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Emerging technology-enabled e-retailer returns processes: *Buy-Online-Return-In-Store* and e-retailer performance

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Abstract

Purpose – "*Buy-Online-Return-In-Store*" (BORIS) cross-channel returns is a notable tactic e-retailers use to attract consumers. Yet, the approach may create operational challenges, motivating concerns regarding its overall impact. This study provides empirical evidence on associations between use of BORIS and e-retailer performance, while also exploring interactions with same-channel free return shipping policies and two promotion tactics (i.e. social media use, sponsored search).

Design/methodology/approach – Using annual data (2013–2019) for the Top 1,000 e-retailers in North America, we employ regressions, robustness checks and endogeneity corrections to examine associations between BORIS and four performance metrics: website sales, order conversion rates, average customer order value and website traffic.

Findings – Fixed-effect model results suggest offering BORIS to online customers provides a negligible direct benefit to website sales and no meaningful impact across performance metrics among pure e-retailers. For bricks-and-clicks e-retailers, BORIS interacts with free return shipping policies to weakly bolster average order value and website traffic. When sponsored search spend is low, BORIS lifts average order value but does not improve conversion rates. Conversely, BORIS drives incremental website traffic via tactical synergies with sponsored search. Endogeneity-corrected random-effect estimates are broadly consistent and further reveal that e-retailers offering BORIS for competitive purposes may experience additional significant consequences from social media moderation.

Originality/value – The study contributes to research by theorizing potential performance impacts of BORIS use and finding empirical outcomes that motivate questions about its overall effectiveness. The nuanced findings show BORIS can provide scope-specific benefits under certain conditions. For e-retail managers, the findings translate anecdotal evidence about the importance of BORIS returns into empirical evidence that BORIS returns policies can matter, yet for some metrics, may exhibit only weak associations with e-retailer performance.

Keywords Cross-channel integration, e-retail, Return-in-store, Free return shipping, Sponsored search, Social media

Paper type Research article

1. Introduction

E-commerce has grown dramatically, but an ongoing challenge has yet to be fully resolved – online customers often cannot accurately assess product fit or quality before purchase. This

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limit drives many customers to desire efficient post-sales returns processing. With the rise of omnichannel retail strategies, the *Buy-Online-Return-In-Store* (BORIS) cross-channel return process offered a new solution (Rooderkerk *et al.*, 2023) and was positively received by business media. BORIS enables customers to return items purchased online to brick-and-mortar stores, sometimes even at store locations of different retailers (e.g. http://Amazon.com purchases returned to Kohl's stores).

Unlike purchase-oriented omnichannel services, such as Buy-Online-Pickup-In-Store (BOPIS) and Ship-To-Store (STS), that enhance order fulfillment by leveraging store inventory and reducing delivery costs (Gallino and Moreno, 2014), BORIS affects customers' post-purchase experience (i.e. reverse logistics). By offering an additional return option alongside traditional mail-in methods, cutting return hassle costs (e.g. return shipping costs, time to receive refunds), BORIS reduces customer online shopping risks, boosting purchase confidence (Xie *et al.*, 2023a). It also bridges customers' online and offline shopping experiences, helping retailers build trust and satisfaction, which in turn drive repeat purchases and positive word-of-mouth (Hao *et al.*, 2024; Nageswaran *et al.*, 2020). Moreover, similar to BOPIS and STS, which increase physical stores' traffic and sales through cross-channel interactions (Akturk *et al.*, 2018; Mahar and Wright, 2017), BORIS can drive additional foot traffic to physical stores and lift offline sales (Hwang *et al.*, 2022).

However, BORIS processes also present retailers with operational complexities requiring careful evaluation. First, there are operational and financial burdens. As with lenient return policies raising returns (Lantz and Hjort, 2013; Patel *et al.*, 2021; Petersen and Kumar, 2010), BORIS too increases returns (Huang and Jin, 2020; Yan *et al.*, 2020), hurting e-retailer profits. Implementing BORIS also entails infrastructure investment and process change (Yan *et al.*, 2022; Mahar and Wright, 2017), such as physical space for returned items, store staff trained to process returns and integrated IT systems to manage online and offline returns. Beyond these tangible costs, a second critical issue concerns uncertainty about BORIS's impact on online business. Comparable omnichannel strategies show mixed results for cross-channel performance. For example, cross-channel BOPIS and STS have been observed to divert online demand (Akturk *et al.*, 2018; Gallino and Moreno, 2014). Yet, the convenience of in-store returns at physical stores lets customers evaluate extra products, creating opportunities for cross-selling and online purchases (Kumar *et al.*, 2019). These conflicting insights leave managers unsure if BORIS helps or harms online performance, reflecting a practitioner need to clarify its operational impact.

Analytical literature extensively models theoretical impacts of BORIS on pricing strategy of dual-channel retailers (e.g. Mandal *et al.*, 2021; Nageswaran *et al.*, 2020; Yan *et al.*, 2022; Yan *et al.*, 2020) or cooperating retailers (e.g. Chen *et al.*, 2024b; Nageswaran *et al.*, 2025). Yet, empirical studies on BORIS are scarce. Only Hwang *et al.* (2022) provide evidence on associations of return partnerships and store retailer partners' sales, leaving BORIS's impacts on e-retailers' business performance underexplored. A few studies have examined associations of BORIS and customer behavioral intent (Hao *et al.*, 2024; Xie *et al.*, 2023a). Their findings do not capture actual consumer decisions or firm-level performance outcomes. This gap motivates a first research question: *What is the impact of offering a BORIS cross-channel return service on e-retailer business performance?*

Drawing on transaction cost theory (TCT) (Chircu and Mahajan, 2006; Williamson, 1985), we examine BORIS's influence on website sales revenue and its drivers (i.e. website traffic, conversion rate, average order value). TCT posits customers evaluate transactions based on cumulative costs incurred throughout a purchase journey, spanning pre- and post-purchase stages. Complementing this view, operations management (OM) literature highlights that services at both pre- and post-purchase stages play an important role in shaping consumer satisfaction and purchase intention in e-commerce (e.g. Park *et al.*, 2015; Peinkofer and Jin, 2023). As an added beneficial post-purchase service, BORIS is expected to reduce post-purchase transaction costs typically associated with returns, including monetary costs (e.g. fees associated with returning a product), time costs (e.g. waiting for a refund) and psychological costs (e.g. uncertainty and hassle). Hence, we posit BORIS enhances e-retailer performance by bolstering customer purchase confidence.

TCT also highlights how customers evaluate and choose among transaction options by seeking to minimize anticipated costs (Williamson, 1985). With returns under consideration, relevant post-purchase cost comparisons come into play. Thus, the value of BORIS can hinge on how its associated costs compare to those of standard post-purchase, same-channel alternatives (i.e. mail-in returns). A key factor influencing this comparison is whether a return shipping fee is charged for the mail-in option. Accordingly, we propose that return shipping fees moderate the effect of BORIS.

Although return policy leniency is multidimensional, covering return time windows, monetary costs, procedural effort and returnable item scope (Janakiraman *et al.*, 2016; Abdulla *et al.*, 2019), we focus on return shipping fees for three reasons. First, this fee is the most direct, salient monetary cost for return initiators and is strongly linked to purchase and return decisions (Luo *et al.*, 2025; Patel *et al.*, 2021). It is also a well-established and central element in the return policy literature (Abdulla *et al.*, 2019). Second, this focus is timely amid retail strategic divergence: while some retailers, such as Nordstrom [1], continue to offer postage-paid return labels to match consumer preferences, others, including Crew, H&M and Macy's [2], now require customers to pay return shipping fees. This trend reflects retailers' operational cost considerations and underscores the need for research into its broader implications. Third, empirical evidence on return shipping fees remains contentious. Some show that such fees reduce purchase rates and post-return spending (e.g. Bower and Maxham, 2012; Wood, 2001), whereas others find age-dependent effects (Luo *et al.*, 2025) and that such fees can discourage returns and soften their performance harm (e.g. Patel *et al.*, 2021). These mixed findings imply that a singular view of return shipping fees is insufficient. Their effect likely depends on other factors in the return ecosystem. Thus, examining their interplay with BORIS is a necessary step. Accordingly, we pose a second research question: *How does offering free (versus fee-based) return shipping for same-channel returns moderate the effect of providing (versus not providing) the cross-channel return option BORIS on e-retailer business performance?*

Moreover, pre-purchase information search and comparison costs shape how customers enter a purchase funnel and make decisions (Chircu and Mahajan, 2006; Teo and Yu, 2005), and thus may influence how they value BORIS's post-purchase assurance. Digital marketing is a key retailer-controlled determinant of such costs. It reaches diverse audiences via digital channels, enhancing product visibility and accessibility while reducing pre-purchase costs. However, it also triggers impulse purchases and product mismatch risks (Sun *et al.*, 2020). Hence, influences of flexible BORIS returns may differ across consumer groups with or without exposure to promotions, meaning BORIS's performance impact likely depends on e-retailer promotion management. Understanding conditional associations can help retailers better allocate tactical resources and align marketing tactics with retail operations (Akturk *et al.*, 2018; Gallino and Moreno, 2014). Yet, prior research is unclear whether promotions usefully influence return policy associations, motivating a third research question: *Does BORIS's impact on e-retailer business performance vary among e-retailers using different promotion tactics?*

We focus on two leading forms of digital marketing: sponsored search and social media advertising (Sun *et al.*, 2020). These tactics are more commonly used in North America compared to other digital promotion options [3], such as live streaming. Loyalty programs and email marketing are also very popular in North America, but they rely on existing customer lists and have a narrow reach, limiting the potential to alter consumers' pre-purchase experience across diverse segments. In contrast, sponsored search and social media advertising leverage public digital platforms to broadly target potential customers before purchase, directly shaping pre-purchase costs. These considerations lead us to examine sponsored search and social media as salient moderators.

To address the three questions, we analyze multi-year panel data from *Digital Commerce 360*, covering leading North American e-retailers. Results reveal that offering BORIS does not enhance longitudinal website sales for all, web-only or bricks-and-clicks dataset subsets. We thus refocused on e-retailer subsets and examined sales contributors (i.e. conversion rate, average order value and website traffic). Web-only e-retailers show no meaningful BORIS associations. However, bricks-and-clicks e-retailers experience complex dynamics. From a within-retailer perspective, endogeneity-corrected fixed-effect (FE) models show BORIS use is associated with higher average order values, and bolstered by free return shipping, but attenuated by sponsored search use. BORIS also exhibits a positive synergy with free return shipping and sponsored search in driving website traffic. BORIS lowers conversion rates when sponsored search use is low. From a between-firm competitive perspective, endogeneity-corrected random-effect (RE) models affirm that most within-retailer effects persist and uncover additional outcomes. For example, social media advertising moderates BORIS to boost average order values yet reduce website traffic. We contribute to the literature by preparing theoretical foundations for BORIS's e-retail impacts and providing empirical nuance to temper overly optimistic performance expectations about BORIS. The findings also offer insights to help e-retailers optimize omnichannel tactics.

2. Literature review

This study builds on three streams of retail OM literature: consumer return policies, cross-channel integration practices and managing promotion processes.

2.1 Consumer return policies

Much retail OM research considers return policy design (see Abdulla *et al.* (2019)'s review). From analytical perspectives, studies explore optimal return policies to maximize retailer performance (Altug and Aydinliyim, 2016; Chen *et al.*, 2024a; Lin *et al.*, 2020; Shang *et al.*, 2017a). Empirical research explores impacts of return policy leniency levers on consumer behaviors, via monetary levers (Bower and Maxham, 2012; Chen *et al.*, 2023; Lantz and Hjort, 2013; Pei *et al.*, 2014; Wood, 2001), time levers (Ertekin and Agrawal, 2021; Rao *et al.*, 2018), effort requirements (Janakiraman and Ordóñez, 2012; Jones *et al.*, 2024; Suwelack *et al.*, 2011), scope of returns (Kim and Wansink, 2012; Wood, 2001) and other levers.

Monetary levers receive much research attention, examining the refund amount relative to the purchase price, restocking fees and return shipping fees. For instance, Pei *et al.* (2014) demonstrate that full refunds enhance consumer perceived policy fairness, resulting in favorable intentions. The positive effect, however, can be attenuated by other cost-related policy elements. Shang *et al.* (2017b) find nonrefundable forward shipping fees undermine the positive value perception of a full-refund policy. Focusing on return shipping fees, literature reveals a contentious landscape. Bower and Maxham (2012) find that such fees diminish consumer perceptions of cost fairness, reducing post-return spending. In a related vein, Luo *et al.* (2025) show positioning free return policies (i.e. waiving return shipping fees) late in the shopping process boosts purchase rates, with this effect proving particularly salient for young customers. In contrast, Patel *et al.* (2021) use order-level data from a Swedish fashion e-retailer to show fee-based return services are beneficial in deterring consumer returns. Expanding the inquiry scope, Abdulla *et al.* (2022) compare the effects of monetary and nonmonetary levers on consumer purchase intent.

Despite these studies in single-channel settings, little work quantifies how return channel type affects online sales channels. To our knowledge, Xie *et al.* (2023a) and Xie *et al.* (2023b) are among the few studies using survey data to investigate how a cross-channel return option (i.e. BORIS) affects online consumer behavior intentions. Still, they do not address how retailers address trade-off decisions for cross-channel returns process integration. Moreover, the potential interactions between same-channel return policies and cross-channel return options remain unexplored. As discussed above, the influence of same-channel free returns (i.e. free return-by-mail) is nuanced and contingent. Understanding how this policy shapes or is shaped by an available cross-channel alternative presents a critical next step. Our work addresses these gaps by using firm-level data to examine performance implications of a BORIS option and the contingent associations derived from same-channel return policies. We extend the inquiry by investigating how the cross-channel return option interacts with promotion tactics, a key factor in the pre-purchase stage that drives consumers to enter the purchase funnel. This extension provides a more holistic view of how pre- and post-purchase levers jointly shape the performance of cross-channel returns.

2.2 Cross-channel integration practices

The second literature stream studies cross-channel integration practices, such as using showrooms (Bell *et al.*, 2018; Gao *et al.*, 2022), offering a BOPIS service (Gallino and Moreno, 2014; Mahar and Wright, 2017), offering a STS option (Akturk *et al.*, 2018; Gallino *et al.*, 2017), or offering a Ship-From-Store (SFS) option (He *et al.*, 2021). Such strategies may improve order fulfillment flexibility and better satisfy customer needs, yet potentially also change customer purchasing behavior. In a quasi-experiment, Bell *et al.* (2018) find that opening offline showrooms leads to higher online consumer demand and reduced returns. Analyzing a US retailer's data, Gallino and Moreno (2014) show BOPIS can cause online customers to migrate to physical stores, resulting in more store sales but lower online sales. Akturk *et al.* (2018) find retailer STS adoption associates with online sales declines, yet an increase in offline sales, with online purchases returned to brick-and-mortar stores increasing. Some research explores how retailers can use financial incentives to encourage consumers to choose such fulfillment methods, like BOPIS, curbside pickup and ship-to-locker (e.g. Brockhaus *et al.*, 2025).

When it comes to the return process, cross-channel strategies include Buy-In-Store-Return-Online (BISRO) and BORIS (Rooderkerk *et al.*, 2023). BORIS has received growing attention (e.g. Gao *et al.*, 2022; He *et al.*, 2020; Huang and Jin, 2020; Jin *et al.*, 2020; Nageswaran *et al.*, 2020; Yan *et al.*, 2022; Yan *et al.*, 2020). From a theoretical perspective, Yan *et al.* (2020) study, in a monopoly environment, influences of offering BORIS on product demand, return quantity, optimal pricing and return service charge decisions. Nageswaran *et al.* (2020) and He *et al.* (2020) investigate retailers' optimal pricing, ordering and return policy decisions when customers can return online purchases to physical stores. Gao *et al.* (2022) examine how the number and size of physical stores associate with e-retailer BORIS use. Recently, research notes BORIS can be achieved via cooperation between e-retailers and offline stores. Some studies explore when e-retailers and offline retailers benefit by establishing a return partnership (Chen *et al.*, 2024b; Nageswaran *et al.*, 2025; Xie *et al.*, 2024).

Despite the many analytical studies, to our knowledge, few empirical studies examine the associations of BORIS use and retailer performance. Hwang *et al.* (2022) investigate the economic value of BORIS, showing that physical store retailers may improve sales by offering BORIS functions to e-retailers. Doing so may bring in new customers and increase existing customer interactions, stimulating demand. Hao *et al.* (2024) studied the impacts of BORIS experience on customer repurchase intentions. Different from those, our study focuses on how BORIS use may benefit e-retailers.

2.3 Managing promotion processes

Finally, we draw on literature about managing promotion tools, focusing particularly on sponsored search and social media – two nonprice promotion tactics increasingly used in modern digital marketing and highly visible to consumers (Sun *et al.*, 2020, 2024). Literature on sponsored search mostly deals with effects on click-through rates. Yang and Ghose (2010) demonstrate a positive relationship via panel data of a large chain retailer advertising on Google. Narayanan and Kalyanam (2015) suggest that the position of an advertisement determines paid search effectiveness in increasing click-through rates. Sun *et al.* (2020) show sellers' sponsored search on e-commerce platforms may increase their online traffic and sales.

Research on social media marketing mainly discusses firm-generated content (FGC) and user-generated content (UGC) on social media platforms. Goh *et al.* (2013) analyze the roles of FGC and UGC on Facebook when promoting customer apparel. Lee *et al.* (2018) divide FGC into two types: content about brand personality (e.g. emotion and humor) and content conveying information (e.g. price and deals). They find that the former improves customer engagement, while the latter improves customer engagement when combined with the former. Wang *et al.* (2021)'s empirical study finds results similar to Goh *et al.* (2013): using social media helps drive offline automobile sales. They also find FGC more influential than UGC.

The above studies provide valuable insights into outcomes of using sponsored search and social media marketing. Still, research remains unclear on how such tactics influence the performance of return policies. Given the importance of precise execution of omnichannel retailing operations (Akturk *et al.*, 2018; Gallino and Moreno, 2014), future research should jointly analyze promotion tactics along with return policies. Our study complements the above by examining how sponsored search and social media marketing affect the results of a cross-channel return policy (i.e. BORIS).

3. Theoretical background and hypotheses

3.1 Transaction cost theory

This study aims to explain the influences of BORIS on e-retailer performance via TCT. TCT posits that market transactions involve not only explicit price payments but also implicit costs associated with a transaction process, including *ex ante* costs (e.g. information search, negotiation) and *ex post* costs (e.g. monitoring, dispute resolution) (Coase, 1937; Williamson, 1985). Specifically, information search costs refer to the time and effort spent gathering information about products, prices, or policies. Negotiation costs come from communication and reaching agreements. Monitoring costs are incurred while overseeing transaction execution. Dispute resolution costs arise when settling post-transaction problems. These varied costs collectively determine individuals' and organizations' decisions about whether and how to engage in transactions.

TCT has been applied widely in online retail contexts to study consumer purchase intentions or behaviors (e.g. Akturk *et al.*, 2018; Chintagunta *et al.*, 2011; Griffis *et al.*, 2012; Shang *et al.*, 2019; Teo and Yu, 2005). In this setting, a transaction refers to an exchange between a consumer and an e-retailer, where consumer transaction costs are embedded throughout the shopping journey: pre-purchase (e.g. product search, alternative evaluation, policy review), purchase (e.g. order, payment) and post-purchase (e.g. return, customer service). Prior research further categorizes the transaction costs into three types: monetary, time and psychological (Abdulla *et al.*, 2022; Chircu and Mahajan, 2006). During the pre-purchase phase, monetary-type costs may include subscription or membership fees; time-type costs stem from search and comparison efforts; and psychological-type costs arise from information overload or lack of guidance. During the purchase phase, monetary-type costs consist of product price, shipping fees and taxes; time-type costs result from account creation or checkout delays; and psychological costs may derive from payment security concerns. In the post-purchase phase, monetary-type costs encompass return shipping or return charges; time-type costs can stem from return processing time; and psychological costs relate to embarrassment, frustration or anxiety during returns. According to TCT, consumers will systematically evaluate these transaction costs when making purchase decisions.

OM research further highlights how online customers' evaluations of services in both the pre- and post-purchase stages play a critical role in shaping their satisfaction, quality perception and purchase intention (Park *et al.*, 2015; Peinkofer and Jin, 2023). Viewed through the lens of TCT and these insights, BORIS enhances consumers' evaluation of post-purchase supportive services, and by offering return flexibility, alleviates their anticipated post-purchase transaction costs. This, in turn, should enhance consumer perceptions of the complete online retail transaction process, contributing to e-retailer performance. This aspect distinguishes BORIS from sales/fulfillment-oriented omnichannel services such as BOPIS, STS or SFS, which address purchase-stage costs by waiving forward shipping fees and streamlining fulfillment, thereby directly stimulating sales. In this sense, BORIS plays a distinct role in influencing e-retailer performance.

As online consumers' purchase decisions reflect both pre- and post-purchase evaluations, the cost-saving effectiveness of BORIS is likely moderated by factors shaping perceived transaction costs in these stages. In the post-purchase phase, when a return is necessary, return shipping fees constitute a major determinant of post-purchase monetary burdens (Bower and Maxham, 2012), and thus may moderate how consumers value BORIS. In the pre-purchase stage, search and comparison costs significantly affect customers' purchase decision quality (Chircu and Mahajan, 2006; Teo and Yu, 2005), thereby influencing return likelihood and reliance on post-purchase services like BORIS. Online marketing tools (e.g. social media and search engine advertising) provide means for altering such transaction costs by reaching consumers before purchase, and thus are expected to moderate the association between BORIS and e-retailer performance.

Together, grounded in TCT, we examine BORIS's influence on e-retailer performance amid moderating roles of return shipping fees and digital marketing tool usage. This examination aligns with TCT's emphasis on managing transaction costs throughout the customer purchase journey due to their impacts on purchase decisions. We next provide detailed explanations of the effects.

3.2 Impact of cross-channel return process: BORIS

Based on TCT, online consumers often evaluate potential return-related transaction costs when making purchases. BORIS offers consumers an in-store return option, supplementary to mail-in returns. Even with limited store coverage, BORIS improves return flexibility and convenience for consumers and thus reshapes consumers' perceptions of post-purchase transaction costs. While BORIS may raise retailers' operational transaction costs, via higher risk of return abuse or added labor needs, this study's theorizing centers on the consumer side, consistent with prior consumer-centric TCT applications (e.g. Akturk *et al.*, 2018; Chintagunta *et al.*, 2011; Shang *et al.*, 2019). Retailer transaction costs fall outside this scope of investigation, as rollout of BORIS is typically driven by such considerations. Once BORIS is introduced, consumer perceived transaction costs may differently influence purchase intentions, and consequently, online retailer outcomes.

First, BORIS helps alleviate consumer post-purchase monetary burdens. The return process often involves transaction costs (e.g. shipping, repackaging, or restocking fees) for consumers. Without BORIS, consumers can only choose mail-in returns and must cover shipping fees if the retailer does not. In contrast, BORIS offers an in-store return alternative, allowing some consumers (i.e. those local to a BORIS drop-off location) to avoid shipping transaction costs, effectively reducing their direct monetary burden (Hwang *et al.*, 2022; Mahar and Wright, 2017). Additionally, while many retailers uniformly charge or waive restocking fees across online and offline returns, some retailers only apply restocking fees to online returns while waiving them for in-store returns (e.g. Zara, Abercrombie and Fitch)[4, 5]. This potentially further lowers the monetary transaction costs for consumers. Thus, the introduction of BORIS generally reduces the financial risks associated with returns and increases the appeal and perceived safety of e-retail transactions.

Even in cases where a retailer covers transaction costs, such as mail-in shipping, or charges the same restocking fee for online and offline returns, such as Best Buy [6], BORIS may still reduce implicit time and psychological transaction costs. With time-type transaction costs, the carrier-enabled return process typically involves multiple steps, such as filling out forms, printing return labels, repackaging items and waiting for return processing, each of which requires consumers to invest time and effort (Janakiraman and Ordóñez, 2012; Rintamäki *et al.*, 2021). A 2024 Deloitte report underscores this friction, noting that among the firms studied, the median return processing timeframe was 14 days after a mailed return was received; consequently, customers may face waits of up to three weeks to receive a refund [7]. A http://Forbes.com survey shows most consumers (54%) prefer returning items in store, due to growing impatience with mail-in processes [8].

While mail-in returns remain available, adding an in-store option enables consumers to flexibly choose the return method that best fits their schedules and locations. For those seeking to avoid time-consuming preparations and shipping delays, in-store returns can, in most cases, shorten the return cycle by eliminating transit times and offering quicker refunds. For consumers who prefer or rely on mail-in returns, the presence of BORIS imposes no additional burden. Hence, the availability of BORIS overall should help lower the average perceived time-type transaction costs of returns by simplifying and accelerating the return process.

Consumers also face psychological costs (e.g. anxiety, frustration) associated with a return process (Abdulla *et al.*, 2019; Rintamäki *et al.*, 2021), driven by concerns such as lack of control over procedures or return failures. When consumers rely solely on mail-in returns, they can feel uncertain about the return status and disconnected from the process, leading to higher perceived psychological transaction costs. They also may be unable to reach service representatives and might have to rely on chatbots, which makes about half dissatisfied, as suggested by 2024 data from Digital Commerce 360 [9]. In contrast, the added availability of BORIS gives consumers more flexibility in choosing a return method that best aligns with their preferences and expectations. This added flexibility helps reduce anxiety and frustration transaction costs caused by procedural uncertainty or information asymmetry. In-store returns are typically transparent and offer direct communication and immediate feedback. Thus, BORIS also allows consumers to fully oversee the return process in real time, increasing their perceived control (Kumar *et al.*, 2019). Collectively, consumers' post-purchase psychological-type transaction costs should reduce with a BORIS option, and online purchase behaviors should be enhanced. For retailers, the return process is an opportunity to manage customer relationships and build loyalty. When consumers return products at stores, salespersons can offer personalized and targeted assistance to address dissatisfaction (Mahar and Wright, 2017). With this expectation, consumers may exhibit a less-negative response. In summary, via TCT perspectives, we propose adding a BORIS return option should nourish positive consumer purchase intentions and thus, overall e-retailer performance.

H1. Offering a Buy-Online-Return-In-Store (BORIS) service is positively associated with e-retailer business performance.

3.3 Moderating effect of same-channel return service: return shipping charge

As part of post-purchase service options, e-retailers may provide both online and offline channel return services that determine how consumers experience and bear the costs associated with post-purchase returns. We expect an interaction between same-channel return options (i.e. charging vs. waiving return shipping fees) and cross-channel return options (i.e. BORIS vs. no BORIS). While many retailers (e.g. Amazon, BestBuy and Target) offer free return shipping [10], a considerable number of retailers require consumers to bear this transaction cost. A 2023 survey of over 200 US retailers found 24% had increased return shipping fees [11], reflecting a trend toward shifting return costs to consumers. For example, Kohl's asks online customers to pay for return postage [12]; Macy's charges a $9.99 return shipping fee for mail-in returns by non-Star Reward members [13]; J. Crew and H&M deduct $7.50 and $3.99 from refunds, respectively, if using prepaid return labels [14, 15].

Consumer-borne return shipping fees represent typical post-purchase monetary-type transaction costs that can lower consumers' perceived utility, especially when product fit or satisfaction is uncertain. Prior studies show that such monetary stringency in return policies increases consumers' perceived transaction costs and discourages purchase intention (Abdulla *et al.*, 2022; Janakiraman *et al.*, 2016). Beyond financial transaction costs, return shipping fees can induce psychological-type transaction costs, leading to negative consumer perceptions linked with returns, such as annoyance or dissatisfaction (Chircu and Mahajan, 2006). Empirical work shows that placing responsibility of product returns on consumers and asking them to bear return shipping fees can undermine consumer fairness perceptions and generate regret (Bower and Maxham, 2012).

Thus, when consumers must pay transaction costs for mail-in returns, an in-store return process can become a preferable alternative. This option typically incurs no shipping fees or additional fees, offering consumers an economical solution. In contrast, if return shipping is free, the value of BORIS diminishes. Nageswaran *et al.* (2020) suggest that charging for online returns can trigger consumers to return items in stores. Notably, return shipping fees differ from restocking fees. As discussed above, the former are channel-specific and thus often avoidable via BORIS, as they are associated with logistics transaction costs of mailing returns. In contrast, restocking fees (if any) are intended to cover handling or inventory processing transaction costs and are typically deducted from refunds regardless of return channels. Taken together, we expect BORIS benefits to be more salient when a return-by-mail option is more costly for consumers. We hypothesize:

H2. The positive association between BORIS service and e-retailer business performance is more pronounced for e-retailers charging consumers a return shipping fee (vs. not charging).

3.4 Moderating effect of promotion strategies: social media usage and sponsored search

As argued for H1, BORIS primarily mitigates post-purchase transaction costs associated with product returns, enhancing consumer confidence and e-retailer performance. We further propose that the magnitude of this effect should depend on pre-purchase conditions shaped by digital marketing.

Many e-retailers set up official accounts on different social media platforms and post content to share product visuals (e.g. usage scenarios, styling), reinforce branding, promote deals and engage with consumers (Lee *et al.*, 2018; Wang *et al.*, 2021). These activities provide consumers with rich and accessible information about products compared to traditional online listings, allowing consumers to gain a clearer understanding without extensive independent research. From a TCT perspective, social media activities reduce consumers' pre-purchase search and evaluation transaction costs by helping them discover products easily and form initial impressions through less cognitive effort (Mangold and Faulds, 2009; Rishika *et al.*, 2012). Reduction of pre-purchase effort transaction costs may facilitate less deliberative, more impulsive purchases (Huang, 2016).

While boosting conversion rates, it also raises the risk of transaction costs in the form of post-purchase regret and dissatisfaction (Lantz and Hjort, 2013). In such situations, lenient return options, such as BORIS, become more valuable, providing a safety net that alleviates consumers' concerns about the transaction costs of returning products, including monetary, time and psychological burdens. Thus, when social media advertising is actively used, the BORIS service will likely play a more significant role in enhancing e-retailer performance by reducing post-purchase friction transaction costs and preserving customer satisfaction. We hypothesize:

H3. The positive association between BORIS service and e-retailer business performance is more pronounced for e-retailers with greater use of social media advertising.

Sponsored search advertising is another promotional strategy where product sellers pay Internet search engines to display their products prominently when customers search for certain keywords (Yang and Ghose, 2010). Similar to social media, sponsored search aims to draw customer attention and boost customer spending (Sun *et al.*, 2020). The targeted visibility reduces the time and effort (i.e. transaction costs) consumers need to find and compare relevant products, effectively lowering their pre-purchase search costs (Agarwal *et al.*, 2015). However, this convenience often leads consumers to make faster purchase decisions with less thorough research about alternatives (Lu and Zhao, 2014), increasing the likelihood of less-informed purchases. As a result, consumers may face higher post-purchase risks and greater uncertainty (i.e. transaction costs) about product satisfaction. In this case, BORIS availability can help mitigate consumer concerns by signaling lenient return policies. Hence, we expect BORIS to be more useful in boosting performance for e-retailers spending more on sponsored search.

H4. The positive association between BORIS service and e-retailer business performance is more pronounced for e-retailers with greater use of sponsored search.

4. Methods

4.1 Data sources

Our sample consists of each year's top 1,000 e-retailers in North America, ranked annually based on web sales revenue, as identified by data service provider *Digital Commerce 360*[16]. The leading e-retailers, known for substantial influence and market share in North America, provide a solid basis for analyzing e-commerce trends and dynamics. We procured, cleaned and merged data (2013–2020) from *Digital Commerce 360*s database, which contains annual operating information. The database covers online performance, omnichannel operations, website features and functions, customer services, marketing tactics and other facets of online operations. Many published studies use the same database for different years (e.g. Chuang *et al.*, 2014; Fuller *et al.*, 2022; Jones *et al.*, 2022; Perdikaki *et al.*, 2015). Our dataset forms an unbalanced panel due to the evolving composition of the top 1,000 retailer list. For the main analysis, we exclude the year 2020 due to the extraordinary impact of the COVID-19 pandemic, which may introduce systematic bias.

4.2 Variables

Table 1 provides definitions and measurements of the variables used in the main regression models.

4.2.1 Dependent variables. We employed multiple variables to measure e-retailer business performance. E-retailer sales performance (*Sales*) was measured as annual website sales revenue. This metric equals an e-retailer's total yearly sales, while for multichannel retailers, it denotes the portion of overall sales generated via online channels. To address data skewness, the variable was log-transformed (*LnSales*). In robustness checks, we used the e-retailer's annual rank (*Rank*) as the dependent variable. The rankings are determined by *Digital Commerce 360* based on e-retailers' annual sales.

To further understand how BORIS policy affects granular e-retailer performance, we also used three metrics, which together contribute to online sales: conversion rate (*ConversionRate*), average order value (*AverageOrderValue*) and website traffic (*WebsiteTraffic*). Conversion rate is the percentage of website visitors who make a purchase. Average order value measures the average amount spent per transaction, indicating the value of each sale. Website traffic is approximated by the average monthly visitors to the e-retailer's website. To reduce skewness and control for potential outliers, a logarithmic transformation was applied to each to generate *LnConversionRate*, *LnAverageOrderValue* and *LnWebsiteTraffic*.

4.2.2 Independent variables. To examine associations between BORIS and e-retailer performance (Hypothesis 1), we created a dummy variable *BORIS*, which takes a value of 1 when an e-retailer is reported to offer BORIS service and 0 otherwise. Table 2 reports the number and percentage of e-retailers offering BORIS by merchant type. BORIS adoption is

Table 1. Variables and measurement

	Variable name	Description	Source
Dependent variables	Sales; LnSales	An e-retailer's annual website sales revenue. Natural logarithm transformation to address skewness	DC360
	Rank	Sales rank of the e-retailer, based on annual website sales. Rank of 1 reflects the highest sales, while 1,000 reflects the lowest sales among the Top 1,000 e-retailers	DC360
	ConversionRate; LnConversionRate	Estimated percent of website visitors who make a purchase. Natural logarithm transformation to address skewness	DC360; calculated
	AverageOrderValue; LnAverageOrderValue	Estimated average amount spent ($) per customer order transaction. Natural logarithm transformation to address skewness	DC360; calculated
	WebsiteTraffic; LnWebsiteTraffic	Approximate average monthly visitors to an e-retailer's website. Natural logarithm transformation to address skewness	DC360; calculated
Independent variables	BORIS	Equals 1 when an e-retailer is reported to use Buy-Online-Return-In-Store, 0 otherwise	DC360
	FreeReturnShipping	Equals 1 when an e-retailer offers a free return-by-mail service, 0 otherwise	DC360
	SocialMedia AdjSocialMedia	The number of social media platforms on which an e-retailer has accounts during a year, out of 7 (i.e. Facebook, Instagram, Twitter, Pinterest, YouTube, Snapchat and Blog). Due to missing data for 2019, the values for 2019 are assigned as the maximum used during any year. The adjusted variable is mean-differenced relative to each year's mean use for the whole industry	DC360; calculated
	SponsoredSearch; LnSponsoredSearch	Estimated e-retailer expenditure on sponsored search advertising during a year. Natural logarithm transformation to address skewness	DC360; calculated
Control variables	FirmAge	Age of e-retailer. Calendar year minus the year of an e-retailer's founding	DC360; calculated
	Type	Merchant type	DC360
	Category	Merchandise product category	DC360
	AdjCustomerServices AdjOmnichannelServices AdjWebsiteFunctions AdjPaymentSystems	E-retailer's annual count of service/system/function use, minus the same year's industry-wide mean use of the same group of services/systems/functions. Reflects e-retailer's divergence from the population mean	DC360; calculated
	GenderMale	The proportion of customers who are male for an e-retailer during a year	DC360
	Customer age distribution	The proportion of an e-retailer's customers in an age group, categorized into five groups: 18–24, 25–34, 35–44, 45–54 and 55+	DC360
	CategoryHHI	Herfindahl–Hirschman Index of sector concentration based on merchandise category membership and annual reported website sales	Calculated

Note(s): DC360 = *Digital Commerce 360*
Source(s): Authors' own work

Table 2. BORIS adoption by e-retailer type

E-retailer type	Observations non-BORIS	Observations offering BORIS	Total firm years	% offering BORIS
Web only	2,682	170	2,852	5.96%
Brand manufacturer	1,025	381	1,406	27.10%
Catalog/call center	704	108	812	13.30%
Retail chain	594	1,076	1,670	64.43%

Source(s): Authors' own work

naturally higher among retail chains and brand manufacturers, yet some web-only retailers also report offering BORIS.

We constructed a dummy variable *FreeReturnShipping*, coded 1 if an e-retailer offers free return-by-mail service in a year and 0 otherwise. This variable operationalizes a return shipping policy which, as literature shows, presents a mixed picture: its potential to foster loyalty and spending (Bower and Maxham, 2012) is contingent (Luo *et al.*, 2025) and can be offset by increased return rates and costs (Patel *et al.*, 2021). This tension underscores a need to better understand how its roles vary across contexts. Thus, we examine (Hypothesis 2) an interaction of free return shipping and the BORIS cross-channel return option to assess its moderating role.

For Hypothesis 3, we measured an e-retailer's use of social media advertising (*SocialMedia*), reflected by an e-retailer's number of social media platform accounts, out of 7 (i.e. Facebook, Instagram, Twitter, Pinterest, YouTube, Snapchat and Blog). Social media data were not reported for 2019, which would reduce the range of years for regressions. Since e-retailers tend to keep using a social media channel once started, for 2019, we defined this variable as the maximum count for that e-retailer across prior years. The variable was mean-differenced, using an industry-wide annual mean to control for variations in overall social media usage, to create *AdjSocialMedia*.

For Hypothesis 4, we measured e-retailer spend on sponsored search advertising (*SponsoredSearch*), representing the amount of paid online ads displayed in search engine results. The spending level reflects dedication to promoting products or services via targeted online advertising. We log-transformed this variable (*LnSponsoredSearch*).

4.2.3 Control variables. We included retailer- and industry-level factors as control variables. At the e-retailer level, we account for the e-retailer age (*FirmAge*), merchant type (*Type*) and merchandise category (*Category*). Since operational experience, growing market awareness and existing customer bases can impact the sales performance and business growth of e-retailers, it is important to control for e-retailer age. We measured *FirmAge* as the number of years since an e-retailer's founding.

Based on *Digital Commerce 360*, we controlled for four merchant types (i.e. web-only, retail chain, catalog/call center and consumer brand manufacturer) using three dummy variables. These types differ in their business models and operations, potentially affecting website sales. We also included 11 dummy variables for merchandise categories (e.g. apparel and accessories, consumer electronics, food and beverage, and sporting goods). These categories exhibit slight year-to-year variation and can impact performance due to differences in market demand, competitive dynamics and consumer preferences (Chuang *et al.*, 2014).

Fixed-effect (FE) models will drop *Type* and *Category* indicators if all e-retailers never change their business models. In that idealized situation, the indicators would be differenced out of the dataset. An alternate means to control for merchandise category in FE models is via a metric of industry concentration. At an industry level, we controlled for sector concentration via a Herfindahl–Hirschman Index (*CategoryHHI*). This variable was calculated by squaring the market share of each e-retailer within a category annually and summing the values (Perdikaki *et al.*, 2015).

We controlled for e-retailer offerings for customer services (*CustomerServices*), omnichannel services (*OmnichannelServices*), website functions (*WebsiteFunctions*) and payment systems (*PaymentSystems*). e-retailers often involve various customer services, such as live chat, automatic replenishment, free delivery and next-day delivery. We measured *CustomerServices* as a count of such services an e-retailer offers. In addition to BORIS, e-retailers may offer other omnichannel services, such as ship-from-store, buy-online-pickup-in-store and reserve-online-pickup-in-store. To control for potential influences of these services (Jones *et al.*, 2022), we included *OmnichannelServices* to measure the number of logistics-oriented offerings used. Website functions (e.g. customer reviews, image search and voice search) also may impact user experiences, shopping decisions and sales performance. We controlled for *WebsiteFunctions*, measured as a count of functions offered by e-retailers. e-retailers providing more payment options enhance flexibility for customers, potentially boosting satisfaction scores and conversion rates. Hence, we included *PaymentSystems*, which measures the total number of payment methods used by e-retailers. To address year-to-year inconsistencies in the types of customer services, omnichannel services, website functions and payment systems reported by the database, the four count variables were adjusted relative to the annual industry mean use (i.e. *AdjCustomerServices*, *AdjOmnichannelServices*, *AdjWebsiteFunctions* and *AdjPaymentSystems*).

We also controlled for customer profiles, including gender (*GenderMale*) and customer age distribution proportions (age groups: 18–24, 25–34, 35–44, 45–54 and 55+). We omitted the 55+ group. Finally, year dummy variables were used to account for the operating year, omitting the first year from the regression. Descriptive statistics and correlations for untransformed as well as transformed variables are summarized in Online Appendix A.

4.3 Model specification

We performed regression analysis using Stata 19.5. The following model is formulated for H1:

$$Y_{it} = \beta_0 + \beta_1 BORIS_{it} + \beta_2 FreeReturnShipping_{it} + \beta_3 AdjSocialMedia_{it} + \beta_4 LnSponsoredSearch_{it} + \beta_5 X_{it} + u_i + \epsilon_{it} \tag{1}$$

Subscripts i and t denote e-retailer and year, respectively. Y_{it} is $LnSales_{it}$, representing the online sales performance of e-retailer i in year t. We later use $Rank_{it}$, $LnConversionRate_{it}$, $LnAverageOrderValue_{it}$, or $LnWebsiteTraffic_{it}$ as dependent variables. *BORIS, FreeReturn Shipping, AdjSocialMedia* and *LnSponsoredSearch* are key variables of interest. X_{it} is a vector of explanatory variables that may influence the performance of e-retailer i in year t. ϵ_{it} represents the error term, accounting for unobserved factors and random disturbances. The main models employ fixed-effect (FE) regressions via Stata's xtreg, fe command. Hence, u_i is incorporated to capture e-retailer i's specific effect that persists over time. We use the estimate of coefficient β_1 to assess H1.

Next, we extend the base econometric model as follows in Equation (2), reflecting the fully specified set of hypothesized phenomena:

$$\begin{aligned} Y_{it} = {} & \beta_0 + \beta_1 BORIS_{it} + \beta_2 FreeReturnShipping_{it} + \beta_3 AdjSocialMedia_{it} \\ & + \beta_4 LnSponsoredSearch_{it} + \beta_5 BORIS_{it} \times FreeReturnShipping_{it} \\ & + \beta_6 BORIS_{it} \times AdjSocialMedia_{it} + \beta_7 BORIS_{it} \times LnSponsoredSearch_{it} + \beta_8 X_{it} + u_i \\ & + \epsilon_{it} \end{aligned} \tag{2}$$

$BORIS_{it} \times FreeReturnShipping_{it}$, $BORIS_{it} \times AdjSocialMedia_{it}$ and $BORIS_{it} \times LnSponsoredSearch_{it}$ are interaction terms of *BORIS* with *FreeReturnShipping*, *AdjSocialMedia* and *LnSponsoredSearch* of e-retailer i in year t. Coefficients β_5, β_6 and β_7 are used to examine the moderating effects of same-channel free returns and the two promotion types (i.e. H2, H3 and H4). Other variables are largely the same, as in Equation (1). For all models, we use Huber–White robust standard errors.

5. Empirical results

5.1 Main findings: web sales

Table 3 presents main analysis results for annual website sales revenue. Hausman specification test statistics suggest FE models are more appropriate than RE models. Model 2 includes only

Table 3. Regression results: web sales (2013–2019)

Dependent variable	*LnSales* (1) Controls	(2) Main variables	(3) Interactions
BORIS		−0.062	0.042
		(0.050)	(0.217)
FreeReturnShipping		0.009	0.008
		(0.022)	(0.023)
AdjSocialMedia		0.017	0.022
		(0.013)	(0.013)
LnSponsoredSearch		0.022***	0.023**
		(0.006)	(0.007)
BORIS*FreeReturnShipping			0.002
			(0.045)
BORIS*AdjSocialMedia			−0.019
			(0.026)
BORIS*LnSponsoredSearch			−0.008
			(0.020)
FirmAge	−0.013	−0.017	−0.016
	(0.022)	(0.022)	(0.022)
AdjOmnichannelServices	0.005	0.012	0.013
	(0.016)	(0.014)	(0.014)
AdjCustomerServices	−0.002	−0.004	−0.004
	(0.006)	(0.006)	(0.006)
AdjWebsiteFunctions	0.004	0.003	0.003
	(0.003)	(0.003)	(0.003)
AdjPaymentSystems	0.019*	0.018*	0.018*
	(0.008)	(0.009)	(0.009)
CategoryHHI	0.043	0.019	0.015
	(0.123)	(0.128)	(0.129)
Gender (Male)	−0.167*	−0.138	−0.147
	(0.077)	(0.093)	(0.092)
Customer age categories	Included	Included	Included
Merchant type dummies	Included	Included	Included
Year dummies	Included	Included	Included
Constant	Included	Included	Included
Retailer FE	Yes	Yes	Yes
N	5,341	4,725	4,725
Within R^2	0.450	0.438	0.439
Hausman FE vs RE X^2 (p)	763.53 (0.000)	905.47 (0.000)	932.98 (0.000)

Note(s): ***p < 0.001, **p < 0.01, *p < 0.05; Robust standard errors are shown in parentheses
Source(s): Authors' own work

main effects for the variables of interest. BORIS exhibits an insignificant negative association with website sales ($\beta = -0.062, p > 0.05$), not supporting H1. It also finds no significant associations of free return shipping ($\beta = 0.009, p > 0.05$) or social media usage ($\beta = 0.017, p > 0.05$) with sales. Sponsored search has a significant positive association ($\beta = 0.022, p < 0.001$).

Model 3 examines moderating associations of free return shipping, social media use and sponsored search advertising on BORIS. Results show the interaction between BORIS and free returns is insignificant ($\beta = 0.002, p > 0.05$), indicating free online returns did not moderate a BORIS process's effect on sales. H2 is not supported. Next, the interactions for BORIS and social media use ($\beta = -0.019, p > 0.05$) and for BORIS and sponsored search ($\beta = -0.008, p > 0.05$) are insignificant. Thus, H3 and H4 are not supported.

5.2 Robustness checks: web sales

To verify the main results for annual website sales, we conducted several robustness checks. Detailed descriptions for each are in Online Appendix B. Table 4 provides a high-level summary of the checks. First, to examine how measurement of the dependent variable affected findings, we replaced annual sales with online sales rank (*Rank*) and the year-to-year difference between web sales (*DeltaLnSales)*. Second, to explore the influence of panel balance, we estimated models using both a fully balanced subset of firms and the remaining unbalanced observations. Third, to gauge impacts of e-retailer type, we dropped web-only e-retailers. We also include web-only results for comparison. Fourth, to compare alternate metrics of market makeup, we replaced the merchandise category HHI index (*CategoryHHI*) with category dummies. Fifth, a major US *de minimis* duty exemption change occurred in 2016, so we added controls for this policy shift and for foreign headquarters location to ensure it did not confound results. Sixth, to check empirical sensitivity to the time frame, we re-estimated models over shorter periods (i.e. 2013–2018, 2014–2019). Seventh, to address possible timing and reverse-causality concerns, we used a one-year lagged BORIS variable (*LagBORIS*). Finally, to correct for potential endogeneity in BORIS and its posited moderators, based on the rationale found in Online Appendix C, we applied the Lewbel (2012, 2018) method for constructing synthetic endogeneity IV corrections under both fixed-effects (FE) and random-effects (RE) frameworks.

Across the checks, the findings for the hypotheses remain largely consistent with the baseline results: BORIS shows little direct association with web sales. The three interactions are also mostly insignificant. Sponsored search advertising, and social media use to a lesser extent, show positive associations with sales. The checks suggest the findings for BORIS-to-sales associations are robust to adjusted variable definitions, sample compositions, model specifications and methods.

5.3 Examining contributing factors underlying web sales

Since associations for BORIS and web sales were infrequently significant using the full dataset, we decomposed aggregate sales performance into three granular drivers: conversion rate, average order value and website traffic. These metrics more directly reflect customer actions influenced by BORIS availability. The metrics multiplicatively determine web sales. Following the review team's suggestion, we focused the analysis on bricks-and-clicks e-retailers, whose physical locations likely facilitate utilization of BORIS. For comparison, we also conducted regressions for the full sample of all e-retailers (see Table A1 in the Appendix) and for the subsample consisting solely of pure e-retailers (see Table A2). The results show that for pure e-retailers, all associations across the three outcome variables are statistically insignificant. By contrast, meaningful effects emerge when web-only e-retailers were omitted. Thus, in Table 5 and related tables, we present findings only for bricks-and-clicks subsamples.

Specifically, Model 1 in Table 5 indicates BORIS exhibits an insignificant association with *LnConversionRate* ($\beta = 0.004, p > 0.05$), not supporting H1. Yet, the extent of omnichannel

Table 4. Summary of robustness checks for sales performance

Robustness check	Dependent variable	BORIS	FRS	AdjSM	LnSS	BORIS *FRS	BORIS *AdjSM	BORIS *LnSS
Alternate DV	*Rank*	0.046	−0.016	−0.013	−0.017***			
		0.014	−0.011	−0.014	−0.017**	−0.017	0.001	0.003
Alternate DV	*DeltaLnSales*	0.003	−0.017	−0.003	0.001			
		−0.060	−0.023	−0.004	−0.0001	0.019	0.003	0.005
Fully balanced panel subset	*LnSales*	−0.124†	0.028	0.021	0.023*			
		−0.054	0.018	0.031	0.024*	0.026	−0.032	−0.005
Unbalanced shorter panels	*LnSales*	0.042	0.005	0.005	0.022*			
		0.127	−0.002	0.001	0.023**	0.043	0.033	−0.010
Drop web-only e-retailers	*LnSales*	−0.050	0.011	0.034†	0.016			
		0.078	0.028	0.040*	0.020	−0.035	−0.015	−0.010
Only web-only e-retailers	*LnSales*	−0.076	−0.014	−0.007	0.022***			
		0.055	0.028	0.043*	0.021	−0.041	−0.019	−0.008
Merchandise categories	*LnSales*	−0.062	0.009	0.017	0.022***			
		0.027	0.009	0.021	0.023***	−0.0001	−0.017	−0.007
De minimis	*LnSales*	−0.062*	0.009	0.017†	0.022***			
		0.042	0.008	0.022*	0.024***	0.001	−0.019	−0.008
Data sample 2013–2018	*LnSales*	−0.041	−0.004	0.023†	0.022***			
		0.040	−0.004	0.026*	0.022***	−0.002	−0.014	−0.006
Data sample 2014–2019	*LnSales*	−0.061	0.001	0.005	0.025***			
		0.042	−0.002	0.012	0.026***	0.010	−0.033	−0.008
Lag BORIS	*LnSales*	−0.086†	0.006	−0.001	0.031***			
		−0.134	0.010	0.002	0.030***	−0.013	−0.012	0.005
Lewbel FE	*LnSales*	0.001	0.006	0.054*	0.007			
		0.146	0.029	0.059*	0.012	−0.002	−0.031	−0.014
Lewbel RE	*LnSales*	0.014	−0.108	0.092***	0.296***			
		−4.420***	0.018	0.097***	0.238***	−0.023	−0.183***	0.400***

Note(s): FRS = Free Return Shipping, AdjSM = AdjSocialMedia, LnSS = LnSponsoredSearch; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$; †$p < 0.1$; Lewbel checks only instrument the four main variables of interest

Source(s): Authors' own work

Table 5. Regression results: web sales contributors – dropping web-only (2013–2019)

Dependent variable	Contributors to web sales LnConversionRate (1)	(2)	LnAverageOrderValue (3)	(4)	LnWebsiteTraffic (5)	(6)
BORIS	0.004	0.065	0.002	0.462*	0.151**	−0.151
	(0.027)	(0.154)	(0.045)	(0.212)	(0.057)	(0.449)
FreeReturnShipping	−0.010	−0.047†	0.018	−0.012	0.038	−0.019
	(0.025)	(0.026)	(0.037)	(0.040)	(0.058)	(0.083)
AdjSocialMedia	−0.004	−0.002	0.019	0.016	0.020	−0.013
	(0.013)	(0.013)	(0.013)	(0.015)	(0.046)	(0.054)
LnSponsoredSearch	0.006	0.008	0.005	0.018	0.024	0.019
	(0.006)	(0.008)	(0.010)	(0.013)	(0.027)	(0.029)
BORIS*FreeReturnShipping		0.077†		0.065		0.119
		(0.045)		(0.070)		(0.101)
BORIS*AdjSocialMedia		−0.005		0.015		0.087
		(0.017)		(0.029)		(0.057)
BORIS*LnSponsoredSearch		−0.006		−0.041*		0.012
		(0.014)		(0.017)		(0.038)
FirmAge	0.008	0.008	−0.006	−0.006	−0.031†	−0.034†
	(0.006)	(0.006)	(0.010)	(0.009)	(0.017)	(0.018)
AdjOmnichannelServices	0.037***	0.035***	−0.016	−0.014	0.083***	0.075**
	(0.009)	(0.010)	(0.013)	(0.013)	(0.024)	(0.024)
AdjCustomerServices	0.005	0.005	0.0007	−0.0002	−0.029*	−0.028*
	(0.005)	(0.005)	(0.007)	(0.007)	(0.014)	(0.014)
AdjWebsiteFunctions	−0.0005	0.0002	−0.008*	−0.008*	0.0009	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)
AdjPaymentSystems	0.010	0.010	0.0009	0.002	0.038*	0.037*
	(0.006)	(0.006)	(0.008)	(0.008)	(0.016)	(0.016)
CategoryHHI	−0.157†	−0.160†	−0.005	−0.023	0.292	0.298
	(0.087)	(0.089)	(0.171)	(0.171)	(0.270)	(0.266)
Gender (Male)	−0.137	−0.145	−0.179*	−0.183*	−0.553***	−0.522*
	(0.097)	(0.096)	(0.082)	(0.080)	(0.247)	(0.243)
Customer age categories	Included	Included	Included	Included	Included	Included
Merchant type dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included
Retailer FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,599	2,599	2,609	2,609	2,617	2,617
Within R^2	0.160	0.160	0.026	0.035	0.135	0.138
Hausman FE vs RE X^2 (p)	67.10		156.05		286.65	
	(0.000)		(0.000)		(0.000)	

Note(s): ***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1; Robust standard errors are shown in parentheses
Source(s): Authors' own work

service availability is positively associated with the conversion rate ($\beta = 0.037, p < 0.001$). Sector concentration (*CategoryHHI*) marginally reduces conversion ($\beta = -0.157, p < 0.1$). Model 2 shows among the hypothesized BORIS moderations, only the interaction with *FreeReturnShipping* (i.e. H2) reaches weak significance ($\beta = 0.077, p < 0.1$).

Model 3 for *LnAverageOrderValue* shows an insignificant BORIS parameter estimate. Model 4 indicates that BORIS use has a significant positive association ($\beta = 0.462$, $p < 0.05$), particularly when sponsored search is at low levels, giving partial support for H1. While contrary to Table 3 findings, this finding does indicate a lower-level association, which gets washed out when the data is aggregated into overall web sales. Model 4 also shows that sponsored search lessens BORIS's positive association with average order value ($\beta = -0.041, p < 0.05$), against H4.

Model 5 for *LnWebsiteTraffic* indicates that BORIS use has a significant positive association $(\beta = 0.151, p < 0.01)$, providing support for H1. Yet, in Model 6, when moderations are included, BORIS exhibits insignificant parameters, and no significant moderation effects are observed.

In summary, for bricks-and-clicks e-retailers, BORIS shows a positive association with customer order values when sponsored search spend is at low levels. BORIS exhibits a direct positive association with website traffic. BORIS has a weak positive interaction with free returns for the conversion rate. The proposed moderations for social media usage are generally insignificant.

5.4 Robustness checks: web sales contributors

Since the non-web-only e-retailers are better positioned to implement BORIS, we conducted several robustness checks on these BORIS-capable retailers to verify result reliability for the three component variables. Key results are summarized next.

Merchandise Category Dummies vs. CategoryHHI Again, we replaced the product category HHI index with the product category dummies. The results are similar.

Alternative Sample Periods We restricted the sample period to 2013–2018. In a model comparable to Model 2 in Table 5, *FreeReturnShipping* has a similar weakly significant parameter estimate, while *BORIS*×*AdjSocialMedia* is weakly significant $(\beta = -0.031, p < 0.1)$. We find a similar significant association between *BORIS* and *LnAverageOrderValue* $(\beta = 0.420, p < 0.1)$, with a similar *BORIS*×*LnSponsoredSearch* interaction $(\beta = -0.037, p < 0.05)$. The sample range was narrowed to 2014–2019 for reanalysis. The findings for *LnConversionRate* end up insignificant. The results for the moderation model for *LnAverageOrderValue* show similar magnitude, yet insignificant BORIS parameters. The findings for *LnWebsiteTraffic* end up similar. Overall, some findings are robust to short data windows.

Lagged BORIS Variable To address concerns that the timing of BORIS implementation may not align with the same-year business outcomes, we replaced the BORIS variable with a one-year lagged version (*LagBORIS*), lessening concerns that high sales in the same year might drive BORIS adoption. The results for *LnConversionRate* are insignificant. In contrast, *LagBORIS* in the moderated model is significantly positive for *LnAverageOrderValue* $(\beta = 0.743, p < 0.01)$, with a significant interaction with *LnSponsoredSearch* $(\beta = -0.069, p < 0.01)$, aligning with Model 4 in Table 5. *LagBORIS* is also significant and positively associated with *LnWebsiteTraffic* $(\beta = 0.136, p < 0.05)$ in the model comparable to Model 5. In the Model 6 equivalent, *LnWebsiteTraffic* is significantly associated with *LnSponsoredSearch* $(\beta = 0.083, p < 0.05)$ and with the interaction *LagBORIS* × *LnSponsoredSearch* $(\beta = 0.063, p < 0.1)$.

Addressing Endogeneity For these component variables, endogeneity concerns arise from forces similar to those affecting web sales. As detailed in Online Appendix B, managers may deploy BORIS for internal performance goals or to enhance competitive positions. Thus, for each component variable, we used a Lewbel (2012, 2018) endogeneity correction to generate synthetic IVs for within FE models and between RE models. Across them, we keep models comparable by instrumenting all four variables of interest. In general, with this approach, the set of tests for weak identification, overidentification, and the presence of heteroskedasticity end up reasonable. While an underidentification test statistic is calculated, Stata does not present a critical value for some models involving multiple endogenous variables. Table 6 presents findings.

Focusing on *LnConversionRate* in Table 6, we observe that the IV-corrected results suggest BORIS reduces the conversion rate in certain conditions, conflicting with H1. We observe no support for H2 or H3. Yet, in these models, the interaction with sponsored search ends up positive and significant in the FE within $(\beta = 0.029, p < 0.05)$ and RE between $(\beta = 0.049, p < 0.01)$ runs. The findings provide evidence for H4.

Table 6. Addressing endogeneity: web sales contributors – dropping web-only (2013–2019)

Dependent variable	LnConversionRate Within (FE) instrumenting all four (1)	(2)	Between (RE) instrumenting all four (3)	(4)	LnAverageOrderValue Within (FE) instrumenting all four (5)	(6)	Between (RE) instrumenting all four (7)	(8)	LnWebsiteTraffic Within (FE) instrumenting all four (9)	(10)	Between (RE) instrumenting all four (11)	(12)
BORIS	−0.045	−0.338*	0.111	−0.585**	−0.028	0.308*	−0.119	0.381†	0.110	−0.838	0.444*	−1.959***
	(0.031)	(0.135)	(0.102)	(0.205)	(0.021)	(0.144)	(0.106)	(0.211)	(0.070)	(0.556)	(0.175)	(0.417)
FreeReturnShipping	0.009	−0.019	−0.008	−0.0003	0.004	−0.042†	0.132	0.103	0.031	0.070	−0.324**	−0.120
	(0.021)	(0.021)	(0.067)	(0.052)	(0.024)	(0.023)	(0.083)	(0.065)	(0.053)	(0.074)	(0.113)	(0.080)
AdjSocialMedia	0.027	0.015	0.016	0.033*	−0.005	0.002	−0.005	−0.036†	0.114	0.067	0.094**	0.107***
	(0.020)	(0.019)	(0.017)	(0.014)	(0.027)	(0.020)	(0.025)	(0.020)	(0.070)	(0.064)	(0.031)	(0.023)
LnSponsoredSearch	0.000	−0.006	−0.038**	−0.024*	0.002	0.004	0.005	0.043***	−0.051†	−0.021	0.387***	0.368***
	(0.005)	(0.005)	(0.015)	(0.012)	(0.005)	(0.008)	(0.018)	(0.012)	(0.028)	(0.025)	(0.032)	(0.024)
BORIS*FreeReturnShipping		0.049		0.056		0.058†		−0.056		0.148†		0.167
		(0.032)		(0.070)		(0.035)		(0.084)		(0.081)		(0.118)
BORIS*AdjSocialMedia		−0.017		−0.031		0.002		0.101***		0.043		−0.174***
		(0.018)		(0.022)		(0.021)		(0.031)		(0.055)		(0.044)
BORIS*LnSponsoredSearch		0.029*		0.049**		−0.026*		−0.045*		0.077†		0.198***
		(0.011)		(0.018)		(0.012)		(0.019)		(0.046)		(0.037)
Main model variables	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year Dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Retailer FE	Yes	Yes	No; Clustered	No; Clustered	Yes	Yes	No; Clustered	No; Clustered	Yes	Yes	No; Clustered	No; Clustered
N	2,599	2,599	2,599	2,599	2,609	2,609	2,609	2,609	2,617	2,617	2,617	2,617
Centered R^2	0.140	0.140	0.122	0.135	0.013	0.022	0.145	0.152	0.101	0.111	0.520	0.528
Kleinbergen–Paap rk Wald *F* (*p*): Weak identification test	115.310**	113.583***	121.770***	132.036***	118.607***	114.795***	121.041***	130.524***	118.978***	115.786*	120.840***	130.916***
Cragg-Donald Wald *F* (*p*): underidentification test	3.807[na]	4.886[na]	5.986[na]	77.299[na]	3.782[na]	4.930[na]	5.960[na]	77.955[na]	3.837[na]	5.004[na]	5.911[na]	78.261[na]
Hansen *J* (*p*): overidentification test	66.856	90.484	75.632	98.525	64.437	73.442	99.181*	115.745*	74.541	99.199	119.651***	140.453***
Pagan-Hall X^2 (*p*): heteroskedasticity test	250.873***	288.285***	229.814***	308.489***	210.306***	195.016***	353.476***	383.829***	228.354***	259.847***	299.968***	447.883***
Estimation method	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s	GMM2s

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$; †$p < 0.1$; Robust standard errors are shown in parentheses; "na" = critical values not available; All four variables of interest (i.e. BORIS, FreeReturnShipping, AdjSociaMedia and LnSponsoredSearch) are instrumented in every specification

Source(s): Authors' own work

Similar to Table 5, the estimates for *LnAverageOrderValue* in Table 6 suggest BORIS does not exhibit a significant main effect on average order value in the baseline model. But, after accounting for the interactions, the BORIS coefficient turns positive in both the FE within and RE between models, partially supporting H1. In this situation, *BORIS*×*FreeReturnShipping* has a weak positive coefficient in the FE model ($\beta = 0.058, p < 0.1$), opposite of H2. We observe strong significant support for H3 in the RE model ($\beta = 0.101, p < 0.001$). Yet, we observe negative significant BORIS interactions with sponsored search in both models, contrary to H4.

Results for *LnWebsiteTraffic* in Table 6 show somewhat different findings for FE and RE perspectives. FE within treatment shows no evidence that BORIS directly affects traffic, but a weak significant coefficient exists for the free return shipping interaction ($\beta = 0.148$, $p < 0.1$), contradicting the hypothesized negative relationship in H2. A weak significant coefficient is also found for H4 related to the sponsored search interaction ($\beta = 0.077, p < 0.1$). From the RE between relative performance perspective, we observe many significant parameters. The base model evidence for a BORIS direct effect ($\beta = 0.444, p < 0.05$) supports H1. We also observe a finding against H3 for the social media interaction ($\beta = -0.174, p < 0.001$) and support for the H4 sponsored search interaction ($\beta = 0.198, p < 0.001$).

The models using Lewbel synthetic IVs show somewhat different findings from Table 5, suggesting endogeneity correction matters. We generally observe the significant findings from Table 5, but also observe several significant parameters underestimated by a basic FE regression.

6. Discussion and conclusions

Motivated by customer return challenges, e-retailers are considering the adoption of BORIS. Industry studies suggest that by 2024, nearly a third of retailers had used BORIS (NRF/Happy Returns, 2025). Still, surveys also suggest BORIS has become problematic, causing an estimated 14.58% product returns rate ($215 Billion dollars), much higher than returns attributed to in-store sales or online purchases returned online (Appriss Retail/Deloitte, 2024). As such, BORIS merits more research.

This study analyzes annual business-level impacts of BORIS via panel data of top North American e-retailers. The findings suggest BORIS provided little meaningful benefit to lift annual online sales. At best, BORIS may have enhanced the impact of sponsored search expenditures in driving sales, albeit at a cost of undermining the consequences of social media marketing.

Among three granular performance metrics, endogeneity-corrected FE and RE results show BORIS interacts differently across the metrics for bricks-and-clicks e-retailers. BORIS did not directly improve conversion rates, yet appears to complement sponsored search in driving conversion. BORIS can lift average order value when free return shipping is offered, as social media tactics grow, and when sponsored search spend is low. BORIS may also boost website traffic via divergent synergies. Overall, opposing phenomena across the three metrics appear to counteract each other when coming together to determine annual website sales.

6.1 Theoretical contributions

Our study contributes to return policy evaluation research in two ways. First, we move beyond the common empirical focus on same-channel return policies (e.g. Abdulla *et al.*, 2022; Ertekin and Agrawal, 2021; Patel *et al.*, 2021; Rao *et al.*, 2018) by theorizing and quantifying performance implications of a cross-channel return service (i.e. BORIS). Despite BORIS's prevalence, few studies explore its firm-level effects, beyond micro-level analyses of customer intentions (e.g. Xie *et al.*, 2023a). Our study provides the first robust empirical evidence on

BORIS's impacts on e-retailers' operating performance by leveraging a multi-year panel dataset.

Our analysis reveals that the use of a BORIS process stimulates a bricks-and-clicks e-retailer's average customer order value and website traffic, though these effects are context-dependent. This finding aligns with TCT: as a flexible complement to standard mail returns, by lowering perceived purchase risks and transaction costs (Abdulla *et al.*, 2022), BORIS encourages higher spending and site exploration. Yet, BORIS's nonsignificant or conditional negative effect on conversion rates implies BORIS may lead to delayed or abandoned purchases, as consumers take advantage of easy returns to browse extensively, postponing purchases. In combination, no measurable impact of BORIS on aggregate sales is observed. The insights extend return policy literature by highlighting how cross-channel returns can shape customer behavior without raising overall sales.

Notably, we find BORIS impacts bricks-and-clicks retailers but not pure e-retailers, suggesting its effectiveness hinges on implementation approach. Per TCT, BORIS is hypothesized to reduce psychological costs (e.g. anxiety from process uncertainty) and time-based costs (e.g. waiting periods) beyond monetary costs in return scenarios. Bricks-and-clicks retailers can achieve this via integrated online-offline systems and trained staff, enabling targeted support to mitigate psychological costs. Their BORIS processes facilitate on-site returns with clear and efficient refund arrangements (e.g. instant cash, standard card refunds), curbing time costs. In contrast, pure e-retailers rely on third-party return partners (e.g. Amazon via Staples or Kohl's) whose staff often lack product familiarity and may not provide tailored assistance. This is reflected in consumer complaints about Happy Returns [17]: "associates aren't super knowledgeable in the retail brands they claim to support." These partnerships can also introduce operational frictions such as liability disputes or data disconnects. For instance, Lands' End customers using Happy Returns reported ambiguous responsibility attribution across the various returns partner retailers [18]. Amazon users described unclear package tracking and even package loss via Staples, leading some to advise photographing items at drop-off [19]. Consequently, for pure e-retailers, BORIS fails to lower psychological or time-based costs, explaining its limited effectiveness in that segment.

A specific focus on traffic reveals that while bricks-and-clicks retailers can leverage BORIS to drive site visits, pureplay e-retailers remain reliant on traditional traffic-acquisition methods (e.g. via proactively reaching consumers through digital advertising and free return policies). This reinforces the insight that BORIS's core advantage stems from online-offline synergy, a capability pureplay e-retailers tend to lack. As a result, mainly bricks-and-clicks retailers can convert this advantage into traffic. Collectively, our novel finding of BORIS's heterogeneous effects across retailer types, which are rooted in its two implementation forms (proprietary vs. partner-collaborative channels), advances the understanding of cross-channel return practices by identifying BORIS implementation forms as a critical boundary condition.

Second, prior research shows divergent findings on free return shipping (Bower and Maxham, 2012; Luo *et al.*, 2025; Patel *et al.*, 2021) and largely ignores the complexities of return policies across channels. We advance the literature by examining interactions between BORIS and return shipping policies. Our endogeneity-corrected FE models for bricks-and-clicks retailers show weak positive interactions between BORIS and free return shipping for average order value and website traffic, suggesting complementarity. This likely occurs because free returns address monetary costs but not time/effort costs associated with returns, such as packaging and waiting (Janakiraman and Ordóñez, 2012; Rintamäki *et al.*, 2021), while BORIS reduces these nonmonetary burdens. They together empower consumers to avoid different return cost types based on their needs, enhancing purchase interest. This interaction is absent in pure e-retailers, implying multi-channel customers are more sensitive to combined cost savings. These findings add nuance to the return policy literature and uncover a contingency determining how return shipping fees shape outcomes.

Our investigation also contributes to cross-channel integration research. Existing studies mainly use analytical models to assess BORIS's impact on pricing and channel strategies (e.g.

Gao *et al.*, 2022; Mandal *et al.*, 2021; Nageswaran *et al.*, 2020; Yan *et al.*, 2022). Our study provides data-driven evidence of its operational value for the online channel. Prior research often conceptualizes BORIS as beneficial and recommends its adoption as a competitive strategy (e.g. He *et al.*, 2020; Huang and Jin, 2020), yet our empirical results show its benefits are scope-specific and conditional, challenging the assumption of BORIS's consistent performance gains. Meanwhile, our finding of BORIS's insignificant impacts for pure e-retailers compared to its notable effects on bricks-and-clicks e-retailers delineates effectiveness boundaries for cross-channel return tactics and extends the theoretical discourse on return partnerships (Chen *et al.*, 2024b; Nageswaran *et al.*, 2025; Xie *et al.*, 2024). Our findings also complement Hwang *et al.* (2022), who document BORIS's positive effect on the return partner's offline performance.

On the other hand, prior research on cross-channel fulfillment strategies such as BOPIS and STS shows that, while designed to improve the shopping experience, they do not enhance online sales performance and even induce channel shifting (i.e. redirecting purchases from online to offline channels) (Akturk *et al.*, 2018; Gallino and Moreno, 2014). Our results suggest a different pattern for BORIS. Although BORIS generally exerts no direct promotional effect on aggregate online sales, BORIS can raise average order value and website traffic. This contrast points to potentially different underlying mechanisms. While BOPIS and STS affect where transactions are completed and often cannibalize online sales, BORIS operates post-purchase by lowering customer perceived transaction costs and increasing their trust in e-retailers, thus encouraging higher-value purchases and greater website visits. These insights point to a need to distinguish between fulfillment-based and return-based tactics in omnichannel integration research.

Finally, we advance the marketing-operations interface by adding to discussions on marketing complexities within omnichannel retailing (Rooderkerk *et al.*, 2023), investigating how promotional tactics (social media and sponsored search) moderate BORIS effectiveness. While prior studies highlight digital marketing tools (Sun *et al.*, 2020, 2024), we reveal their nuanced interactions with BORIS across e-retailing performance metrics. Our endogeneity-corrected results show BORIS and sponsored search spend interact positively for conversion rate and website traffic. Yet, increased sponsored search weakens BORIS's impact on average order values, pointing to a countervailing dynamic between cutting pre-transaction search costs and reducing post-transaction return costs. Although BORIS encourages bolder browsing and larger shopping baskets by lowering post-purchase costs, sponsored search – targeting high-intent buyers seeking specific products (Sun *et al.*, 2020) – reduces the need for extensive exploratory browsing, offsetting BORIS's effect. That is, intent-driven customers may be less sensitive to BORIS's transaction cost reduction, making flexible return policies less influential for high order values.

In contrast, between-panel results show that BORIS and social media usage synergize to lift order values. Yet, they negatively interact on website traffic, likely because social media advertising draws more browsing-oriented users with lower purchase intent, who prioritize peer content and social signals (e.g. likes, shares) over formal service policies. As such, they exhibit diminished responsiveness to BORIS's safeguard function, making it less influential. The findings underscore that applying TCT in retail contexts requires attention to channel-specific consumer intent or needs.

6.2 Managerial implications

Our findings provide guidance for e-retailers aiming to optimize return services and enhance sales. First, the results suggest BORIS cross-channel returns can increase customer average order amounts and website visits, but do not boost overall sales. Thus, managers can position BORIS mainly as a tool to enhance purchase value and website traffic. As such, it is advisable to target high-value customer segments (e.g. frequent shoppers, premium members) with

BORIS as a premium service, or integrate it with high-priced product pages (e.g. electronics, appliances), to encourage large order amounts and strengthen customer commitment.

To maximize BORIS benefits, e-retailers with physical stores should invest in efficient return processes, such as dedicated BORIS counters for quick service, staff trained to handle returns and digital tools to speed return processing. Clear, customer-centric communication, including in-app notifications about return eligibility, step-by-step return guides, real-time status and digital reminders, is essential to building trust and reducing hesitation. Notably, our analysis reveals that the positive effects of BORIS are not as pronounced for pure e-retailers as for bricks-and-clicks e-retailers. For pure e-retailers, collaborating with third-party partners that operate physical stores requires careful consideration of potential BORIS limitations. Managers should assess whether a partnership can yield other benefits, such as reducing reverse logistics costs or streamlining operational complexity. If not, the collaborations are not recommended.

Second, e-retailers should carefully evaluate the interaction of BORIS with promotional tactics. Our findings indicate that social media use and sponsored search advertising interact differently with BORIS across the different performance metrics, highlighting a need for a channel-specific approach. Managers should align BORIS with marketing strategies while focusing on the metrics most critical to their business objectives, rather than assuming universal benefits. For example, e-retailers prioritizing average order value should avoid excessive reliance on sponsored search once BORIS is in use, allowing it to operate more effectively. Resources might be shifted from short-term promotion to ensure the use of BORIS and enhance in-store returns service quality.

Finally, the findings suggest a positive albeit weak link between providing a BORIS return service and the availability of free online return shipping for bricks-and-clicks e-retailers. That is, simultaneously offering free by-mail returns and a BORIS return option is beneficial for increasing customer order value and website traffic. Hence, bricks-and-clicks e-retailers might combine these two return policies as a value-added service package to drive key performance metrics. In contrast, based on our finding of an insignificant interactive effect between BORIS and free by-mail returns for pure e-retailers, those pure e-retailers that have adopted BORIS are suggested to design and optimize these return policies individually, tailoring them to specific customer segments and usage contexts to maximize effectiveness. For instance, BORIS can be promoted to high-value customers who value immediate resolution and in-person assistance, while the online return-by-mail option may better suit customers wanting contactless returns and privacy.

6.3 Limitations and future research

This study offers valuable insights into the impacts of BORIS adoption on e-retail performance, but it does have several limitations. First, the unbalanced data set may affect model estimates. We employed appropriate econometric methods and robustness checks to control for potential concerns. We suggest expanding the data in future research to enhance generalizability of findings by incorporating more periods, a broader range of e-retailers and post-COVID years.

Second, our findings are situated within the North American e-retailing context. E-retailer practices and customer returns expectations and habits can differ markedly across other major markets, such as Europe and Asia, due to distinct legal frameworks and cultural nuances (Gäthke *et al.*, 2022). Future studies should examine whether the observed relationships hold in these other markets, thereby enhancing the external validity of our findings.

Third, due to lack of financial or customer experience data, our analysis is limited to BORIS's effects on e-retailers' sales and related metrics. Sales revenues are an important outcome, but they may not fully capture BORIS's mechanisms. Since BORIS primarily concerns return convenience, its impacts may be more evident in customer return behavior, satisfaction or loyalty. Future research could examine these metrics alongside financial outcomes (e.g. profit margin) to deliver a more thorough BORIS evaluation. In addition, our analysis adopts a consumer-side transaction costs lens, not considering retailer-side transaction costs (e.g. return fraud, additional investments) associated with BORIS use. Although these operational costs are not directly linked to our study's outcomes (e.g. online sales, conversion rates), they will influence e-retail profitability and efficiency. Future research could incorporate consumer- and retailer-side transaction costs, examining retailers' net profit or cost structures as added outcomes.

Fourth, our data comes from a third-party source lacking precise start dates for e-retailers' practices (e.g. BORIS). Thus, we implicitly assume these practices were in effect all year, which may slightly affect estimates. We addressed this by using a one-year lagged BORIS variable, getting consistent results and partly lessening timing and reverse causality concerns. Future research could collect more fine-grained data to validate our findings. Analyzing BORIS adoption timing at a granular level (e.g. monthly) should yield more precise insights.

Finally, we explored moderating hypotheses for two promotion tactics: social media use and sponsored search advertising. To deepen understanding of the marketing-operation interface, one might investigate how BORIS interacts with other modern promotional tactics like influencer marketing or live streaming. Doing so may reveal broader consequences of BORIS.

Appendix

Regressions of web sales drivers by e-retailer type (all vs web-only)

Table A1. Regression results: web sales contributors – all e-retailers (2013–2019)

	Contributors to web sales					
	LnConversionRate		*LnAverageOrderValue*		*LnWebsiteTraffic*	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
BORIS	−0.035	0.009	−0.002	0.404**	0.083	−0.472
	(0.029)	(0.136)	(0.040)	(0.153)	(0.058)	(0.412)
FreeReturnShipping	0.017	0.004	0.014	0.005	0.103*	0.069
	(0.019)	(0.020)	(0.024)	(0.024)	(0.048)	(0.060)
AdjSocialMedia	0.006	0.007	0.010	0.006	0.091**	0.080*
	(0.010)	(0.010)	(0.011)	(0.011)	(0.034)	(0.037)
LnSponsoredSearch	−0.002	−0.001	0.006	0.011	0.038**	0.032†
	(0.004)	(0.004)	(0.006)	(0.007)	(0.017)	(0.018)
BORIS*FreeReturnShipping		0.041		0.034		0.107
		(0.043)		(0.061)		(0.086)
BORIS*AdjSocialMedia		−0.005		0.025		0.038
		(0.017)		(0.025)		(0.049)
BORIS*LnSponsoredSearch		−0.004		−0.036**		0.044
		(0.013)		(0.012)		(0.035)
FirmAge	0.008	0.008	0.004	0.005	−0.024	−0.026
	(0.007)	(0.007)	(0.012)	(0.012)	(0.018)	(0.018)
AdjOmnichannelServices	0.044***	0.043***	−0.005	−0.003	0.094***	0.085***
	(0.009)	(0.009)	(0.012)	(0.011)	(0.023)	(0.023)
AdjCustomerServices	0.008*	0.008*	−0.005	−0.005	−0.014	−0.014
	(0.004)	(0.004)	(0.005)	(0.005)	(0.013)	(0.013)
AdjWebsiteFunctions	−0.002	−0.002	−0.002	−0.002	−0.005	−0.004
	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.007)
AdjPaymentSystems	0.007	0.007	−0.0002	0.0003	0.051**	0.049**
	(0.005)	(0.006)	(0.006)	(0.006)	(0.017)	(0.017)
CategoryHHI	−0.081	−0.083	−0.014	−0.021	−0.295	−0.279
	(0.077)	(0.078)	(0.111)	(0.110)	(0.238)	(0.238)
Gender (Male)	−0.242*	−0.246*	−0.112*	−0.111*	−0.842***	−0.823***
	(0.077)	(0.077)	(0.056)	(0.055)	(0.198)	(0.196)
Customer age categories	Included	Included	Included	Included	Included	Included
Merchant type dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included
Retailer FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,683	4,683	4,698	4,698	4,724	4,724
Within R^2	0.130	0.131	0.020	0.026	0.102	0.103

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$; Robust standard errors are shown in parentheses

Source(s): Authors' own work

Table A2. Regression results: web sales contributors – pure e-retailers ONLY (2013–2019)

Dependent variable	Contributors to web sales *LnConversionRate* (1)	(2)	*LnAverageOrderValue* (3)	(4)	*LnWebsiteTraffic* (5)	(6)
BORIS	−0.100†	0.403	0.047	−0.034	−0.256	−0.720
	(0.054)	(0.302)	(0.080)	(0.164)	(0.157)	(0.689)
FreeReturnShipping	0.049†	0.045	−0.003	0.003	0.169*	0.070*
	(0.028)	(0.029)	(0.027)	(0.029)	(0.079)	(0.083)
AdjSocialMedia	−0.0008	−0.003	−0.002	−0.006	0.135**	0.143**
	(0.013)	(0.012)	(0.017)	(0.016)	(0.050)	(0.051)
LnSponsoredSearch	−0.006	−0.006	0.007	0.007	0.044†	0.044†
	(0.005)	(0.005)	(0.008)	(0.008)	(0.023)	(0.023)
BORIS*FreeReturnShipping		0.033		−0.086		−0.011
		(0.095)		(0.071)		(0.191)
BORIS*AdjSocialMedia		0.048		0.080		−0.173
		(0.050)		(0.063)		(0.124)
BORIS*LnSponsoredSearch		−0.048		0.006		0.049
		(0.027)		(0.016)		(0.059)
FirmAge	0.004	0.005	0.023	0.022	−0.009	−0.009
	(0.017)	(0.016)	(0.029)	(0.029)	(0.043)	(0.043)
AdjOmnichannelServices	0.048**	0.048**	0.060*	0.060*	0.010	0.009
	(0.018)	(0.018)	(0.027)	(0.027)	(0.061)	(0.061)
AdjCustomerServices	0.012†	0.012†	−0.012	−0.013	0.006	0.007
	(0.007)	(0.007)	(0.008)	(0.008)	(0.025)	(0.025)
AdjWebsiteFunctions	−0.0004	−0.0003	−0.0002	0.0001	0.001	0.001
	(0.004)	(0.004)	(0.007)	(0.007)	(0.012)	(0.012)
AdjPaymentSystems	0.002	0.001	0.003	0.002	0.046	0.048
	(0.009)	(0.009)	(0.012)	(0.012)	(0.034)	(0.034)
CategoryHHI	−0.065	−0.057	−0.033	−0.011	−1.170**	−1.210**
	(0.107)	(0.107)	(0.130)	(0.132)	(0.402)	(0.406)
Gender (Male)	−0.390**	−0.390**	−0.094	−0.090	−0.685*	−0.691*
	(0.128)	(0.128)	(0.086)	(0.086)	(0.321)	(0.320)

(*continued*)

Table A2. Continued

Dependent variable	Contributors to web sales *LnConversionRate* (1)	(2)	*LnAverageOrderValue* (3)	(4)	*LnWebsiteTraffic* (5)	(6)
Customer age categories	Included	Included	Included	Included	Included	Included
Merchant type dummies	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Constant	Included	Included	Included	Included	Included	Included
Retailer FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,084	2,084	2,089	2,089	2,107	2,107
Within R^2	0.136	0.139	0.048	0.051	0.130	0.131

Note(s): ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$; Robust standard errors are shown in parentheses

Source(s): Authors' own work

Notes

1. https://www.nordstrom.com/browse/customer-service/return-policy
2. https://www.cnn.com/2023/12/26/business/returns-shopping-gifts-charge/index.html
3. https://www.statista.com/topics/4312/search-advertising/
4. https://www.zara.com/us/en/help-center/HowToReturn
5. https://www.abercrombie.com/shop/us/help/online-return-exchange-policy
6. http://bestbuy.com/site/help-topics/return-exchange-policy/pcmcat260800050014.c?id=pcmcat260800050014
7. https://www.deloitte.com/content/dam/assets-zone3/us/en/docs/industries/consumer/2024/deloitte-omnichannel-competitive-landscape-services-returns-study.pdf
8. https://www.forbes.com/sites/shelleykohan/2022/10/30/consumers-say-hassle-free-returns-are-more-important-than-ever/
9. https://www.digitalcommerce360.com/2024/09/11/returns-consumer-survey-2024/?utm_source=chatgpt.com
10. https://thekrazycouponlady.com/tips/store-hacks/free-return-shipping
11. https://www.businesswire.com/news/home/20240115115468/en/Returns-Pose-a-Significant-Challenge-for-U.S.-Retailers-According-to-Recent-Blue-Yonder-Survey
12. https://www.kohls.com/faq/article/893
13. https://customerservice-macys.com/articles/what-is-macys-return-policy
14. https://www.jcrew.com/help/returns-exchanges
15. https://www2.hm.com/en_us/customer-service/returns.html
16. http://www.digitalcommerce360.com
17. https://www.trustpilot.com/reviews/6449665fa2c0161bc89b3622
18. https://www.trustpilot.com/reviews/68ee9970f486a72e8d3534c4
19. https://www.youtube.com/watch?v=r_pkAzH2wTk

Supplementary material

The supplementary material for this article can be found online.

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