Acquiring customers through online marketplaces? The effect of marketplace sales on sales in a retailer's own channels

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Abstract

Online retailers are increasingly using third-party online marketplaces (e.g., Amazon, Taobao) as an alternative sales channel to their website. While cross-channel sales elasticities have been established for many sales channel combinations (e.g., adding bricks to clicks), we lack an understanding of whether the use of third-party marketplaces grows or cannibalizes a retailer's sales. Practitioners argue that firms can build their e-commerce business through acquiring customers by selling on the marketplace. Indeed, a marketplace could complement a retailer's offering (e.g., acquiring new customer segments), although inventory effects might mitigate this complementarity. Alternatively, cannibalization might occur from losing customers from one's website to the online marketplace. The present research investigates which of the two opposing forces prevails using a time series of category sales data from one of the largest global marketplace sellers. The authors use vector autoregressive modeling to show that marketplace sales increase sales on a retailer's website (0.014% for every 1% in marketplace sales). This effect is strongest for categories with large choice and low product prices. Acquiring customers through the marketplace might be cheaper than through other sources (estimated at 24% of initial sales). However, online retailers should be aware that this strategy strengthens the marketplace and may have potential negative long-term consequences (e.g., through marketplace control of the customer relationship).

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1. Introduction

Many retail managers are currently considering selling their assortment on third-party online marketplaces, such as Amazon (marketplace sales volume $160 billion; Amazon, 2019) or Taobao ($428 billion; Alibaba Group, 2019), that provide an open platform also to retailers (Reinartz et al., 2019; Zhang et al., 2019). As a result, retailer sales on marketplaces have been growing substantially in recent years (Standing et al., 2010; Wang et al., 2013). Practitioners, however, disagree as to whether selling on the marketplace is a good decision. Some recommend selling on a marketplace “to build an e-commerce brand” (Masiello, 2017) through acquiring new customer segments on the marketplace (Danziger, 2018), as the latter is often the first step in customers’ purchase journeys (EMarketer, 2020). In contrast, other practitioners advise focusing on one’s own website rather than on the marketplace (Kumar, 2018) because, for instance, existing customers might defect to the marketplace. We contribute to this debate by investigating how selling on a marketplace affects a retailer’s own webshop.

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A core motivation for retailers to sell on a marketplace is the hope for efficient customer acquisition, which can help optimize their channel system’s performance (Kannan et al., 2016; Verhoef et al., 2015). The total net sales effect across channels of selling on the marketplace is difficult to predict, however, as channels are endogenously related (Avery et al., 2012; Pauwels & Neslin, 2015), and activity in one channel (i.e., marketplace sales) is, consequently, likely to affect the other channels (i.e., a retailer’s own online shop).

On the one hand, selling on the marketplace might help retailers acquire new customers for their websites. As the marketplace addresses different and wider customer segments than the retailer, new customers might encounter a retailer’s brand for the first time (e.g., through a retailer brand logo on the product page or a branded product packaging; touchpoint effect: Baxendale et al., 2015; Neslin et al., 2006). These customers might then have an incentive to switch from the marketplace to the retailer’s own online shop—for instance, because they might be able to find a larger product selection on the retailer’s website (vs. the department-store-like marketplace; Reinartz et al., 2019), search the assortment more easily, or expect lower prices (e.g., no marketplace commission is due). This complementarity between the own webshop and the marketplace likely is category specific, depending on the retailer’s assortment (e.g., a limited choice in the webshop), or budgetary (e.g., as a result of high product prices; Ansari et al., 2008; Kim & Park, 1997). On the other hand, activity on the marketplace might cannibalize sales on a retailer’s website, as customers might migrate from the website to the marketplace (e.g., to take advantage of the convenience of an existing registration, to check for lower prices, to profit from the many reviews on the marketplace).

Understanding these interactions across channels is analytically difficult for retailers and marketplace operators for several reasons. First, because the marketplace is a third party, neither the retailer nor the marketplace operator has access to individual customer journey data across the two channels. The present analysis, therefore, uses time series of daily transaction data from an online retailer, which is also one of the largest sellers on an international marketplace, though still rather small in its main market, to assess the marketplace sales effect. Second, the causal relationship between sales in both channels is difficult to establish and potentially obscured by unobserved variables. Therefore, we apply a vector autoregressive model (VAR) with endogeneity control through a rich data approach. Third, the cross-channel effects might differ by category, so we use a panel VAR model to investigate the degree of complementarity for product categories that differ in the strength of the suggested effects.

This research offers relevant insights for retailers, marketplace operators, and researchers, answering calls for research on the retailer–marketplace interaction (Reinartz et al., 2019; Standing et al., 2010). Our findings offer an initial assessment of the effect that selling on a marketplace has on the sales of a retailer’s own online shop. Investigating this cross-channel sales effect is substantively relevant (Neslin & Shankar, 2009), considering that, in the United States, for instance, marketplace sales on Amazon alone constitute almost 25% of total online sales in 2019 (EMarketer, 2018).

On the one hand, we find that brand building on the marketplace works: marketplace sales increase sales in the retailer’s own channel (0.014% for every 1% marketplace sales). Further, it may be cheaper for a retailer to acquire new customers through the marketplace than through traditional acquisition channels; we calculate this cost to be 24% of the generated revenue (an estimated 6 percentage points cheaper than the traditional way). This complementarity of marketplace sales, however, is category specific, such that it depends on the retailer’s assortment characteristics by category (through inventory effects). Thus, we show that channel relationships depend on not only the functional capabilities of the channels as a whole (Avery et al., 2012) but also category-specific assortment characteristics. On the other hand, we also find cannibalizing effects, showing that customers migrate from the website to the marketplace, although the benefits of selling on the marketplace exceed its downsides.

For marketplace operators, our findings imply that although they might lose some customers to specialized retailers active on the marketplace, they also acquire additional sales from these retailers’ customers through the latter’s marketplace presence. Retailers, in contrast, might acquire additional customers through the marketplace, but may be faced with losing the customer relationship to the marketplace in the long run.

2. Literature and theory

Electronic marketplaces are multisided platforms (Evans & Schmalensee, 2016; Parker et al., 2016) that “allow the participating buyers and sellers in some markets to exchange information about prices and product offerings” (Bakos, 1997, p. 1676). As such, marketplaces (e.g., Amazon, Taobao) involve three stakeholders: sellers and buyers as the parties between which the exchange happens, and the operators of the marketplace as a third party (Yul Lee et al., 2013). In contrast to traditional retail models, which specialize in procuring the best products from suppliers and offering them to potential customers, marketplaces leave the interaction of supply and demand unmanaged; they simply provide a platform and do not manage the marketing mix on it (Parker et al., 2016; Rangaswamy et al., 2020; Wirtz et al., 2019). Consequently, a retailer selling on the marketplace can freely decide when, what, and how much to offer, for instance, depending on its own website sales, which causes an endogenous relationship between a retailer’s marketplace and own webshop performance, and vice versa. Note that when we speak about “online marketplaces”, we refer to what is often also called “platforms” (Reinartz et al., 2019; Zhang et al., 2019).

Selling on a third-party marketplace differs systematically from established retail channel configurations. Traditionally, offline retailers were the interface between producers and customers (Fig. 1, Panel A): success factors such as “location, location, location” (Jones & Simmons, 1987, p. 1) drove sales, and retailers functioned as gatekeepers to the consumer. With the advent of online retailing (Panel B), substantial online marketing became necessary for customer acquisition, with search engines increasingly functioning as gatekeepers between the retailer (and direct sales websites of producers) and the customer. In addition, brick-and-mortar stores have become increasingly dependent on search engines, for instance, through proximity search on digital maps (e.g., Google Maps, Baidu Maps) or as consumers search for opening hours online prior to visiting a store. Consequently, the cost of customer acquisition through online marketing has risen substantially (Dennis, 2017; Gupta et al., 2004; e.g., costs per click increased...
with 30% per annum to more than $2; Hochman, 2017). Customer acquisition through the marketplace (Panel C) might be an alternative to winning customers via search engines or other forms of digital marketing.

Three streams of extant research are informative about the effect of selling on marketplaces on a retailer’s own sales channels. First, research on cross-channel sales effects assesses the effects of new channels on a retailer’s established sales channels (see Table 1). Research initially focused on the effect of adding online channels to traditional brick-and-mortar stores (e.g., Pauwels et al., 2011; Van Nierop et al., 2011) or catalogs (e.g., Ansari et al., 2008). More recent studies have investigated the effect of adding brick-and-mortar stores to an e-commerce channel (e.g., Pauwels & Neslin, 2015; Wang & Goldfarb, 2017) and the effect of mobile sales (e.g., Huang et al., 2016; Wang et al., 2015).

However, selling on the marketplace is a unique context, and knowledge from existing studies on cross-channel relationships cannot be transferred to the effect of marketplaces for several reasons. First, marketplaces are usually a second online channel and not an online channel addition to a brick-and-mortar sales network (as in, e.g., Pauwels et al., 2011). For instance, the ten currently most active global sellers on Amazon all operate their own online stores (Marketplace Pulse, 2020). This difference is nontrivial, because the benefits extant research has established for a channel are usually associated with a given channel type (i.e., online vs. offline, e.g., in terms of permanent availability; Avery et al., 2012) and not with differences within one channel type (here: online). Second, compared with previous channel analyses, the causal relationship between the channels is fundamentally different, as the marketplace is an independent third party. For instance, the retailer has less control over the marketplace channel, as competition can change prices or pay the marketplace to rank higher with a certain product (e.g., through sponsored products). Thus, the effect of marketplaces as an additional channel might differ from the effects established in extant cross-channel research. Third, analytically, retailers do not have access to the marketplace’s customer data. For instance, the Amazon marketplace prohibits sellers from integrating sales information from its marketplace (e.g., customer name and address) into their customer database, which means that researchers cannot obtain individual customers’ data across the channels, which are commonly used to assess cross-channel elasticities (e.g., Huang et al., 2016). Our analysis, therefore, relies on aggregate sales information.

Table 1

<table>
<thead>
<tr>
<th>Article</th>
<th>Cross channel sales effects</th>
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<tbody>
<tr>
<td>Driven by channel</td>
<td>Online</td>
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<tr>
<td>Ansari et al., 2008</td>
<td>✓</td>
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<td>Gensler et al., 2007</td>
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<td>Dholakia et al., 2005</td>
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<td>Pauwels et al., 2011</td>
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<td>Avery et al., 2012</td>
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<td>Pauwels &amp; Neslin, 2015</td>
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<td>Wang &amp; Goldfarb, 2017</td>
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<td>Grewal et al., 2018</td>
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<td>Wang et al., 2015</td>
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The second literature stream that could be informative about the effect of selling on marketplaces on a retailer’s own sales channels consists of research on retailers’ marketplace activities, which to date has focused on a retailer’s decision to develop a marketplace (vs. a pure wholesale model, e.g., Hagiu & Wright, 2015; Young et al., 2017). In contrast, the effect of marketplace sales across different sales channels has not yet been investigated. While cross-channel sales effects of marketplace activity for nonretail service providers have been assessed (e.g., movie producers: Gong et al., 2015; restaurants: Zhang et al., 2019), these studies only apply to contexts in which the service providers add the marketplace to a previous single-channel offline business (e.g., a restaurant) and also continues to serve customers out of this channel. Consequently, literature reviews on marketplaces have called for investigations of marketplace trading (Standing et al., 2010).

The third literature stream that could shed light on how selling on marketplaces can affect retailers’ own sales pertains to research on the activity of branded manufacturers (e.g., Levi Strauss, Michael Kors). However, it does not inform the present context because brands can distribute their products through the channels of retailers (e-commerce or brick-and-mortar), or utilize channels that they more directly control, such as brand stores, their own websites or a branded store on a marketplace (Gielens & Steenkamp, 2019). Besides a general evaluation of strengths and weaknesses of the different channels (Steenkamp, 2020), extant research does not, to the best of our knowledge, explore the effect of marketplace activity of brands on other channels. Instead, research focuses on the decision to offer products on the marketplace (e.g., in the presence of counterfeit products; Sun, Zhang, & Zhu, 2019). Furthermore, studies of the marketplace sales effect for branded manufacturers are difficult to compare with our context, because the motivation for channel selection is likely very different for brands and retailers (e.g., marketplaces are just one of many outlets brands can use). In summary, retailers selling on the marketplace is a unique context, and extant research does not yet provide information on its effect.

2.1. Overall effect of marketplace sales

Research distinguishes between segment- and task-specific capabilities of a channel (Fürst et al., 2017). We suggest that (1) the marketplace complements a retailer’s other channels as it might bring new customer segments in touch with the retailer brand. However, (2) task-specific complementarity, that is, a reason for consumers to switch from marketplace to the retailer in their purchase task, is necessary for a retailer to profit from the segment-specific brand effect. The same task-specific reasons, however, might also cause a reverse effect and a (3) cannibalization of a retailer’s sales.

2.1.1. Segment-specific brand effect

New customer acquisition is likely to arise because the marketplace and a retailer’s own channel target different segments (Coelho et al., 2003). Specifically, the marketplace might help retailers build their brand with customers that use this channel. Many marketplaces (e.g., Amazon, Taobao, eBay) have high brand awareness and loyal customers (e.g., through Amazon Prime), far exceeding the brand awareness of many retailers. Marketplaces are, therefore, the default choice for many consumers (e.g., 89% of U.S. consumers visit Amazon at least once a month [Feedvisor, 2019]). For these customers, seeing or buying from a specific third-party retailer brand on the marketplace might induce brand consideration (touchpoint effect; Baxendale et al., 2015).

This segment-specific brand effect, however, requires that customers actually come in contact with the retailer brand on the marketplace. Prior to purchase, specific information on the marketplace’s product website might introduce the retailer brand to new customers. For instance, marketplaces allow their sellers to display a brand name or logo next to the presented product. Additionally, Amazon’s marketplace allows (branded) merchants to position themselves as sponsored brands. After a consumer purchases from a retailer on the marketplace, a retailer’s post purchase brand activity could cause a brand effect. For instance, the package of the marketplace order or information accompanying the product (e.g., a branded bill, a flyer) could carry the retailer’s branding. In line with this reasoning, many practitioner guides recommend “using Amazon to build an ecommerce brand” (Masiello, 2017; for similar arguments, see Danziger, 2018; Patel, 2019). This brand awareness itself, however, is insufficient if customers see no benefit of switching from marketplace to the retailer.

2.1.2. Task-specific complementarity

Customers will only migrate between channels if one channel’s purchase task–specific capabilities exceed that of another (Ansari et al., 2008). The assortment of the retailer website (vs. the marketplace) might appear complementary to consumers in three aspects: choice, search convenience, and expected price.

First, assortment choice might be larger on a retailer’s website (e.g., the retailer might offer a larger assortment in a specific category), and customers generally appreciate a larger choice (Betancourt et al., 2016). Typically, marketplace choice is extensive but not specialized (i.e., like a department store; Reinartz et al., 2019); in contrast, retailers that sell on the marketplace are often specialized on a set of product categories and, consequently, might offer more products in that category on their websites. A small field study among a convenience sample of retailers active on a global marketplace (n = 11; one in each of the major product categories, e.g., fashion) reveals that retailers on average only present 45% of their products on the marketplace (median = 20%; see Web Appendix 1). Retailers could have multiple motivations for limiting their offering on the marketplace, such as the aim to save marketplace fees, the strategy to offer premium products exclusively on their own website, or the difficulty of presenting the whole assortment attractively on the marketplace. In line with this, senior management from the retailer with which we cooperated informed us that they offered fewer products on the marketplace than on their own website (in our small field study, only ~5% of products are sold on the marketplace).
Second, a retailer’s website is often more convenient to search than the offering on the marketplace. Marketplace operators often restrict the functions with which a seller’s product assortment can be presented and searched (Li et al., 2019), unless explicitly paid for. For example, on the Amazon marketplace, the assortment of a marketplace merchant (i.e., a retailer or a manufacturer) cannot be searched in a structured way (e.g., no differentiation by product category). Moreover, the merchant’s marketplace page cannot be directly accessed (e.g., through a search of the merchant name). The marketplace operator might purposely introduce these search frictions, because it prefers to sell products on its own (Ngwe et al., 2019) and does not want to compete with secondary retail brands on its own marketplace. These search frictions might make it more convenient for consumers to switch to the retailer’s website for a detailed search, rather than staying on the marketplace.

Third, customers might expect lower prices on a retailer’s website because of marketplace metacognition (Wright, 2002); that is, customers are increasingly aware of high marketplace fees and might expect that retailers can make a better offer on their own website.

In summary, we suggest that assortment differences enable task-specific complementarity between the channels. This makes channel migration plausible for new segments of customers who had not been in contact with the retailer before encountering the latter’s brand on the marketplace. If a new customer on the marketplace has actually purchased from the retailer, we expect the retailer’s brand-building effect to be strongest, inducing a switch to the retailer’s website for at least some customers (e.g., those highly satisfied or with a repurchase need). We, thus, hypothesize a positive effect of marketplace sales (see Fig. 2):

**H1.** Higher retailer sales on a marketplace increase sales on the retailer’s own website.

### 2.1.3. Task-specific cannibalization

However, this complementarity effect might also reverse due to the high brand awareness of the marketplace. Most customers are already registered on the marketplace (e.g., ~50% of the population in both the United States [Amazon: CIRP, 2020] and China [Alibaba’s Taobao: Alibaba Group, 2019]). After visiting a retailer’s website, a customer might switch to the marketplace as their default place of purchase to reduce risk or compare prices (Gensler et al., 2012), as large marketplaces often function as baseline comparison (EMarketer, 2020). If a retailer also offers products on the marketplace, consumers might perceive greater convenience in purchasing the products on the marketplace website where they are already registered, especially for routine purchases (Reinartz et al., 2019). Further, global marketplace are likely to offer a higher volume of user-generated content, such as reviews, compared with individual retailers (Liu et al., 2019), which might be another reason to switch from retailer to the marketplace.

Visitors to the retailer’s website might, thus, also be lost to the marketplace rather than buying directly on the retailer’s website. We expect that a portion of the lost visitors will purchase from the same retailer on the marketplace, as long as products and prices are consistent. In this, the retailer’s website functions as an acquisition channel for the retailer’s offering on the marketplace, where the final purchase might happen. Formally:

**H2.** More visits on a retailer’s website increase that retailer’s sales on the marketplace.

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Fig. 2. Conceptual model (all possible paths empirically modeled).
Even after a purchase on a retailer’s website, customers might be lost to the marketplace for the reasons described previously: loyalty to a retailer is low in e-commerce (Ansari et al., 2008), and customers might simply purchase the same product from the most convenient or safest channel (Gensler et al., 2012) – which might be the marketplace if a similar product is available. Formally:

**H3.** Higher sales on a retailer’s website increase that retailer’s sales on the marketplace.

Note that we do not hypothesize effects of or on total visits to the marketplace (i.e., to the marketplace as a whole, not the retailer’s product pages on the latter). Given the enormous scope of global marketplaces, the high volume of visits they attract is likely unrelated to the activity on individual retailers’ websites (see dotted arrows in Fig. 2).

### 2.2. Assortment characteristics as moderator of the marketplace sales effect

Thus far, we have argued that complementarity of a retailer’s website relative to the marketplace relies on assortment differences (choice, search convenience, and expected price). In this context, inventory effects might mitigate the complementarity between the channels (Ansari et al., 2008), as customers can only buy one or few units in a particular time period. These inventory effects can reduce the positive sales effect of the marketplace, depending on the retailer’s assortment characteristics. Consumer inventory effects have two drivers: consumers’ stock levels and budgetary restrictions. Stock-level inventory effects relate to the number of products consumers require from a given category (e.g., one mobile phone per person, two cans of beans). Budgetary restrictions relate to consumers’ limited financial resources (e.g., budget covers either a new mobile phone or a new TV set).

#### 2.2.1. Stock-level inventory effects

Consumers hold a stock of certain products, which affects their future purchases (Jeuland et al., 1980; Kim & Park, 1997). For instance, discounts increase sales during the discount period but reduce them in subsequent periods due to inventory effects (Van Heerde et al., 2000). Applied to multi-channel purchase situations, if consumers purchase a product in one channel (e.g., the marketplace), they are unlikely to purchase it in another (e.g., the retailer’s own webshop): a substitution occurs (Weltevreden, 2007). This might reduce assortment-based complementarity.

We expect that the assortment-based complementarity between the marketplace and a retailer’s webshop will be mitigated when fewer alternative product choices are available within a category in the retailer’s webshop. If only two choices are available in a category on the retailer’s website (e.g., two smartwatches), it is unlikely that a customer will migrate to the retailer in that category, thereby eliminating any positive segment-specific effect. In contrast, when more options are available, it is more likely that the additional offering of the retailer in that category is complementary to the marketplace, inducing repurchases with the retailer. For instance, a marketplace sale of a book could induce a customer to visit the retailer’s website, where she finds an extensive selection of other books from her favorite author. We, therefore, distinguish between categories with low product choice on the retailer’s website, for which complementarity between the channels is likely to be limited, and categories with a large assortment, which enable complementarity.

#### 2.2.2. Budgetary inventory effects

Budgetary restrictions are the second driver that can mitigate complementarity between marketplace and retailer. They occur because consumers have only a certain share of wallet available for consumption at a given time, which reduces repurchase probability after an initial purchase (Besanko et al., 2003; Kim & Park, 1997). The more expensive a purchase, the more strongly budgetary constraints affect subsequent purchases. For example, if a customer buys a single book, she is likely to have sufficient budget remaining for potential repurchases. In contrast, the purchase of an expensive new laptop makes subsequent budget constraints likely. Therefore, we expect that complementarity between the channels cannot arise if the initial purchase is too costly.

The mitigating effects of the two drivers of inventory effects on the complementarity between the marketplace and a retailer’s own online store are summarized in the conceptual framework in Fig. 3. Complementarity between the marketplace and a retailer’s webshop is limited in categories for which product choice on the retailer’s website is small and prices are high (quadrant 1; e.g., expensive smartwatches). In contrast, categories that offer a large product choice and a low average product price are likely to profit from complementarity (quadrant 3; e.g., books). Intermediate cases are categories in which products are not very expensive but the retailer offers a limited number of product choices (quadrant 2; e.g., over-ear headphones); or categories in which the retailer has an extensive offering but high average prices (quadrant 4; e.g., mobile phones). We formally hypothesize the following:

**H4.** The positive effect that sales on a marketplace have on a retailer’s website sales is mitigated in categories with (a) fewer product choices and (b) more costly products on the retailer’s website.

As H4 relates to the assortment-based capabilities of the webshop (vs. the marketplace), we refrain from explicitly adding a hypothesis on the reverse effect. The latter is based on convenience, risk, and price comparison and, thus, should not vary that strongly by category.
3. Methodology

We model the relationships between the marketplace and the retailer’s webshop through two vector autoregressive (VAR) models. We apply VAR models because such models are specifically suited for modeling the dynamic interplay between endogenously related variables (Pauwels, 2017) and, thus, are common for assessing channel relationships (Bang et al., 2013; Pauwels et al., 2011). Further, as customer-level data are not available for transactions on the marketplace (as mentioned previously, the marketplace is a third party and does not release customer information to its sellers), we cannot resort to customer- or segment-specific approaches to investigate cross-channel effects (e.g., latent class segmentation; Pauwels et al., 2011). This context necessitates methods that work well with aggregate data, such as VAR. Moreover, the complex dynamic nature of the interrelationships depicted in Fig. 2 requires the flexibility of VAR models, which allow us to identify dynamic marketing phenomena (Pauwels, 2017), such as the complimentary or cannibalizing effects between two channels. We conduct our analyses in two steps, as outlined in the following subsections.

3.1. Step 1: overall effect

First, we assessed the overall effect of sales on the marketplace (H1), computing a VAR model controlling for exogenous influences (VARX). In our case, the marketplace sales of the retailer on day t (MP_SALE_t) and the overall visits to the marketplace (MP_VISIT_t, acquired from Amazon Alexa.com, an online tool to assess the performance of third-party websites, as the retailer does not receive actual visit data from the marketplace), the retailer’s own website visits (WS_VISIT_t), and own website sales (WS_SALE_t) on day t should be endogenously related.

Although VAR models focus on modeling endogenous relationships, a potential endogeneity bias is still a concern (Papies et al., 2017). In Table 2 we present potential sources of endogeneity. First, demand may slow down, which might lead retail management to reduce the offering on the marketplace (e.g., offering fewer products on the marketplace in a contracting market, as fees must still be paid even though marketplace conditions are less favorable). Similarly, second, supply shocks might make offering on the marketplace more attractive (e.g., more supply to be distributed) or less so (e.g., less supply, such that retailers must pick the most profitable channel). Third, competitive actions (e.g., a price adjustment on their website, increasing demand) through countermeasures (e.g., also adjusting pricing) or through adjusting the offering on the marketplace, leading to an increase in the offering on the marketplace. If the supply on the marketplace is endogenously affected by any of these factors, the relationship between marketplace and webshop sales would be biased. Following Germann, Ebbes, & Grewal...

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**Table 2**

<table>
<thead>
<tr>
<th>Source</th>
<th>Theoretical explanation</th>
<th>Exogenous control variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand shock</td>
<td>As demand goes down, management reduces offering on marketplace, because sales can be made on own website</td>
<td>Google Trend Demand for relevant categories (TREND_DEMAND_t) – see Web Appendix 2 for details.</td>
</tr>
<tr>
<td>Supply shock</td>
<td>As supply of products changes, management adjusts offering on marketplace</td>
<td>Google Trend Supply for relevant categories (TREND_SUPPLY_t) – see Web Appendix 2 for details.</td>
</tr>
<tr>
<td>Competitive action</td>
<td>Management reacts to competitive action (e.g., a price adjustment on their website, increasing demand) through countermeasures (e.g., also adjusting pricing) or through adjusting the offering on the marketplace</td>
<td>Competitor website visits (COMP_VISIT_t)</td>
</tr>
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Fig. 3. Conceptual framework on inventory effects within categories (H4).
(2015), we address this issue through a rich data approach that includes exogenous controls for the unobserved variables (see Table 2). As we explain in Web Appendix 3, the rich data approach is preferable over an instrumental variable approach because it does not violate the exclusion restriction (Papies et al., 2017). In this case, including exogenous control variables is preferable to instruments (Rossi, 2014). The rich data approach is in line with the treatment of exogenous events in extant research on cross-channel elasticities (Bang et al., 2013; Pauwels & Neslin, 2015). As a robustness test, we used control function and Gaussian copula as alternative approaches (see Web Appendix 3). These robustness checks are consistent.

In addition to these endogeneity-related control variables, we included other exogenous variables common in research of cross-channel sales effects (Bang et al., 2013; Pauwels & Neslin, 2015): a monthly time trend increasing by one for each month in the data set (TREND), a dummy for the Christmas period (CHRISTM; for the last eight weeks of the year), six day-of-the-week dummies (\(\sum_{i=1}^{6} DAY_{i,t}\)), and the company’s paid marketing visitors (MARK) as a proxy for advertising activity. In addition, we controlled for the share of marketplace sales in total sales (MP\_SHARE), because the latter changed over time (from ~14% to 10%) and might influence the effect of marketplace sales in a given period (e.g., high marketplace sales relative to website sales would exacerbate the effect of a marketplace sales).

This results in an unrestricted VARX model of order \(P\), where \(\mu\) is a \((4 \times 1)\) vector of intercepts, \(\Phi^p\) a \((4 \times 4)\) matrix of coefficients for the endogenous variables in period \(t - p\), \(\Psi\) a \((4 \times 3)\) matrix containing the coefficients for the endogeneity controls, \(\Theta\) a \((4 \times 10)\) matrix with coefficients for the other exogenous control variables, and \(\epsilon_t\) a \((4 \times 1)\) vector of error terms (Eq. (1)).

\[
\begin{bmatrix}
WS\_VISIT_t \\
WS\_SALE_t \\
MP\_VISIT_t \\
MP\_SALE_t
\end{bmatrix} =
\begin{bmatrix}
\mu + \sum_{p=1}^{P} \Phi^p \times \\
\Psi \times \\
\Theta \times
\end{bmatrix}
\begin{bmatrix}
Y_{t-p} \\
TREND\_SUPPLY_{t-p} \\
COMP\_VISIT_{t-p} \\
MARK_{t-p}
\end{bmatrix}
+ \epsilon_t
\]

3.2. Step 2: within-category moderation of the effect

Second, we investigate whether complementarity of marketplace and website sales depends on the assortment characteristics of the product category (H4) through a series of panel vector autoregressive models (PVAR; Holtz-Eakin et al., 1988). Although such models have not been applied to research on cross-channel sales effects, they are appropriate for modeling effect differences between different groups (e.g., of subjects: Sismeiro et al., 2012). Furthermore, a panel model controls for heterogeneity between the product categories and, therefore, should be less susceptible to a potential aggregation bias (Horváth et al., 2005; Horváth & Wieringa, 2008). Similar to Srinivasan et al. (2004), we specify separate PVAR sub-models for each of the four category groups that we identified in Fig. 3. Each of the category groups contains a number of categories, indicated by \(n\), which varies over the groups. Within each category group, we define for category \(i\), \((i = 1, ..., n)\),

\[
Y_{i,t} = \begin{bmatrix}
WS\_SALE_{i,t} \\
MP\_SALE_{i,t}
\end{bmatrix}
\]

where, in line with the overall VARX model, the elements of \(Y_{i}\) are website sales for category \(i\) in period \(t\) and marketplace sales for category \(i\) in period \(t\), respectively. Note that the retailer did not record category-specific visits; thus, we do not include them in the model. We include supply and demand variables as category-specific endogeneity controls:

\[
C_{i,t} = \begin{bmatrix}
TREND\_DEMAND_i \\
TREND\_SUPPLY_i
\end{bmatrix}
\]

The elements of \(C_{i}\) are Google trend demand and Google trend supply for category \(i\) in period \(t\) (see Web Appendix 2 for details). The time-related exogenous control variables are the same across categories, while the marketplace share varies by category:

\[
X_{i,t} = \begin{bmatrix}
DAY_{i,t} \\
DAY_{i,t} \\
TREND_{i,t} \\
CHRISTM_{i,t} \\
MP\_SHARE_{i,t}
\end{bmatrix}
\]

Using this notation, we write the unrestricted PVAR extension of the earlier VARX model for each category group as

\[
\begin{bmatrix}
Y_{1,t} \\
Y_{2,t} \\
\vdots \\
Y_{n,t}
\end{bmatrix} =
\begin{bmatrix}
\mu_1 \\
\mu_2 \\
\vdots \\
\mu_n
\end{bmatrix} + \sum_{p=1}^{P} [\epsilon_{t-p} \Phi^p] 
+ \begin{bmatrix}
Y_{1,t-p} \\
Y_{2,t-p} \\
\vdots \\
Y_{n,t-p}
\end{bmatrix} + [\epsilon_{t-p} \Psi] \times 
\begin{bmatrix}
C_{1,1} \\
C_{2,1} \\
\vdots \\
C_{n,1}
\end{bmatrix} + [\epsilon_{t-p} \Theta] \times 
\begin{bmatrix}
X_{1,1} \\
X_{2,1} \\
\vdots \\
X_{n,1}
\end{bmatrix} + \begin{bmatrix}
\epsilon_{1,t} \\
\epsilon_{2,t} \\
\vdots \\
\epsilon_{n,t}
\end{bmatrix}
\]
where the intercepts and the error terms are now category specific, as indicated by the indices 1, ..., n, with n, the number of categories, varying for each of the category groups.

4. Data description

We obtained data from an international retailer of refurbished electronics and used media. The company operates its own webshop and is present on a large global marketplace. It offers products in 16 categories, consisting of various media (e.g., books, DVDs, CDs) and electronics (e.g., mobile phones, cameras, tablet computers). The data set includes aggregated daily sales data from each of the categories on both the retailer’s website and the retailer’s offering on marketplace, as well as visits to the retailer’s website in the company’s largest country of activity. The products sold by the retailer on the marketplace are also available from other sellers on the marketplace and can also be legally sold there (i.e., there are no grey market or manufacturer restrictions; see Web Appendix 2). Although the company is one of the top sellers on the marketplace, the company itself is rather small in its main market of activity (10%-15% of the largest competitor in its main category; <0.2% of e-commerce sales in the main market) and the brand is not generally known – thus, the goal to build the e-commerce brand through the marketplace can be realistically analyzed with the present data. Note that no customer-level data are available for sales on the marketplace because the marketplace operator does not share these data with its sellers and also prohibits an integration of sales information (e.g., based on shipping address) into the retailer’s customer relationship management.

The data cover a period of 95 weeks from January 2017 to October 2018.1 To conceal the actual data, the retailer applied a multiplier to all time series, and therefore, we refer to the currency as monetary units (MUs). The company’s year-to-year revenue growth was on average 17% during the period of analysis. Fig. 4 provides an overview of the development of the four endogenous variables (data aggregated to a weekly level and indexed to the first week). While website visits and sales are trending upward, overall marketplace visits and the retailer’s marketplace sales are more stable. All time series show a strong seasonality effect around Christmas. The retailer’s marketplace sales substantially drop around week 65 of the data set because the retailer briefly reduced its offering on the marketplace.

All endogenous and exogenous variables in the model on the overall effects (Step 1) are summarized in Table 3, while Table 4 reports the correlation coefficients. Despite the fact that some correlations exceed 0.7, our results are not affected by multicollinearity issues (i.e., only two of 60 possible variance inflation factors reach a level of ~6.5). The panel VARX model (Step 2) employs website and marketplace sales for the 16 categories and includes endogeneity controls, a control variable for a category’s marketplace share, and controls for time dummies.

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1 This time period is in line with other investigations of cross-channel sales effects (Van Nierop et al. (2011): 47 weeks; Bang et al. (2013): 52 weeks; Pauwels et al. (2011): 67 weeks; Pauwels and Neslin (2015): 128 weeks).
We estimated the VAR model using Stata’s VAR package. We next computed a pairwise Granger causality test (Wald test) with the previously selected lag length of two, as recommended by the Akaike information criterion (AIC). However, we also see a reverse effect of a cannibalization of sales on the retailer’s website: the retailer’s marketplace sales are Granger caused by website sales, which is why the coefficient on website sales is negative (Wald test, χ² = 11.61, p < .01). We log-transformed all endogenous variables, which has general (e.g., controlling for outliers) and VAR-specific advantages, because doing so allows us to directly interpret the points of the impulse response functions (IRFs) as elasticities (Nijs et al., 2001). This facilitates a comparison of the effect sizes, which is specifically relevant in a VAR context because the change in the variable for which an elasticity is to be estimated is endogenous to the model (i.e., influenced by the shock) and, therefore, cannot be easily quantified. Extant research, therefore, suggests estimating the VAR model based on log-transformed endogenous variables, interpreting the IRF coefficients as elasticities (Wieringa & Horváth, 2005), as widely applied (e.g., Pauwels et al., 2016).

5. Results

5.1. Step 1: results of the overall effect

We first assessed the stationarity of the variables and found that all are individually stationary (augmented Dickey-Fuller method: all ps < .001; Phillips-Perron test: all ps < .001) and trend stationary (Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test: null hypothesis not rejected for all variables, even at the 10% level). We selected the optimal lag length of one based on Schwarz’s Bayesian information criterion (SBIC) and confirmed it using the Hannan–Quinn information criterion (HQIC), in line with extant research (Bang et al., 2013; Pauwels & Neslin, 2015).2 These model specifications imply an observation-to-parameter ratio of 35.2, well above the critical threshold of 5 (Lee et al., 2015). We log-transformed all endogenous variables, which has general (e.g., controlling for outliers) and VAR-specific advantages, because doing so allows us to directly interpret the points of the impulse response functions (IRFs) as elasticities (Nijs et al., 2001). This facilitates a comparison of the effect sizes, which is specifically relevant in a VAR context because the change in the variable for which an elasticity is to be estimated is endogenous to the model (i.e., influenced by the shock) and, therefore, cannot be easily quantified. Extant research, therefore, suggests estimating the VAR model based on log-transformed endogenous variables, interpreting the IRF coefficients as elasticities (Wieringa & Horváth, 2005), as widely applied (e.g., Pauwels et al., 2016).

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We estimated the VAR model using Stata’s VAR package. We next computed a pairwise Granger causality test (Wald test) with the previously selected lag length of two, to determine which variables are endogenously related. Table 5 summarizes the results of a Granger causality test (Wald test), confirming the hypothesized endogenous relationships: website sales (χ² = 11.61, p < .01) and website visits (χ² = 3.22, p = .07) are Granger-caused by marketplace sales. This points toward purchase-task-specific complementarity between marketplace and website, bringing the customers from the marketplace to the retailer’s website.

However, we also see a reverse effect of a cannibalization of sales on the retailer’s website: the retailer’s marketplace sales are Granger caused by website sales (χ² = 5.57, p < .05) and website visits (χ² = 5.96, p < .05). These paths highlight that there are also reasons for consumers to switch from the retailer to the marketplace (e.g., convenience, price comparison, more certainty from higher volume of reviews). Although website visits are not directly influenced by website and marketplace sales, they do

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2 A robustness check confirmed that all estimation results remain consistent when using a lag order of two, as recommended by the Akaike information criterion (AIC).
influence the latter two. Only total marketplace visits are unaffected by the other variables, likely because they are very high compared with the small traffic coming from an individual retailer, and as they are influenced by many other variables (e.g., the marketing activity of the marketplace itself, or visits originating from other retailers).

To assess the impact of marketplace sales, we computed orthogonalized IRFs based on the estimated VAR system parameters for all endogenous variables in the order of Model 1.\(^3\) We obtained confidence intervals through bootstrapped residuals (\(n = 500\)), ensuring that the results are robust against deviations from the residual assumptions. Fig. 5 shows the results to a shock in website visits, website sales, and marketplace sales (all variables as \(log\)). The log-log IRFs can be interpreted as elasticities at a given point in time (Nijss et al., 2001), but the cumulative IRF values cannot (Wieringa & Horváth, 2005).\(^4\)

The data confirm the complementarity of the marketplace: in line with \(H1\), we see a significant positive effect of marketplace shocks on website sales (Fig. 5, Panel C: elasticity \(\hat{e}_{max} = 0.014\)). This elasticity appears small, but it originates from the different levels of the variables: a small shock variable (marketplace sales, which is only \(-10\%\) of website sales) is applied to a high website sales number. Fig. 5 shows that the effect of marketplace sales on own-website sales does not occur immediately: own-website sales respond with some delay to a shock in marketplace sales. The delayed effect for sales appears externally valid, as it coincides with common delivery times (where, e.g., the package might be branded). In addition, some of the positive effects are likely to arise immediately, upon customers learning of the retailer brand on the marketplace.

However, cannibalizing effects also occur: visitors are lost to the marketplace and purchase the retailer’s products there, rather than on the retailer’s website (\(H2\)). This effect is smaller than the website conversion (Fig. 5, Panel B: \(\hat{e}_{max} = 0.033\) vs. Panel A: \(\hat{e}_{max} = 0.071\)) but still substantial. Additionally, existing customers repurchase with the retailer on the marketplace instead of on the retailer’s website (Panel D: \(\hat{e}_{max} = 0.012\)), although the confidence interval to this effect remains close to zero. These patterns are substantially robust against a reordering of the endogenous variables (see Web Appendix 4).

Robustness check. We also conducted a small experiment as a robustness test to ensure that our main finding of a positive effect of marketplace sales on the sales of a retailer webshop is not due to an endogeneity bias (see Web Appendix 5 for details) and to gain some insights on the theorized drivers of the process (namely, the segment-specific complementarity).

We randomly assigned a student sample (\(n = 125\), mean age = 30.4 years, 37% female) to one of three experimental conditions for the purchase of a tablet computer on a global marketplace: (1) a control condition in which the marketplace operator sold the product itself (i.e., as part of its retail offering); and treatment conditions in which an independent retailer sold the product on the marketplace (2) with a brand logo on the product page of the marketplace and (3) with a branded parcel. As brands, we used Amazon as marketplace operator and an electronics retailer that did not operate in the country of the experiment. As dependent variables, we asked for participants’ purchase intent with (a) the marketplace operator, (b) the focal retailer, and (c) a set of six filler retail brands (seven-point Likert scale; 1 = low, and 7 = high). Results show that selling on the marketplace (conditions 2 and 3) increased consumers’ purchase intention with the selling retailer (F(2,123) = 3.25, \(p < .05\)), although to a small extent. Analyzing the conditions separately, we find that the treatment condition (2) with limited retailer branding (only on marketplace) marginally differed from the control condition (1) (F(1, 87) = 3.36, \(p < .10\); \(M_1 = 1.12\), \(M_2 = 1.69\)), while the treatment (3) with stronger retailer branding (on marketplace and parcel) significantly increases the purchase intention with the retailer to almost twice the purchase intention in the control condition (F(1, 69) = 6.27, \(p < .05\), \(M_3 = 2.08\)). We observed no significant effect on purchase intention with any of the six other retailer brands nor the marketplace operator. In summary, the experiment confirms the robustness of our finding that customers can be acquired on the marketplace but also points to the need for a branding effort of the retailer that operates on the marketplace.

\(^3\) We rely on orthogonalized IRFs (as in, e.g., Vieira et al. (2019); Pauwels et al. (2002)) instead of generalized IRFs (e.g., Pauwels et al. (2011)), for three reasons: (1) the order of the variables is theoretically mandated (e.g., visits must come before sales), (2) some of the effects in the system are unlikely to occur instantaneously as implied by the simultaneous shock in a generalized IRF. Instead, customers usually take multiple days to convert even on one website (e.g., 9 days in Li and Kannan (2014)), as also senior management confirmed. Finally, (3) generalized IRFs yield the sum of all simultaneously shocked variables on the response variable, which might either exacerbate (if all shocks point to the same direction) or mitigate the effect (if the simultaneous shocks are contrasting); orthogonalized IRFs avoid this by specifying an order. Our main finding of a positive effect of marketplace sales on website sales remains consistent, although the reverse (i.e., cannibalizing) effects are no longer significant.

\(^4\) We still report cumulative IRF values for the significant periods because retailers are likely to be more interested in the total effect.
5.2. Step 2: results of the within-category moderation of the effect

We conducted Step 2 of the analysis first for the pooled data (i.e., across all categories: Step 2a) and then within the theoretically suggested category groups (Step 2b), using generalized methods of moments (GMM). Before running the analyses, we first confirmed the stationarity of both the marketplace and the website sales – both overall and within the individual categories: the augmented Dickey–Fuller root test showed p-values below 0.1% for all categories, and the KPSS test also indicated stationarity.

To investigate our hypotheses, we estimate the PVAR model that was specified in the previous section using Stata’s PVAR package, accommodating category-specific fixed effects (Abrigo & Love, 2016). We selected the optimal lag length of two for the endogenous part of the model, based on established selection criteria (MBIC, MQIC, and MAIC; Andrews & Lu, 2001). We specified the number of instrumental lags to be a minimum of three; further instrumental lags would improve estimation efficiency (Abrigo & Love, 2016; e.g., MBIC or MAIC decrease) but substantially reduce sample size in categories in which marketplace sales data have gaps. Because of these potential gaps, we followed recommendations to set missing values for the instrumental lags to zero (Holtz-Eakin et al., 1988), which is correct as the sales on these days were in fact zero. The estimated effects are slightly smaller but substantively consistent without this setting.

An estimation of the effect across all categories shows a Granger-causal effect of marketplace sales on own website sales ($\chi^2 = 97.8, p < .001$) but not vice versa ($\chi^2 = 1.4, p = .49$). In line with H1 and our previous findings, the IRF shows a significant positive effect of a shock in marketplace sales on website sales in a category, indicating complementarity ($e_{max} = 0.092$; see Web Appendix 6, Fig. A.5). In line with H3, we also find a smaller customer loss ($e_{max} = 0.060$), although the effect vanishes quickly and has a large confidence interval.

To investigate H4, we classified the product categories according to their average price level and the number of available product choices in the category on the retailer’s website (see Web Appendix 6, Table A.2 and Fig. A.6). We first calculated the average (non-log) item price per day and category, using the average across all days as a way to group the products according to price. As a consequence, a category cannot change its group within the analysis period. We split the product categories according to the median price (137 MUs). We then grouped the categories according to the median number of available product choices (in terms of stock keeping units [SKUs]) in each category on the retailer’s website (1900). We used data manually gathered after the assessment period as a basis, where each different product (SKU) would be counted as an option. As the category split is based on median data, the median category in each dimension (i.e., cameras and headphones) could be sorted both ways. As a robustness test, we calculated alternative models that grouped the median categories differently; results remained substantively consistent.
We next ran separate panel VAR models for products with a low versus a high price and for a low versus a high choice on the retailer’s website in a given category. Causality tests indicate that marketplace sales have a significant influence on website sales for both products with a high ($\chi^2 = 46.0, p < .001$) and a low choice ($\chi^2 = 36.0, p < .001$), but only for low- ($\chi^2 = 21.9, p < .001$) and not for high-priced products ($\chi^2 = 0.8, p = .68$). In line with our previous findings, none of the reverse effects reaches significance.

The orthogonalized IRFs support H4a and H4b (see Fig. 6; confidence intervals obtained through Monte Carlo simulation with $n = 200$). In absence of a standardized statistical test, we interpret nonoverlapping confidence intervals of the IRFs as indication of a statistical difference between the two levels (Cumming & Finch, 2005, e.g., high vs. low choice). Product categories with fewer choice options on the retailer website show a significantly less positive effect of sales on the marketplace than those categories with more choice options (H4a: $e_{\text{max}} = 0.050$ vs. $e_{\text{max}} = 0.100$; confidence intervals only overlap in period 2). In addition, the sales effect of product categories with a higher or lower average price differs (H4b), but not as consistently: categories with high-priced products do not profit significantly from sales on the marketplace ($e_{\text{max}} = 0.006$; confidence interval always includes zero, $e_{\text{cum}} = 0$; consequently), while categories with cheaper products profit from a positive marketplace sales effect ($e_{\text{max}} = 0.046$; confidence interval always excludes zero). However, the confidence intervals of both IRFs are only nonoverlapping in periods 0, 1, and 10. This pattern is robust to a reordering of the variables (see Web Appendix 6, Fig. A.6).

To assess the joint interaction of price level and choice, we next ran separate panel VAR models for each of the four category groups. Causality tests indicate that marketplace sales have a significant influence on website sales in three of the four quadrants ([2] low price, low choice: $\chi^2 = 38.2, p < .001$; [3] low price, high choice: $\chi^2 = 11.8, p < .01$; and [4] high price, high choice: $\chi^2 = 6.4, p < .05$), but not on product categories in which the retailer offers few product choices at a high price ([1]: $\chi^2 = 0.5, p = .66$). However, none of the reverse cases of customer loss reaches significance.

The IRFs reveal that the degree of complementarity between the marketplace and the retailer differ between categories in line with our expectations (see Fig. 7): as expected, the effect of marketplace sales on own website sales is most positive for categories with low prices and a high number of available product choices (quadrant 3; the website sales response elasticity equals $e_{\text{max}} = 0.049$ in $t = 2$), followed by categories with low prices but fewer available product choices (quadrant 2; $e_{\text{max}} = 0.047$ in $t = 2$; also larger confidence interval). In contrast, the effect vanishes for categories with high product price and limited choice (quadrant 1; $e_{\text{min}} = 0.015$ in $t = 1$, effect nonsignificant, as the confidence interval includes zero). The effect for products with high price and a large product choice is positive but small (quadrant 4; $e_{\text{max}} = 0.022$ in $t = 2$). Web Appendix 6 (Fig. A.7) also provides an overview of the impulse response functions for a shock in website sales to the marketplace: these effects are positive, but the confidence intervals include zero for most periods.

Validity check. Because we cannot investigate the individual customer’s decision process with our aggregate data, we conducted a validity check for our hypothesized category-specific effects. We obtained another individual-level data set from the same retailer with which we can investigate repurchase behavior – but only on the retailer’s website (see Web Appendix 7 for additional details on the data and calculation). We expect that repurchases should be highest in categories in which a purchase does not cause inventory effects but rather may be acting as a complement to further purchases. In line with our expectations, the quadrants of the four product category groups significantly influence repurchase propensity ($\chi^2 = 321.1, p < .001$): A repurchase is most likely in categories in which the retailer offers a large product choice at low prices (quadrant 3; $M_{\text{repurchase, Q4}} = 0.21$, different at $p < .001$ from all other quadrants). Also as expected, categories with low price and limited choice (quadrant 2) have the second highest repurchase rate ($M_{\text{repurchase, Q2}} = 0.13$). Furthermore, in line with our previous findings, both quadrants 1 and 4 have considerably lower repurchase rates ($M_{\text{repurchase, Q1}} = 0.08$, $M_{\text{repurchase, Q4}} = 0.05$). In summary, the customer data analysis supports our suggestion that inventory effects drive the purchase probability on the retailer’s website.

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**Fig. 6.** Orthogonalized impulse response functions in the panel VAR by moderator. Notes: Shock of +1 SD in log marketplace sales per category (dashed lines: 95% confidence intervals); cumulative IRFs only for significant periods.
6. Discussion

The present research shows the positive effect of selling on marketplaces: across all categories, a 1% increase in a retailer’s marketplace sales increases sales on the retailer’s website by 0.014% (in period 2). We suggest, although we are not able to explicitly test this with the retailer’s aggregate data, that this effect is based on the acquisition of new customer segments, which are acquired through the additional touchpoint that the marketplace provides. Because the offering on a retailer’s website is likely complementary in terms of assortment (e.g., choice, ease of search and expected price), repurchases of customers newly in contact with the retailer might occur on the retailer’s website.

This assortment-based complementary, however, depends on two category characteristics: the fewer products a retailer offers on its own website within a category and the more costly these products, the more strongly inventory effects arise, reducing complementarity between the channels. Marketplace sales have the strongest positive effect in categories with low prices and either a high number of available product choices (here: e.g., media items; maximum elasticity 0.049% for every 1% sales on the marketplace) or a low number of alternative product choices (here: e.g., headphones; 0.047%). In contrast, budgetary inventory effects limit the effect for categories in which the retailer’s offering has high prices and many options (0.022%) and turns insignificant when prices are high and few options are available (−0.015%).

In contrast to these positive effects, we also see that selling on the marketplace can be cannibalistic: a share of the visitors to a retailer’s webshop migrates to the marketplace (0.033% increase in marketplace sales for every 1% of visitors to the retailer’s webshop), and also existing customers of the retailer are lost to the marketplace (+0.012% in marketplace sales for every 1% in webshop sales). The elasticities of the positive complementary effects (conversion and customer acquisition), however, exceed the elasticities of the negative cannibalistic effects (visitor and customer loss).

To ease interpretation, we converted the cumulated elasticities (based on the log-log estimates) into absolute effects (see Web Appendix 8 for details). This confirms the positive evaluation that complementary customer acquisition outweighs cannibalizing loss: a new visitor to the webshop generates 0.42 MU sales in the retailer’s own webshop but only 0.03 MU sales on in the retailer’s marketplace sales. Further, every monetary unit sold on the marketplace generates 0.64 MU in sales on the website (complementary customer acquisition), while the cannibalization (i.e., webshop sales’ effect on marketplace sales) amounts only to 0.01 MU (per MU sold in the webshop).

6.1. Managerial implications

Beyond the effectiveness of customer acquisition, the efficiency of marketplaces is key to retailers (Kannan et al., 2016), with practitioners disagreeing whether marketplaces can be used to “to build an ecommerce brand” (Masiello, 2017) or not (Kumar,
Based on the calculated cross-channel effects and the common marketplace fees (see Web Appendix 8 for details), we compute an average acquisition costs of 24% of the sales volume. This marketplace customer acquisition cost varies by category: expensive products with a large assortment choice are cheaper (10%) than acquisitions in categories with cheaper products (low choice: 22%; high choice: 35%). These customer acquisition costs on the marketplace are likely cheaper than acquiring customers through the retailer’s own website, although we cannot compute the exact website acquisition costs for our data, as the retailer did not share its costs per click. An estimation based on common industry click costs, conversion rates, and basket sizes suggests website acquisition costs of 30% (see Web Appendix 8 for details). The 24% acquisition cost we find herein is also far below the recommended maximum acquisition costs of 100% of sales in the first year (Bernazzani, 2020). The loss through a reverse migration to the marketplace is negligible in absolute terms and probably would happen even without the retailer being present on the marketplace.

Strategic caveats to this customer acquisition through the marketplace exist, however: although retailers might be able to acquire new customers more cheaply through the marketplace than through their own websites, it might be strategically unwise in the long run. The positive relationship effect of marketplace sales might have, for instance, just be a spillover of a much stronger brand-building effect of the marketplace itself (Parker et al., 2016). Thus, selling on the marketplace might hurt retailers in the long-run battle to control access to the customers (Reinartz et al., 2019). As our small but significant reverse migration effects indicate, this strength of the marketplace might also lead to a loss of existing customers. Further, through sales on the marketplace, marketplace operators can control the customer relationship. Thus, customer acquisition through the marketplace might be most attractive for relatively unknown retailers, and the disadvantages may outweigh the benefits for more established retailers with a stronger brand. This aligns with research that suggests that marketing mix decisions (e.g., channel choice, media spending) interact with brand familiarity (Pauwels et al., 2016). Finally, success of a retailer on the marketplace might point to a growth opportunity for the marketplace operators. Amazon, for example, is infamous for “cherry-picking” only those categories that are successful to offer itself (vs. marketplace providers), after the marketplace sellers have borne the initial risk of offering new categories (Jiang et al., 2011; e.g., Amazon now also sells refurbished products).

Further, assortment characteristics of a retailer might form a boundary to the complementarity effect: to profit from complementarity, retailers need a more comprehensive and specialized assortment beyond the marketplace to create reasons for customers to migrate to their websites. Our results indicate that “baiting” customers on the marketplace is especially promising in categories with low price and high choice. In contrast, retailers that sell expensive products or have a limited product choice within each product category are less likely to profit from marketplace sales, as inventory effects reduce the complementarity of the marketplace.

Marketplace operators, in turn, should be aware that retailers might aim to encourage a migration of customers from the marketplace to their own websites. In this approach, retailers may offer more tailored assortments, trying to attract customers away from the “department store”-like marketplaces (Reinartz et al., 2019). These retailer attempts are likely to be more effective for retailers that specialize in a certain product segment, offering large choice and lower price products. Marketplace operators might adjust their fees according to differences in the attractiveness of the marketplace for different categories. Amazon, for instance, already varies the fees between different categories, although not based on complementarity. Marketplaces might aim to mitigate retailers’ brand-building attempts by, for instance, taking measures to prevent branding (e.g., restrictions on packaging) or delivering products under their own brand. Further, growing the number of (retail) participants on the marketplace might also negatively affect the marketplace, as it might induce search frictions (Wirtz et al., 2019).

6.2. Theoretical implications

Our research contributes to the omnichannel paradigm (Verhoef et al., 2015) in several ways. First, we close a yet uninvestigated cell of the channel cross-elasticity matrix (Neslin & Shankar, 2009): the effect of marketplace sales on a company’s own webstore. In doing so, we extend work on the effects of marketplace sales for private (Eckhardt et al., 2019; Perren & Kozinets, 2018) or branded producers (Sun et al., 2019) and service providers (Zhang et al., 2019). In line with extant research, we find that channel relationships between digital channels are more complementary than substitutive (Bang et al., 2013; Huang et al., 2016). However, a certain degree of substitution occurs, as some customers are lost to the marketplace.

Second, our findings suggest that channels might be complementary in attracting different segments (Coelho et al., 2003), creating a positive overall “touchpoint effect” for the retailer (Baxendale et al., 2015) through the marketplace as a second channel. Ansari et al. (2008) identify a “migration segment” of customers that can be more easily induced to switch channels. We generalize this observation of segment-specific effects of channel additions (e.g., Pauwels et al., 2011): different customer segments use different channels and can thus be more easily attracted to the retailer’s channel system through them. Interestingly, this effect arises even though retailers have limited control over the channel.

Third, our research offers evidence that the relationships between channels are category specific. This category-specific effect is driven by two assortment-specific moderating factors (price and assortment size); this extends extant research, which finds that category-specific effects are based on general channel capabilities (e.g., sensory products profiting more from a brick-and-mortar store addition; Pauwels et al., 2011; time criticality: Bang et al., 2013). Specifically, assortment-based complementarity of the channel relationships is likely to occur in categories in which choice of the assortment in that category is extensive and product prices are low, in line with suggestions from extant research on consumer repurchase behavior (Ailawadi et al., 2007). Our empirical evidence, thus, establishes the presence of stock-level and budgetary inventory effects beyond promotions and time series of purchases (as in, e.g., Bell et al., 2002; Besanko et al., 2003; Kim & Park, 1997) for channel relationships.
6.3. Limitations

Limitations originate from the characteristics of the data on which this analysis is based. First, we could only investigate the cross-channel sales effects in a situation in which the retailer is already present on the marketplace. Thus, we cannot infer how adding the marketplace changed the relations in the retailer’s channel system, but only use variance in the sales levels to infer how strongly the channels influence each other. Ideally, such effects are established through a field experiment, but this was impossible to arrange in our setting.

Second, the specific industry context of our focal company might threaten the generalizability of the findings. The company is a reseller of refurbished products, which makes it more susceptible to supply variations. This business model differs somewhat from ordinary retail models, in which supply is either flexible (e.g., supply on demand) or fixed (e.g., fixed purchase volume, such as seasonal fashion products). Our rich data model, however, controls for changes in the product supply. Further, as our results are consistent in the cross-category (in which category-specific supply shock should matter less) and category-specific models, we are confident that our results are not biased by supply shocks.

Finally, the available data were limited in multiple aspects that prevented a more detailed testing of the expected mediation process. First, no data were available on the retailer’s available stock levels on the marketplace and the website. Although we compared the latter in a small field study, systematically analyzing the effect of stock level differences between marketplace and website would have been highly interesting, especially regarding the theorizing of an assortment-based complementarity. Senior management, however, ensured us that the availability and price of products did not substantially change in the period of analysis. Second, no data were available on the number of visitors to the retailer’s product pages on the marketplace, as the marketplace operator does not share such information. Consequently, we cannot investigate whether visiting a retailer’s product pages on the marketplace (on the website) induces channel switching to the retailer website (the marketplace). Moreover, information on other drivers, which might cause cross-channel complementarity (e.g., price differences, number of product reviews) were not available. Last, we do not have data on individual customer journeys. The positive effect of marketplace on own website sales suggests that different customer segments are addressed through the marketplace offering, which learn of the retailer and repurchase on the retailer’s website. Our auxiliary experiment with individual repurchase behavior and our investigation of individual purchases on the retailer’s website confirm this finding. In summary, although the aggregate effect is robust and two additional analyses point in the direction of our theorizing, the validity of the mediation process should be investigated further.

6.4. Future research

Future research on the effect of marketplace sales is highly relevant, as a substantial volume is traded over marketplaces and an increasing number of retailers use marketplaces as an additional sales channel. As our research is, to the best of our knowledge, the first to investigate the cross-channel sales effect of marketplace sales, several open questions remain:

- What are the long-term effects of a marketplace usage? Commentators have criticized the loss of customer access (Danziger, 2018; Reinartz et al., 2019).
- Can a company stop its activity on a marketplace without substantial revenue loss, similar to channel eliminations (Konuš et al., 2014)? The answer might be different than for one’s own channels, as the brand of the marketplace differs.
- How does marketplace selling affect profitability? We estimated the costs of customer acquisition, but other factors affect profitability (e.g., returns, product mix).
- How can marketplace operators prevent brand-building activities of their sellers? And how do marketplace sales contribute to a potentially independent retail business of the marketplace operator (e.g., Amazon direct and marketplace sales)?

We hope that our study sparks further research in this relevant area.

Web Appendix

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2020.09.007.

References


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