, while dashed ones display unidirectional

like new sales and new customer acquisitions, thus highlighting the power and importance of different digital media types in business markets.

Cumulative impulse response functions

The VARX model simulation enables the comparison of the evolution of these elasticities using Cumulative Impulse Response Functions (COIRFs), considering the response of performance eight steps ahead. Impulses on earned social media and organic search achieve their peak six periods ahead (Table 5), while impulses on owned media and inbound marketing are permanent, thereby exhibiting higher elasticities that extend to two months (eight steps ahead). Earned social media refers to "free media" that influences the hub's capacity of generating new sales. The effect exhibited by earned social media is possibly explained by engagement: posts on social networks evoke more "engaged customer behaviors (i.e., like

Table 4 Average cumulative elasticities of different media formats on the two main response variables and FEVD

Digital communication strategy	Impulse of 1% shock on	Response on new sales				Response on customer acquisition			
		Mean	SD	Min	Max	Mean	SD	Min	Max
Firm-initiated digital communication	Paid Media	−.15	.12	−.39	.22	−.02	.07	−.14	.10
	Owned media	.47	.32	−.25	1.06	.26	.13	−.00	.50
	Inbound marketing	.38	.45	−.42	1.27	.02	.04	−.08	.16
Market-initiated digital communication	Earned Social Media	.06	.16	−.34	.46	−.05	.06	−.21	.07
	Organic search	.06	.18	−.34	.40	−.03	.05	−.14	.04
Error	Variables	FEVD of new sales				FEVD of customer acquisition			
		Mean	SD	Min	Max	Mean	SD	Min	Max
Forecast error variance decomposition of media formats	Earned Social Media	.01	.01	.00	.06	.01	.01	.00	.05
	Paid Media	.00	.00	.00	.02	.01	.01	.00	.03
	Owned media	.04	.02	.00	.09	.04	.04	.00	.13
	Inbound marketing	.03	.03	.00	.12	.00	.00	.00	.02
	Organic search	.01	.01	.00	.04	.00	.00	.00	.03

Cumulative elasticities (Cumulative Orthogonalized Impulse-Response Functions) represent the sum of the individual period impulse-responses for the 5040 VARX possible orderings. Means are average effects of all orderings

SD standardized deviation; *Min* minimum; *Max* maximum

Table 5 Period by period average cumulative elasticities of different media formats

Period by period	Impulse on Earned Social Media		Impulse on Paid media		Impulse on Owned media		Impulse on Inbound marketing		Impulse on Organic search	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
New B2B sales										
Contemporaneous	−.09	.12	.02	.08	−.10	.10	−.15	.16	−.07	.09
1	.09	.14	−.06	.09	.16	.08	−.09	.16	−.14	.11
2	.13	.16	−.07	.10	.36	.08	−.02	.17	−.07	.13
3	.08	.14	−.16	.09	.26	.07	.08	.14	−.00	.11
4	.05	.14	−.23	.09	.46	.06	.35	.12	.18	.12
5	.04	.14	−.25	.08	.61	.06	.54	.11	.17	.13
6	.12	.15	−.17	.08	.74	.07	.74	.12	.20	.15
7	.09	.16	−.21	.09	.84	.07	.09	.12	.14	.16
8	.09	.17	−.20	.09	.89	.07	1.07	.12	.13	.17
Customer Acquisition										
Contemporaneous	−.03	.04	−.04	.04	.01	.02	−.01	.03	−.02	.03
1	−.00	.04	−.03	.05	.13	.02	−.00	.03	−.05	.03
2	−.01	.05	−.03	.06	.21	.03	.00	.03	−.04	.04
3	−.04	.05	−.05	.07	.19	.03	.00	.03	−.06	.04
4	−.07	.05	−.04	.07	.27	.03	.02	.03	−.02	.04
5	−.07	.05	−.04	.07	.33	.03	.03	.03	−.03	.05
6	−.06	.05	−.00	.07	.37	.03	.05	.03	−.01	.05
7	−.08	.05	−.00	.07	.41	.03	.05	.03	−.02	.05
8	−.09	.05	.00	.07	.43	.03	.07	.03	−.02	.06

and share the post, include a positive comment), which can benefit the firm's performance over time" (Kumar et al. 2017, p. 270).

The positive pattern found for these elasticities, specifically for owned media and inbound marketing, possibly indicates a carryover effect, which extends beyond the campaign period for these media types. Accordingly, with regard to inbound marketing, as the clients are repeatedly exposed to content messages on multiple occasions, it "gradually increases the impact of the message because of consumers' increasing familiarity with the campaign" (Dekimpe and Hanssens 2007, p. 250). As more people signal their intention to become clients with the company through the website (owned media), they can influence other potential clients. This is endorsed by the observation that word-of-mouth "may be endogenous because it not only influences new customer acquisition but also is itself affected by the number of new customers" (Trusov et al. 2009, p. 91).

We find a positive effect of owned media for B2B customer acquisition. A 1% impulse on owned media achieves .43% response on acquisition in the eighth period. This pattern is also noticed for inbound marketing but with smaller elasticities ranging from .02 (fourth period) to .07 (eighth period). Contemporaneous effects are all negative, except for owned media (for B2B customer acquisition) and paid media (for new B2B sales).

Response variables over time and model performance

Figure 4 (a-d) shows the Cumulative Orthogonalized Impulse Response Functions (COIRFs) of inbound marketing and owned media on new B2B sales and B2B customer acquisition. The solid blue line is the effect of the simulations resulting from different VARX orderings, considering eight weeks ahead (two months). The gray area indicates 90% confidence intervals. The data presents a positive, permanent and increasing effect of inbound marketing on new B2B sales for eight weeks (Fig. 4a), which is stronger when compared to B2B customer acquisition (Fig. 4b).[4] The effects of owned media on the two response variables (Fig. 4c, d) are also both positive, with an increasing pattern.

Figure 5 shows the in-sample forecasts for new B2B sales and customer acquisition (Step 5 in Table 2). The solid lines are used for observed values, while dashed blue lines are for forecasts. We use 70% of the data as estimation sample and the remainder as validation sample, according to the procedures detailed by Hewett et al. (2016) and Trusov et al. (2009). Parametric standard errors were obtained for the forecasts due to the absence of asymptotic standard errors with exogenous VAR estimations. We conducte an additional procedure of comparison of the estimated VARX model against competing models (De Vries et al. 2017), based on means, random walks and autoregression of the endogenous variables (Appendix 3, Table 10). The proposed model is appropriate considering the context of media investments and marketing performance in an emerging market.

Post-hoc analysis: Multiplicative alternative models

In order to verify the reliability of our VARX model, we create an alternative multiplicative model to challenge the estimative (detailed in Appendix 5). The alternative multiplicative model has all the digital communication strategies as independent variables, and new B2B sales and customer acquisition as

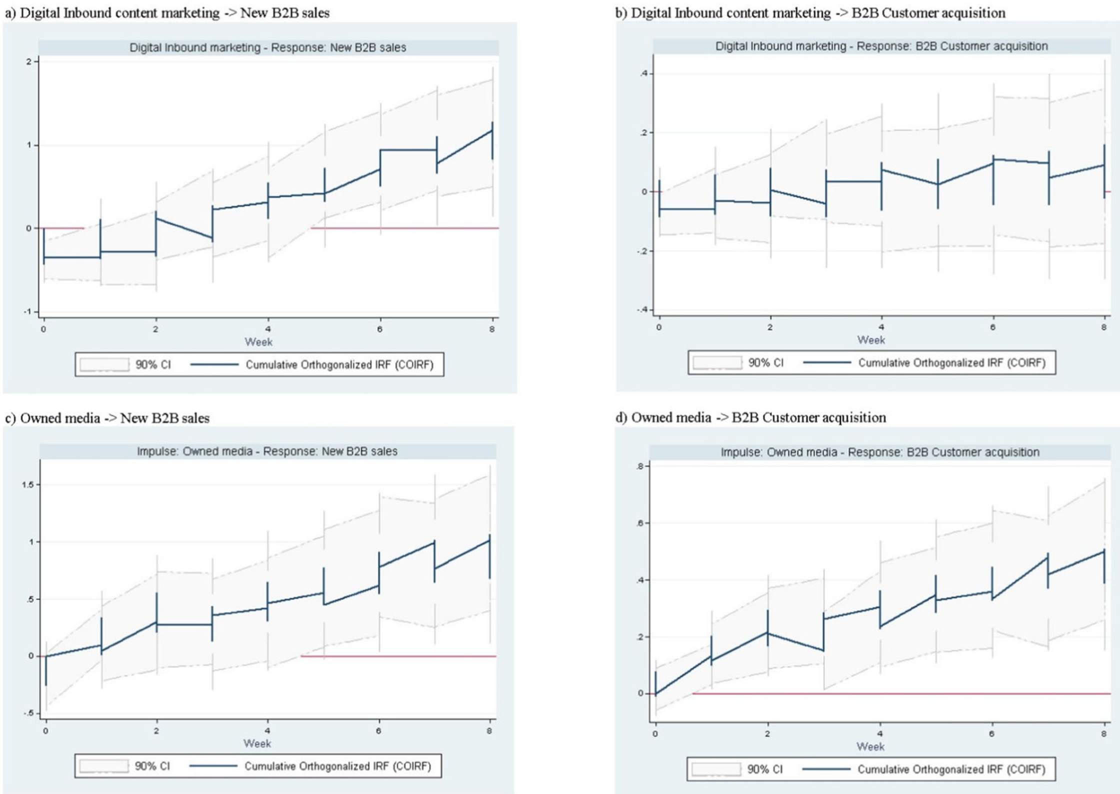


Fig. 4 a-d Cumulative orthogonalized impulse response functions of inbound marketing and owned media on new sales and customer acquisition

two separate dependent variables. Our assumption is to check the elasticities and compare them with the proposed VARX set up. To estimate alternative model and check for elasticity, we resort to an instrumental-variable free method (Leeflang et al. 2017) based on Gaussian Copula transformation. We compute copula transformed variables for earned social media, paid media, inbound marketing and organic search. Based on Danaher and Smith (2011), the Gaussian Copula for each media variable is defined in Eq. 2 as:

$$\text{Copula}_{xt} = \Phi^{-1}[H_x K_{xt}] \tag{2}$$

where Φ^{-1} is the inverse distribution function of the standard normal, and H_x is the empirical cumulative distribution function of media (*K's*) variables (earned social media, paid media, inbound marketing and organic search), according to Datta et al. (2017). We did not compute a copula-transformed owned media variable since it is represented as individual weekly contacts initiated by potential clients via the website, making endogeneity concerns highly unlikely.

We follow the specification used by Leeflang et al. (2015) on two alternative multiplicative models using single dependent variables. Hence, new B2B sales and customer acquisition are the response variables of these models.[5] These models use Gaussian Copulas as control functions for endogeneity among media and response variables. Copula terms must be added to the single equations alongside the potential endogenous media variables as a standard procedure (Leeflang et al. 2017). The full specifications are shown in Eqs. 3 and 4:

Alternative model for new B2B sales

$$\begin{aligned}\ln(\text{New B2B Sales})_t = {} & \ln\alpha + \beta_1 \ln(\text{Earned Social Media})_t + \beta_2 \ln(\text{Paid Media})_t + \\ & \beta_3 \ln(\text{Owned Media})_t + \beta_4 \ln(\text{Inbound Marketing})_t + \beta_5 \ln(\text{Organic Search})_t + \\ & \beta_6 \ln(\text{Copula–Earned Social Media})_t + \beta_7 \ln(\text{Copula–Paid Media})_t + \\ & \beta_8 \ln(\text{Copula–Inbound Marketing})_t + \beta_9 \ln(\text{Copula–Organic Search})_t + \ln\varepsilon_t\end{aligned} \tag{3}$$

Alternative model for B2B customer acquisition

$$\begin{aligned}\ln(\text{B2B Customer Acquisition})_t = {} & \ln\alpha + \beta_1 \ln(\text{Earned Social Media})_t + \\ & \beta_2 \ln(\text{Paid Media})_t + \beta_3 \ln(\text{Owned Media})_t + \beta_4 \ln(\text{Inbound Marketing})_t + \\ & \beta_5 \ln(\text{Organic Search})_t + \beta_6 \ln(\text{Copula–Earned Social Media})_t + \beta_7 \ln\Big(\text{Copula–} \\ & \text{Paid Media}\Big)_t + \beta_8 \ln(\text{Copula–Inbound Marketing})_t + \beta_9 \ln\Big(\text{Copula–} \\ & \text{Organic Search}\Big)_t + \ln\varepsilon_t\end{aligned} \tag{4}$$

We use Copula transformations after verifying normality violation assumption using Shapiro-Wilk normality test.

[5] We thank the anonymous reviewer for this recommendation.

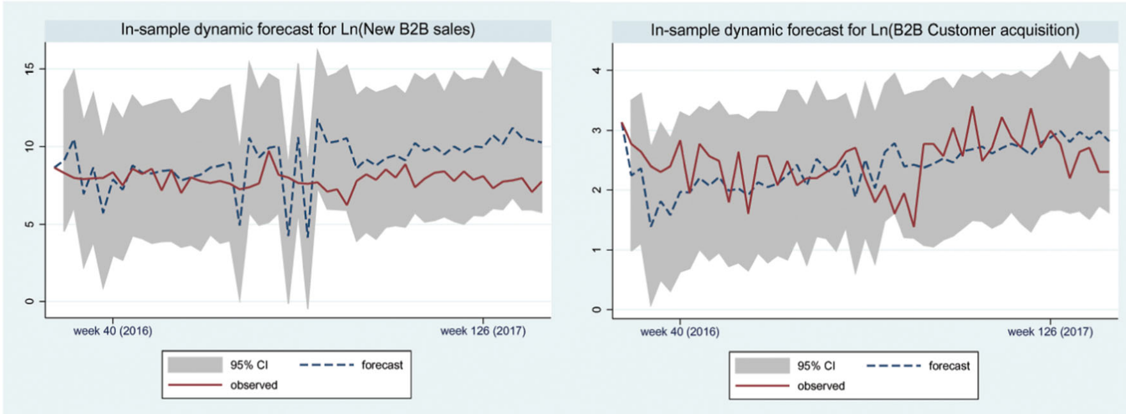


Fig. 5 Dynamic forecasts for the two main response variables

Leeflang et al. (2017) and Datta et al. (2017) recommended this procedure. The results for this test on media variables are all at $p < .001$. An additional procedure is to bootstrap standard errors (5000 runs) for parameter estimation following Park and Gupta (2012). We also conduct Ramsey Regression Equation Specification Error Test (RESET) for omitted variables and Breusch-Godfrey LM test for autocorrelation (as we have time series data) on both regression models after the estimation. As expected, the results in Table 6 support the elasticities of our VARX model when compared to alternative multiplicative models.

Discussion

The dawn of the digital age has greatly transformed the marketplace in today's world, starting from developed economies and proceeding to emerging markets. While earlier, a purchase funnel was used to best describe the decision-making path of a typical customer, the situation has significantly changed over the years, primarily for firms competing in growing markets where the pace and volume of digital usage is rapid. A modern customer, in this digital age, follows a purchase–consumption circular loop, and with the proliferation of information in the

Table 6 Coefficients for alternative models (Gaussian Copula models)

Variable	Alternative Model for Ln(New B2B Sales)				Alternative Model for Ln(B2B Customer Acquisition)			
	Coef.	Bootstrap S.E[1]	z	P > | z |	Coef.	Bootstrap S.E[1]	z	P > | z |
Ln(Earned Social Media)	−.27	.31	−.90	.36	−.08	.08	−.96	.33
Ln(Paid Media)	.19	.27	.73	.46	.15	.06	2.24	.02**
Ln(Owned Media)	.38	.18	2.05	.04**	.21	.05	4.13	.00***
Ln(Digital Inbound Marketing)	.25	.19	1.33	.18	.04	.04	.83	.40
Ln(Organic search)	.26	.35	.77	.44	−.01	.09	−.21	.83
Controls								
Copula term - Ln(Earned Social Media)	.43	.60	.72	.47	.09	.16	.55	.58
Copula term - Ln(Paid Media)	.05	.45	.12	.90	−.05	.12	−.46	.64
Copula term - Ln(Digital Inbound Marketing)	−.22	.39	−.56	.57	.09	.12	.72	.47
Copula term - Ln(Organic search)	−.55	.40	−1.35	.17	.06	.12	.51	.60
Constant	3.49	1.04	3.36	.00***	.54	.26	2.09	.03**
R^2	.31				.55			
Adjusted R^2	.26				.51			
Ramsey RESET test - F (3, 115)[2]	1.45				.87			
Breusch-Godfrey LM test Chi-Square[3]	.96				3.06*			

*** p value < .01; ** p value < .05; * p value < .10

[1] 5000 runs

[2] Both models failed to reject the null hypothesis of this test ("model has no omitted variables")

[3] Both models failed to reject (at the 99% and 95% levels for B2B Customer Acquisition) the null hypothesis of this test ("no serial correlation")

Table 7 Results of the Granger causality tests, correlations and structural break test

Granger-Caused by	Focal variable						
	New B2B sales	B2B customer acquisition	Earned social media	Paid media	Owned media	Digital inbound marketing	Organic search
Granger-Caused							
New B2B sales	–	.00	n.s.	.06	.01	.00	.00
Customer acquisition	.01	–	n.s.	n.s.	.02	.00	.01
Earned Social Media	n.s.	.05	–	.01	.06	n.s.	n.s.
Paid media	n.s.	.07	n.s.	–	n.s.	n.s.	n.s.
Owned media	.02	.00	.03	n.s.	–	.02	.01
Inbound marketing	n.s.	.00	n.s.	n.s.	n.s.	–	.05
Organic search	.05	.00	n.s.	n.s.	.07	.00	–
Correlations							
Ln New B2B sales	1						
Ln B2B Customer acquisition	.81***	1					
Ln Earned social media	.12	.03	1				
Ln Paid media	.21**	.18**	.43***	1			
Ln Owned media	.10	.16*	.08	−.25	1		
Ln Digital inbound marketing	.21**	.13	.25**	.67***	−.18**	1	
Ln Organic search	−.06	−.03	.09	.04	−.01	−.10	1
Descriptive Statistics							
Mean	2049.23	6.98	49.23	148.64	41.39	874.75	12.50
Std. deviation	2092.83	6.15	149.40	164.59	23.11	924.64	11.39
Minimum	.00	.00	.00	.00	.00	.00	.00
Maximum	16,691.00	29.00	1055.00	724.19	95.00	2616.25	47.29
Structural Break Test							
Zivot and Andrews (1992)	−11.97***	−4.65	−12.216***	−4.49	−7.34***	−7.17***	−9.56***

n.s. is non-significant bidirectional causality among variables. Numbers on cells for Granger causality tests are minimum *p*-values across four lags. Correlations among model variables are de-trended

*** p value < .01; ** *p* value < .05; * *p* value <.10; weekly data

Obs. 132; For estimating Zivot and Andrews (1992) test, AIC and BIC minimizing values for lag selection of ZA test returned roughly the same results for all variables. We used BIC values for the routine. a. The critical values for the ZA test are: −5.57 (1%-level); −5.08 (5%-level); −4.82 (10%-level)

digital space, the customer is more informed, enabling the firms to start with a narrower consideration set (Court et al. 2009). This phenomenon is particularly pronounced in the business markets since B2B customers fall under the high-involvement category (Edelman 2010).

B2B customers generate a plethora of content that is highly useful to marketers, albeit unstructured and difficult to comprehend. This is particularly important in emerging markets because of the institutional voids that prevail in such markets, which make it hard for marketers to gain access to relevant information (Pedada et al. 2019). This study, set in a Brazilian B2B context, examines the relative effectiveness of firm-initiated digital communication, such as paid media, owned media and inbound marketing, as well as market-initiated digital communication, such as organic search and earned social media, on new sales and customer acquisition. A unique longitudinal dataset with B2B sales and customer acquisition as marketing response metrics adds significant rigor as marketing scholars argue over the importance of return on investment parameters in solving problems related to adverting effect (Lewis and Rao 2015).

The findings of the study contribute to the marketing literature in several ways. First, our findings suggest that the association of owned media with new sales is the strongest among all media types. By presenting new information, product releases and updated content in their own websites, emerging firms can control media activity that might influence customer interest. This finding highlights the importance of the market development strategy for emerging markets, which emphasizes on shaping customers' expectations instead of assessing them (Sheth 2011). Companies should analyze and choose the best content for presenting in their own channels while considering keywords such as online resellers, virtual stores, online sale, marketplace, multichannel, and sales.

Second, our results suggest that the association of earned social media on new sales is positive but low. This indicates that spontaneous communications generated by customers in the social media environment positively associate with new sales—similar to the effects of traditional word-of-mouth. In that sense, we expand the results of previous research on traditional word-of-mouth (Villanueva et al. 2008; Lovett et al. 2013), suggesting that earned social media positively associates with a firm's sales performance as customers might create a 'megaphone effect' (McQuarrie et al. 2013), whereby their comments might influence the purchase decisions of customers of other businesses. Hence, different media activities play a pivotal role in empowering customers and building the pathway to optimal brand experience. While paid, owned and earned social media may influence customers differently (either cognitively or emotionally), collectively, they play a positive role in the purchase decision making process. They also lay the path to a digital "trial and error" approach, whereby customers use user-generated content, digital referrals, and comments/feedbacks in updating their preferences constantly by comparing brands/products through the purchase loop (Powers et al. 2012; Srinivasan et al. 2016).

Third, we bring managers' attention to the usefulness of certain digital components and their role in B2B digital marketing in an emerging economy (i.e., Brazil) context. We initially expected that paid media would positively associate with sales and customer outcomes as customers, through Facebook sponsored posts and Google AdWords, become better informed about the hub firm and its services. However, empirical findings suggest that this is not the case for the hub firm. New sales and customer acquisition elasticities for paid media are, on average, negative at −.15 and − .02, respectively. Also, customer acquisition elasticity for earned social media is negative at −.05. Notably, in our study paid media is the money invested in Facebook sponsored posts and Google AdWords. Earned social media is the total number of likes, shares, and comments on hub posts in social media (Facebook and Instagram). Recent studies have reported similar findings of negative association between paid media and sales. For example, Dinner et al. (2014) report that an increase in paid search expenditures is associated with a decrease in click through rates, largely due to information substitution effect. It indicates that traditional ads supply relevant information to customers, which could be provided by paid ads/click throughs. In our study, a possible interpretation is that buyers gather relevant content and knowledge about sellers and their offerings through owned media and inbound media channels, which substitute information garnered through paid media. Such findings in the B2B context of a Brazilian hub firm strengthens further differences between B2C and B2B digital marketing approaches.

Fourth, we provide details about the role of digital inbound marketing. There is a dearth of empirical research on the effectiveness of digital inbound marketing in increasing firm performance. Although previous literature (Lusch and Vargo 2009; Halligan and Shah 2009; Steenburgh et al. 2011) defines and conceptualizes this variable in developed markets, a gap in understanding its role in emerging markets continues to prevail due to the lack of effective empirical results. We bridge this gap with our findings that hub investments in digital inbound marketing might help the firm target potential customers through online platforms. In targeting these potential clients, inbound marketing creates specific and customized content to help convert a possible lead into a customer. Emerging markets, as in Brazil, are starting to use inbound marketing as a way of obtaining and generating customized content for comprehending customers' needs and influencing their behavior. We advance this stream of literature and demonstrate that inbound marketing plays a critical role in sales and customer acquisition for the Brazilian hub firm. These findings, although based on one firm's setting, support the relevance of customized content for generating leads and transforming them into clients. The average elasticity of inbound marketing was found to be .38 for new B2B sales and .02 for customer acquisition.

Finally, we demonstrate feedback loops among digital media investments and marketing performance outcomes. These results suggest that when firms generate higher revenues and newer clients through different firm−/market-initiated digital mediums, they subsequently invest further in digital marketing strategies. These interactive effects unfold as the proposed digital echoverse structure. This cyclical echoverse framework was initially tested by Hewett et al. (2016), displaying the interconnected elements of firms, consumers and news media on business outcomes. We focus and expand on the digital components, providing a comprehensive treatment of how varied digital mediums of two actors—firm and the market—contribute to outcomes in business markets. This is extremely important to digital markets in emerging economies like Brazil, which is seeing a rapid growth in e-commerce for business markets (PagBrasil 2019).

Managerial implications

Keeping in mind that digital strategy is new to emerging markets and B2B firms, and that managers need guidance on the same, we empirically explore a digital echoverse of a Brazilian hub firm operating in business markets. In doing so, we offer several key contributions to practice. A high-level takeaway is the emergence of a digital echoverse system; we term this O-I-E-O model of digital echoverse in B2B context, i.e., "owned-inbound-earned-organic search," in that order of magnitude, have cyclical and reciprocal effects on new B2B sales and B2B customer acquisition. Specifically, the results of the study suggest a positive association between owned media and company outcomes. Interactive and innovative content posted on owned media, mostly *websites,* can show how valuable a company can be, and what products and services the firm has to offer. As a result, content published on owned media can arouse the interest of potential customers and initiate new sales.

Next, our findings suggest that the average effect of organic search on sales is positive. Firms can enhance audience's interest in their products and services by creating an indexed search on Google Trends. They can track the most relevant and used terms, and generate strategies targeted to address customers' demands. In addition, companies can spread their organic search strategy by: (*i*) paying for performance in organic search (in which the company pays for sponsored links and banners) and (*ii*) optimizing organic search (which refers to the approaches used to get a high ranking on a search engine results page). Furthermore, according to recent reports, firms operating in the B2B context in emerging markets can integrate videos narrating their story or mission into the company's marketing plan, thereby providing a clear picture of the firms' business idea. Video content, published either through paid media or owned media, helps providing a concise and comprehensive idea of the brand and enables the customers to have a precise knowledge of the benefits offered by the company.

It is possible that managers can combine different digital media types, specifically owned, inbound marketing, earned and organic search, to effectively implement account-based marketing (ABM). ABM is an evolving go-to-market strategy in business marketing, wherein, using customized content, specific prospects or customer accounts are marketed and managed in a personalized way. In ABM, using the knowledge of potential buyers derived through different digital sources, marketers can precisely identify target customers. They can then progressively profile such customers in real time, engage with them through hyper personalized campaigns and build lasting relationships. Eventually, this helps build long-term trust and loyalty with buyers. In this study, we investigated the O-I-E-O model with regard to new business customers. It would be novel and useful to study the effects of O-I-E-O on engaging a portfolio of new and existing customers within the realm of ABM. Additionally, with the recent and growing prominence of inside-sales and consultative selling in B2B (Mantrala and Albers 2012), using firm- and market-initiated digital mediums to synergize marketing and sales efforts is testable. Future research could explore the influence of inside sales on the effects of O-I-E-O media on business outcomes.

In appropriating value through earned social media, firms should analyze and respond promptly to customer demands, interactions, and complaints to amplify the positive effects of earned online word-of-mouth. When companies are responsive to customer demands, potential buyers may perceive value and be interested in becoming new customers who may subsequently influence prospects (Agnihotri et al. 2016). By interacting within their social circles, existing customers can introduce new customers, thus increasing sales. Furthermore, with the newer AI systems, the firm may target marketing promotions to customers in real time (Vázquez et al. 2014).

Purchase decisions can no longer be considered to consist of just the two steps of consideration and choice. It is, rather, a circular process, in which marketers have to engage with the customers throughout their journey. They should nurture brand ambassadors, act as multimedia publishers, and deploy data science to gather and use digital content in their attempt to engage with customers. Both the firm-generated and user-generated digital content could be used in uncovering the stages of customer decision journey for precise marketing interventions.

Limitations and future research

First, while we have gathered data only from Facebook and Instagram, we recognize that a variety of other reliable sources for multiple social media types exist (e.g., MySpace, LinkedIn, Google Groups). In the case of our investigation, LinkedIn was implemented by the company only in the final months of data collection. This kind of earned social media can have an effect that is different from that on Facebook and Instagram; future research may aim to analyze this perspective. Second, while our results apply to a single hub functioning in a single emerging marketplace, online resellers typically deal with multiple hubs in order to offer products in different marketplaces. Data obtained from each online reseller/virtual retailer, selling in different marketplaces, can be analyzed using panel data of different online retailers. Future investigations can adopt this approach to analyze sales across time and different online resellers in digital contexts. Third, our results about organic search are based on Google Trends. We are aware that there are others organic search engines, such as Bing, Yahoo, etc. These search engines can generate organic information about the hub and influence sales as well. Fourth, firms can use inbound marketing from two different perspectives: (1) inbound marketing generated by an agency or (2) inbound marketing generated by a firm's own marketing team. Our findings are based on digital inbound marketing generated by an agency contracted by the hub. The hub works with only one third-party agency for its digital inbound marketing on a weekly-fee basis. The agency implements the digital inbound marketing campaign on behalf of the firm under specific budgets set by the firm. We treat such investment as a proxy for digital inbound marketing. Future research could analyze if self-generated content marketing is more effective than when outsourced to an external agency. For paid media, we studied the traditional online display/sponsored ads. It would be interesting to study the effects of native ads (Wang et al. 2019), a recent and increasingly popular disguised online display ads managed by companies like Outbrain. While in our study, we find negative association of paid digital media, it would be interesting and useful to identify the effect size and valence of native ads as a paid digital media in a B2B context.

This study does not capture the non-digital channels of communication. Firms, in a traditional format, communicate through advertising, press release, etc., and customers react to it through online WOM and social media, to which firms subsequently respond, thus leading to a loop formation. Hence, an ideal data set would comprise traditional ad-spends, corporate communications, and press releases, along with digital communications. However, in our study, we have a sharper focus on the digital echoverse in a B2B context. The digital channels play a critical role in transforming business marketers from being vendors of products/services to reliable consultants of businesses and trusted advisors to business problems. Given our focus on a digital echoverse (firm-initiated digital communications, market-initiated digital communications, and sales outcomes), the hub firm fits the criteria well. However, in order to assess the complete echoverse (digital and traditional), future researchers may want to work with an organization who diversifies its marketing expenditure accordingly.

Appendix 1

Table 8 Test for the VARX model dimension and Lagrange-multiplier test for autocorrelation of the fitted VARX model

Test for the VARX model dimension							Lagrange-multiplier test for autocorrelation of the fitted VARX model			
lag	LL	LR	FPE	AIC	HQIC	SBIC	lag	chi^2	df	Prob > chi^2
0	−1326.74	–	5.705	21.605	22.112	22.853	1	53.76	49	.29
1	−940.071	773.35	0.0294	16.329	17.279*	18.668*	2	63.18	49	.08
2	−884.548	111.05	.02695*	16.227*	17.621	19.658	3	48.80	49	.48
3	−848.810	71.477	0.0342	16.434	18.272	20.957	4	52.50	49	.34
4	−797.831	101.96*	0.035	16.4036	18.685	22.018	5	50.76	49	.40

*indicates lag order selected by each criterion and for Lagrange-multiplier no autocorrelation at lag order

Appendix 2

Table 9 Unit root and structural breaks routines on model variables in levels and logs

Variable	Additive outlier (AO) routine[1]			Innovation outlier (IO) routine[2]			Final interpretation
	1st break (t)	2nd break (t)	(rho – 1)[3] (t)	1st break (t)	2nd break (t)	(rho – 1) (t)	
New B2B Sales	4.65***	1.09	−8.77***	3.77***	0.31	−8.70***	Stationary with a structural break
Ln(New B2B Sales)	3.63***	1.24	−8.27***	4.42***	0.34	−11.15***	Stationary with a structural break
B2B customer acquisition	8.10***	3.46***	−4.00	5.46***	3.82***	−6.51***	Stationary with multiple breaks
Ln(B2B customer acquisition)	3.79***	6.37***	−6.80***	3.92***	4.54***	−10.20***	Stationary with multiple breaks
Owned media	−2.22**	7.00***	−7.48***	−2.50***	4.25***	−7.50***	Stationary with multiple breaks
Ln(Owned media)	−2.95***	5.89***	−4.22	−6.12***	7.15***	−7.18***	Stationary with multiple breaks
Earned social media	2.00**	−1.32	−3.25	1.34	−1.51	−6.66***	Stationary with a structural break
Ln(Earned social media)	−6.32***	−6.93***	−2.88	2.16	−2.22**	−3.25	Stationary with multiple breaks
Digital inbound marketing	17.13***	18.84***	−2.14	7.75***	8.03***	−8.72***	Stationary with multiple breaks
Ln(Digital inbound marketing)	31.15***	7.47***	−1.49	24.25***	12.57***	−24.25***	Stationary with multiple breaks
Paid media	22.26***	−13.65***	−3.89	5.56***	−4.94***	−5.91***	Stationary with multiple breaks
Ln(Paid media)	37.44***	−6.35***	−3.41	21.00***	−12.93***	−20.79***	Stationary with multiple breaks
Organic search	4.38***	4.39***	−4.27	2.89**	3.26***	−4.35	Stationary with multiple breaks
Ln(Organic search)	3.87***	1.93*	−7.05***	3.39***	2.83**	−9.61***	Stationary with multiple breaks

A concise version of this table is in the paper (Table 4)

*** p value < .01; ** p value < .05; * p value < .10

[1] The additive outlier (AO) routine captures a sudden mean of a given series. T-statistics for structural breaks significances are displayed on the 1st and 2nd ‘break’ columns

[2] The innovation outlier (IO) routine allows for a gradual shift in the mean of a series. T-statistics for structural breaks significances are displayed on the 1st and 2nd ‘break’ columns

[3] Results for the Clemente et al. (1998) unit root hypotheses in all series (levels and logs). Alternative hypothesis is that the series is stationary with breaks. Critical value is −5.49 (5%) to all of them

Appendix 3

Table 10 Root Mean Square Error (RMSE) of simulated out-of-sample forecasts: testing VAR improvement against alternative methods

Variable		Method				% of Improvement		
	Horizon (Periods ahead)	Mean	Random Walk	AR	VAR	Mean	Random Walk	AR
Ln(New B2B sales)								
	2	1.73	.70	1.74	.58	66	17	67
	4	1.75	.84	1.75	.63	64	25	64
	8	1.97	1.38	1.95	1.23	38	11	38
Ln(B2B Customer acquisition)								
	2	1.07	.51	1.06	.50	54	4	53
	4	1.09	.67	1.08	.54	50	19	50
	8	1.11	.75	1.11	.62	44	17	44
Ln(Earned Social Media)								
	2	2.24	1.43	2.19	1.65	26	−16	25
	4	2.27	1.51	2.22	2.22	2	−47	0
	8	2.22	2.06	2.18	2.57	−16	−25	−18
Ln(Paid Media)								
	2	2.84	.52	2.70	.70	75	−33	74
	4	2.78	.61	2.65	.88	68	−44	67
	8	2.66	.67	2.54	1.21	54	−82	52
Ln(Owned media)								
	2	.90	.39	1.02	.50	44	−30	50
	4	.91	.39	1.02	.59	35	−51	42
	8	.90	.42	1.02	.72	20	−71	29
Ln(Digital Inbound marketing)								
	2	3.86	0.17	3.77	.25	94	−47	93
	4	3.89	0.25	3.80	.35	91	−39	91
	8	3.96	0.35	3.87	.44	89	−26	89
Ln(Organic search)								
	2	1.41	1.14	1.42	.97	31	14	32
	4	1.46	.90	1.47	.78	46	13	47
	8	1.49	.95	1.49	.74	50	22	50

Table displays RMSE for each forecast horizon and the percentage improvement of the VAR forecasts compared with alternative methods

Simulations used two lags, instead of four, due to observation constraints

Appendix 4: Forecast error variance decompositions (FEVDs) of inbound marketing and owned media on new sales and customer acquisition

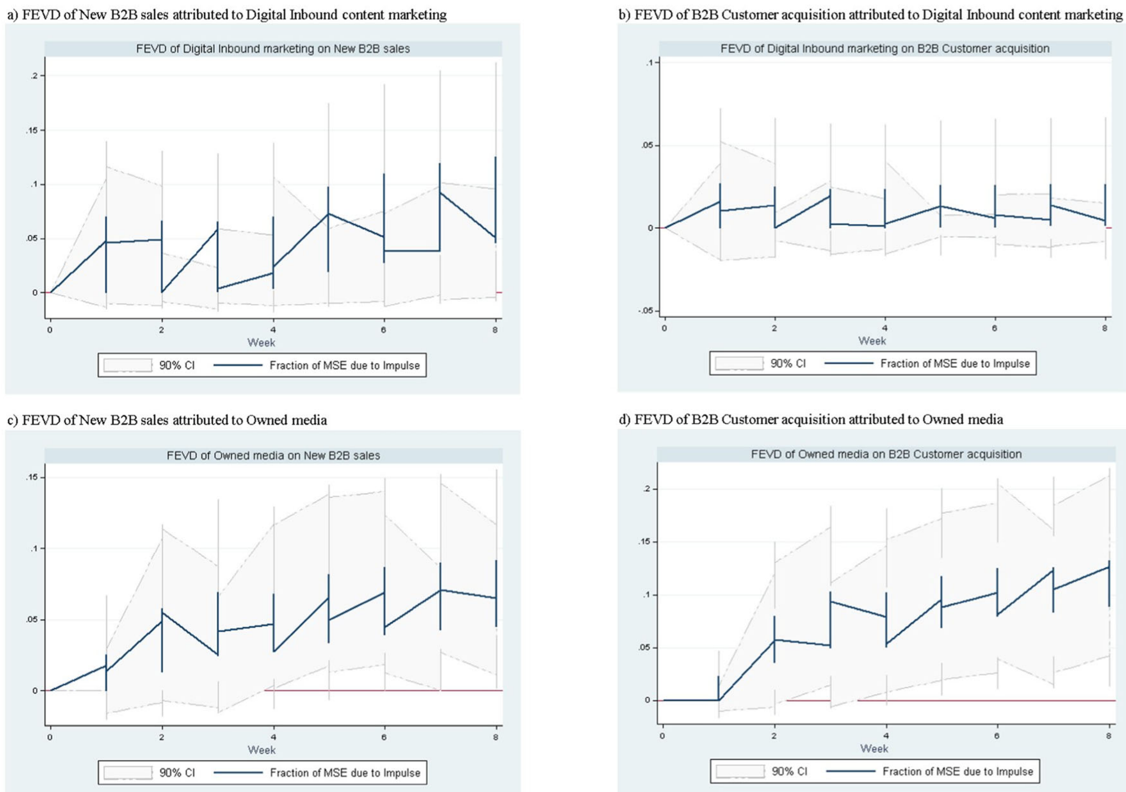


Fig. 6 **a**-**d** The solid blue line is the resulting FEVD of the simulations due to different VARX orderings considering eight steps (weeks) ahead. The dashed lines show 90% confidence intervals

Appendix 5: Assumptions and potential limitations of (alternative) multiplicative models

As multiplicative regression models are nonlinear in parameters, to linearize, we used a logarithmic transformation resulting in a double-log format. These are widely used in marketing response models as the estimated betas can retrieve the elasticities of marketing performance (here, new B2B sales and customer acquisition) with respect to marketing decision variables (here, media efforts) (Hanssens et al. 2001).

Two major limitations emerge with this specification. The most important issue revolves around treating potential endogeneity that could bias the coefficients. In dealing with endogeneity, we resort to recommendations using Copula transformation offered by Danaher and Smith (2011) and Park and Gupta (2012). Additionally, we conducted two specification tests to assess autocorrelation and general specification. We were able to obtain stable multiplicative models to produce interpretable elasticities.

The second limitation is related to the nature of multiplicative models and the implications of the estimated elasticities. As a reduced form specification, multiplicative models are prone to the 'Lucas Critique' (cf. Heerde et al. 2005). Therefore, a multiplicative-fixed parameter estimation may not be the most appropriate empirical setting. So, we follow Heerde et al. (2005) suggestions in using VAR. VAR models are more suitable for capturing dynamic effects in tactical day-to-day marketing operations (e.g. digital media context) as the ones we proposed in our digital echoverse model.

References

Agnihotri, R., Dingus, R., Hu, M. Y., & Krush, M. T. (2016). Social media: Influencing customer satisfaction in B2B sales. *Industrial Marketing Management, 53*(February), 172–180.

Agnihotri, R., Trainor, K. J., Itani, O. S., & Rodriguez, M. (2017). Examining the role of sales-based CRM technology and social media use on post-sale service behaviors in India. *Journal of Business Research, 81*(December), 144–154.

Alavi, S. (2016). New paradigm of digital marketing in emerging markets: From social media to social customer relationship management. *International Journal of Management Practice, 9*(1), 56–73.

Ancillai, C., Terho, H., Cardinali, S., & Pascucci, F. (2019), Advancing social media driven sales research: Establishing conceptual foundations for B-to-B social selling. *Industrial Marketing Management*. Available online 26 February 2019. https://doi.org/10.1016/j.indmarman.2019.01.002.

Atsmon, Y., Kuentz, J. F., & Seong, J. (2012). Building brands in emerging markets. *McKinsey Quarterly, 4*(September), 50–57.

Baum, C. F., Barkoulas, J. T., & Caglayan, M. (1999). Long memory or structural breaks: Can either explain nonstationarity real exchange rates under the current float? Journal of International Financial Markets. *Institutions & Money, 9*(4), 359–376.

Becker, R., Enders, W., & Lee, J. (2006). A stationarity test in the presence of an unknown number of smooth breaks. *Journal of Time Series Analysis, 27*(3), 381–409.

Berman, R., & Katona, Z. (2013). The role of search engine optimization in search marketing. *Marketing Science, 32*(4), 644–651.

Berthon, P. R., Pitt, L. F., Plangger, K., & Shapiro, D. (2012). Marketing meets web 2.0, social media, and creative consumers: Implications for international marketing strategy. *Business Horizons, 55*(3), 261–271.

Bronnenberg, B. J., Mahajan, V., & Vanhonacker, W. R. (2000). The emergence of market structure in new repeat-purchase categories: The interplay of market share and retailer distribution. *Journal of Marketing Research, 37*(1), 16–31.

Bucklin, R., Rutz, O., & Trusov, M. (2010). Exploring the long tail in paid search. In *Advertising, 32nd INFORMS Marketing Science Conference*. Germany: University of Cologne.

Carrière-Swallow, Y., & Labbé, F. (2013). Nowcasting with Google trends in an emerging market. *Journal of Forecasting, 32*(4), 289–298.

Carro, R. (2018). Urban Brazil. *Digital News Report*. Avaliable at http://www.digitalnewsreport.org/survey/2018/brazil-2018/. Accessed 13 Feb 2019.

Clemente, J., Montañés, A., & Reyes, M. (1998). Testing for a unit root in variables with a double change in the mean. *Economic Letters, 59*(2), 175–182.

Colicev, A., Malshe, A., Pauwels, K., & O'Connor, P. (2018). Improving consumer mindset metrics and shareholder value through social media: The different roles of owned and earned media. *Journal of Marketing, 82*(1), 37–56.

Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). The consumer decision journey. *McKinsey Quarterly, 3*(June), 96–107.

Danaher, P. J., & Smith, M. S. (2011). Modeling multivariate distributions using copulas: Applications in marketing. *Marketing Science, 30*(1), 4–21.

Datta, H., Ailawadi, K. L., & Heerde, H. J. V. (2017). How well does consumer-based brand equity align with sales-based brand equity and marketing-mix response? *Journal of Marketing, 81*(3), 1–20.

De Vries, L., Gensler, S., & Leeflang, P. S. (2017). Effects of traditional advertising and social messages on brand-building metrics and customer acquisition. *Journal of Marketing, 81*(5), 1–15.

Dekimpe, M. G., & Hanssens, D. M. (1995). The persistence of marketing effect on sales. *Marketing Science, 14*(1), 1–21.

Dekimpe, M. G., & Hanssens, D. M. (2007). Advertising response models. In G. J. Tellis & T. Ambler (Eds.), *The SAGE handbook of advertising* (pp. 247–263). Thousand Oaks: SAGE Publications.

Dinner, I. M., Van Heerde, 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.

Dotson, J. P., Fan, R. R., Feit, E. M., Oldham, J. D., & Yeh, Y. H. (2017). Brand attitudes and search engine queries. *Journal of Interactive Marketing, 37*(1), 105–116.

Du, R. Y., & Kamakura, W. A. (2012). Quantitative trendspotting. *Journal of Marketing Research, 49*(4), 514–536.

Edelman, D. C. (2010). Four ways to get more value from digital marketing. *McKinsey Quarterly, 6*(March), 1–8.

Evans, L., & Wells, G. (1983). An alternative approach to simulating VAR models. *Economic Letters, 12*(1), 23–29.

Fang, E., Li, X., Huang, M., & Palmatier, R. W. (2015). Direct and indirect effects of buyers and sellers on search advertising revenues in business-to-business electronic platforms. *Journal of Marketing Research, 52*(3), 407–422.

Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Science, 55*(10), 1605–1622.

Gilfoil, D. M. (2012). Mapping social media tools for sell vs buy activities into emerging emerging and developed markets. *International Journal of Management & Information Systems (Online), 16*(1), 69.

Grewal, R., Lilien, G. L., Bharadwaj, S., Jindal, P., Kayande, U., Lusch, R. F., et al. (2015). Business-to-business buying: Challenges and opportunities. *Customer Needs and Solutions, 2*(3), 193–208.

Haan, E., Wiesel, T., & Pauwels, K. (2016). The effectiveness in different froms of online advertising for purchase conversion in a multiple-channel attribution framework. *International Journal of Research in Marketing, 33*(3), 491–507.

Halligan, B., & Shah, D. (2009). *Inbound marketing: Get found using Google, social media, and blogs*. New Jersey: John Wiley & Sons.

Hanna, R., Rohm, A., & Crittenden, V. L. (2011). We're all connected: The power of the social media ecosystem. *Business Horizons, 54*(3), 265–273.

Hanssens, D. M., & Parsons, L. J. (1993). Econometric and time-series market response models. In Marketing: *Handbooks in operations research and management science*. Eds. J.

Hanssens, D. M., Parsons, L.J., & Schultz, R.L. (2001). *Market Response Models: Econometric and Time Series Analysis*. 2nd edition, Kluwer Academic Publishers.

Hanssens, D. M., & Pauwels, K. H. (2016). Demonstrating the value of marketing. *Journal of Marketing, 80*(6), 173–190.

Heerde, H. J. V., Dekimpe, M. G., & Putsis, W. P., Jr. (2005). Marketing models and the Lucas critique. *Journal of Marketing Research, 42*(1), 15–21.

Henningsen, S., Heuke, R., & Clement, M. (2011). Determinants of advertising effectiveness: The development of an international advertising elasticity database and a meta-analysis. *Business Research, 4*(2), 193–239.

Hewett, K., Rand, W., Rust, R. T., & Heerde, H. J. V. (2016). Brand buzz in the echoverse. *Journal of Marketing, 80*(3), 1–24.

Holliman, G., & Rowley, J. (2014). Business to business digital content marketing marketers' perceptions of best practice. *Journal of Research in Interactive Marketing, 8*(4), 269–293.

Järvinen, J., & Taiminen, H. (2016). Harnessing marketing automation for B2B content marketing. *Industrial Marketing Management, 54*(April), 164–175.

Jobs, C. (2012). A comparative analysis of the adoption rates of social networking and microblogging between industrialized and developing nations. *Journal of International Business Research, 11*(1), 107–118.

Kannan, P. K., & Li, H. A. (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing, 34*(1), 22–45.

Katsikeas, C. S., Morgan, N. A., Leonidou, L. C., & Hult, G. T. M. (2016). Assessing performance outcomes in marketing. *Journal of Marketing, 80*(2), 1–20.

Kim, H., & Hanssens, D. M. (2017). Advertising and Word-of-Mouth Effects on Pre-launch Consumer Interest and Initial Sales of Experience Products. *Journal of Interactive Marketing, 37*(1), 57–74.

Kumar, V., & Gupta, S. (2016) Conceptualizing the Evolution and Future of Advertising. Journal of Advertising 45 (3):302–317

Kumar, V., Choi, J. B., & Greene, M. (2017). Synergistic effects of social media and traditional marketing on brand sales: Capturing the time-varying effects. *Journal of the Academy of Marketing Science, 45*(2), 268–288.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics, 54*(1–3), 159–178.

Leeflang, P. S. H., Wieringa, J. E., Bijmolt, T. H. A., & Pauwels, K. H. (2015). *Modeling markets: Analyzing marketing phenomena and improving marketing decision making*. New York City: Springer.

Leeflang, P. S. H., Wieringa, J. E., Bijmolt, T. H. A., & Pauwels, K. H. (2017). *Advanced Methods for Modeling Markets*. New York City: Springer.

Levine, R., Locke, C., Searle, D., & Weinberger, D. (2001). *The Cluetrain Manifesto: The end of business as usual*. New York: Basic Books.

Lewis, R. A., & Rao, J. M. (2015). The unfavorable economics of measuring the returns to advertising. *The Quarterly Journal of Economics, 130*(4), 1941–1973.

Li, H., & Kannan, P. K. (2014). Attributing conversions in a multichannel online marketing environment: An empirical model and a field experiment. *Journal of Marketing Research, 51*(1), 40–56.

Lilien, G. L. (2016). The B2B knowledge gap. *International Journal of Research in Marketing, 33*(3), 543–556.

Lovett, M. J., Peres, R., & Shachar, R. (2013, August). On brands and word of mouth. *Journal of Marketing Research, 50*(4), 427–444.

Lumsdaine, R. L., & Papell, D. H. (1997). Multiple trend breaks and the unit-root hypothesis. *The Review of Economics and Statistics, 79*(2), 212–218.

Lusch, R. F., & Vargo, S. L. (2009). Service-dominant logic-a guiding framework for inbound marketing. *Marketing Review St. Gallen, 26*(6), 6–10.

Mantrala, M. K., Albers, S. (2012). Impact of the Internet on B2B sales force size and structure. *Handbook of business-to-business marketing*. Edward Elgar, Northampton, 539–555.

McQuarrie, E. F., Miller, J., & Phillips, B. J. (2013). The megaphone effect: taste and audience in Fashion Blogging. *Journal of Consumer Research, 40*(1), 136–158.

Mele, C., Pels, J., & Storbacka, K. (2015). A holistic market conceptualization. *Journal of the Academy of Marketing Science, 43*(1), 100–114.

Norris I. Bruce, Natasha Zhang Foutz, Ceren Kolsarici, (2012) Dynamic Effectiveness of Advertising and Word of Mouth in Sequential Distribution of New Products. Journal of Marketing Research 49 (4):469–486

Onishi, H., & Manchanda, P. (2012). Marketing activity, blogging and sales. *International Journal of Research in Marketing, 29*(3), 221–234.

Opreana, A., & Vinerean, S. (2015). A new development in online marketing: Introducing digital inbound marketing. *Expert Journal of Marketing, 3*(1), 29–34.

PagBrasil (2019). Brazil, One of the Biggest E-Commerce Opportunities in the World. *Market Insights Brazil*. Available at https://www.pagbrasil.com/market-insights-brazil/. Accessed 13 Feb 2019

Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science, 31*(4), 567–586.

Pauwels, K., Silva-Risso, J., Srinivasan, S., & Hanssens, D. M. (2004). New products, sales promotions, and firm value: The case of the automobile industry. *Journal of Marketing, 68*(4), 142–156.

Pauwels, K. H. (2017). Modern (multiple) time series models: The dynamic system. In P. S. H. Leeflang, J. E. Wieringa, T. H. A. Bijmolt, & K. H. Pauwels (Eds.), *Advanced methods for modeling markets* (pp. 115–148). Switzerland: Springer.

Pauwels, K. H. (2018). Modeling dynamic relations among marketing and performance metrics. *Foundations and trends in marketing, 11*(4), 215–301.

Pedada, K., Arunachalam, S., & Dass, M. (2019). A theoretical model of the formation and dissolution of emerging market international marketing alliances. *Journal of the Academy of Marketing Science*, (February), 1–22.

Piskorski, M.J. &, Mecall, T. (2010). Vision Statement: Mapping the Social Internet. *Harvard Business Review,* 88 (July–August), 7–8.

Powers, T., Advincula, D., Austin, M. S., Graiko, S., & Snyder, J. (2012). Digital and social media in the purchase decision process: A special report from the Advertising Research Foundation. *Journal of Advertising Research, 52*(4), 479–489.

Rutz, O. J., & Trusov, M. (2011). Zooming in on paid search ads-A consumer-level model calibrated on aggregated data. *Marketing Science, 30*(5), 789–800.

Rust, R. T., Ambler, T., Carpenter, G. S., Kumar, V., & Srivastava, R. K. (2004) Measuring Marketing Productivity: Current Knowledge and Future Directions. Journal of Marketing 68(4):76–89

Schultz, D. (2016). The future of advertising or whatever we're going to call it. *Journal of Advertising, 45*(3), 276–285.

Sethuraman, R., Tellis, G. J., & Briesch, R. A. (2011). How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities. *Journal of Marketing Research, 48*(3), 457–471.

Sheth, J. N. (2011). Impact of emerging markets on marketing: Rethinking existing perspectives and practices. *Journal of Marketing, 75*(4), 166–182.

Srinivasan, S., Rutz, O. J., & Pauwels, K. (2016). Paths to and off purchase: Quantifying the impact of traditional marketing and online customer activity. *Journal of the Academy of Marketing Science, 44*(4), 440–453.

Srinivasan, S., Vanhuele, M., & Pauwels, K. (2010). Mind-set metrics in market response models: An integrative approach. *Journal of Marketing Research, 47*(4), 672–684.

Statista (2019). *Leading countries based on number of Instagram users as of January 2019 (in millions)*. Avaliable at https://www.statista.com/statistics/578364/countries-with-most-instagram-users/. Accessed 13 Feb 2019.

Steenburgh, T., Avery, J., & Dahod, N. (2011). *Hubspot: inbound marketing and web 2.0.* Boston: Harvard Business School Press.

Stephen, A. T., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a microlending marketplace. *Journal of Marketing Research, 49*(5), 624–639.

Swani, K., Brown, B. P., & Milne, G. R. (2014). Should tweets differ for B2B and B2C? An analysis of Fortune 500 companies' Twitter communications. *Industrial Marketing Management, 43*(5), 873–881.

Tirunillai, S., & Tellis, G. J. (2012). Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Science, 31*(2), 198–215.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: Findings from an Internet social networking site. *Journal of Marketing, 73*(5), 90–102.

Vázquez, S., Muñoz-García, Ó., Campanella, I., Poch, M., Fisas, B., Bel, N., & Andreu, G. (2014). A classification of user-generated content into consumer decision journey stages. *Neural Networks, 58*(October), 68–81.

Villanueva, J., Yoo, S., & Hanssens, D. M. (2008). The impact of marketing-induced versus word-of-mouth customer acquisition on customer equity growth. *Journal of Marketing Research, 45*(1), 48–59.

Yao, S., & Mela, C. F. (2011). A dynamic model of sponsored search advertising. *Marketing Science, 30*(3), 447–468.

Wang, P., Xiong, G., & Yang, J. (2019). Serial Position Effects on Native Advertising Effectiveness: Differential Results across Publisher and Advertiser Metrics. *Journal of Marketing, 83*(2), 82–97.

Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics, 10*(3), 25–44.