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Full Length Article

When consumers can return digital products: Influence of firm- and consumer-induced communication on the returns and profitability of news articles

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ABSTRACT

The news industry is being massively disrupted by the digital distribution of news. Consequently, publishers have revised their business models and integrated pay-per-article options. To reduce pre-purchase uncertainty, consumers can use information from firm-induced (e.g., newsletters), or consumer-induced communication (e.g., likes). These communication activities avoid purchases with poor fit but also increase customer expectations. Consequently, their effect on sales, returns, and profitability is unclear. For digital products, these effects are even less clear because product quality is difficult to evaluate pre-purchase, and products can be returned at almost no cost, even after consumption. In this study, we investigate the effects of firm- and consumer-induced communication on digital returns in the context of news articles on a major online platform (Blendle). We rely on a multi-equation model to quantify the effect of firm- and consumer-induced communication activities (i.e., newsletter promotions sent out by the platform and consumer likes from readers) on sales and returns and calculate their profitability impact. Our results show that newsletters decrease returns but do not significantly affect sales. In contrast, consumer likes have a twofold effect by increasing sales and decreasing returns. A simulation shows that both newsletters and likes increase profitability and that likes have a higher potential. Our results offer much needed guidance for online aggregators of digital products (e.g., audiobooks, e-books or news articles), as well as for online publishers based on pay-per-unit business models.

1. Introduction

Product returns are a serious economic problem for retailers. Return ratios for online purchases in the U.S. rank from 15 to 30% (Quenqua, 2017; Zumbach, 2016) and may even climb to 40% for fashion products (Reagan, 2016). Recently, more firms selling digital products are offering a return option to consumers. For example, Amazon offers its customers the possibility to return purchased e-books within 7 days after purchase (amazon.com).[1] At Audible, a platform for audiobooks, customers may return their goods even 365 days after their purchase (audible.com).[2] Furthermore, the Dutch platform Blendle, offering online access to news articles, allows for the return of digital news articles up to 24 h after purchase.[3]

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[1] https://www.amazon.com/gp/help/customer/display.html?nodeId=201252620
[2] http://audible-uk.custhelp.com/app/answers/detail/a_id/5719/~/how-can-i-return-an-audiobook-online%3F
[3] https://www.blendle.support/hc/en-us/articles/212583485-Blendle-s-refund-options-Get-your-money-back-with-one-click

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0167-8116/

From a firm's perspective, offering the possibility to return digital products is a double-edged sword. On the one hand, research has shown that lenient return policies increase purchases more than they increase returns, thus leading to a positive overall effect (Anderson, Hansen, & Simester, 2009; Janakiraman, Syrdal, & Freling, 2016; Petersen & Kumar, 2009; Wood, 2001). On the other hand, returns for digital products may be a risky strategy because consumers can return digital products very easily with almost no cost. This risk is particularly high for digital products that can be consumed (and returned) very fast — such as news articles. In addition, digital goods are more difficult to evaluate pre-purchase than physical goods due to their intangible nature. Thus, customers have a higher pre-purchase uncertainty, leading to purchases with poor fit, which will be returned. To inform customers about their digital products, publishers use different communication instruments, which may be induced by the firms (e.g., newsletters) or the consumers (likes, reviews). The idea is that the new information will allow consumers to make a better evaluation of the quality of the digital products to avoid products with low fit, labeled as a purchase prevention effect (Minnema, Bijmolt, Petersen, & Shulman, 2018; Shulman, Cunha, & Saint Clair, 2015). However, information from firm- or consumer-induced communication also increases expectations, which leads to more purchases and more returns because the product does not meet these expectations, due to the marginal loss aversion effect (Minnema et al., 2018; Shulman et al., 2015). Thus, publishers using pay-per-unit business models need guidance regarding what communication activities they can use to promote their products so that sales increase but returns do not.

Existing research offers limited insight into returns for digital products. A literature review of the growing body of research on product returns shows that until now, returns have been studied in the context of physical products (e.g., Minnema, Bijmolt, Gensler, & Wiesel, 2016; Petersen & Kumar, 2009, 2015; Shulman et al., 2015). These studies analyze the effect of firm-induced (e.g., catalogs, Petersen & Kumar, 2009, 2015), or consumer-induced (consumer reviews, Minnema et al., 2016), communication activities on returns with mixed results. Indeed, these mixed findings reflect the twofold role of communication activities, which may lead to the purchase prevention effect (lowering returns; e.g., Hong & Pavlou, 2014) or the marginal loss aversion effect (increasing returns; e.g., Minnema et al., 2016) to dominate. In addition to this tension in communication effects, it is unclear which of these insights is valid in the context of digital products. Digital products differ from physical ones due to two important factors. First, digital products can be returned without any physical or time effort (repacking, franking and shipping), almost at zero cost. Second, in contrast to physical goods, digital products can often times be returned even after consumption, e.g., a news article that has been read, or an audiobook that has been listened to. Both of these factors affect how pre-purchase information through firm- or consumer-induced communication influences consumers' purchase and return decisions, so it is unclear which of the opposing effects will dominate and what the overall return effect will be. These differences underline the need for specific empirical insights into how communication activities affect returns for digital products. To fill this void, this study analyzes how firm-induced (newsletter promotions) and consumer-induced (likes) communication activities influence returns for digital products and, ultimately, influence the profit of firms in a pay-per-unit digital business model setting.

We use data on news articles from the Dutch online news platform Blendle, which is an international player with more than 1,000,000 registered users (medium.com).[4] Blendle aggregates articles from different print and online newspapers and magazines, e.g., The Wall Street Journal or The Washington Post. Similar to iTunes in the music industry, it unbundles newspapers and makes their content available on a single article basis across different news publishing houses, comparable to digital platforms enabling the exchange between market actors (Perren & Kozinets, 2018). Blendle uses a pay-per-article business model that allows the return of news articles with a one-click return button up to 24 h after purchase (Blendle, 2018).

Our data contains sales and return information for 596 news articles from 2016. We have information on the communication induced by Blendle to promote articles (newsletter), on consumer-induced communication (likes), as well as on article characteristics. In this study, newsletters serve as operationalization of firm-induced communication, and consumer likes serve as operationalization of consumer-induced communication. We build a multi-equation model that assesses the effect of firm-induced and consumer-induced communication on sales and returns, and we correct for endogeneity of both newsletters and likes. Our results show that consumer likes have a twofold positive effect: they increase sales and reduce return share, whereas promoting articles in the newsletter decreases returns but does not yield a significant sales increase. These results are supported by various robustness checks.

We use a Monte Carlo simulation to estimate the profit implications of our findings. The simulation suggests that the incremental profit for firm-induced newsletter communication increases by 5.92% compared to a scenario where the company relies only on external word-of-mouth effects and does not initiate its own communication activities by its newsletter. In the case of an assumed 1% increase in likes, profit would already increase by 2.67%, even without the newsletter. The most profitable scenario is when both firm- and consumer-induced activities are effective — here, the incremental profit increase amounts to 8.42%. These results imply that managers of pay-per-article platforms or newspapers should be aware of the high impact of consumer communication effects through higher sales and lower returns.

This study makes three major contributions. First and foremost, we study the relationship between firm- and consumer-induced communication and sales, returns and profitability of digital products. Thus, we add to the stream of research on product returns, which has thus far studied product returns in a physical product setting (e.g., Hong & Pavlou, 2014; Minnema et al., 2016; Petersen & Kumar, 2015, 2009). In a digital goods context, the return process differs substantially to that of physical products because the quality of products is more difficult to evaluate ex-ante, and the return costs are much lower. Thus, it is not clear how the two-stage purchase and return process will be affected by information provided at the moment of purchase through

[4] https://medium.com/on-blendle/one-million-6390860c2a34

communication activities induced by firms, and consumers. Our results address this gap and show specific findings related to newsletter promotions as a measure of firm-induced communication and consumer likes as a measure of consumer-induced communication. In doing this, our research related a firm's marketing behavior to product returns, which has been identified as a relevant topic for future research in the review article by Minnema et al. (2018). Second, we add to the stream of literature on digital marketing and, specifically, digital business models by showing the impact of different communication activities on an article's sales, returns, and subsequent profitability. Our insights are relevant for firms relying on pay-per-unit digital business models, especially for managers (publishers) who have to decide on the allocation of marketing budgets between customer-initiated and firm-initiated contacts, as highlighted by Wiesel, Pauwels, and Arts (2011). Specifically, our findings offer guidance to managers and publishers on how to plan communication activities with high profit impact in the highly dynamic news market. Last, our findings contribute to the research stream on entertainment media. Extant research provides empirical results on communication effects in the context of videogames, movies and music (see, e.g., the reviews by Eliashberg, Hennig-Thurau, Weinberg, & Wierenga, 2016 or Hennig-Thurau & Houston, 2019). Our results complement existing findings by providing insights into news articles.

2. Literature review

When purchasing digital (experience) goods, consumers face a high degree of uncertainty because they have incomplete information (Nelson, 1970). They cannot touch, feel or try the product and have, thus, limited ability to evaluate the products. To mitigate this pre-purchase uncertainty, retailers offer two major information sources: The first one is *firm-induced communication*, that is, information provided by a company or selling platform through advertising, online product pages, newsletters or catalogs. The second information source is *consumer-induced communication*, such as product reviews or number of likes. Meta-analyses demonstrate the positive effects of both types of communication activities on sales (e.g., Babić, Sotgiu, De Valck, & Bijmolt, 2016; Sethuraman, Tellis, & Briesch, 2011). Extant research has studied the effect of different firm- and consumer-induced communication activities on product returns, showing mixed results (Minnema et al., 2018). In the following, we review the literature on both types of communication in relation to product returns (Table 1).

2.1. Firm-induced communication

Several studies analyze the effects of firm-induced communication activities (emails, catalogs, advertising booklets, product descriptions, technical online shop features and free shipping promotions) on the returns of physical products. In one of the first studies on antecedents and consequences of physical product returns, Petersen and Kumar (2009) show that a consumer's return behavior negatively influences the intensity of a firm's communication activities, as measured by the number of catalogs sent to customers. In a later study, Petersen and Kumar (2015) also include the reverse relationship in their return model, where communication costs (number of sent emails and catalogs) are positively associated with product returns. They ran a field experiment with an online retailer for footwear, apparel and accessories and show that considering product returns in targeting strategies of firms lead to significant benefits compared to best-practice allocation without explicit consideration of future return behavior. Specifically, the study was able to increase profit from purchases by 18.1%, decrease profit loss from product returns by 30.7% and decrease marketing costs by 19.7%.

Bechwati and Siegal (2005) show in an experimental setting that product presentation in advertising (booklets) affects product returns for technical products. Their framework focuses on the mechanisms that underlie consumer choice reversibility, i.e., consumer's likelihood to return products. They analyze consumers' information processing and find that when products are presented simultaneously, customers generate comparative thoughts. In contrast, when products are presented sequentially, customers generate more non-comparative thoughts. Hence, when customers are faced with an alternative that was not in the initial choice set after they decided to purchase, they are more likely to reverse their decision, i.e., to return the previously chosen

Table 1
Literature on product returns investigating consumer- or firm-induced communication.

Authors	Product type	Communication		Success measures		Simulations
	Physical/digital	Firm-induced	Consumer-induced	Sales/choice	Returns	Net revenues/profit
Bechwati and Siegal (2005)	Physical	✓			✓	
De, Hu, and Rahman (2013)	Physical	✓		✓	✓	
Petersen and Kumar (2009)	Physical	✓		✓	✓	✓
Petersen and Kumar (2015)	Physical	✓		✓	✓	✓
Shehu, Papies, and Neslin (2016)	Physical	✓		✓	✓	✓
Shulman et al. (2015)	Physical and educational	✓			✓	
Minnema et al. (2016)	Physical		✓	✓	✓	✓
Sahoo, Dellarocas, and Srinivasan (2018)	Physical		✓	(✓)	✓	
Hong and Pavlou (2014)	Physical	✓	✓		✓	
This study	Digital	✓	✓	✓	✓	✓

Note: Check marks indicate that the variables were reported in the results section of the original study. Those in parentheses indicate that the coefficient was reported, but it was not the focus of the study.

product, especially when comparative thoughts are evoked in their initial purchase. Thus, advertising for a new brand can increase returns for a previously purchased brand. Shulman et al. (2015) analyze the level of firm-induced communication using experimental and archival data on university courses. When using the former, they manipulate the amount of product attribute information that is presented to consumers. When using the latter, they use additional course syllabuses as firm-induced communication. They show that the level of firm-induced communication affects product returns through two contradicting mechanisms: Product information can reduce uncertainty and lead to better informed purchase decisions and lower returns, while at the same time, it can increase expectations that lead to a diminished perceived utility and, thus, to increased returns. The dominance of one or the other depends on contextual factors, such as the relative importance of the respective attribute and remaining uncertainty. Similarly, De et al. (2013) also find contradicting effects. They investigate the relationship between online-shop features (such as product zoom) and returns of women's apparel. The study shows that more factual information (more extensive zoom usage) is associated with fewer returns, whereas the opposite is true for more evaluative information (more alternative product photos). More importantly, they show a negative relationship between marketing activities and product returns, such that products that were promoted in catalogs are returned less often.

Other studies analyze the relationship between free shipping promotions and returns. For example, Shehu et al. (2016) find a positive effect of shipping fee promotions on sales and on product returns. Sahoo et al. (2018) investigate a specialty retailer for apparel, accessories, decoration, and furniture and find no evidence for fraudulent consumer behavior to reach the free shipping threshold, i.e., adding items to the basket to get free shipping and return them afterwards. When the shopping cart value is just above the free shipping fee, the probability of returns decreases.

To summarize, studies analyzing the relationship between firm-induced communication and returns provide contradicting findings. Overall, however, these studies show that there is conflict regarding the effects of firm-induced communication on returns, in that they may increase or decrease returns because of their twofold role as informational cues reducing pre-purchase uncertainty leading to the purchase prevention effect or as advertising cues increasing pre-purchase expected utility, leading to the marginal aversion loss effect (Shulman et al., 2015). Which of these two processes will dominate depends on the context (type of product, type of firm-induced communication). Due to the higher pre-purchase uncertainty, intangible character, and low return costs, it is unclear which of these findings applies for digital products, underlining the need for specific insights in a digital product setting.

2.2. Consumer-induced communication

Several studies analyze the effect of consumer-induced communication on returns for physical products. Consumer-induced communication is measured mostly using three different metrics of consumer reviews: *Volume* is the number of reviews; *valence* explains the positivity/negativity of reviews; and *variation* indicates how like-minded the reviews are, which is often operationalized as the variance of the reviews.

Sahoo et al. (2018) show that the higher the volume of online reviews are at the time of the purchase, the lower the return probability is, with an inverse u-shaped effect. With fewer available product reviews, consumers buy more substitutes, due to the higher uncertainty. Another study by Minnema et al. (2016) shows, in contrast, no effect of review volume or variance on product returns but a negative relationship between review valence and returns. The negative relationship between review valence and returns is stronger for cheaper products.

Hong and Pavlou (2014) analyze the effect of both types of communication (firm- and consumer-induced) and product returns using transactional and survey data. They investigate the moderating role of consumer-induced (product forums), as well as firm-induced (website pictures) communication on product returns mediated through product uncertainty regarding product fit and product quality for search and experience goods. Their results show that both types of communication decrease uncertainty for experience goods, which in turn leads to lower product returns.

Research on consumer-induced effects on returns offers mixed findings, similar to the literature on firm-induced communication activities. Both these streams of research show that firm- and consumer-induced communication can lead to lower returns or — under certain conditions — to higher returns.

All studies analyze returns in physical product settings. For companies relying on a digital business model (e.g., pay-per-unit models for digital products), these findings are of little help because their validity in digital product settings is unclear, as returning digital products is much easier and is associated with lower return costs. Overall, these findings underline the need for specific insights on how communication activities affect returns for digital products.

3. Conceptual framework

We develop two sets of competing hypotheses related to the effects of firm- and consumer-induced communication on returns for digital products (Fig. 1). The framework links firm- and consumer-induced communication activities to sales and returns. The framework also shows that sales influence returns because an article with more sales may also be returned more often (Petersen & Kumar, 2009). Finally, sales and returns and their difference form the net revenues of an article.

3.1. Sales effects

We do not explicitly introduce hypotheses related to sales effects, since these have been established by former research. Nevertheless, our findings help to put previous findings on physical goods into the context of the digital segment.

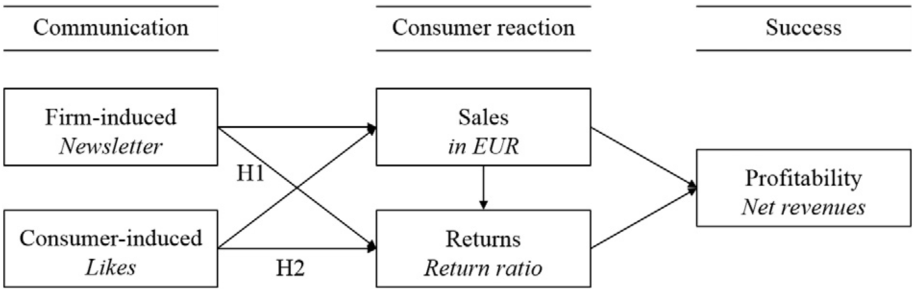

Fig. 1. Conceptual framework: The impact of firm- and consumer-induced communication on sales, returns and profitability of a news article.

The positive effect of advertising on sales has been demonstrated by two meta-analyses. Sethuraman et al. (2011) report an average short-term (long-term) sales elasticity of 0.12 (0.24). Henningsen, Heuke, and Clement (2011) find 0.09 (0.19) for the short-term (long-term) impact of advertising on sales. Both meta-analyses find these effects to be stronger for products that are new to the market, which applies in our case of digital goods.

Three meta-analyses investigated the impact of consumer-induced communication (product reviews, word-of-mouth) on sales (Babić et al., 2016; Floyd, Freling, Alhoqail, Cho, & Freling, 2014; You, Vadakkepatt, & Joshi, 2015). Despite different metrics, all studies show an overall positive effect of consumer reviews on sales. Floyd et al. (2014) find a sales elasticity of 0.69 (0.35) for review valence (volume). You et al. (2015) find a sales elasticity of 0.42 for review valence and 0.24 for volume. Babić et al. (2016) report an average positive correlation of word-of-mouth and sales of 0.091. The correlation is higher for digital products (0.108).

Overall, comparing the effects sizes between firm-induced and consumer-induced communication, the meta-analyses suggest that the elasticities of consumer-induced communication are higher than firm-induced communication activities.

3.2. Return effects

Our focal interest is on the relationship between firm- and consumer-induced communications and digital returns. The literature review suggests that both these communication activities have a twofold role: their information can reduce pre-purchase uncertainty or increase expectations (Minnema et al., 2018). Both these processes lead to opposing return effects, so it is unclear which effect dominates.

When consumers have to decide on buying a product, they have usually incomplete information. In online retailing, consumers have limited possibilities to evaluate the product since they cannot inspect it physically. Thus, consumers inform themselves through different information sources offered by retailers, to assess whether a product fits. The product fit is more difficult to evaluate for experience goods than search goods (Hong & Pavlou, 2014). Digital goods, especially media products, show experience goods characteristics, i.e., due to their intangible nature consumers can hardly evaluate the quality of a media product before consumption (e.g., Hennig-Thurau & Houston, 2019, p. 59). Nevertheless, research shows that consumers also seek new information in the setting of digital media products to reduce this pre-purchase uncertainty and integrate this information in their quality evaluation process (Clement, Wu, & Fischer, 2014; Golder, Mitra, & Moorman, 2012). Consequently, both the effects of purchase prevention (Akerlof, 1970) and marginal loss aversion (Kahneman & Tversky, 1979; Prelec & Loewenstein, 1998) will occur, with an uncertain overall returns outcome.

Briefly, both consumer- and firm-induced communication serve as cues that increase purchase certainty and expectations. Certainty reduces returns due to a smaller number of wrong decisions, whereas expectations increase returns due to expectation failure. Theoretically, it is unclear which of these two effects dominates, and our literature review shows that in physical product setting both these effects emerge, depending on the context. In the digital context, it is even more difficult to predict whether the positive or the negative effect will dominate. The two-step purchase and return decision of digital products differs to that of physical products due to two main factors. First, the quality of digital media products is very difficult to determine before consumption. Second, the return process for digital products implies almost zero cost, and products can be directly returned even after consumption with a few clicks. Due to these differences, the effects of communication activities on sales and returns can be substantially different from those of physical products. At an aggregated level across all customers, this can lead to higher or lower returns.

With respect to *firm-induced communication*, previous literature on physical returns has indeed shown that both effects are present. Studies show that firm-induced communication may lower (Hong & Pavlou, 2014) or increase returns (Shulman et al., 2015) depending on whether the purchase prevention or the marginal loss aversion effect dominates. Both these effects might be prevalent when reading a newsletter promotion. Based on our theoretical reasoning, as well as findings from previous literature, we hypothesize two competing effects (Armstrong, Brodie, & Parsons, 2001) with respect to *firm-induced communication*, i.e., newsletter promotions:

H1a. Firm-induced communication is negatively associated with the return of digital goods.

H1b. Firm-induced communication is positively associated with the return of digital goods.

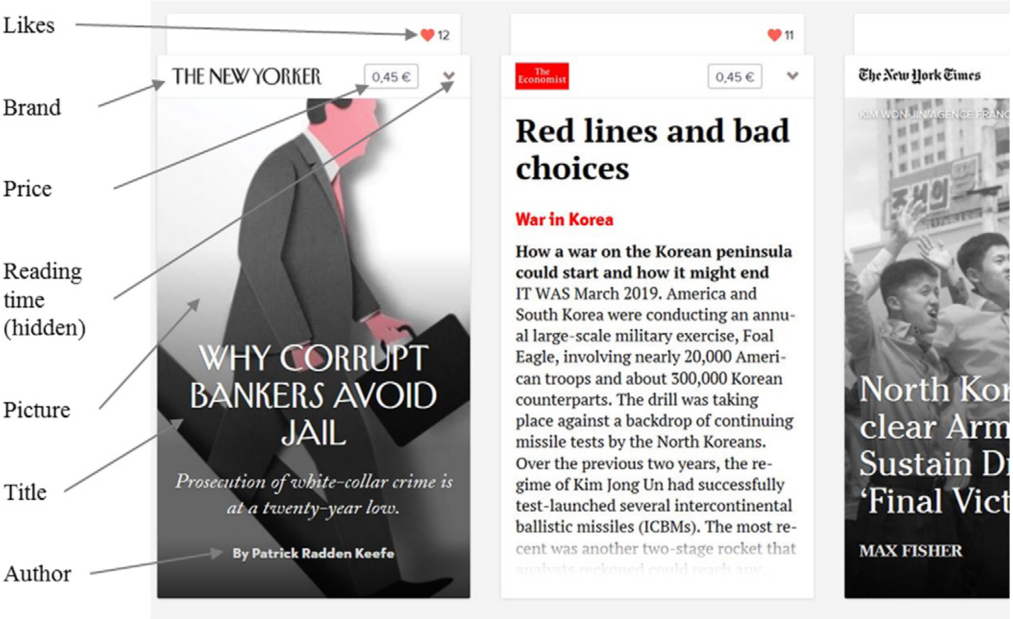

Fig. 2. Screenshot from the portal Blendle.com (Aug 07, 2017).

With respect to *consumer-induced communication*, the theoretical reasoning and findings from previous literature are similar. More customer reviews can reduce uncertainty, resulting in lower returns (Hong & Pavlou, 2014; Sahoo et al., 2018), or they can serve as a quality signal and trigger expectations, which when they are not met, increase returns (Minnema et al., 2016; Sahoo et al., 2018). Consequently, we hypothesize two contradicting effects of the consumer-induced communication:

H2a. Consumer-induced communication is negatively associated with the return of digital goods.

H2b. Consumer-induced communication is positively associated with the return of digital goods.

We test these hypotheses using data from 596 news articles from the online news platform Blendle.

4. Empirical application

4.1. Data

Blendle is a Dutch start-up founded in 2014 that operates internationally in important markets, such as Germany and the U.S. Blendle aggregates articles from different newspapers and magazines, and it offers them to customers on a pay-per-article basis.

When accessing the service, the users are exposed to the starting screen, which gives an overview of the available articles and their main characteristics. Specifically, users see product-related information such as the headline of the article, the author, the price, a teaser picture, and sometimes a text snippet from the teaser or an introduction (see Fig. 2). In addition, users see the number of likes given to an article by other users, as well as the predicted reading time in minutes. Consumers can purchase articles by one-click-purchase. After the purchase, users can return the articles within 24 h. Below each article and on top of the article's screen is an arrow that displays a dropdown menu with the return option among three others (e.g., print). When clicking on it, a pop-up screen asks for the reason (e.g., clicked accidently, price too high, and article too short/long). After selecting a reason, the return is completed and the money is immediately reimbursed. More details about the return process and corresponding reasons are shown in Table A1.

Our data comprise 596 articles from a leading German national newspaper that were sold via Blendle in 2016. We restricted our sample to articles sold at least 30 times.[5] We have aggregated information on sales and returns for each article during 2016. Blendle's major communication tool for promoting articles is an online newsletter comprising approximately 16 articles that the editorial staff selects for a daily promotion to its customers. In 2016, Blendle used only one daily newsletter version that Blendle's journalists curate to the audience.[6] Aside from the newsletter, Blendle does not use other communication actions

[5] Following Minnema et al. (2016) and based on an interview we conducted with the head of online publishing of the respective newspaper in February 2016, we consider only articles that were purchased at least 30 times during our observation period of one year. Articles with fewer sales are likely to have been purchased only by the newspaper's own employees or by the industry's experts.

[6] In 2017, Blendle began to experiment with different variations of newsletters. Specifically, Blendle introduced a customized section in each daily newsletter in addition to two weekly newsletters with the "most clicked articles of the week" and "special interest" articles around one collective topic.

for single-article promotion so that the newsletter serves as our measure of firm-induced communication. We also have information on the number of likes given by other users of the platform, which serves as our measure of consumer-induced communication. Moreover, we collected a number of article-specific characteristics that we control for in our model. Table 2 shows the measures and the descriptive statistics of our variables. We report the pairwise correlations in Table A2 in the appendix.

As dependent variables, we use *sales* (in €) and *return share* (in %) calculated as the ratio of the returned articles value (in €) by the total sales. On average, each article has generated sales of 128.29 € (SD = 160.22). Consumers returned 17% of their purchased articles (SD = 7.18).

Our focal independent variables of interest are firm-induced and consumer-induced communication. Our measure for firm-induced communication is a dummy variable showing whether an article was promoted in the *newsletter*. Some 38% of the articles in our data were promoted in the newsletter by Blendle. We use the overall number of *likes* given by customers for each article as a measure for the consumer-induced communication (Lee, Lee, & Oh, 2015). On average, each article received approximately 19 likes, although there is some variation within our sample (SD = 24.36). The share of likes (i.e., likes divided by number of sold articles) amounts to 11% on average.

We control for a series of article-specific characteristics that were coded by a research assistant and validated by two experts. Specifically, we include characteristics that a potential reader may incorporate in his or her decision to buy or return an article to avoid omitted variable bias. This includes variables that describe the content of an article (news character and opinion versus information orientation), signals (such as headline, famous authors or word count and price) and other reader's comments. We also measure the *news character* of an article building on journalism literature (Noelle-Neumann, Schulz, & Wilke, 2000; Weischenberg, Kleinsteuber, & Pörksen, 2005). The scale measures the recency of the respective event, using a four-point-scale, where 1 indicates events that are not related to current developments and 4 indicates that an article is about events that happened in the last week (M = 2.25, SD = 0.92).

Moreover, we use a dummy variable to measure whether an article is *opinion-oriented* (26%), such as comments, reviews, columns or essays, or has informational content, such as reports and features. We also coded the article *headlines*, in terms of their attractiveness, regarding intelligibility, creativity and the ability to trigger curiosity, on a five-point scale (we rely on the criteria for crafting a headline from Schneider & Esslinger, 2015). We build a formative index of all these single items (index: M = 2.87, SD = 0.73). We control for the buzz level of an article by including consumer *comments* on an article on the website of the newspaper. This website is fully independent of Blendle, so the comments serve as a proxy of the general appreciation of an article and can drive sales and returns.

All articles in our dataset cost EUR 0.29, EUR 0.59 or EUR 0.89. The publisher sets the price of the articles based on their length, i.e., the number of words in an article. Therefore, we use article length in words, as it reflects the reading time (M = 2202.14, SD = 1452.26) and serves as a direct proxy for the article's price (correlation: $r = 0.91$, $p < .001$).

Last, we control for the reputation, i.e., star power, of the author of an article using a dummy variable (Basuroy, Chatterjee, & Ravid, 2003), which is valued one if the article is written by the (vice)editor in chief, a head of a department, a steady columnist, or some other notable author. Approximately 22% of the articles were written by star authors.

We use the natural logarithm for sales and for all continuous independent variables in our model to avoid the violation of normality assumptions (Basuroy, Desai, & Talukdar, 2006; Elberse & Eliashberg, 2003).

4.2. Model

We model the effects of firm-induced and consumer-induced communication on sales (in €) and the return share in separate equations. In our modeling approach, we face two main challenges.

Table 2
Descriptive statistics.

$n = 596$	Measure	Min	Max	Median	Mean	SD
Success measures						
Sales	EUR	8.70	1223.75	63.47	128.29	16.22
Return share	%	2.38	6.47	15.64	16.91	7.18
Communication						
Firm-induced						
Newsletter	Dummy	0.00	1.00	0.00	0.38	0.49
Consumer induced						
Likes	Count	0.00	285.00	1.00	18.75	24.36
Covariates						
News character[a]	Scale 1–4	1.00	4.00	2.00	2.25	0.92
Opinion orientation[a]	Dummy	0.00	1.00	0.00	0.26	0.44
Headline[a]	Scale 1–5	1.00	5.00	3.00	2.87	0.73
Comments	Count	0.00	1426.00	58.00	125.27	165.82
Article length	Word count	273.00	10,302.00	1819.00	2202.14	1452.26
Star power[a]	Dummy	0.00	1.00	0.00	0.22	0.41

Items to measure the headline:
1. The headline is correct, easy to grasp and unambiguously phrased.
2. The headline triggers curiosity.
3. The headline is creative.
[a] Expert coding.

First, both firm-induced and consumer-induced communications do not occur randomly. Consequently, we need to correct for endogeneity of newsletters and likes. The newsletter variable is binary, whereas the consumer likes are a continuous variable. This requires different approaches for endogeneity correction.

Customer-specific communication may be endogenous to sales because likes may be conditional on sales in the sense that consumers need to read articles first before liking them. Consequently, external shocks affecting sales, which are captured by the residuals in the sales equation, may also affect likes, which are an independent variable in the sales equation, leading to endogeneity. In addition, sales and returns may be influenced by factors that are not part of our model specification but that are correlated to consumer likes. As such, likes may be correlated with the error terms u_i^s or u_i^r. In other media industries, researchers face similar endogeneity issues related to consumer-induced communication, e.g., when assessing the effect of consumer review on movie sales (Chintagunta, Gopinath, & Venkateraman, 2010) or the buzz surrounding video game success (Xiong & Bharadwaj, 2014). Since higher sales levels are associated with higher return levels, likes may also be endogenous to returns.

Indeed, a Durbin-Wu-Hausmann χ^2-test shows that likes are indeed an endogenous regressor in the sales equation ($\chi^2(1) = 4.90$, $p = .02$). Similarly, for the returns equation, the Durbin-Wu-Hausman test also provides support that likes are endogenous ($\chi^2(1) = 4.08, p = .04$). Consequently, we need to correct for the endogeneity of likes. For this, we adopt the Gaussian copula method (Park & Gupta, 2012), which has been widely used in recent studies to correct for endogeneity (e.g., Burmester, Becker, van Heerde, & Clement, 2015; Datta, Ailawadi, & van Heerde, 2017; Datta, Foubert, & van Heerde, 2015). For identification, the Gaussian copula method requires endogenous variable to not follow a normal distribution (Park & Gupta, 2012). A Shapiro-Wilk test (w = 0.99, z = 2.14, $p = .03$) shows that this condition is satisfied for likes.

The decision whether to promote an article in the newsletter is also not made randomly. Every morning, Blendle's editorial team selects news articles from all of their contracted outlets for promotion in the newsletter, so Blendle customers usually get their recommendations around breakfast time. For the selection of articles, the editorial board depends on the same product features that we control for, specifically the author's star power and the article's price and length, headline and content. Thus, the selection of which articles are promoted in a newsletter is based on journalistic quality. Indeed, a Durbin-Wu-Hausman test shows that newsletter is an endogenous regressor in the sales equation ($\chi^2(1) = 6.08$, $p = .01$) and the return share equation ($\chi^2(1) = 13.02$, $p = .00$). Due to its binary nature, the newsletter variable is not adequate for copula correction (Park & Gupta, 2012). Thus, we correct for newsletter endogeneity by directly modeling the correlation between the error terms of the sales and returns equations and the endogenous newsletter (Papies, Ebbes, & Van Heerde, 2017, p. 590). We specify a probit equation, with newsletter as the dependent variable and article characteristics as independent variables, which is estimated simultaneously with the sales and the return share equations.

Second, to identify the system of equations, we need specific variables that are unique in each equation and do not appear in the other equations in the system (Greene, 2012, p. 602; Leeflang, Wittink, Wedel, & Naert, 2000, p. 381; Konuş, Neslin, & Verhoef, 2014). Accordingly, we generate instruments for the sales and the newsletter equation based on the genre and price category of a specific article in line with former studies on media products, which also build instruments based on genre (Marchand, Hennig-Thurau, & Wiertz, 2016; Zhu & Zhang, 2010). Articles in our data can be classified in four genre (topics) groups: science and health, business news, politics and society, and arts and culture. Articles not fitting any of these four genre groups are classified as “other”. By combining the genres with the three price categories, we generate 15 groups, which are used to generate the sales and newsletter instrument variables. For sales, we use the average sales of all other articles within the specific group, after excluding the article itself. Similarly, for the newsletter, we take the average newsletter position among all articles within a group, after excluding the specific article itself. This measure is coded such that it equals 0 if an article was not promoted in the article and is valued between 1 and 16,[7] with 16 showing the first place and 1 the last one. By including these two variables, the covariates in all equations differ and the model is identified through exclusion restrictions.

Thus, our system of equations estimates the effect of firm-induced and consumer-induced communication on sales, newsletter and return share simultaneously according to Eqs. (1)–(3). Higher returns are associated with higher sales because customers must first buy products to return them (Petersen & Kumar, 2009). We account for this effect by including sales in the returns equation. Sales and return share are specified as linear equations, whereas the selection decision for an article to be part of the newsletter is a probit specification.

$$sales_i = \beta_{0i}^s + \gamma_1^s newsletter_i + \gamma_2^s likes_i + \beta^s X_i + \varphi^s \overline{sales\_genre}_i + Copula\_correction_i + u_i^s \tag{1}$$

$$newsletter_i = \beta_{0i}^n + \beta^n X_i + \varphi^n \overline{newsletter\_position}_i + u_i^n \tag{2}$$

$$return\_share_i = \beta_{0i}^r + \gamma_1^r newsletter_i + \gamma_2^r likes_i + \beta^r X_i + \varphi sales_i + Copula\_correction_i + u_i^r \tag{3}$$

where γ_1^s and γ_1^r capture the effect of newsletter on sales and return shares, γ_2^s and γ_2^r capture the effect of likes on sales and return share, X_i is a vector of our control variables, and u_i^s, u_i^n and u_i^r are the error terms for the sales, newsletter and return share equations, which are correlated. In the sales equation we include the average sale of all articles $\overline{salesgenre}_i$ and the average newsletter position of all articles $\overline{newsletterposition}_i$ within the same genre-price group as article i (excluding article i

[7] The position of our newspaper's articles in Blendle's newsletter is always between 1 and 16.

Table 3
Results of the simultaneous estimation of sales, newsletter and return share.

	Sales in EUR (ln)		Newsletter		Return share	
	β (se)	p	β (se)	p	β (se)	p
Newsletter	−0.039 (0.129)	0.764			−0.051 (0.019)	0.006
Likes (ln)	2.808 (0.268)	0.000			−0.183 (0.055)	0.001
News character (ln)	−0.049 (0.040)	0.220	0.030 (0.119)	0.801	0.004 (0.007)	0.570
Opinion orientation	−0.025 (0.044)	0.571	0.219 (0.127)	0.085	0.027 (0.007)	0.000
Headline (ln)	0.277 (0.072)	0.000	0.476 (0.195)	0.015	−0.008 (0.012)	0.547
Comments (ln)	0.010 (0.009)	0.244	0.023 (0.026)	0.368	−0.002 (0.001)	0.161
Word count (ln)	0.068 (0.044)	0.123	0.272 (0.098)	0.005	−0.019 (0.008)	0.013
Star power	0.146 (0.043)	0.001	0.024 (0.130)	0.855	−0.002 (0.007)	0.835
Sales (ln)					0.027 (0.013)	0.039
Sales (instrument)	0.529 (0.042)	0.000				
Newsletter (instrument)			−0.495 (0.171)	0.004		
Likes (copula correction)	−1.989 (0.261)	0.000			0.135 (0.049)	0.006
Constant	−6.006 (0.697)	0.000	−2.500 (0.723)	0.001	0.683 (0.137)	0.000
Observations			596			
log likelihood			127.58			

itself) for identification purposes. $Copula\_correction_i$ represents the copula correction terms for likes, defined by the following equation:

$$Copula\_correction_i = \phi^{-1}(H_{Likes}(Likes_i)) \quad (4)$$

where $\phi^{-1}$is the inverse of normal cumulative distribution function and $H_{Likes}(Likes_i)$ denotes the empirical cumulative distribution function of likes.[8]

4.3. Results

4.3.1. Main results

Table 3 shows the estimates; we report cross-equation correlations in Table A3. The results show that both firm-induced and consumer-induced communication decrease the return share: Being promoted in the newsletter decreases the return share of an article ($\beta = -0.05$, se = 0.019, $p < .01$), which provides support for the competing hypothesis H1a: higher levels of firm-induced communication decrease returns.

Similarly, consumer-induced communication measured by likes decreases returns ($\beta = -0.183$, se = 0.055, $p = .001$), providing support for the competing hypothesis H2a: return share is lower for higher levels of consumer-induced communication.

With respect to sales, we expect positive effects of newsletters and likes. Indeed, we see a positive sales effect of likes on sales ($\beta = 2.808$, se = 0.268, $p < .001$), although the newsletter effect is not significant ($\beta = -0.039$, se = 0.129, $p = .764$). Although this effect may seem surprising, from a behavioral perspective, firm-induced communication potentially increases the pre-purchase certainty, as discussed above, which may lead to the purchase prevention effect. Thus, consumers may purchase more products that they consider fit their needs. However, the information contained in the newsletter may also prevent consumers to buy articles because they are more certain that the product will not fit their preferences. These two effects might balance each other out so that overall, the newsletter does not significantly increase sales.

In summary, Table 3 shows that firms selling digital products can benefit from both these types of communication. The mechanisms of these effects differ: Consumers' likes have a twofold positive effect, since they increase sales and lower returns, whereas promoting articles in newsletters only lowers returns. We explore the impact of each of these communication mechanisms on a news article's profitability using a Monte Carlo simulation (Section 4.4).

[8] We exclude 6 observations in the sales and return share equation due to missing values of the copula correction term.

4.3.2. Additional results

Table 3 shows that the instruments for sales and newsletters have a significant impact on sales and the newsletter decision as expected. The results also show that higher sales are indeed associated with higher returns ($\beta = 0.027$, se $= 0.013$, $p = .039$); this outcome in line with former research showing this effect using customer-level data (e.g., Petersen & Kumar, 2009).

Table 3 also reveals article-specific characteristics that influence sales and returns. The attractiveness of article headlines ($\beta = 0.277$, $p < .001$) and the star power of authors ($\beta = 0.146$, $p < .001$) are positively associated with sales. Clearly, they work as purchase signals, whereas the headline also influences the newsletter decision ($\beta = 0.476$, $p = .015$). The return share is higher for articles with opinion orientation ($\beta = 0.027$, $p < .001$) and lower for longer and more expensive articles ($\beta = -0.019$, $p = .013$). Last, the copula correction term is significant in both sales and returns equations, showing the need to correct for endogeneity of likes (Datta et al., 2015).

Table 3 also shows that the firm's decision to promote articles in its newsletter is driven by the opinion orientation of an article ($\beta = 0.219$, $p = .085$), by its length and price ($\beta = 0.272$, $p = .005$) and by headline attractiveness ($\beta = 476$, $p = .015$). That is, Blendle prefers to promote longer articles, articles that focus on opinion-oriented content instead of informational content, and articles with catchy headlines in its newsletter.

Interestingly, the news character and the popularity of an article, measured by its “buzz” (comments), show no significant effects in either of the equations in our model. It seems that aspects other than news character play a role in the choice of an article. With respect to buzz, we speculate that our findings indicate that Blendle users do not read the same article on the publisher's outlet (and therefore do not see the comments) because they rely on the integrated service offer within Blendle.

4.3.3. Robustness estimations

To examine the robustness of our results, we conduct multiple sensitivity analyses and provide the results in Tables 4–6. First, we assess whether our results are sensitive to *the measure for returns*. Accordingly, we re-estimate Eqs. (1)–(3) simultaneously but measure returns by the value of returned articles in €, instead of the return share. Table 4 shows that our results are robust to the use of an alternative return measure.

Second, our results are based on the model with endogeneity correction for consumer likes. To assess the sensitivity of these results, we also run Eqs. (1)–(3) without the copula correction term for likes. Table 5 shows that the main results remain unchanged, although the effects for likes differ from those of our main model, showing the need to correct for endogeneity (Leenher, Van Heerde, Bijmolt, & Smidt, 2007). In addition, length (price) becomes significant in the sales equation at the 10% level.

Third, we add the genre dummies in each of Eqs. (1)–(3) and re-estimate the model with the “science & health” group serving as the reference group. Table 6 shows that our focal effects remain unchanged.

Table 4
Operationalization of returns as return value (in €).

	Sales (in €, ln)		Newsletter		Return (in €, ln)	
	β (se)	p	β (se)	p	β (se)	p
Newsletter	0.071 (0.135)	0.599			−0.468 (0.077)	0.000
Likes (ln)	2.829 (0.268)	0.000			−0.875 (0.263)	0.001
News character (ln)	−0.049 (0.038)	0.204	0.039 (0.117)	0.739	0.004 (0.036)	0.902
Opinion orientation	−0.032 (0.043)	0.457	0.222 (0.124)	0.075	0.166 (0.039)	0.000
Headline (ln)	0.256 (0.071)	0.000	0.502 (0.191)	0.009	0.011 (0.064)	0.865
Comments (ln)	0.009 (0.008)	0.285	0.016 (0.025)	0.524	−0.008 (0.008)	0.296
Word count (ln)	0.056 (0.043)	0.196	0.222 (0.095)	0.020	−0.067 (0.038)	0.083
Star power	0.144 (0.042)	0.001	0.011 (0.127)	0.930	−0.015 (0.040)	0.703
Sales (ln)					1.007 (0.061)	0.000
Sales (instrument)	0.537 (0.041)	0.000				
Newsletter (instrument)			−0.359 (0.149)	0.016		
Likes (copula correction)	−2.010 (0.260)	0.000			0.662 (0.232)	0.004
Constant	−6.017 (0.695)	0.000	−2.282 (0.708)	0.001	1.057 (0.663)	0.111
Observations			596			

Table 5
Results of the model without the copula correction term for consumer likes.

	Sales (in €, ln)		Newsletter		Return share	
	β (se)	p	β (se)	p	β (se)	p
Newsletter	−0.063 (0.154)	0.682			−0.043 (0.020)	0.033
Likes (ln)	0.739 (0.021)	0.000			−0.042 (0.01)	0.000
News character (ln)	−0.046 (0.043)	0.282	0.029 (0.119)	0.806	−0.003 (0.007)	0.638
Opinion orientation	−0.000 (0.048)	0.996	0.222 (0.128)	0.082	0.023 (0.007)	0.001
Headline (ln)	0.297 (0.078)	0.000	0.478 (0.197)	0.015	−0.011 (0.013)	0.398
Comments (ln)	0.011 (0.009)	0.224	0.026 (0.026)	0.320	−0.002 (0.001)	0.107
Word count (ln)	0.084 (0.048)	0.079	0.274 (0.098)	0.005	−0.021 (0.008)	0.011
Star power	0.124 (0.047)	0.008	0.030 (0.13)	0.819	0.000 (0.007)	0.979
Sales (ln)					0.025 (0.013)	0.055
Sales (instrument)	0.530 (0.045)	0.000				
Newsletter (instrument)			−0.527 (0.175)	0.003		
Constant	−0.966 (0.267)	0.000	−2.488 (0.727)	0.001	0.346 (0.044)	0.000
Observations			596			

4.4. Profit impact

Thus far, we have discussed the results of our econometric model, where we simultaneously considered the impact of newsletter and consumer likes as measures of firm- and consumer-induced communication on sales and returns. From a managerial perspective, firms are interested in the profitability effects. In this section, we aim to assess these effects.

We estimate four different scenarios, using our model estimates from Table 3. In the first scenario, we calculate the profit for the case where the firm does not send the newsletter, but consumer likes are at their actual level in the data. In the second scenario, we calculate the incremental profit of introducing newsletter promotions versus Scenario 1. Profitability will depend on the extent to which newsletter decreases return share and, thus, increases net revenues and ultimately profit. Next, we calculate the incremental profit for the case in which consumer likes increase by 1% for the case where the company does not send a newsletter (Scenario 3) and when the company sends a newsletter to its customers (Scenario 4). The purpose of this simulation is to show the relative impact of both these communication paths on sales, returns and profitability. Managers can decide whether to use a newsletter, but they cannot control consumer-induced communication. However, companies can try to enhance consumer communication on their platforms, e.g., by positioning the like button prominently on the platform or by actively asking consumers to evaluate the articles. Thus, this simulation aims to show the separate effect of each communication path, firm- and consumer-induced, as well as their common effect, when both are operative.

For all scenarios, we use Monte Carlo simulations of our model. We use estimates of Eqs. (1)–(3) to generate sales and returns for each article in our sample. We then take the average value for sales and return share across all articles to calculate the *net revenues*. As the publisher has produced the content for its own outlets, we assume that the production costs are sunk. Furthermore, we assume that the variable costs of distributing the content digitally are negligible, and the revenue share per article given to Blendle is constant. We conclude by assuming that the net revenue is a very good proxy for the article's profitability on Blendle. Table 7 shows the results of our simulations.

In Scenarios 1 and 2, the average sales for a news article amount to 75.57 € because the newsletter does not affect sales significantly, and the likes are equal in both scenarios. However, the return share decreases to 13.7% in Scenario 2 versus 18.81% in Scenario 1 due to the negative effect of the newsletter on return shares. This outcome leads to a profit increase of 5.92%.

In Scenarios 3 and 4, we simulate a setting in which the number of consumer likes increases by 1% overall. An increase in consumer likes translates into higher sales (77.49 € in both scenarios since the newsletter does not affect sales). At the same time, the return share decreases from 18.81% in Scenario 1 to 18.65% in Scenario 3 due to the 1% higher level of likes. Although this difference may seem small, it leads to an increase in the net revenues and, consequently, a profit increase of 2.67% toward the baseline Scenario 1.

When both newsletters and a 1% higher level of likes are effective, the return share decreases even more to 13.54% (Scenario 4). This outcome translates into a higher net revenues level in Scenario 4 and increases the profit by 8.42%. Note that we do not account for additional costs related to the newsletter introduction or to the increase of number of likes. These additional costs will likely depend on the type of action. For example, technical improvements implemented in the platform to increase the number of likes, e.g., through a

Table 6
Results of the model with genre-specific dummy variables.

	Sales (in €, ln)		Newsletter		Return share	
	β (se)	p	β (se)	p	β (se)	p
Newsletter	−0.026 (0.131)	0.840			−0.045 (0.02)	0.025
Likes (ln)	2.802 (0.268)	0.000			−0.187 (0.056)	0.001
News character (ln)	−0.046 (0.041)	0.271	0.102 (0.126)	0.418	0.003 (0.007)	0.690
Opinion orientation	−0.026 (0.045)	0.553	0.193 (0.129)	0.134	0.025 (0.007)	0.001
Headline (ln)	0.272 (0.072)	0.000	0.453 (0.196)	0.021	−0.008 (0.012)	0.526
Comments (ln)	0.010 (0.009)	0.271	0.021 (0.026)	0.421	−0.002 (0.001)	0.107
Word count (ln)	0.064 (0.045)	0.159	0.300 (0.1)	0.003	−0.021 (0.008)	0.009
Star power	0.150 (0.044)	0.001	0.045 (0.132)	0.733	−0.002 (0.007)	0.777
Sales (ln)					0.250 (0.013)	0.030
Genre: Business	−0.046 (0.067)	0.490	−0.151 (0.201)	0.454	0.004 (0.011)	0.703
Genre: Politics & society	0.010 (0.068)	0.884	−0.405 (0.198)	0.041	0.001 (0.011)	0.894
Genre: Culture & arts	0.004 (0.062)	0.955	0.014 (0.192)	0.941	0.015 (0.01)	0.142
Genre: Others	0.007 (0.057)	0.902	−0.032 (0.174)	0.852	0.003 (0.009)	0.786
Sales (instrument)	0.535 (0.043)	0.000				
Newsletter (instrument)			−0.603 (0.192)	0.002		
Likes (copula correction)	−1.982 (0.261)	0.000			0.137 (0.049)	0.005
Constant	−5.982 (0.697)	0.000	2.498 (0.734)	0.001	0.691 (0.138)	0.000
Observations			596			

pop-up button, would lead to overhead costs, which are spread across the whole platform, whereas actions dedicated to single articles, e.g., sponsored ads, would generate costs related to a single article. However, it seems reasonable to assume that both these activities will have some costs, which will lower the profit impact of the newsletter and likes, but not to the extent of fully compensating for the profit increase. Thus, Scenarios 3 and 4 are likely to remain profitable. In summary, when companies have to decide whether to introduce a newsletter or increase consumer likes, they should first focus on the newsletter, since this would increase the profit by 6%, assuming that they have full control over this decision. However, this action is of a finite nature because a newsletter cannot promote an infinite number of articles. Consumer likes, however, are not limited in that sense, yet it might be more difficult for companies selling digital products to encourage likes. If they do so successfully, an increase of likes by 1% increases profit by 3%, even without introducing the newsletter. The most profitable scenario is when companies use both communication channels; in this case, profit will increase by more than 8%.

It should be noted that Scenarios 3 and 4 are quite conservative in terms of the increase in consumer likes by 1% — in our sample, the average number of likes is 19, and the 1% increase corresponds, thus, to less than one like per article. The profit impact of

Table 7
Profit impact of newsletter and consumer likes.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Newsletter = 0, Likes = likes	Newsletter = 1, Likes = likes	Newsletter = 0, Likes = likes + 1%	Newsletter = 1, Likes = likes + 1%
Sales	75.57	75.57	77.49	77.49
Return share	18.81%	13.70%	18.65%	13.54%
Returns	14.22	10.36	14.45	10.49
Net revenues/profit[a]	61.35	65.21	63.03	66.99
Incremental profit increase		5.92%	2.67%	8.42%

[a] The calculation is based on the assumptions that the production costs of the article by the publisher are sunk, the variable costs of distributing the content digitally on Blendle are negligible, and the revenue share per article given to Blendle by the publisher is constant across all scenarios. Thus, we use net revenues as a profit measure.

likes is already much stronger if we assume that companies can increase likes by one like on average for each article — in this case, the profit increases by 27.4%, showing the high potential of consumer induced communication as an instrument to increase sales, decrease returns and improve profitability.

5. Discussion

5.1. General discussion

Amazon, Audible, and Blendle provide their customers with the option to return their purchased digital products. The firm's decision to provide a return option for digital products can be risky for the overall business model because consumers may purchase an article and return it at almost no cost, even after consumption. Here, the context of digital products is specific. This makes the investigation of digital returns important, as it differs substantially from physical returns, where returning products requires effort regarding repacking, postmarking, and shipping. In addition, consumers usually cannot return physical products after consumption. Due to the higher risk of returns in the digital setting, companies offer their consumers information through different communication activities, which may be initiated by the companies themselves (newsletters or emails) or by the consumers (consumer reviews or likes). Communication activities, however, trigger two effects with opposing effects on returns: they avoid purchases with low fit by informing consumers and decreasing pre-purchase uncertainty, leading to the so-called purchase prevention effect (Minnema et al., 2018; Shulman et al., 2015). At the same time, they increase expectations, leading to more purchases and more returns when these expectations are not fulfilled, the so-called marginal loss aversion effect (Minnema et al., 2018; Shulman et al., 2015). The first effect reduces returns, whereas the second increase them. The overall effect depends, thus, on which of these effects will dominate, and the literature has demonstrated mixed results of communication activities in the physical product setting. However, due to the specific characteristics of digital goods, discussed above, it is not clear which of these two mechanisms will dominate in a digital setting. Consequently, the managers of digital product companies need specific insights on how communication effects influence sales, returns and overall profitability. Extant research has studied the effects of communication activities on sales of digital products (Babić et al., 2016; Sethuraman et al., 2011), but insights on return effects are lacking.

In this paper, we empirically study the effect of firm- and consumer-induced communication on returns for digital products. Interestingly, despite the easier return process with almost no cost and the possibility for fraudulent behavior, the average return share in our data is only 17%, which is lower than, e.g., the return share for fashion products. However, due to the direct financial impact, managers of digital products need insights into how to promote their products such that sales are increased but returns are not.

We use data from an online article platform that offers a pay-per-click and return-per-click strategy to its users to analyze the effect of newsletter promotions and consumer likes on returns. Specifically, we have data on 596 articles for one year and estimate a multi-equation model to assess the effects of firm- and consumer-induced communication on sales and return share. Lastly, we calculate the profit impacts relying on Monte Carlo simulations. Our results show that firms selling digital products in pay-per-unit models can benefit from both firm-induced and consumer-induced communication. The effects, however, differ. Consumer likes show a positive effect on sales and a negative effect on returns, whereas the newsletter lowers returns without a sales effect. A simulation shows that both of these communication activities increase profits compared to a baseline scenario without the newsletter and with the current number of likes. A change in the number of likes by 1% (which on average is less than 1 like for each article) already improves profits by 2.67%. Informing consumers through a newsletter has also a positive impact effect by 5.92%. Thus, we show that companies selling digital products benefit from both types of communication.

Regarding sales effect, we do not find a positive effect of firm-induced communication, measured by newsletter promotions. This finding differs from previous studies, which find positive effects for physical products (e.g., De et al., 2013; Petersen & Kumar, 2015). One potential reason for these different effects may be the specific form of the firm-induced communication itself. From a theoretical perspective, the effect can be explained by the purchase prevention effect of the newsletters. Newsletters give additional information to potential readers, decreasing his/her pre-purchase uncertainty, avoiding purchases with poor fit, and increasing purchases with high fit. These two opposing effects seem to balance out across all customers, so we do not see an effect on aggregated sales. In addition, users of these aggregation platforms might make decisions independently from editorially compiled information, which has been the standard in the industry for a long time. Rather than relying on editorially compiled information, users might appreciate the opportunity to rely on other readers' recommendations.

Likes, in contrast, increase sales with an elasticity of 2.81. This effect is higher than word-of-mouth effects on sales reported in meta-analyses. Floyd et al. (2014) and You et al. (2015) report mean elasticities below 0.7 for review valence and volume. Babić et al. (2016), however, show that eWOM has a stronger link to sales of new and digital products, as well as products sold on e-commerce platforms. All these boundary conditions apply in our setting and can explain the higher identified effect of likes. In addition, this elasticity is in line with effects of review scores applied and reported in entertainment product research. For example, Xiong and Bharadwaj (2014) report elasticities ranging from 1.47 to 2.19 for video games, and Lee et al. (2015) report an elasticity of 1.23 for Facebook likes. Altogether, our findings indicate that consumer-induced communication has a higher impact in the realm of digital news than for physical products, or other media products.

5.2. Theoretical contribution

Our findings contribute to the existing research along three dimensions. First, our study adds to the *literature on product returns* by analyzing the effects of firm- and consumer induced communication on returns and profitability in a digital product setting.

While the effects of firm- or consumer-induced communication on sales of digital products have been studied in the past (Babić et al., 2016; Sethuraman et al., 2011), the effects on return have not been considered in any academic research so far. Our study links the communication activities of companies as a part of their marketing behavior and product returns, addressing one of the avenues for future research identified (Minnema et al., 2018, p. 114; Petersen & Anderson, 2015). In addition, we complement insights from research that study product returns in a physical product setting (e.g., Minnema et al., 2016; Petersen & Kumar, 2015). We show that for digital products, both firm- and consumer-induced communication are related to lower returns. This finding is in line with what Hong and Pavlou (2014) find for experience goods. The positive effect of consumer likes on returns differs from the physical product setting, where consumer reviews are reported to increase returns (Minnema et al., 2016). Overall, our findings make an important contribution because they indicate that in the digital products setting, the purchase prevention effect of communication effects dominates over the marginal aversion loss effect, i.e., newsletters and likes inform consumers, avoiding purchases with lower fit and decreasing returns.

Our results also add to the research that links product characteristics and product returns (e.g., Hong & Pavlou, 2014; Petersen & Kumar, 2009). We provide insights on the product characteristics of digital products that influence returns. The return share is lower for longer and more expensive articles and higher for articles with opinion orientation. By this, we added to the literature that links product characteristics to their returns (Hong & Pavlou, 2014). Overall, our findings expand the understanding on what drives product returns for digital news articles. Our findings are generalizable to similar digital products, such as e-books or audiobooks.

Second, our findings add to the literature on *digital marketing*, especially related to the literature on digital business models in the publishing industry (Sridhar, Mantrala, Naik, & Thorson, 2011; Pauwels & Weiss, 2008; or Deleersnyder, Geyskens, Gielens, & Dekimpe, 2002). We show the profit effects of different communication types for digital pay-per-unit business models. Our findings indicate that both newsletters and likes have beneficiary effects for companies relying on pay-per-unit business models. Interestingly, in our setting, newsletters increase profits through their negative effect on returns, but there is no sales effect. We can only speculate about the reasons for this effect, but these results indicate that users of aggregated platforms might make their purchase decisions independently of editorially compiled information, such as a newsletter. In the news industry, editorially compiled information has been the standard for a very long time. It seems that users of these platforms appreciate the technologically fostered possibility to rely on other readers' recommendations. Information generated by other newsreaders is a strong quality cue for other potential newsreaders and has a high potential to increase profits.

Last, our findings add to the research on *media products*. Extant research has analyzed the effects of firm- and consumer-induced communication, as well as other success drivers such as star power, in the context of movies (Hofmann, Clement, Völckner, & Hennig-Thurau, 2017), video games (Burmester et al., 2015) or books (Schmidt-Stölting, Blömeke, & Clement, 2011). We add to this body of research by providing insights from the field of news consumption. Our results show that articles with attractive headlines and with highly regarded authors are positively related to sales. However, they do not directly influence the return share, which confirms their role as purchase signals. With respect to content, articles expressing opinions (such as reviews, essays, or columns) are more likely to be promoted in the newsletter, despite their positive relationship to returns. Blendle's editors seem to value the expression of opinions, while newsreaders do not seem to embrace their recommendations. Taken together with the purchase signals, these findings suggest that authors should build a strong "human brand," motivate attractive and convincing headlines, and carefully calibrate the amount of opinion orientation.

5.3. Managerial implications

Our results offer guidance for managers of content-aggregating platforms (such as Blendle), publishers (such as The News York Times) and content creators (the authors or journalists). The most important finding is that both newsletters and consumer likes have a positive profit effect. Thus, managers should use both communicational channels. For digital companies in which sales are developing in a satisfactory manner but that are facing high returns, the newsletter communication may be a cost-efficient instrument to reduce returns and improve profitability. The negative relationship between returns and newsletter promotion can be a promising tool to prevent high return ratios for digital products. However, companies that want to increase sales and lower returns should seek ways on how to enhance consumer communication, increase consumer likes, and integrate consumer likes in their platform. Companies could, for example, implement like, rating, or share buttons on the product's webpage or ask their customers for ratings via e-mails; however, companies need to also consider potential adverse effects because they might be perceived as intrusive. Another option is to ask for ratings in exchange for benefits, e.g., in the form of free units or coupons. These efforts to increase likes will surely be costly. These costs will reduce profitability due to higher likes, so companies should consider them in their business cases.

Moreover, our results provide insights on the characteristics of news articles that increase returns. Digital platform managers could explicitly offer articles with lower return risks on their platform. We see, for example, that opinion-related articles and shorter articles are associated with higher returns. An obvious solution for Blendle is to avoid offering opinionated articles and shorter articles. Once products with higher return risk are offered on the platform, digital platform managers can advertise those in the newsletter to reduce their specific higher return share due to their characteristics by the negative newsletter effect on returns. Blendle seems to already follow this suggestion: despite the positive return effect, articles with opinion-oriented content, such as reviews, are selected more often for newsletter promotion (in comparison with information oriented content, such as reports).

Last, we have two implications that are relevant for platforms, publishers, and authors alike. The first one pertains to the relevance of headlines, which we identify to be an important sales driver. Consequently, publishers should urge their authors or invest effort in crafting an intelligible, creative and curiosity-triggering headline, and platforms can select articles with appealing headlines for their platforms. Our second recommendation relates to the star power of authors, since our results indicate that notable authors are a purchase signal for newsreaders. This recommendation finds support in the downward trend of branded bundle sales (newspapers). Not facing a branded bundle, newsreaders are likely to take additional quality signals such as an author's name into account, in addition to the newspaper brand. Thus, publishers should build strong "human brands" for their editors/coeditors and offer articles by well-known news authors. Similarly, platforms should favor articles by well-known authors. Last, authors should use this knowledge to create and sell their own brand to newspapers and publishers.

5.4. Limitations and future research

This study also had some limitations that provide avenues for future research. First, we observe only one firm-induced communication channel, namely, one type of newsletter. Future studies should analyze other forms of advertising, such as search-engine marketing or sponsored content on social media platforms, as well as synergies between different firm-induced communication instruments.

Second, our analysis is based on aggregated data on the article level. In this way, we were able to assess the effects on overall sales and returns but not on single individual decisions. It would be interesting to model these competing purchase prevention and marginal loss aversion effects in the context of digital product purchase decisions at an individual level. Future studies could utilize individual data to complement our findings regarding individual return behavior. This would also allow investigating the consequences of individual return behavior on customer retention and ultimately customer value. Third, our data come from only one country and one outlet. Although Germany is of high economic relevance, other studies could use data from multiple countries to analyze the effect of cultural factors — which often play a major role in digital business and marketing (e.g., Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Liu, Furrer, & Sudharshan, 2001). Last, future studies can use longitudinal data to analyze dynamic the effects of firm- or consumer-induced communication.

Our final remark is that although we take a profitability perspective on the news industry, we recognize that investigative journalism has an important role in democracies and sometimes requires the publication of articles that do not target the primary goal of profit maximization, especially in the age of "fake news" and "alternative facts."

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Appendix A. Appendix

Table A1
Details on the return process and return reasons [in %].

$n = 596$	Mean	SD
Return reasons		
Opened accidentally	0.17	0.12
Did not meet expectations	0.14	0.12
Too pricey	0.11	0.10
Article too short	0.04	0.07
Article too long	0.02	0.05
Customized reason	0.02	0.03
Article not readable	0.01	0.03
Other reason	0.01	0.03
Article already copied	0.00	0.01
Article already printed	0.00	0.02
Automatic reimbursements		
10-second rule	0.48	0.17

The focal dependent variable in our study is the return of news articles. Although there are different reasons for returning a news article, we look at all returns, independent of their corresponding reasons. From a managerial perspective, the reasons do not influence the overall profitability of an article. However, as additional information, we elaborate on the return process and the reasons in the following.

Blendle (blendle.com[9]) explains the return policy as follows: "If you have clicked on an article by mistake, for instance, just close it again right away, and you will not be charged. When an article is closed again within 10 s, the price is reimbursed to your Blendle wallet directly and automatically. If you have read an article and found it somewhat disappointing, not worth the set article price, or in any way not worth your money, you can still get it back. At the end of the article, you will find the Blendle refund button (up to 24 h after purchase). Just click, select a reason to let the publishers know why you were not happy — and done! Your wallet will show that the article price has been reimbursed."

Table A1 shows the mean and standard deviation of the average aggregated return ratios per article. After accidental purchases, the most important reasons refer to unmet expectations or dissatisfaction due to price or length. On average, 48% of the returns of an article were due to the 10-second rule — Blendle's automatic refund option.

[9] https://www.blendle.support/hc/en-us/articles/212583485-Blendle-s-refund-options-Get-your-money-back-with-one-click

Table A2
Correlations of the dependent and independent variables.

	1	2	3	4	5	6	7	8	9	10
1. Sales (in €, ln)	1.00									
2. Likes (ln)	0.82***	1.00								
3. Newsletter	0.38***	0.33***	1.00							
4. Return share (ln)	−0.41***	−0.35***	−0.19***	1.00						
5. News character (ln)	−0.10**	−0.05	0.01	0.04	1.00					
6. Opinion orientation	0.00	0.13***	0.05	0.11***	0.08*	1.00				
7. Headline (ln)	0.31***	0.28***	0.12***	−0.14***	−0.02	0.03	1.00			
8. Comments (ln)	0.20***	0.17***	0.06	−0.12***	−0.09*	0.06	0.11***	1.00		
9. Word count (ln)	0.45***	0.24***	0.07*	−0.23***	−0.07	−0.32***	0.09**	0.12***	1.00	
10. Star power	0.08*	0.05	0.01	0.03	0.20***	0.15***	0.00	−0.06	−0.01	1.00

* $p < .1$.
** $p < .05$.
*** $p < .01$.

Table A3
Cross-equation correlation.

	Sales	Newsletter
Newsletter	0.409	
Return	−0.256	0.319

Note: all correlations are significant with $p < .05$.

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