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CAN MOBILE APPS DEFEND PRINT MEDIA?

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Research

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Abstract

The business model of traditional media has come under attack since the diffusion of the Internet. One of the latest disruption waves are mobile apps. In this paper, we analyze the effect a mobile app has on the lifetimes and lifetime values of customers of print media. For this purpose, we use subscription data and develop a model based on survival analysis that captures the interdependence between two content delivery channels, in our context the offline and the mobile channel. We apply our model to a large dataset received from a publisher who offers a newspaper in a print version and a version for a mobile app. The results suggest that there exists a complementary interdependence between these media, as having a subscription to one of them decreases the hazard to cancel a parallel subscription to the other one. Given this complementarity, we find that the mobile app increases the lifetimes and lifetime values of print customers and vice versa. We also analyze the attribution of these effects.

Keywords: Mobile apps, Print media, News, Substitution, Complementarity, Customer lifetime value, Survival analysis

1 Introduction

The term “mediamorphosis” has been coined for the ever-changing media economy, which suggests that incumbent media have to adapt when new media become relevant for customers (Fidler, 1997). This is because the presence of new media may change the customer-publisher relationship, affecting its duration as well as its monetary value to the publisher (Hennig-Thurau et al., 2010).

During the last two decades, the media industry faced two such disruptions. The first occurred in the mid-1990s and was triggered by the diffusion of the Internet. Publishers started to experiment with the new possibility of distributing their content online in order to reach a new audience and not to lose their existing customers to competitors. Possibly unintended, this led to a dramatic change in media consumption behavior: Customers soon became accustomed to the opportunity of accessing content at any time and largely free of cost. This, in turn, forced publishers to increase their investments in the online channel. However, this channel did not give them much competitive advantage but quickly became a necessity to avoid competitive disadvantage. At the same time, the offline channel suffered from the rise of the Internet, as it was less frequented. In the case of news, for example, many customers switched from reading printed newspapers to Internet information sources. This problem was exacerbated by the fact that new Internet portals often specialized on classifieds (such as jobs, used cars, or dating) and took most of this market from newspapers. Besides, advertisers recognized that some customers can better (or only) be reached via the Internet and that ads in this channel can be better targeted and monitored than ads in the offline channel. For these reasons, traditional publishers soon experienced losses in advertising revenues as well. A number of print products disappeared; some publishers transferred their content to the Internet as an additional or exclusive content delivery channel, while others acquired the new online competitors.

While the Internet enabled any-time access to content, customers were still bound to certain access points, that is, stationary Internet connections (e.g., their office desk), potentially complemented by wi-fi connections at other fixed points. Soon, the demand to overcome this restriction emerged. It was met by extending the functionality of mobile phones to media consumption. This led to the second disruption in the media industry, as publishers saw the need to deliver content in a form suitable for the new devices. In the beginning, they had to adjust their websites for this purpose, since these had originally been built for stationary use and were not designed for small screens, low resolutions, and small input keys. When mobile phones became “smart”, however, the possibility to install applications (apps) on them created an alternative for distributing mobile content independently of websites. In addition, tablets emerged on the market as another type of end device suited for surfing on the Internet or running apps. The number of end devices suitable for mobile content delivery soon surpassed the number of PCs. This, again, increased the number of potential customers and their sense of urgency and need for consumption everywhere and anytime. The second disruption has forced publishers to invest further while the monetization of content remains a problem.

Resulting from these disruptions, customers nowadays can choose between three channels for consuming content: offline, online, and mobile. This decision is not exclusive; that is, they may also use more than one channel. Publishers need to determine whether it is economical to meet this demand and to serve each channel. Setting up, maintaining, and serving a channel is expensive, but it may bring additional revenues due to new customers who would not have consumed content using another channel. Furthermore, the presence of a new channel may also affect the behavior of existing customers. On one hand, it is possible that some of them consume content using the new channel complementarily to a channel they have used before. This may increase their value to the publisher and prevent them from switching to competitors. On the other hand, some existing customers may substitute a channel they have used before with the new one, so that the latter may cannibalize revenues. The total effect of this substitution depends on the different profitabilities of the channels.

In this paper, we investigate the decision of a publisher who already serves the offline channel to also serve the mobile channel. More concretely, we examine whether a mobile app can “defend” print media in that it prevents existing subscribers from cancelling their subscription, that is, whether it can prolong their average customer lifetime (CL). We also evaluate how this translates to changes in their average customer lifetime value (CLV). Our analysis reveals the value of the individual channels to the publisher as well as their interdependence and its impact. We apply our model to the case of a respected newspaper, as newspapers in their traditional, printed form are typical representatives of print media. Note that we will use the term “newspaper” in the following to refer to a product that contains news augmented by background information, opinions, letters by readers, puzzles, and so on, independently of the medium through which it is consumed. This is in order to differentiate it from “naked” news, as delivered by some news agencies, or, for example, posts by individuals on Twitter.

The remainder of this paper is structured as follows. Next, we review literature related to our work. In section 3, we develop our model. Section 4 contains its application. The results are presented and discussed in section 5. Section 6 concludes this paper with implications and limitations.

2 Related Research

Broadly, this paper contributes to two streams of research: one that investigates the relationship between different content delivery channels and one that takes a lifetime value view on customers. We will review these two streams in the following. A particular focus is given to the news industry, as it is the field of application for our model and has been analyzed in many previous studies.

2.1 Relationship between content delivery channels

After the first disruption in the media industry due to the advent of the Internet, research has started to investigate the relationship between the online and the offline channel. For example, Althaus and Tewksbury (2000) have conducted a survey on news consumption behavior among students. They have

found that the reported time spent for consuming news online is positively associated with the reported time spent for reading newspapers, which indicates a complementary relationship between these media, but not with the reported time spent for watching news on television. In a comparable approach, Chan (2005) has come to similar conclusions. In contrast, Simon and Kadiyali (2007) have found that the number of sales of a print magazine decreases when it offers free content online. This suggests a substitutive relationship between these channels, which the authors have shown to be moderated by the degree of overlap between their contents. Some of these results may be transferrable to the mobile channel, but due its special characteristics (such as the portability of mobile devices), this should not be assumed without explicit research (e.g., Shankar and Balasubramanian, 2009).

In fact, a new branch of research that analyzes the relationship between the online and the mobile channel has emerged after the second disruption in the media industry. For example, Bang et al. (2013) have compared the suitability of these channels for product selling. Their results suggest that whether the relationship between the channels is complementary or substitutive depends on the time criticality and the information intensity of the product. Chyi and Chadha (2012) have found in a survey that there is a complementary relationship between consuming news using a stationary PC and consuming news using a mobile device. They have argued that the fit of a device with what is desirable for news consumption is a determinant of its usage for this purpose. This may also apply to mobile apps. Böhmer et al. (2011) have identified the context of consumers (such as their location and the time of the day) to be a further factor influencing mobile app usage.

Most closely related to this paper are studies that have investigated the relationship between the offline and the mobile channel. N and Gupta (2015) have considered this relationship from a technology acceptance perspective. Their results suggest that the dissonance between attitudes toward offline and mobile news consumption is a predictor of the intention to use a mobile news app. Thorson et al. (2015) have compared newspapers and mobile apps in a contingency model to explain how individual characteristics influence channel choice. Analyzing secondary survey data, they have found that these characteristics, especially age, can be a moderator of whether the offline and the mobile channel complement or substitute each other. Another survey by Chan (2015) has led to similar conclusions. Westlund and Färdigh (2015) have found that many people consume news using rather a single channel than several ones and that there is a shift in this usage from the offline toward the mobile channel (and/or the online channel), indicating a substitutive relationship between them.

To summarize, research is not unanimous about the relationship between content delivery channels. Many studies in this area have relied on surveys. Such data are mostly subjective and, thus, usually less accurate than actual performance data (e.g., Bertrand and Mullainathan, 2001). Furthermore, while indications for channel interdependence have been found, few authors have aimed at capturing this interdependence in a model. Without a model, however, it can hardly be quantified and the influence of covariates can hardly be controlled for. We address these gaps by a model that is able to capture and quantify channel interdependence from subscription data.

2.2 Lifetime value view on customers

The lifetime value view on customers is not new for newspaper publishing. For example, Keane and Wang (1995) have used CLVs to segment customers for improving advertising and circulation figures of newspapers. They have demonstrated that the lifetime value model is appropriate to investigate the impact of customer retention (i.e., prolonging a customer's lifetime) on a publisher's profits. The link between CLs and CLVs is theoretically well-established (see, e.g., Anderson and Mittal, 2000) and has been confirmed in many empirical studies (e.g., Gupta et al., 2004).

Against this background, a new content delivery channel can affect profits in (at least) two ways. On one hand, it may contribute to customer retention. E.g., Boehm (2008) has shown that bank customers who use online banking (i.e., the online channel) have a longer CL than those who use only the offline channel. On the other hand, the new channel may be different from the traditional ones in terms of

profitability (and, thus, CLVs). E.g., Gensler et al. (2012) have found that bank customers generate more revenue and can be served with less cost if they use online banking. In analogy, it may be desirable for publishers to migrate their customers to other channels (see also Ansari et al., 2008).

It has often been stressed that it is important to account for potential differences between channels when calculating CLVs. This is, on one hand, in order to understand where profits come from (Neslin and Shankar, 2009) but, on the other hand, also in order to avoid customer heterogeneity regarding channel choice being a source of serious bias (Fader and Hardie, 2010). In particular, many studies have suggested that customers who use several channels have a different value to a publisher than customers who use only a single channel (e.g., Kumar and Venkatesan, 2005).

To summarize, previous research has confirmed that customers' channel choice can have a significant impact on the profits of a publisher. It has also been demonstrated that this impact can be measured by CLVs and their antecedents, the CLs. We contribute to this stream of research by analyzing the effects a mobile app has on the CLs and CLVs of customers of print media, and vice versa. While the perceived (added) value of a mobile app from the customers' perspective has already been a topic in previous research, the publishers' perspective has not been sufficiently investigated yet.

3 Model

We now present a survival analysis-based model with which the CL and the CLV of a customer i at a certain point in time t_0 (normalized to $t_0 = 0$) can be quantified from her subscriptions to up to two content delivery channels. We index these channels by $j \in \{1; 2\}$, where in our context $j = 1$ means the offline channel and $j = 2$ means the mobile channel.

3.1 Structural model

The central component of our model is the probability $S_{i,j}(t)$ that i will retain a subscription that is active in t_0 for at least t time units in the future (that is, up to the point in time t). Formally, we define $S_{i,j}(t) := P[T_{i,j}^{\text{end}} \geq t | T_{i,j}^{\text{end}} \geq 0]$ for $T_{i,j}^{\text{end}} \geq 0$, where $T_{i,j}^{\text{end}}$ is a random variable that represents the point in time at which the subscription ends. For convenience of notation, we define $S_{i,j}(t) := 0$ for the cases that i had a subscription to j but cancelled it before t_0 ($-\infty < T_{i,j}^{\text{end}} < 0$) or that she never had a subscription to j ($T_{i,j}^{\text{end}} = -\infty$). In a time-discrete context, which is advised for modeling subscriptions (Schmittlein et al., 1987), $S_{i,j}(t)$ can for $T_{i,j}^{\text{end}} \geq 0$ be expressed as

$$S_{i,j}(t) = \prod_{t'=1}^t (1 - h_{i,j}(t')). \quad (1)$$

Here, $h_{i,j}(t)$ denotes the hazard of i cancelling her subscription to j at (the end of) t , given that she has not done so before; formally, $h_{i,j}(t) := P[T_{i,j}^{\text{end}} = t | T_{i,j}^{\text{end}} \geq t]$. This hazard, which often is also referred to as the churn rate, is a crucial element in the calculation of the CLV because it is the only element that describes actual customer behavior. A customer's decision to cancel a subscription may depend on various factors, which we will investigate below. However, one factor needs special consideration: It may be (and is, as argued earlier, likely) that the decision of i to cancel a subscription to j is influenced by whether she has a parallel subscription to the other channel j' at t . Formally, $h_{i,j}(t)$ may in this case take a value $h_{i,j}^2$ that is different from the value $h_{i,j}^1$ that it takes when the subscription to j is the only active one at t . It is important to account for this potential dependency in order to avoid biases. This can be done by calculating $h_{i,j}(t)$ as

$$h_{i,j}(t) = (1 - S_{i,j'}^2(t)) \cdot h_{i,j}^1 + S_{i,j'}^2(t) \cdot h_{i,j}^2, \quad (2)$$

where $S_{i,j'}^2(t) = \prod_{t'=1}^t (1 - h_{i,j'}^2)$. The explanation for (2) is that if i has an active subscription to j' at t_0 , it cannot be foreseen whether she will have cancelled it up to t or not. Therefore, $h_{i,j}^1$ and $h_{i,j}^2$ need both

to be considered and to be weighted by the probabilities of the respective cases. By definition, $h_{i,j}(t)$ is calculated based on the assumption that $T_{i,j}^{\text{end}} \geq t$, i.e., that i has not cancelled her subscription to j up to t . The probability of her also not having cancelled her subscription to j' is, therefore, not given by $S_{i,j'}(t)$ but by a similar function $S_{i,j'}^2(t)$ that accounts for the knowledge that $h_{i,j}^2$ has been the factual cancellation hazard since t_0 .

Assuming for the moment that $h_{i,j}^1$ and $h_{i,j}^2$ are given, we can calculate the expected remaining lifetime $SL_{i,j} := E[T_{i,j}^{\text{end}} | T_{i,j}^{\text{end}} \geq 0]$ that a subscription has in t_0 (see, e.g., Misra, 1992, p. 180 ff.):

$$SL_{i,j} = \sum_{t=1}^{\infty} S_{i,j}(t). \quad (3)$$

Its expected remaining lifetime value ($SLV_{i,j}$) results, in principal, from weighting $SL_{i,j}$ by the value $v_{i,j}$ it generates per time unit to the publisher. $v_{i,j}$ can usually be expressed in terms of profits, i.e., $v_{i,j} = m_j \cdot p_{i,j}$, where $p_{i,j}$ is the price that i pays at each point in time t (which we assume to happen at the beginning of t) and m_j is the publisher's profit margin. However, these future profits need to be discounted to account for the publisher's time preference. Representing this preference by a discount rate r , $SLV_{i,j}$ can be calculated as follows (e.g., Berger and Nasr, 1998):

$$SLV_{i,j} = \sum_{t=1}^{\infty} \frac{S_{i,j}(t) \cdot v_{i,j}}{(1+r)^t}. \quad (4)$$

So far, we have considered the lifetime and the lifetime value of a subscription, while we are rather interested in the lifetime and the lifetime value of a customer. The customer-level figures can be defined as an aggregation of the subscription-level ones. For the CL of i (CL_i), we use the aggregation

$$CL_i := \max(SL_{i,j}; SL_{i,j'}). \quad (5)$$

That is, we define the lifetime of a customer as the maximum of the expected lifetimes of her subscriptions. Note that this does not equal the expected maximum lifetime of her subscriptions, which would be an alternative definition. Both definitions describe the total duration of the customer's relationship to the publisher regarding the two focal channels.

Finally, the CLV of i (CLV_i) can, in principal, be calculated by summing the lifetime values of all her subscriptions.¹ However, customers often get a discount when they have subscriptions to several channels. This discount reduces the publisher's profit and, thus, the CLVs, so that it has to be subtracted from the sum of the subscription lifetime values. i gets a discount (d_i) in t only if her subscriptions to j and j' (if applicable) are both still active by then, which happens with the probability $S_{i,j}^2(t) \cdot S_{i,j'}^2(t)$. Therefore, after accumulating the expected discount over time, CLV_i is given by

$$CLV_i := SLV_{i,j} + SLV_{i,j'} - \sum_{t=1}^{\infty} \frac{S_{i,j}^2(t) \cdot S_{i,j'}^2(t) \cdot d_i}{(1+r)^t}. \quad (6)$$

Similar definitions of the CLV have been used in previous research (e.g., Donkers et al., 2007).

Note that our concept of subscription and customer lifetimes and lifetime values is a purely residual one. That is, we have defined these values on the basis of the expected future behavior of existing customers, ignoring their behavior up to t_0 , as it is not relevant anymore for decisions at t_0 and later. This is a common view in the literature on the CLV (e.g., Kumar and Reinartz, 2012, p. 305).

¹ Note that if i has no active subscription for j' in t_0 , $S_{i,j'}(t) = 0$ for all t . This implies $SL_{i,j'} = 0$ and, thus, $SLV_{i,j'} = 0$. Therefore, CL_i and CLV_i collapse to $SL_{i,j}$ and $SLV_{i,j}$, respectively.

3.2 Measurement model

To complete our model, we have to specify the formation of the hazard values $h_{i,j}^1$ and $h_{i,j}^2$. They can be derived from empirical data, as these contain the corresponding latent utilities $U_{i,j}^1$ and $U_{i,j}^2$ that a customer experiences when she cancels a subscription. We model the relationship between $h_{i,j}^J$ and $U_{i,j}^J$ for $J \in \{1; 2\}$ by a logit-formed link function; that is,

$$h_{i,j}^J = \frac{\exp(U_{i,j}^J)}{1 + \exp(U_{i,j}^J)}. \quad (7)$$

For the latent utility $U_{i,j}^1$ of cancelling a subscription to one channel in the absence of a parallel subscription to the other channel, we use the model

$$U_{i,j}^1 = \beta_{0,j} + \beta_{1,j} \cdot \text{Duration}_{i,j} + (\beta_{2,j} + \beta_{3,j} \cdot \text{BPI}_i + \beta_{4,j} \cdot \text{Age}_i + \beta_{5,j} \cdot \text{Gender}_i) \cdot \text{Individual}_i. \quad (8)$$

This is motivated by the following considerations:

First, one aim of this study is to investigate the differences between the offline and the mobile channel. Therefore, we use separate intercepts ($\beta_{1,1}$ and $\beta_{1,2}$) for $U_{i,1}^1$ and $U_{i,2}^1$. An essentially equivalent approach would be to use a common intercept and to include a dummy variable that describes which channel is modeled. We also let the coefficients of the independent variables differ between channels in order to recognize potential differences in the influence of these variables.

Next, we expect the total duration of a subscription from the point in time at which it started ($t_{i,j}^{\text{start}}$) up to t_0 , $\text{Duration}_{i,j} = -t_{i,j}^{\text{start}}$, to influence the cancellation hazard. The direction of this influence, however, is unclear. On one hand, one may assume that long-time customers are less likely to cancel their subscription(s) because they are more accustomed to consuming the publisher's content (e.g., Bolton, 1998). Furthermore, compared to rather new customers, they can be assumed to have more thoroughly evaluated the content (e.g., in terms of quality), so that their expectations are more likely to be met. On the other hand, customers may lose their interest in the content over time or find competitive publishers who suit their needs better (e.g., Zeelenberg and Pieters, 2004).

We also account for customer heterogeneity, which means that different customers may cancel their subscription(s) with different probabilities. For this purpose, we include various customer characteristics in (8). First, not only individuals but also organizations (such as companies, universities, associations, etc.) can subscribe to a publisher's content, so that we include a dummy variable (Individual_i) to control for differences between the former ($\text{Individual}_i = 1$) and the latter ($\text{Individual}_i = 0$) group. Such differences are reflected in the coefficients $\beta_{2,j}$, while $\beta_{3,j}$, $\beta_{4,j}$, and $\beta_{5,j}$ capture differences within the group of individuals. Concretely, we control for an individual's age at t_0 (Age_i), gender ($\text{Gender}_i = 0$ for men and $\text{Gender}_i = 1$ for women), and income. Since the dataset to which we intend to apply our model does not contain information on the customers' incomes, however, we use a buying power index of the region in which they live as a proxy variable (BPI_i).

Now that we have specified possible determinants of the decision to cancel a subscription to one channel, we aim to investigate how this decision is influenced by the presence of a parallel subscription to the other channel. To capture this influence, we decompose the corresponding latent utility $U_{i,j}^2$ into an intrinsic component, which equals $U_{i,j}^1$, and an extrinsic component γ_j :

$$U_{i,j}^2 = U_{i,j}^1 + \gamma_j. \quad (9)$$

A similar approach has been developed in previous research to model the interdependence between two different types of search engine results (Yang and Ghose, 2010). It can be interpreted as follows. γ_j measures the influence of channel j' on channel j , which may be different from the reverse effect. If γ_j is zero, j' has no influence on j : The latent utility of cancelling a subscription to j in the presence of a parallel subscription to j' is the same as if the subscription to j were the only active one ($U_{i,j}^2 = U_{i,j}^1$). If γ_j differs significantly from zero, however, an influence of j' on j exists, as $U_{i,j}^2 \neq U_{i,j}^1$. A positive value

of γ_j indicates a substitutive influence: A parallel subscription to j' increases the hazard of cancelling a subscription to j . Contrarily, a negative value of γ_j means that a parallel subscription to j' decreases the hazard of cancelling a subscription to j , indicating a complementary influence.

3.3 Comments on estimation

We estimate our model by maximum likelihood, using the BFGS algorithm (Broydon, 1970; Fletcher, 1970; Goldfarb, 1970; Shanno, 1970). As we will explain below, the data to which we intend to apply our model describe (the transition between) only two points in time. In this case, the likelihood function of our model is essentially the same as for a standard logit model. When (transitions between) more than two points in time are analyzed, estimation is more difficult due to the time-varying cancellation hazard as specified in (2). However, this situation can be reduced to the one that we consider; see (Therneau, 2015) for details.

For the calculation of $SL_{i,j}$, $SLV_{i,j}$, and the accumulated discount in (6), we sum over a horizon of 1,200 points in time (corresponding to 100 years for our dataset), as we cannot sum to infinity in practice. As it is to be expected, none of these values changes notably when a larger horizon is used, reflecting that hardly any customer retains a subscription for such a long time after t_0 .

4 Application and Dataset

We now apply our model to a dataset that we have received from a publisher of a respected national German daily newspaper. Due to a confidentiality agreement, we can neither identify this publisher nor describe it in much detail. The newspaper appeals to a general audience, as it covers all common subject areas: politics, finance, culture, sports, and so on. It is published in three delivery channels: offline, online, and mobile. In the offline channel, it appears in a print version, which enjoys a large subscriber base. In the online channel, articles are published on a website. However, in order not to cannibalize subscribers to the print version, these articles are usually shorter and less elaborated. Furthermore, they are surrounded by different forms of advertisement. There also exists an exact copy of the print version for the Internet that requires a payment. In the mobile channel, the publisher offers a mobile-enabled website and several mobile apps. One of the latter allows customers to read the exact copy of the print version on their mobile devices. It includes a few additional ads and has some suitable features such as an automatic search for articles that contain user-specified keywords. While it can be downloaded for free, it can only be used with a paid subscription. We choose the print version and this mobile app for our analysis of interdependence between the offline and the mobile channel. This is, on one hand, because these media are typical representatives of the respective channels and, on the other hand, because they are perfect substitutes in terms of content, so that there are no differences in content that could influence the results.

The publisher offers different subscription models for both, the offline and the mobile channel. For better comparability, we consider only one of these models and choose one that is available for both channels. The chosen subscription model is the one that is selected most frequently by customers. Pricing is similar but not identical between channels: The subscription to the mobile channel is slightly cheaper than the one to the offline channel. Customers who subscribe to both channels receive a significant discount. They can cancel each channel independently of the other but lose the (future) discount in this case. The publisher's profit margin after subtracting the costs of distribution is much higher for the mobile channel than for the offline channel, as it is to be expected.

Our dataset contains data on the subscriptions to the focal channels and on the customers who hold these subscriptions. It is a "snapshot" of the publisher's database at a single day (September 04, 2015), which corresponds to t_0 . Importantly, it contains only data on subscriptions that still have been active at t_0 . This makes it difficult to reliably analyze subscription behavior, as the absence of historical subscriptions that have been cancelled before t_0 could bias the results. The analysis of subscription

cancellation behavior at and beyond t_0 (which we carry out in this paper), however, is not biased by this truncation (as long as the cancellation hazard does not change over calendar time).

Obviously, one can hardly judge from a snapshot of all active subscriptions which will be cancelled in the future. However, some of them already carry an end date. This can happen for (at least) two reasons. First, some customers may have actively cancelled an unlimited subscription, whereupon the date of last delivery (after a cancellation period) is saved in the database. Others may not have extended a fixed-term subscription that ends at the indicated time up to t_0 . Our data do not allow us to distinguish these cases. Besides, the latter case carries the chance that such customers will eventually extend their subscription. Therefore, we choose a relatively short interval of one month between t_0 and the next point in time t_1 and consider such subscriptions as ended that are planned to end up to then.

We have conducted some pre-processing of our dataset before analysis. First, we have augmented it by the (proprietary) buying power index obtained from a market research company (GfK, 2016). Second, we have excluded all customers who live outside of Germany. This was in order to reduce the influence of potential cultural differences, which we do not investigate in this paper. We have also excluded all customers who have more than one subscription to the same channel. This can happen, for example, when organizations purchase subscriptions for each of their employees, which is not representative of “usual” customer behavior. Third, for customers who have not provided their age, we have imputed it based on a linear regression on their gender and their buying power index. We cannot reveal the exact numbers of customers or subscriptions that remain in our dataset after pre-processing due to confidentiality, but both numbers are in the six-figure range, so that no statistical problems are to be expected even for seldom-observed combinations of the qualitative variables. The characteristics of the pre-processed dataset are summarized in Tables 1a and 1b.

<i>Subscription(s)</i>	Group		Individuals		Organizations	Total
	Men	Women	Men	Women		
Only offline			59.62%	19.40%	12.63%	91.65%
Only mobile			4.39%	0.99%	0.82%	6.20%
Both			1.29%	0.30%	0.56%	2.14%
Total			65.30%	20.68%	14.01%	100%
<i>Other characteristics</i>	Mean	Std. dev.	Mean	Std. dev.		
Age (in years)	63.11	17.87	56.68	20.13		
BPI	106.06	16.49	107.15	17.59		

Table 1a. Overview of customers in our dataset.

<i>Status</i>	Channel		Mobile		Total
	Offline	Mobile	Mean	Std. dev.	
Active up to t_1			89.44%	8.04%	97.48%
Ended before t_1			2.39%	0.14%	2.52%
Total			91.83%	8.17%	100%
<i>Other characteristics</i>	Mean	Std. dev.	Mean	Std. dev.	
Duration up to t_0 (in months)	70.37	94.20	18.82	7.83	

Table 1b. Overview of subscriptions in our dataset.

Some statistics are particularly noteworthy. First, women are obviously under-represented in our dataset. A possible explanation is that often only one member of a family holds a subscription, but the content is shared with the other members of the household. This usually is the main earner, who in Germany is mostly a man (Destatis, 2016). Second, only comparatively few customers have subscribed to both channels; the average number of subscriptions per customer is 1.02 (which still suffices for statistical purposes). Third, the mean duration of a subscription to the mobile channel is low compared to its equivalent for the offline channel. This simply results from the fact that the former has been established just a few years ago, while the latter has been served for several decades.

5 Results and Discussion

5.1 Measurement model

Table 2 shows the results of our estimations regarding the measurement model. We have not mean-centered the quantitative variables, as there are several interesting “means”. Therefore, the intercepts and the intercept-like coefficients of Individual_{*i*} should not be interpreted on their own. For the other coefficients, a positive (negative) sign indicates an increase (decrease) in the cancellation hazard, corresponding to a decrease (increase) in the remaining lifetime and lifetime value of a subscription.

Variable	Offline channel				Mobile channel			
	Coef.	Std. err.	p		Coef.	Std. err.	p	
(Intercept)	-3.2721	0.0666	<0.0001	***	-3.9516	0.5420	<0.0001	***
Duration	-0.0189	0.0007	<0.0001	***	-0.1125	0.0115	<0.0001	***
Individual	+1.6739	0.1687	<0.0001	***	+0.9916	1.0583	0.3488	
Individual x BPI	-0.0020	0.0013	0.1175		+0.0110	0.0060	0.0642	
Individual x Age	-0.0193	0.0012	<0.0001	***	-0.0056	0.0071	0.4300	
Individual x Gender	+0.3111	0.0436	<0.0001	***	+0.1739	0.2033	0.3924	
Other channel (γ_j)	-0.4599	0.1739	0.0082	**	-1.5365	0.3602	<0.0001	***

Notes: Pseudo-R² (Nagelkerke, 1991): 9.31%. Significance is as follows: * p < 0.05; ** p < 0.01; *** p < 0.001.

Table 2. Determinants of the hazard to cancel a subscription.

The results show that longer-lasting subscriptions are cancelled less often than shorter-lasting ones. This holds true for both channels. Regarding consumer heterogeneity, the channels differ: While no significant differences in cancellation behavior are found between men and women of different ages and incomes for the mobile channel, some differences exist for the offline channel. This indicates that customers who subscribe to the latter behave more heterogeneously than those who subscribe to the former. More concretely, older customers are found to cancel their subscription to the offline channel (their offline subscription) less likely than younger ones. This is consistent with results from previous research suggesting that old people stick to their accustomed news consumption behavior rather than to change it (Chan, 2015). Furthermore, women are found to cancel their subscription more likely than men. This may again be explained by the fact that it usually is a man who holds a subscription in a family, so that women cancel theirs, e.g., when they marry. No significant differences are found between customers from richer and poorer regions, although the corresponding coefficient is not far from being significant; this also is the case for the mobile channel.

Our main result is that γ_1 is significant, which means that the mobile channel has an influence on the offline channel. As γ_1 is negative, this influence is complementary: The hazard of cancelling an offline subscription is significantly reduced for customers who have a parallel subscription to the mobile channel (a mobile subscription). For an average customer, this reduction is from 1.26% to 0.80% (-36.56%). We define an average customer as one who is a man, a woman, or an organization with respective probabilities derived from the relative frequencies given in Table 1a, with mean values for all quantitative variables. Interestingly, we also find evidence for a complementary effect of the offline channel on the mobile channel, as γ_2 is as well significant and negative: Having a parallel offline subscription reduces the hazard to cancel a mobile subscription from 1.24% to 0.27% (-78.25%).

A possible explanation for this mutual complementarity stems from the theory of uses and gratifications (e.g., Ruggiero, 2000). Many customers read printed newspapers when they are at home, but they may prefer to consume the content via a mobile app when they are in a situation unsuitable for printed newspapers (e.g., when they travel in a crowded bus). This is supported by the aforementioned findings that mobile app usage depends on the context (Böhmer et al., 2011) and may explain why the relationship between these media is not substitutive. Now, if the customers are satisfied after having used one of them (e.g., because their information need has been fulfilled), this may increase the likelihood to keep the other one, as satisfaction is a key determinant of customer retention (Anderson and Mittal, 2000). Thus, both media are complementary to each other.

5.2 Structural model

The average hazard and retention curves (i.e., the plots of $h_{i,j}(t)$ and $S_{i,j}(t)$) are depicted in Figure 1a and 1b, respectively. For better comprehensibility, they have been interpolated between points in time, although they are discrete in reality. From Figure 1a it can be seen how the interdependence between both delivery channels induces a time-dependency in the cancellation hazards of subscriptions that are accompanied by a parallel subscription to the respective other channel (dual subscriptions). If this interdependence would not exist, the hazards were constant over time and would coincide with those of single subscriptions. As a consequence, this would also apply to the corresponding survival curves. One can see from Figure 1b that this is not the case, as dual subscriptions are retained longer than single subscriptions. The figure also illustrates that, after controlling for differences in their duration up to t_0 , mobile subscriptions are, on average, retained longer than offline subscriptions.

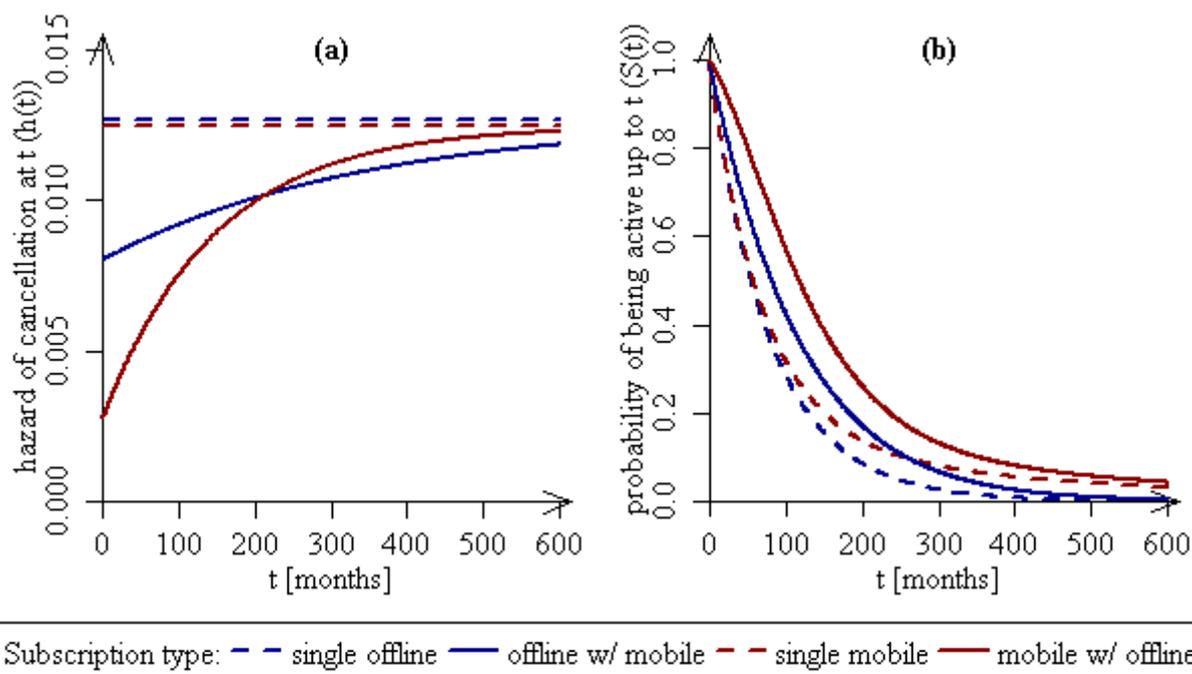
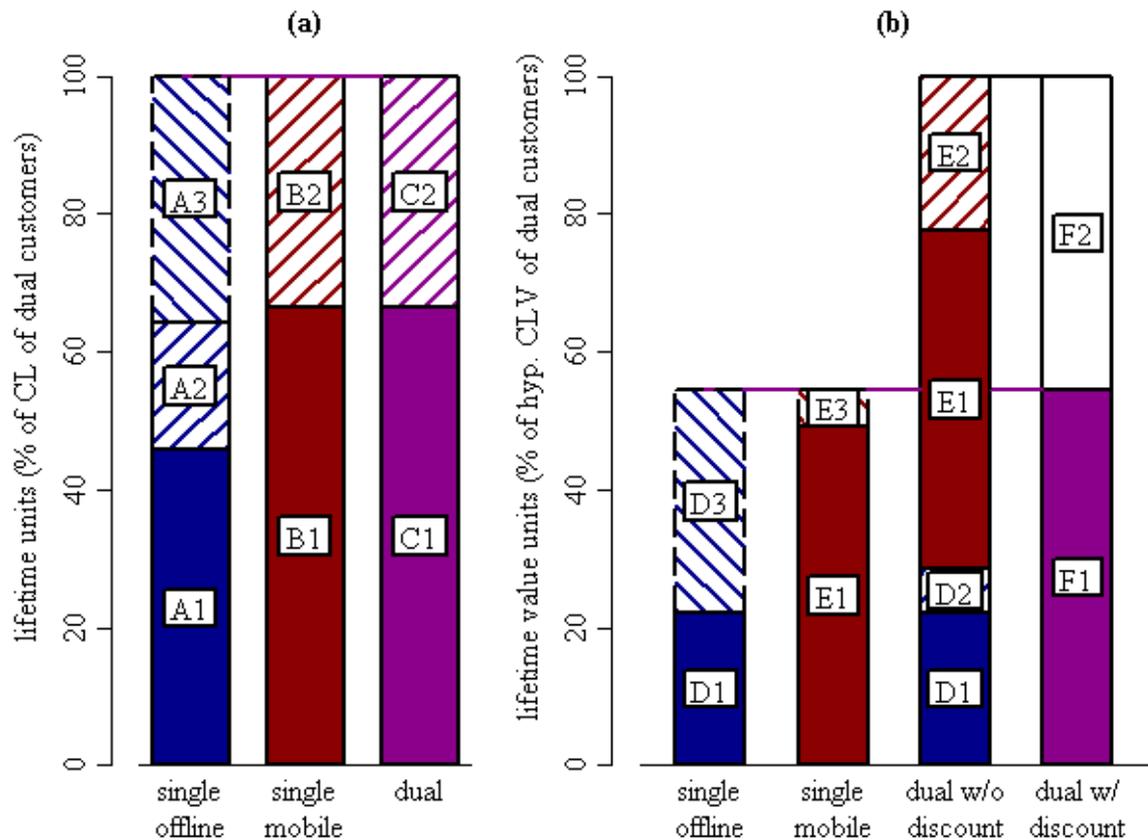


Figure 1. Average (a) hazard curves and (b) survival curves by subscription type.

Figure 2a shows how the hazard and survival curves translate into subscription and customer lifetimes. Since we cannot reveal the absolute values of these figures due to confidentiality, we give them in percentages of the CL of a customer with a dual subscription (a dual customer) and refer to these percentages as lifetime units. One can see that the subscription lifetime (SL) of a single offline subscription (marked as A1, 45.71 units), which equals the CL of the corresponding customer, is lower than its mobile equivalent (B1, 66.52 units). The difference (+45.54%) describes by how much the CL of a dual customer would be higher than the CL of a customer with a single offline subscription if the channels were independent. However, since a complementary interdependence exists, the lifetime of an offline subscription is higher by 40.76% (A2) if it is accompanied by a parallel mobile subscription. The reverse effect is even stronger (50.32%, B2), so that the CL of a dual customer is determined by the SL of her mobile subscription. It can be partitioned into two components: one that describes her hypothetical CL if the channels were independent ($C1=B1$) and one that measures the increase in CL that is caused by their complementarity ($C2=B2$). An important insight now is that if a parallel mobile subscription can be sold to a customer who has a single offline subscription, her CL increases in total by 118.78% (A2+A3), which is much greater than the reverse effect (B2). On one hand, this is simply due to the difference in the baseline SLs (B1-A1). On the other hand, such a customer's lifetime is prolonged not only due to the effect that channel complementarity exerts on the SL of her existing offline subscription

but, in part, also due to the analog effect on the SL of her new mobile subscription (B2-A2). Note that, conditional on the cancellation hazards, these results do not depend either on subscription prices or on profit margins.

These factors are taken into account when we translate the SLs and CLs to corresponding lifetime values. For their calculation, a discount rate r has to be specified; we set r to 0.48%. This is the current 10-year-average of the interest rates of German government bonds, which represents a risk-free interest rate. This is a common choice (e.g., Roemer, 2006). Figure 2b shows the resulting average values. Again, we cannot reveal them in absolute terms due to confidentiality, so we relate them to the CLV of a dual customer (before subtracting the discount she gets) and refer to the corresponding percentages as lifetime value units. Several insights can be gained from the figure. First, one can see that the subscription lifetime value (SLV) of a single mobile subscription (E1, 49.30 units), which equals the CLV of the customer who holds it, is much higher (by 122.78%) than its offline equivalent (D1, 22.13 units). This is, on one hand, because of the longer SL of mobile subscriptions (after t_0) but, on the other hand, also due to the publisher's higher profit margin for the mobile channel.



Legend:

Customer type	CL			CLV		
	single offline	single mobile	dual	single offline	single mobile	dual
Baseline values from SL(s)/SLV(s) of existing subscription(s)	A1	B1	C1	D1	E1	D1+E1
+ Increase due to channel complementarity on SL(s)/SLV(s) of existing subscription(s)	A2	B2	C2	D2	E2	D2+E2
+ Increase/decrease due to other factors	A3	0	0	D3-D2	E3-E2	-F2
= Total size	A1+A2+A3	B1+B2	C1+C2	D1+D3	E1+E3	F1

Figure 2. Average contribution of dual-channeling to (a) CL and (b) CLV by customer type.

If the channels were independent of each other, the CLV of a dual customer were given by the sum of the CLVs of a customer with a single offline subscription and a customer with a single mobile subscription minus the decrease due to the discount (F2, 45.54 units). Notably, the publisher from which we have received our dataset would be better off in this case *not* to offer a customer with a single mobile subscription a parallel offline subscription at the price it currently does, since her CLV were greater without the parallel subscription than with it. This is because the increase in her CLV due to the new subscription would be lower than the decrease due to the discount.

Channel complementarity adds value to the subscriptions of a dual customer; the increase is greater for her mobile subscription (E2, 22.27 units, 45.17%) than for her offline subscription (D2, 6.30 units, 28.47%). Correspondingly, her hypothetical CLV without consideration of the discount increases by 40.00% (D2+E2, 28.57 units). Since these changes result from changes in the SLs and CLs, it is interesting to calculate an “efficiency factor” by dividing them through the latter. This factor is again greater for the mobile channel ($E2/B2 = 66.52\%$) than for the offline channel ($D2/A2 = 31.07\%$), which means that a one-unit increase in the lifetime of a dual customer’s mobile subscription due to channel complementarity is more valuable to the publisher than the corresponding increase in the lifetime of the offline subscription. Regarding the hypothetical CLV, the efficiency factor is 85.33% ($(D2+E2)/C2$), which means that a one-unit increase in the lifetime of a dual customer due to channel complementarity increases her hypothetical CLV by roughly 0.85 units.

Finally, the total effect of offering customers another content delivery channel can be calculated by the differences between the CLV of a dual customer after the discount has been subtracted (F1, 54.46 units) and the CLVs of customers with a single subscription. The results are as follows. If a parallel mobile subscription can be sold to a customer who has a single offline subscription, her CLV increases by 146.12% (D3, 32.33 units). In comparison, a parallel offline subscription sold to a customer who has a single mobile subscription increases her CLV by only 10.48% (E3, 5.16 units). This is, on one hand, because of the analogous result regarding the CL and, on the other hand, due to the publisher’s higher profit margin for the mobile channel. The corresponding efficiency factors of 59.56% ($=D3/(A2+A3)$) and 15.42% ($=E3/B2$) also are in favor for the mobile channel. They mean that a one-unit increase in the CL of a customer who has a single offline subscription due to a new parallel subscription to the mobile channel corresponds to an increase in her CLV by roughly 0.60 units, while the reverse effect is much weaker (roughly 0.15 units).

6 Conclusion and Limitations

In this paper, we have investigated whether mobile apps can defend print media from losing customers and, thus, revenues by a model-based comparison of respective subscription and customer lifetimes and lifetime values. The answer is confirmative, as we have found a complementary effect of the mobile channel on the offline channel. This means that a parallel subscription to the mobile channel can prolong the lifetime of a subscription to the offline channel, which translates to a higher lifetime value. We have also found evidence for an even stronger reverse effect. When it comes to customer lifetimes and their values, however, we have found the increase due to a new parallel subscription to be much greater for customers who only have a subscription to the offline channel than for those who only have a subscription to the mobile channel. This is because the respective baseline values remaining at the time of analysis are lower for the former customers, which results from a slightly greater hazard of cancellation and, regarding lifetime values, from a lower profit margin.

In conclusion, the main practical implication of this paper is that a mobile app can help publishers to retain their customers for a longer time. For the case of the respected newspaper for which we have received data, this translates to higher CLVs and, thus, to a higher revenue. However, as for almost every empirical study, it is not clear how generalizable these results are. A distinction has to be made here between the results regarding channel complementarity and its impact on CLs on one hand and the results regarding CLVs on the other hand. The former results can be expected to be valid for many

publications similar to the one we have considered. They may not directly be transferrable to publications with different attributes, in particular such that are comparatively unknown or that are clearly different from newspapers (e.g., books). Results on CLVs depend, by their nature, on the focal publisher's profit margins and on the discount customers receive when they subscribe to several channels. Therefore, they will certainly vary in magnitude between publishers. However, since they are determined by CLs, our results on these figures (which may often generalize, as aforementioned) imply that a mobile app should increase CLVs also for other publications than the one we have considered (as long as the discount their publishers offer for dual subscriptions is not too large).

Publishers can, moreover, use our model to investigate the relationship between any two content delivery channels they serve in their individual context. Our model is also the main result for use in future research. It is neither bound to the offline and the mobile channel nor to certain industries. Rather, it can be applied to almost any subscription data, so that it should be usable in many sectors that involve subscriptions. Our model informs researchers and practitioners about the (determinants of the) hazard that a subscription to a certain channel is cancelled, the interdependence between channels, the impact of this interdependence on CLs and CLVs, and total CLs and CLVs. Therefore, it can be used to decide which channels should be served.

However, our model has also some limitations. First, while we have analyzed subscription cancellation behavior (that is, existing customers), interdependencies between content delivery channels may also exist regarding subscription behavior (that is, new customers). Second, while our model is able to account for two channels, publishers may serve more channels in practice. In particular, we have not considered the online channel in our study. Third, we have defined CLVs based on the prices and profit margins of subscriptions, while publishers can profit from customers also in other ways (e.g., from advertising or product referrals). Obviously, additional data are needed to address these issues.

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