ELSEVIER

Available online at www.sciencedirect.com

ScienceDirect

Journal of Interactive Marketing 28 (2014) 271 – 284

JOURNAL OF INTERACTIVE MARKETING

www.elsevier.com/locate/intmar

# How Online Consumer Segments Differ in Long-term Marketing Effectiveness

Kerstin Reimer [a] & Oliver J. Rutz [b,*] & Koen Pauwels [c]

[a] *Schauenburgerstraße 116, 24118 Kiel, Germany*
[b] *Foster School of Business, University of Washington, Box 353226, 420 Paccar Hall, Seattle, WA 98195-3226, United States*
[c] *Ozyegin University, Turkey*

Available online 21 November 2014

**Abstract**

Online commerce gives companies not only a growing global sales platform, but also powerful consumers enjoying 24/7 availability, choice proliferation and the power to opt in and out permission-based communication. Unfortunately, our knowledge is limited on long-term marketing effectiveness in this space and on how it differs across customer segments. Managers appear overwhelmed by the combination of rich online data on hundreds of thousands of customers and the typical aggregate-level data on offline marketing spending.

This paper is the first to investigate the long-term impact of coupon promotions, TV, radio, print, and Internet advertising across customer segments for a major digital music provider with over 500,000 customers. We first segment customers and subsequently analyze how these segments respond in the long run to different marketing activities when purchasing music downloads. Our findings reveal that the effectiveness of marketing differs across segments, while standard segmentation approaches fail to identify the most valuable catches in a sea of consumers. In contrast to empirical generalizations on consumer packaged goods, heavy users of digital music products are least sensitive to price and most sensitive to TV advertising and to multiple touch points. Light users, the majority of consumers, are price sensitive and tend to opt out of targeted communication. Our research enables managers in the digital media space to target high-value customer segments with the most effective actions.


*Keywords:* Long-term effectiveness; Segments; Digital music; Online; Synergy; Advertising; Latent-class segmentation; Vector autoregression

## Introduction

The analysis of advertising and price promotion effectiveness as part of the marketing mix has been one of the central quantitative marketing research priorities, and the field has amassed a wealth of knowledge concerning the short-term and long-term effects of the marketing mix across product categories (Hanssens 2009; Tellis 2009). Still, the majority of this research focuses on consumer packaged goods, raising questions as to whether the empirical generalizations apply to the new businesses of the 21st century (Sharp and Wind 2009). Nowadays, online commerce gives consumers 24/7 availability, one-click price comparison and the power to opt in and out of permission-based communication. Media fragmentation and choice proliferation invite consumers on a decision journey unlike the classic purchase funnel: they 'seize control of the marketing process and actively "pull" information helpful to them' (McKinsey 2009, p 5). What is the long-term effect of marketing actions and their interactions (i.e., multiple touch points) in this context?

We investigate short-run and long-run marketing mix effectiveness for different segments in the digital media space. A key sector of digital media is music[1] with firms such as iTunes, Amazon's Kindle store, or zune.net. This new space

* Corresponding author.
*E-mail addresses:* reimer@analytix.de (K. Reimer), orutz@uw.edu (O.J. Rutz), koen.pauwels@ozyegin.edu.tr (K. Pauwels).

[1] Music, the focus of our empirical analysis, is only one of the many media categories that can be digitized and made available to consumers via download. Other examples include books, movies, games and ringtones. For the remainder of the paper we will refer to digital music instead of digital music downloads for the ease of exposition. Note that our approach can easily be applied to other categories of digital media products.

http://dx.doi.org/10.1016/j.intmar.2014.05.002
1094-9968/

brings unique challenges with respect to available data. Firms typically collect Customer Relationship Management (CRM) type data on millions of customers and their transaction records. Marketing activity is captured in two ways: traditional aggregate-level data on "push" mass media (e.g., TV, radio, print, banner ads) and customer-level data on what was "pulled" by the customer to enable purchase (e.g., permission-based communication, coupons claimed, newsletter emails). This combination should allow companies to profile customers based on their responsiveness to push marketing as well as their pull behavior. Potentially, short- and long-term effects of marketing actions in isolation and combination (multiple touch points) can differ substantially across customer segments. If so, a segmentation analysis can generate actionable insights for marketing budget allocation. Unfortunately, realizing this potential is complicated by the sheer size of the customer base and the lack of a modeling framework combining response-based segmentation with long-term effect estimation. This paper introduces a modeling approach that enables managers to quantify marketing effectiveness based on *all* available data. Our approach combines existing "best practice" methods of segmentation and long-run effects modeling to investigate marketing mix effectiveness. Ultimately, we aim to generate new insights into which marketing actions yield long-term benefits for the most valuable customer segments in the digital media space.

We use our framework to study marketing mix effectiveness in the digital music space. Our data come from the leading digital media provider in a large European country.[2] Our contribution is threefold. First, we show how online consumer segments, based on their short-term marketing response, have substantially different sizes and profiles. Second, we quantify for each segment the long-term effects of coupons and advertising media as well as their interactions. In contrast to empirical generalizations from consumer packaged goods, heavy users of digital music are less price sensitive than light users and more responsive to advertising. Third, we show how marketing actions with insignificant direct sales impact (print) may still be worthwhile due to their synergy with effective marketing actions (TV and Internet marketing). The remainder of this paper is organized as follows. First, we discuss how previous literature on CRM and long-term marketing effectiveness may apply differently to digital media products. Next, we present our data and propose a modeling approach that allows combining customer-level purchase data using the whole customer base and customer-level and aggregate-level marketing mix data. The first modeling step involves segmenting customers based on observed purchase behavior while accounting for unobserved heterogeneity using a latent-class approach. The second step involves persistence modeling to investigate the short- and long-run effects of marketing in each segment. We report our results and show that segmenting instead by an ad hoc approach (such as median or quartile splits) does not allow uncovering the marketing response of the most valuable customers. Finally, we discuss how our findings translate into tailored marketing strategies for the digital music space.

## Research Background

Three literature streams are directly relevant to our research: (1) studies on Customer Relationship Management (CRM), characterized by individual-level data being rich in own-customer but poor in non-customer information, (2) studies of long-term marketing effectiveness in brick-and-mortar settings and (3) studies on online consumer behavior.

First, CRM studies share a focus on customer-specific revenues with our research and also use individual customer behavior to capture heterogeneity. But most CRM literature focuses on forecasting customer purchases and/or quantifying customer lifetime value (e.g., Fader and Hardie 2009; Reinartz and Kumar 2000). Marketing-mix information rich enough to permit the study of marketing communication effectiveness is typically lacking. CRM studies that focus on marketing effectiveness have considered the short-term effects of direct marketing activities such as coupon and price promotions, direct mailing campaigns, loyalty programs, or recommendation systems (Bodapati 2008; Simester, Sun, and Tsitsiklis 2006; Zhang and Wedel 2009). Common performance measures are the revenue of the campaign or the purchase probability at the customer-level. While our dependent variable (weekly revenues per customer) is similar to that in many CRM studies, we add to this research stream by incorporating rich information on marketing mix actions on both individual and aggregate level, and by demonstrating how customers may be segmented and how long-term marketing effectiveness can be quantified on a segment-level.

Second, the long-term effectiveness of the marketing mix has been analyzed by several authors using scanner panel data across CPG categories (Hanssens 2009; Tellis 2009). With respect to the relative order of effectiveness, five findings stand out:

(1) Price incentives create a large short-term sales boost, but few, if any, long-term benefits (Nijs et al. 2001; Pauwels, Hanssens, and Siddarth 2002).
(2) Heavy users are more price sensitive than light users (Lim, Currim, and Andrews 2005; Neslin, Henderson, and Quelch 1985).
(3) Price incentives have a larger sales elasticity than advertising (Tellis 2009).
(4) TV advertising has a larger sales elasticity than either radio or print advertising (Jamhouri and Winiarz 2009; Rubinson 2009; Sharp, Beal, and Collins 2009).
(5) Interaction effects are substantial and exist among radio and print (Jagpal 1981), TV and radio (Edell and Keller 1989), and TV and print advertising (Naik and Raman 2003).

Specific research on quantifying elasticities in traditional (physical media) music sales is scarce and considered the effects of radio play and billboard lists but not of price (Moe and Fader 2001). Thus, we see no reason why the empirical

[2] The company wishes to remain anonymous.

generalizations would not apply to traditional music sales. Indeed, buying CDs is expensive and thus represents a substantial share of wallet for heavy users. As a result, price incentives should be especially powerful in driving their purchase. In contrast, light users may annually only buy one or a few CDs they fell in love in with, thus exhibiting lower price sensitivity.

Third, online commerce has been analyzed in several research studies that identify its unique aspects and challenges. While some consumers purchase more when gaining access to online information, others reduce spending as the online experience partly substitutes for offline shopping (Pauwels et al. 2011). The Internet is an excellent search-and-purchase medium for digital media products and very different from a traditional brick-and-mortar shopping experience (Fan, Kumar, and Whinston 2007). Indeed, the Internet offers not just lower search and information costs (e.g., Ratchford, Lee, and Talukdar 2003), but also a convenient way to easily sample music, movies, or games in order to assess their value and utility, as well as a convenient way to purchase them — namely, by downloading them (Choudhury and Karahanna 2008). The unbundling of music albums in separate songs available online now allows empowered consumers to cherry pick exactly the songs they want (Elberse 2010).

## Expectations

Despite a wealth of research in each of these three relevant streams, the current literature is not very clear on which marketing actions work best for digital media products. We propose two ways in which marketing effectiveness and segmentation may work for these novel products (see Table 1).

First, we expect the *size of the segment of heavy users* to be small for digital media products, in contrast to the typical 'median-split' set-up traditionally used in CPG products. At any given time, products on the Internet are available to many more potential customers than those in a brick-and-mortar store. However, the vast majority of visitors to a brick-and-mortar store are in a shopping mode, while the millions surfing the Web may have other priorities and demands on their time. Online consumers are often not set on a particular product to satisfy their media needs (Google 2011; McKinsey 2009), which means they may engage in fast and opportunistic "frictionless" shopping (Brynjolfsson and Smith 2000). Such opportunism may translate into the consumption of free versus paid media (e.g., pirated music) or into coupon usage. In contrast, heavy users of a particular provider, e.g., iTunes, have "bought into" a specific digital media platform,[3] and their purchasing and consumption may have become so habitual that they are unlikely to consider outside options. Therefore, a large group of low-involved deal-prone consumers may make up the majority of a company's customers, while a small, heavily involved group provides the majority of revenues and profits. A key implication for segmentation is that median splits (or similar ad hoc segmentation strategies such as quantiles) can be very deceiving in the digital media space, as they may mask the presence of small but important segments. In contrast, median splits make more sense as a basis for analysis in traditional consumer goods, where they have been used to separate customers into heavy and light users (Lim, Currim, and Andrews 2005).

Table 1
How consumer behavior differs translate into marketing implications.

| Consumer behavior differs for online entertainment versus consumer packaged goods | Implication for marketing effectiveness and segmentation |
|---|---|
| (1) 24/7 availability<br>(2) One-click price comparison<br>(3) Platform lock-in for heavy users | Expectation 1<br>► There is a large segment of "opportunists" who shop opportunistically and a small segment of heavy users who spend most of the money. |
| (4) Each product is unique<br>(5) Not consumed in use | Expectation 2<br>► Heavy users are less price sensitive than light users are. |

**Expectation 1**. (a) Heavy users of digital music make up a small percentage of the total consumer population, which makes (b) the results of behavioral-based segmentation differ substantially from those of median splits.

Second, we investigate *marketing mix sensitivity across segments*. Traditionally, findings relating to price sensitivity show that the usage of the category is an important antecedent of consumer behavior when it comes to price. For example, research in the domain of CPG goods shows that heavy users are more enticed by price-based incentives. These heavy users typically buy for their large households and stockpile additional units for future consumption (Lim, Currim, and Andrews 2005; Neslin et al. 2006). Why may this empirical generalization not apply to the digital music space? First, heavy users of music are often connoisseurs of music, having a strong intrinsic preference to consume music. Second, heavy users do not buy for a large household but mostly for themselves (e.g., Fallows 2004). Third, each piece of music (or music product) is unique. Fourth, music is not consumed with use and can be reused many times over. Fifth, listening to music is hedonic in nature, driven by the desire to "have fun" (Holbrook and Hirschman 1982), and influenced by situational factors, emotions, and moods (Lacher 1989). Thus, consumers will be in an experiential shopping mode (Babin, Darden, and Griffin 1994) and should be most swayed by marketing actions that help them experience the unique product (e.g., by acquiring it via download). In our context, TV, Internet, and radio advertising allow sound, in contrast to print advertising, which does not. We posit that heavy users, who have a self-revealed high need for this form of digital product, are less likely to be swayed by price-oriented and more by experiential (i.e., advertising) marketing actions. In contrast, we expect light users, with a lower intrinsic need for music, to be more opportunistic, and thus more responsive to price-oriented marketing actions, aided by one-click price comparisons and easy sampling (Diehl, Kornish, and Lynch 2003) and less

[3] For example, a customer of Apple's iTunes music store will have installed the iTunes software, which is not compatible with other providers' digital music format.

responsive to experiential marketing actions. The unbundling of music albums in separate songs available online (Elberse 2010) now allows light users to cherry pick cheap options. Thus, their lower reservation price and higher price sensitivity — previously masked by the high threshold of the bundled CD — can now show up in sales data (Elberse 2010).

**Expectation 2**. Heavy users are less price sensitive, while light users are more price sensitive in the digital music space.

Despite a general intuition about these differences in consumer behavior, current literature lacks a systematic analysis of what this means for consumer segmentation and long-term effectiveness of online marketing, offline marketing and their interactions in the digital music space. Research on online advertising (e.g., Ghose and Yang 2009; Manchanda et al. 2006) typically focuses on the effect of online advertising and does not take offline advertising into account. While the communication channel fit suggests that online advertising should be key in driving online sales, recent findings on cross-channel effects (e.g., Wiesel, Pauwels, and Arts 2011) indicate that offline advertising may be very important as well. Our investigation is the first to provide evidence for these emerging themes, by developing a modeling framework based on the novel data available in the digital music space combining the analysis of long-term marketing effectiveness with the customer-centric view prevalent in CRM research.

## Industry and Data Description

Our empirical analysis focuses on digital music, which represents one of the most important and well-known product categories in the digital media space. The opening of Apple's iTunes store on April 28, 2003 was a disruptive event for the music industry and created a blue ocean (Kim and Mauborgne 2005) for digital music. It has even been said that "iTunes killed the (old) music industry" (Gollijan 2013). In 2004, one year after the inception of iTunes, music industry revenues stemmed overwhelmingly from physical (digital) products (98.5% vs. 1.5%). In 2012, digital products have overtaken physical products (40.4% vs. 39.5%).[4] Digital music is distributed via web-based stores allowing for 24/7 availability, easy price comparisons, sampling and immediate purchase of a very wide variety of popular and long-tail music (Elberse 2010; Elberse and Oberholzer-Gee 2007).

As typical for industries with high price transparency, digital media providers charge prices similar to the competition and are limited in their power to attract competitors' customers. Our conversations with these providers reveal a strong focus on increasing spending among existing customers. Increasing share of wallet can be implemented along two dimensions in the digital media space: 1) shifting offline purchases to online and 2) stimulating demand by offering greater variety[5] (e.g., a larger catalog of media), easier trial (e.g., instant sampling from the comfort of one's own home), and more convenience (e.g., 24/7 availability at a touch of a button). Without the ability to charge lower base prices, providers rely heavily on promotions in the form of online coupons as well as costly advertising to stimulate demand. Thus, it is imperative for providers to understand the effectiveness of these marketing mix instruments in their space.

Our data come from the leading digital media provider in a large European country and contains all data relating to its digital music division.[6] At the point of the data collection, the firm had close to three quarters of the national market. The data represent over 500,000 customers and stretch a period of 87 weeks starting in January 2005. These data are on a mixed aggregation-level: they include information on individual customer behavior as well as on aggregate marketing actions. On a customer level, we have information on € sales per customer and week, customers' coupon usage and the customers' use of "pull" media such as newsletters or permission-based emails. On an aggregate level, we have weekly information on marketing actions via TV, print, radio, and Internet. Comparing these data to the typical individual-level or aggregate data traditionally used in marketing mix studies reveals three important differences:

a. *Own-customer focus*. The data are rich in own-customer but poor in non-customer and competitor information (similar to applications in Customer Relationship Management).
b. *Heterogeneity*. The data capture heterogeneity across *all* customers. Specifically, our data contains sales records of half a million distinct customers over a period of 20 months — making it unlike typical panel data that assumes an unbiased, representative sample in order to generalize to the population of shoppers.
c. *Mixed on marketing instrument level*. The data contain a mix of customer-targeted and mass-media marketing.

For company confidentiality reasons, we can only provide approximate values of key metrics. Customers, when active, spent just over € 6 per week on digital music (standard deviation of € 0.7). On average, each customer uses 0.48 coupons per week (standard deviation of 1.04 and a maximum of 52). These coupons consist of a code that the customer can use when downloading music and generally have a face value between € 5 and € 10. The coupons are available to any interested customer, as they are accessible (1) directly in several magazines, (2) via e-mails sent by the firm, or (3) retrievable on request via e-mail. Finally, for each customer we have information on whether she or he signed up for the newsletter e-mails and for "permission" mailings (both for around 1/5 of all customers). Newsletter e-mails are sent out once every week, while permission mailings are always related to special events or holidays (recorded as date indicators). These data, summarized in Table 2, are thus useful for profiling customer segments rather than for explaining variation in spending.

[4] In addition, many physical CDs are bought online and delivered offline, but this is not the focus of our study.

[5] In this space, digital providers allow easy access of low-volume items, e.g., collectors' items or obscure pieces of music, that were generally not available in offline stores due to low demand and limited shelf-space.

[6] The company wishes to remain anonymous.

Table 2
Descriptive statistics of marketing actions and customer information.

| | | Mean | Median | Maximum | Minimum | SD |
|---|---|---|---|---|---|---|
| Per week | TV | 35.87 | 20 | 139 | 0 | 38.38 |
| | Print | 1.68 | .94 | 7.88 | 0 | 1.95 |
| | Radio | 16.26 | 0 | 299 | 0 | 56.53 |
| | Internet days | 3.70 | 7 | 7 | 0 | 3.51 |
| | Coupons used | 2963.85 | 1695 | 50,906 | 708 | 5733.5 |
| Per customer | Relationship duration (years) | 1.21 | 1.21 | 3.01 | .01 | .59 |
| | Newsletter | .19 | 0 | 1 | 0 | .39 |
| | Permission | .18 | 0 | 1 | 0 | .38 |
| | Gender | .72 | 1 | 1 | 0 | .45 |

In addition to providing us with this unique customer-level information, the data also contain aggregate-level information on the firm's print (offline), radio, and TV advertising.[7] All offline advertising is measured in gross rating points (GRPs), and most of the spending is focused on TV (see Table 2), followed by radio. The firm also advertised online using banner ads. These banner ads feature the company logo, sometimes mentioning new products or bestsellers, and are placed on homepages of different magazines and categories covering a broad range of interest areas (daily/weekly news, finances, computer, TV, sports, women, etc.). Banner ads are either used on a certain day or not on the ad network the firm used. Thus, we create a weekly measure of the number of days banner ads were used in a given week. Among all variables used in our model, correlations are lower than .60 in absolute value, with the highest correlation between print and Internet marketing. None of the correlation patterns reveals concerns for multicollinearity.

The data also include information that enables us to control for seasonality as well as for exogenous demand shocks. Such shocks include new releases of famous artists and bands, major events such as the soccer world championship in the summer of 2006, and trade shows related to the music industry. Absent from our data set is any information about competitive activity, as is typical in database marketing applications. Though such data would be useful, our ranking of the most effective marketing actions per segment is unlikely to be affected, because (1) all competitors together have less than 30% market share, and (2) past studies reported that competitive reactions inflict only limited harm to the performance of the firm initiating (frequently used) marketing actions (Pauwels 2004, 2007; Srinivasan et al. 2004; Steenkamp et al. 2005).

Our performance variable — *weekly customer spending* — displays a consistent temporal pattern across customers, as shown in Fig. 1. In the first 52 weeks of the observation period, weekly spending shows a positive trend, which then turns into a slightly negative trend. This temporal pattern is consistent with previous studies on customer purchase behavior in the digital music space (Fader, Hardie, and Lee 2005) and is captured with a linear and quadratic time trend in the model. Besides this temporal pattern, weekly spending shows several peaks, which may be related to marketing activity and/or exogenous demand shocks such as holidays and music events.

## Modeling Approach

Our objective is to propose a sound and managerially useful method to estimate long-term marketing effects for distinct customer segments with the type of data typically found in the digital music space combining existing "best practice" approaches. In particular, our data set — consisting of more than 500,000 customers — contains a mixture of customer-level as well as traditional aggregate marketing information. Many approaches have been suggested in the marketing literature for investigating the effectiveness of marketing mix instruments on either customer-level or aggregate-level data. On the one hand, current customer-level approaches are computationally limited to a few hundreds of customers and do not readily incorporate long-term effects of aggregate marketing spending. On the other hand, aggregate-level time series models do not incorporate the additional individual-level information that is readily available for online purchases where customers are required to sign-up initially and sign-in when purchasing. Implementing a standard aggregate analysis would mean that we risk leaving potentially valuable customer-level information unused. Given marketing literature's findings on the importance of correctly addressing unobserved customer heterogeneity, we prefer to make use of the available customer-level information.

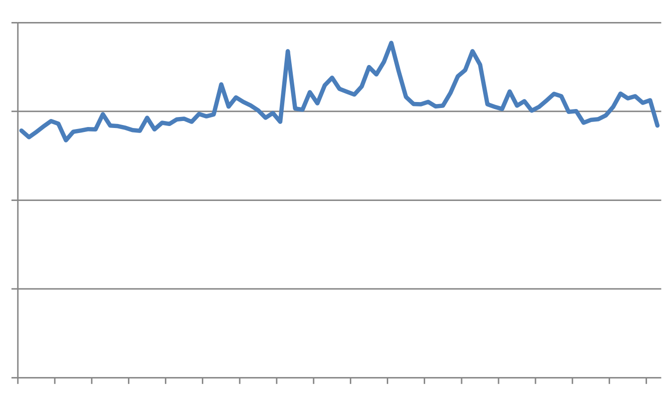


Fig. 1. Average weekly spending per customer.

[7] Note that the firm did not use search engine marketing during 2005–2006 either in the form of search engine optimization or sponsored (paid) search.

We propose a two-step approach to investigate the long-run effects of the marketing mix that accounts for unobserved consumer heterogeneity. As a first we use the individual-level data, i.e., purchases and individual-level marketing mix exposure, to segment the consumer based on their estimated responsiveness to the marketing mix. Note that we do so in a choice-model set-up and focus on short-run differences in response accordingly. We posit that a consumer's short-run responsiveness to the marketing mix is a proxy for a consumer's long-run response. Based on the estimates of consumer short-run responsiveness we create segments of homogenous consumers. In the second step we investigate the long-run effectiveness of the marketing mix within these homogenous segments.

Our approach combines the best of both worlds in a two-step procedure implemented in a sequential estimation strategy (see Table 3). In the first step, we segment all customers based on their observed weekly purchase behavior using the four advertising instruments (TV, print, radio, and Internet) as explanatory variables (Table 3, step 1). We implement the segmentation in a choice framework leveraging the panel structure of the purchase data and are taking a direct marketing (or direct response) view. As the dependent variable, we model whether a customer purchased a digital music product in a given week (or not) based on observed *consumer characteristics* and the above-described *marketing activities*. We capture unobserved heterogeneity with a latent-class approach in accord with most research on consumer preferences and segmentation. We posit that customers are heterogeneous across but, for our purpose of actionable segmentation, approximately homogeneous within segments. We include segment-specific fixed effects to account for unobserved systematic factors not included in the marketing activities. For example, a fixed effect can capture a segment's affinity for music: we might have a "music lovers" segment and a "casual listener" segment.

We specify the utility of buying digital music in a given week $t$ for a customer $i$ as linear in marketing activities conditional on being in segment $k$ as follows:

$$u_{it} = \beta_{ok} + x_t^{\prime}\beta_k + \varepsilon_{it}, \tag{1}$$

where

| | |
|---|---|
| $k$ | indicates that the latent segment customer $i$ is assigned out of $K$ extant latent segments, |
| $\beta_{ok}$ | are segment-specific fixed effects, |
| $\beta_k$ | are segment-specific response parameters, and |
| $\varepsilon_{it}$ | is a logit error. |

We follow Kamakura and Russell (1989) and estimate, for a given number of segments $K$, the response parameters of interest, $\{\beta_0, \beta\}$, and segment sizes $\pi_k$ (where $\sum_{k=1}^{K} \pi_k = 1$) using a maximum-likelihood approach. We use the Bayesian information criterion (BIC) to determine the optimal number of segments, $K$. Based on the results from the latent-class model, we classify the customers as belonging to one of the $K$ segments based on their purchase behavior in combination with the model estimates (see Appendix A). Lastly, in each segment, we aggregate across customers assigned to it. This leaves us with $K$ aggregate data sets in which the customers are approximately homogeneous.

In most applications of choice models in the marketing literature, the typical data contain only between 250 and 500 distinct consumers; substantially less than in our case. Estimating a choice model using 500,000 customers is infeasible due to the size of the likelihood. To address the estimation issue generated by the size of the data, we employ a subsampling approach (Musalem, Bradlow, and Raju 2009) to calibrate the model. We took multiple random subsamples of 10% of the customers and estimated the latent-class logit choice model as described above on each subsample.[8] Comparing the results, we find that subsampling generates robust estimates of the underlying heterogeneity distribution and results in, for all purposes, identical estimates and segmentation schemes. In order to segment the other 90% of the customers, we use the resulting coefficients of one subsample estimation and assign each of the remaining (90%) customers to one of the $K$ segments based on the likelihood. (Please see Appendix A for details.)

In the second step, we treat the $K$ aggregate data sets as separate and use time-series methods to investigate the short- and long-run effects of the marketing mix on the $K$ different segments. We proceed in three steps, as outlined in Table 3 (steps 2–4). First, we perform Granger (1969) causality tests to examine the potential endogeneity among customer spending, advertising, and promotion, testing each variable pair for up to 20 lags (Trusov, Bucklin, and Pauwels 2009). Second, unit root and cointegration tests establish the potential for permanent marketing effects (Dekimpe and Hanssens 1999). Third, in the absence of cointegration, we specify a vector autoregressive model with exogenous variables (VARX) that accounts for endogeneity, the dynamic response and interactions between marketing variables, and customer weekly spending on digital music. We explicitly include long-term interaction effects among offline and online advertising instruments and promotions. The nine endogenous variables are the logarithms of (1) the segment average of weekly customer spending, (2) the number of coupons used [=claimed], (3) TV GRPs, (4) radio GRPs, (5) print GRPs, (6) the presence of Internet advertising, (7) the interaction between TV and Internet advertising, (8) the interaction between print and Internet advertising, and (9) the interaction between print and radio advertising (remaining interactions can not be included due to multicollinearity issues). Note that these same-period interactions are in addition to the cross-period interaction already captured thanks to the VAR's dynamic system of equations (Trusov, Bucklin, and Pauwels 2009).

Exogenous (control) variables include a constant, a linear and quadratic trend, indicator variables for monthly seasonality (using January as the benchmark) and for holidays, the weekly number of releases of major albums and singles, award events,

[8] Our approach is robust to alternative subsampling schemes, e.g., using 5% instead of 10%. Obviously, larger subsampling schemes, e.g., 20%, lead to computational issues in terms of size of likelihood.

Table 3
Overview of methodological steps.

| Methodological step | Relevant literature | Research question |
|---|---|---|
| 1. Latent-class analysis | Kamakura and Russell (1989) | How can we capture unobserved consumer heterogeneity using a segmentation approach? |
| 2. Granger causality tests | Granger (1969)<br>Trusov, Bucklin, and Pauwels (2009) | Which variables are temporally causing which other variables? |
| 3. Unit root and cointegration | | |
| Augmented Dickey–Fuller Test | Enders (2010) | Are any variables evolving… accounting for unknown breaks? |
| Zivot–Andrews test | Zivot and Andrews (1992) | |
| Cointegration analysis | Johansen, Mosconi, and Nielsen (2000) | Are evolving variables in long-run equilibrium? |
| 4. Vector autoregression | | |
| Lag selection and residual diagnostics | Lütkepohl (1993), Franses (2005) | What is the dynamic interaction among variables? |
| Generalized impulse response | Dekimpe and Hanssens (1999) | What is the net performance impact of a marketing change… |
| Cumulative marketing elasticity | Pauwels, Hanssens, and Siddarth (2002) | accounting for all significant impulse response coefficients? |

and trade shows. The model is displayed in matrix form in Eq. (2):

$$Y_t = A + \sum_{k=1}^{p} \Phi_k Y_{t-k} + \Psi X_t + E_t, \quad t = 1, \ldots, T, \tag{2}$$

where

$A$ is a 9 × 1 vector of intercepts,
$Y_t$ is the 9 × 1 vector of the endogenous variables,
$X_t$ is the vector of exogenous control variables listed above,
$E_t \sim MVN(\bar{0}, \Sigma)$ and $\Sigma$ is the full variance–covariance matrix of the residuals,
$A$, $\Phi$, $\Psi$, $\Sigma$ and $p$ are parameters to be estimated.

Based on the estimated VARX coefficients, we quantify marketing effects over time by means of generalized impulse response functions, which do not require a causal ordering to produce short-term (same-week) and long-term effect estimates (Dekimpe and Hanssens 1999). Because the variables are presented in logarithms in the model, we directly obtain the spending elasticity to the marketing actions (Pauwels, Hanssens, and Siddarth 2002). Finally, we compare the effects between the four segments using the standard error approach outlined in Pauwels (2004) and discuss the significant differences.

Summing up, we note that Eqs. (1) and (2) are at different levels of analysis: Eq. (1) specifies the individual utility function, while Eq. (2) explains the segment-average revenues. Both models explain their dependent variable with the four advertising instruments. Eq. (1) is focused on classifying customers based on short-term response. Eq. (2) is focused on long-term marketing effects at the segment-aggregate level and thus adds 1 lag of each endogenous variable. Endogeneity is explicitly treated by adding an equation explaining each advertising instrument. We use the segments to explore the long-run effects of marketing in this direct marketing setting, which to our best knowledge has not been done before.

Table 4
Performance criteria for the latent-class segmentation.

| | LL | BIC | McFadden $R^2$ |
|---|---|---|---|
| 1 segment | −1,094,931 | 2,189,939 | .00 |
| 2 segments | −1,038,328 | 2,076,825 | .05 |
| 3 segments | −1,030,017 | 2,060,295 | .06 |
| **4 segments** | **−1,022,831** | **2,046,015** | **.07** |
| 5 segments | −1,022,801 | 2,046,139 | .07 |

BIC = −2LL + $K$Ln($T$), where LL* is the maximized log likelihood value, $T$ is the sample size, and $K$ is the number of parameters. Bold values indicate significance at $t > 1$.

## Results

We first present the results of the latent-class model described in Eq. (1) using the four advertising instruments as independent variables and the purchase event of customer $i$ in week $t$ as the variable to be explained.[9]

### *Latent-class Segmentations*

We find that a four-segment model fits the data best (Table 4): A large segment containing 63% of the customers (segment 1), two medium segments containing 20.2% and 14.4% (segments 2 and 3, respectively) and a small segment containing 2.4% of customers (segment 4). This segmentation provides a first intuition that a median split may have been misleading, as segments 2–4 would be combined. Finer splits (e.g. quartiles, quintiles) would still miss segment 4. This matters because responsiveness to marketing actions differs significantly across segments, indicating substantial unobserved heterogeneity across customers. Sensitivity to coupons and radio is high for segment 1, but low for segment 2, which is more sensitive to banner ads. Relative to segment 2, segment 3

[9] As detailed in the methodology section, the latent-class model (Eq. (1)) uses a 10% sample, after which we classify the remaining 90% of customers based on the estimates. The long-term marketing effectiveness analysis (Eq. (2)) uses the total customer base (500,000 customers) and is accounting for unobserved customer heterogeneity uncovered by our latent-class model.

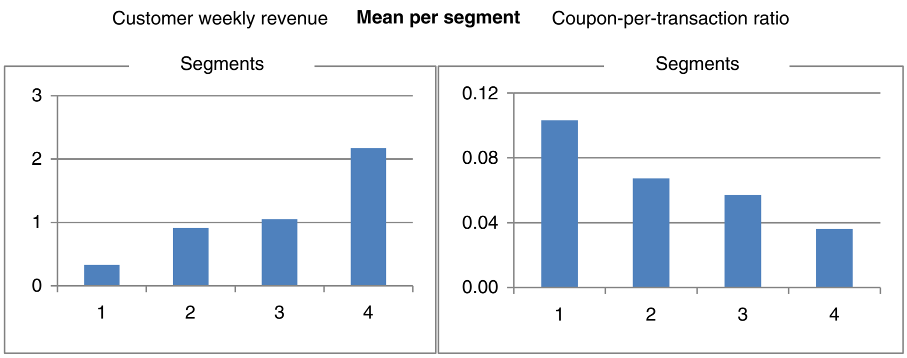


Fig. 2. Descriptive statistics of the four segments.

is more sensitive to coupons, TV and radio, while segment 4 is more sensitive to TV and radio.

Next, we investigate whether the segments differ in terms of purchasing behavior. Fig. 2 shows that the main differences lie in customer weekly revenue and coupon usage. A negative correlation between customer weekly revenue and coupon usage emerges. Moving from segment 1 to segment 4, customer weekly revenue increases, and coupon usage decreases. Specifically, revenue is highest in segment 4 (just above € 2), then in segment 3 (~€ 1), segment 2 (slightly less than € 1), and segment 1 (~€ 0.3). As a result, customers in segment 4 are almost *seven times more valuable* than customers in segment 1.

Leveraging our segmentation results, we characterize the four segments as follows. The first segment contains very light users, mostly existing customers with mean relationship duration of 1.33 years, the highest coupon usage, and lowest rate for permission e-mails (Table 5). Due to high coupon usage, we label this segment as "deal-prone consumers". The second segment consists of fairly new customers, "new users", with an average relationship duration of 0.7 year and medium activity. The percentage of male customers and of newsletter subscription users is lowest here while the proportion of permission e-mail users is slightly higher than in the first segment. In the third segment (14.4%) are long-term customers with an average relationship duration of 1.5 years and medium activity, the "steady users." In this segment, no characteristics stick out (Table 5). The last segment (2.4%) is composed of heavy long-relationship users, the "heavy users". The average relationship duration is 1.7 years and, most interesting, these "heavy users" have the lowest coupon usage. The low usage of coupons indicates that these customers have the lowest price sensitivity. Substantially, this is a novel (and actionable) insight in stark contrast to the traditional wisdom with regard to price responsiveness that "heavy customers are the most price-sensitive". Customers in segment 4 also have the highest subscription rates for both newsletter and permission e-mails. These music enthusiasts are using novel "pull" marketing to help fulfill their needs with regard to consuming music. Lastly, segment 4 includes the highest percentage of male users.

Three key insights emerge from the latent-class analysis. First, we find a very small segment of heavy users, consistent with our Expectation 1(a). These heavy users are the most attractive segment in terms of revenue per customer. Second, these high-value customers are predominantly customers with a long company relationship, whereas most short- and medium-relationship customers are not as valuable. Third, the high-value customers are "allowing" exposure to more marketing activities, as they opt into permission emails and newsletters "pulling" relevant (marketing) information from the company. We conclude that addressing unobserved customer heterogeneity seems paramount for targeting decisions before investigating the long-term marketing effectiveness of marketing actions for each segment, to which we turn next.

### *Long-term Marketing Effectiveness*

Granger causality tests demonstrate that marketing drives customer revenue, and unit roots tests show that all variables are stationary around the quadratic trend pattern evident from Fig. 1. Moreover, a lag of 1 week was selected for each model by the Schwartz criterion, which is a consistent estimator of lag length (Lütkepohl 1993). Each equation in the VAR-model uses 86 observations (87 weeks, lagged once) to estimate 28 parameters (for the 9 lagged endogenous variables and the 19 exogenous variables), for a data-to-parameter ratio of 3. All segment-level VAR models provided adequate explanatory power and pass the diagnostic tests on residual autocorrelation (Franses 2005).

Based on the estimated VAR models, we derive short-term effectiveness as same-week response and long-term marketing effectiveness as the sum of all significant impulse response coefficients over time. Additional information gained from the impulse response function results, e.g., wear-in/wear-out times, are similar across segments and consistent with previous work in consumer packaged goods.[10] For instance, coupons work right away (high immediate elasticity, no wear-in), but may be followed by a post-promotion dip, while TV advertising effects show wear-in (peak effect reached after a week) and remain positive for two weeks after that (wear-out). In contrast, the segments differ in terms of the size of the short-term (same

[10] For space considerations, we do not report details on additional information gained from the impulse response functions, such as the wear-in and wear-out time of marketing effects.

Table 5
Segment differences in relationship duration, newsletter, permission, and gender.[a]

| | % of customers | % of sales | Relationship duration (years) | Newsletter | Permission | Gender (1 = male) |
|---|---|---|---|---|---|---|
| Segment 1 | 63% | 40% | 1.33 | 16.6% | 17.5% | 72.1% |
| Segment 2 | 20.2% | 15% | 0.7 | 19.4% | 18.3% | 68.9% |
| Segment 3 | 14.4% | 31% | 1.5 | 20.8% | 18.5% | 71.8% |
| Segment 4 | 2.4% | 13% | 1.7 | 21.7% | 21.7% | 73.3% |

[a] Differences are significant on a 5% level except for newsletter subscription between segments 3 and 4, for permission rates between segments 2 and 3, and for male percentage between segments 1 and 3.

week) and long-term (cumulative) elasticity, as shown in Tables 6–7 and Figs. 3–4.

Short-term elasticities (Table 6, Fig. 3) show the typical ordering of price (i.e., coupons claimed) having a stronger elasticity than non-price communications (for all segments but segment 2). Next comes Internet (banner) advertising, which is significantly more effective for segment 2 compared to segment 1. In contrast, offline marketing actions radio and TV fail to significantly drive short-term revenues in segment 2, but succeed for the other segments, with about equal short-term elasticity. All four segments show similar short-term response to the TV–banner ads interaction, indicating the synergy among offline and online touch points. Print fails to obtain a significant main effect on revenue in any segment, as does the interaction between print and radio. Finally, the interaction among print and banner ads is significant for revenue response in segment 4 only.

A different marketing rank ordering emerges when we move to long-term elasticities, which on average are lower for price due to negative lagged effects, but higher for marketing communication due to positive lagged effects. First, *coupons* have the highest long-term elasticity *only for segment 1* (deal prone consumers). Thus, price appears to be a key driver for 63% of the company's customers. Second, *Internet banner ads* have the highest long-term elasticity for *segments 2 and 3*. Thus, both new users and steady users are most responsive to marketing communication in the medium that fits the purchase (download) action. We infer that convenience is a key driver for these 35% of customers. Compared to segment 2, segment 3 is more responsive to offline marketing actions: TV, radio and TV–banner ads interaction. Thus, steady users pay more attention to the company's communication outside of the buying medium. Finally, heavy users (segment 4) have a significantly higher response than other segments to the TV–banner ads and print–banner ads interactions. These *multiple touch points* substantially increase weekly revenue from these customers. Note that the effect size of the synergy is close to the main effect for TV and for banner ads, while print is only effective when combined with banner ads.

### *Managerial Implications: Interpreting Segment Differences in Marketing Response*

The majority of customers for our digital music provider can be described as *deal prone* (segment 1), being most responsive to price-oriented marketing actions, tempted by the opportunity of purchasing music at a low price easily via download (Diehl, Kornish, and Lynch 2003). They are also very responsive to banner ads, which conveniently bring the user to the purchase (download) option. Thus, these customers are mostly stimulated by (price) advertising taking place at the point of sale (i.e., presenting a good deal) as compared with other online activities. However, offline marketing including TV and radio also drives deal prone consumers to spend more, as does the synergy between TV and the Internet. We infer that deal prone consumers tend to go online during or shortly after watching TV, as Nielsen reports show that over 60% of people simultaneously watch TV and use the Internet at least once a month (NielsenWire 2010). Interestingly, most deal prone consumers have been with the company for a while (average relationship of 1.33 years), so their price sensitivity and low revenue does not reflect lack of knowledge on what the company has to offer. This is a key difference to the traditional Customer Lifetime Value (CLV) notion that customers grow their revenues over time with the company (Reichheld and Sasser 1990). Our results add to Reinartz and Kumar's (2000) findings that long-lived customers are not necessarily more profitable nor do they pay higher prices than recently acquired customers.

The *new users* (segment 2) have the shortest relationship with the company (0.7 years on average) and do not respond significantly to radio ads. Instead, they are most responsive to banner ads, followed by TV and the TV–banner ad interaction. We infer that these are 'digital natives' who prefer to listen to

Table 6
Vector-autoregression model results on short-term elasticities for each segment.[a]

| | Segment 1: Deal prone | S2: New users | S3: Steady users | S4: Heavy users |
|---|---|---|---|---|
| Coupon elasticity | 0.0301 | 0.0140 | 0.0224 | 0.0188 |
| (standard error) | (0.0047) | (0.0022) | (0.0034) | (0.0028) |
| TV elasticity | 0.0045 | | 0.0047 | 0.0047 |
| (standard error) | (0.0009) | | (0.0008) | (0.0006) |
| Radio elasticity | 0.0085 | | 0.0065 | 0.0057 |
| (standard error) | (0.0014) | | (0.0010) | (0.008) |
| Banner ad elasticity | 0.0120 | 0.0167 | 0.0158 | 0.0150 |
| (standard error) | (0.0023) | (0.0027) | (0.0024) | (0.0030) |
| TV * Banner elasticity | 0.0034 | 0.0045 | 0.0044 | 0.0049 |
| (standard error) | (0.0008) | (0.0009) | (0.0008) | (0.0011) |
| Print * Banner elasticity | | | | 0.0085 |
| (standard error) | | | | (0.0020) |

[a] Only significant elasticities (t-value > 1, see Pauwels, Hanssens, and Siddarth 2002) are displayed.

Table 7
Vector-autoregression model results on long-term elasticities for each segment.[a]

| | Segment 1: Deal prone | S2: New users | S3: Steady users | S4: Heavy users |
|---|---|---|---|---|
| Coupon elasticity | 0.0256 (0.0076) | 0.0140 (0.0022) | 0.0224 (0.0034) | 0.0188 (0.0028) |
| TV elasticity | 0.0141 (0.0025) | 0.0067 (0.0023) | 0.0185 (0.0022) | 0.0188 (0.0020) |
| Radio elasticity | 0.0153 (0.0027) | | 0.0089 (0.0023) | 0.0083 (0.0024) |
| Banner ad elasticity | 0.0244 (0.0034) | 0.0167 (0.0027) | 0.0236 (0.0044) | 0.0150 (0.0030) |
| TV[a] banner elasticity | 0.0098 (0.0019) | 0.0045 (0.0009) | 0.0114 (0.0018) | 0.0131 (0.0020) |
| Print[a] banner elasticity | | | | 0.0143 (0.0031) |

[a] Only significant elasticities (t-value > 1, see Pauwels, Hanssens, and Siddarth 2002) are displayed.

digital music as opposed to programmed radio. These features do not make them the best customers though. New users do not spend much on the company's paid downloads, likely because they can enjoy digital music by other means. Moreover, less than 20% of new users allow the company to send newsletter emails.

Steady users (segment 3) have been with the company for 1.5 years on average and more than 20% have opted into newsletter and emails. This does not mean that they are unresponsive to mass media actions: their spending is strongly driven by both online (banner ads and coupons) and offline marketing (TV, radio and the TV–banner ads synergy). Thus, the company should not contend with direct marketing alone, even for customers it has a relatively long relationship with.

Finally, *heavy users* (segment 4) have the longest relationship (1.7 years on average) and thus resemble the combination of most profitable and longest-lived segment in Reinartz and Kumar (2000). TV advertising has the same long-term elasticity as price (online coupons) for these consumers. Banner ads follow in main effect, and enjoy high synergy with TV and print. Apparently, segment 4 customers are the only ones paying attention to the company's ads in the traditional printed

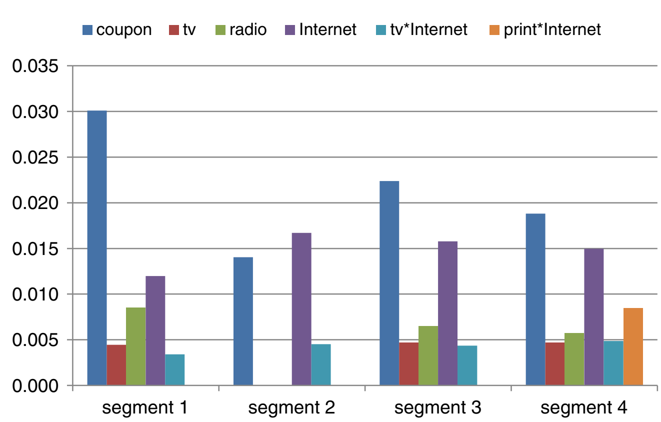


Fig. 3. Short-term elasticities of customer spending in response to marketing.

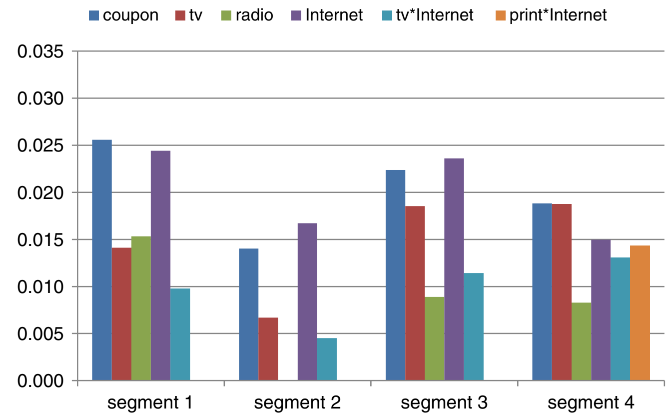


Fig. 4. Long-term elasticities of customer spending in response to marketing.

press. We infer that heavy users are more 'old school' than the other segments; being exposed to many offline information sources and more willing to pay for digital music. These inferences are in line with previous results from a survey on Internet users (Dufft et al. 2005) which conclude that marketing efforts should not only focus on young users but also particularly target older high-skilled professionals having more money to spend on new music but little time to discover. This in turn requires strong and coordinated marketing efforts, such as the synergetic TV and print advertising we identified in our study.

## *Comparison with Findings Based on an Ad-hoc Segmentation Approach*

How important is our latent-class segmentation approach for the substantive findings we obtained? First, we have shown that the effectiveness of marketing mix actions (short- and long-term) differs significantly and systematically across consumer segments. Thus, a model that simply aggregates over all consumers and does not utilize the available consumer-level information seems not advisable from our perspective. However, a better comparison of our model is found in earlier papers on segment-level long-term effects (e.g., Lim, Currim, and Andrews 2005), which group together consumers based on a priori descriptive data using a median split approach (e.g., heavy versus light users), with further divisions if desired. Given that we obtained four segments, it is logical to compare our approach with that of taking quartiles of consumers based on their purchase frequency (the same variable used to determine the latent-class segments). For each of these quartile segments, Fig. 5 shows the long-term elasticity of consumer spending in response to marketing actions.

The key observation is that the quartile analysis masks the important differences found among smaller segments in the latent-class segmentation. Coupon elasticity is the highest, followed by Internet advertising, in all four quartiles. Based on these results, managers would be inclined to perceive the market as relatively homogeneous, and focus on one-size-fits-all coupons and Internet ads. This would lead to overspending on

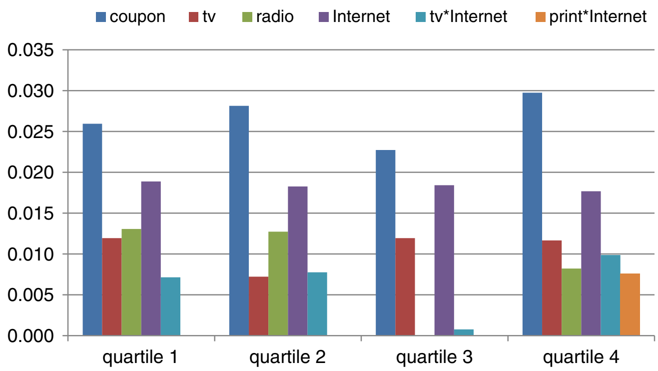


Fig. 5. Long-term marketing elasticities across purchase frequency quartiles.

specific ad forms and at the same time leaving money on the table by over-reliance on coupons even for consumer groups that are not very price sensitive. We conclude that our latent-class segmentation is better suited to uncover key insights with regard to unobserved heterogeneity in long-term marketing effectiveness, especially in the presence of small segments with high value per customer. This is consistent with our Expectation 1(b).

### *Comparison of Marketing Effectiveness for Digital Music Versus CPGs*

Lastly, we relate our findings to empirical generalizations regarding marketing effectiveness in consumer packaged goods (CPGs) and discuss the substantial differences that arise. Table 8 summarizes the key findings of marketing mix effectiveness from the CPG industry and contrasts them with our novel findings based on the study of the digital music space. On price incentives (Table 8, row 2), our results show one consistent and one different finding compared to CPGs. First, we find that price incentives (in our case, coupons) do obtain high immediate effects, but do not have any permanent effects, a finding that is consistent with, for example, Pauwels, Hanssens, and Siddarth (2002). The different operationalization makes this finding interesting: because online coupons are typically available on a continuous basis, we have data on coupons claimed, not coupons distributed. Second, consistent with our Expectation 2, we find that price incentives are more effective for light users than for heavy users — in contrast to the findings for CPGs (Lim, Currim, and Andrews 2005; Neslin, Henderson, and Quelch 1985). This contrast ties back to our observation (Table 1) that heavy users of CPGs typically buy for others, while heavy users of digital music typically buy for themselves (Fallows 2004). Instead, the light users of digital music have lower intrinsic need for it and thus will respond more opportunistically to price-oriented marketing actions, aided by one-click price comparisons and easy sampling (Diehl, Kornish, and Lynch 2003).

As for relative marketing effectiveness (Table 8, row 3), we find first that price incentives only have the highest long-term elasticity for light users. Medium users in the digital music space are more swayed by Internet advertising, while heavy users are also most affected by TV advertising. Fourth, consistent with CPG findings, we observe that TV advertising has a higher elasticity than print advertising and radio advertising for 3 out of 4 segments. However, the majority of the company's customers (deal prone segment 1) are more responsive to radio than to TV ads. This is likely due to the fit of the advertising medium with the category. As observed in Table 1, consumers in an experiential shopping mode (Babin, Darden, and Griffin 1994) should be most swayed by marketing actions that help them experience the unique product. Moreover, TV advertising is less important than Internet advertising for all segments except heavy users. This is intuitive given the sampling and purchase availability online, but our study makes this intuition actionable by quantifying the elasticities and showing how they differ for heavy versus lighter users.

We also find that interactions between marketing actions are significant and substantial — in our case between Internet advertising (all segments) and TV and print advertising (for heavy users). This synergy between new online and traditional offline media is substantially higher than what researchers have found among offline media (e.g., Naik and Raman 2003). Our findings are in line with the notion of a complicated 'consumer decision journey' (McKinsey 2009), where consumers are exposed and expose themselves to multiple touch points. This exposure often occurs without an immediate need for purchase, i.e. at the 'Zero Moment of Truth' (Google 2011), when consumers are still uncertain as to which product category would be interesting to consider. In such context, consumer spending on the company's products is driven by repeated exposure to product- and company-related information through multiple media. High synergy among those touch points is consistent with this journey (Naik and Peters 2009).

Table 8
Overview — new insights into the effectiveness of the marketing mix.

| Findings | In consumer packaged goods (previous literature) | In digital media (this study) |
|---|---|---|
| *Price response across segments* | • Large short-term effect<br>• Little if any long-term effect<br>• *Heavy-users* are most price-sensitive | • Large short-term effect<br>• Little if any long-term effect<br>• *Light-users* are most price-sensitive |
| *Advertising response across segments and media* | • Effective, while smaller elasticity compared to price<br>• TV advertising more effective than either radio or print | • *More effective* than price for medium- and heavy-users<br>• Medium-users are most responsive to Internet advertising<br>• Heavy-users are most responsive to TV advertising<br>• For all segments, TV advertising more effective than radio or print |

## Conclusion

The rise of the Internet and broadband access such as DSL has revolutionized the way digital media are marketed and sold. While forgoing the actual physical product (and consequently certain features of the physical product, such as liner notes), consumers are now able to purchase media at any given time and consume it immediately. With music, consumers have gained the additional benefit of "unbundled" songs, as it is now possible to buy individual songs without the need to buy the rest of the album. These dramatic changes in the actual product as well as in the way the products are marketed and sold, combined with the sheer size of the online entertainment industry, raise many questions that have not been addressed in marketing research as of yet.

In this paper we investigate the short- and long-run effectiveness of the marketing mix across segments that substantially differ in size, profile and marketing response. Based on our analysis of hundreds of thousands of consumers of a major European music download provider, we find that standard segmentation approaches fail to identify the most valuable catches in a sea of consumers. In contrast to empirical generalizations on consumer packaged goods, heavy users of digital music products are least sensitive to price and most sensitive to TV advertising and to multiple touch points. Light users, the vast majority of digital music consumers, are price sensitive and tend to opt out of targeted communication. Our methodology accounts for data at different levels: the market and the individual consumer. Firms still use traditional marketing instruments such as offline advertising and the data on these marketing actions are available in the typical aggregated form well known from many other industries. However, data on purchases and some other marketing instruments, e.g., coupons, is available on a customer-level. We propose a two-stage model to accommodate these different levels of aggregation and show how simply aggregating over customers leads to aggregation bias in estimating response to marketing actions.

Our substantive findings have several implications for managers and business instructors alike. In most classrooms, the effectiveness of the marketing mix is demonstrated based on findings from the CPG domain, and, as we find, some of these findings do not translate well to the digital music domain. First, our segmentation reveals interesting differences among segments of substantially different profiles and sizes, differences that would not have come to light had we used a quantile segmentation approach as is often employed when studying CPGs. Second, patterns with respect to long-term marketing effectiveness show a quite different behavior compared with empirical generalizations based on CPGs. Thus, we believe that some of the common wisdom in marketing (from CPGs) may not apply to hedonic products on the Internet, such as digital entertainment products. In particular, we find that light users are most price sensitive, while heavy users are most advertising sensitive. Contrary to many findings on coupons, heavy users in our industry do not exhibit high coupon usage. We find that heavy users are a very small segment of the market, and that they respond most to advertising actions, while the much larger group of occasional customers is swayed by price incentives. This means that price elasticities are not necessarily bigger than advertising elasticities: especially for the most valuable customers. This is quite a novel finding and shows significant potential for more detailed studies of products such as music downloads. Lastly, segmentation is important as consumer heterogeneity is more pronounced in the long tail of the preference distribution, as confirmed by the very small segment of heavy users. Our findings enable managers to better segment the market, inform their targeting decisions and allow them to develop specific marketing plans for chosen segments. The plans they develop should make full use of the synergy between online and offline marketing actions, as we find substantial interaction effects.

As for theory implications, our findings add substantially to the three research streams of Customer Relationship Management, long-term marketing mix effectiveness and online commerce. First, we show how segmentation can be used to bring together CRM methods and investigation of long-term marketing effectiveness. We do so by proposing to combine the best practices on segmentation and long-run response modeling in a framework that is easy to implement and harnesses the power of the methods normally not employed together. Second, we add substantially to the knowledge on long-term marketing mix effectiveness in terms of novel digital products purchased (and potentially consumed) online. We find that many of the "staples" of marketing mix effectiveness findings do not hold for these novel products. Long-established (and taught) principles such as price response by segments, e.g., heavy users are most price-sensitive, do not translate well into the digital product space we investigate. Third, we extend the research on (digital) music by going beyond bundling (e.g. Elberse 2010) and radio play effects (Moe and Fader 2001). To the best of our knowledge, this paper is the first in quantifying the short-term and long-term effects of price (coupons), marketing communication and its interactions for digital media products. Thus, our findings refine the understanding of online consumer behavior and enable firms to target the right segments with marketing mix levers to which digital media consumers are most responsive.

Limitations of the current study include the absence of data on competitors' marketing actions, which are typically not available in (offline or online) database marketing applications. Likewise, we do not have data on potentially important sales drivers such as web page content changes and advertising content. Moreover, we only study one retailer in a specific time period and geographic location. Furthermore, developing a simultaneous model and alleviating the need for subsampling are worthwhile endeavors for future research. We note that we did not focus on finding the "best" model but on proposing a managerially useful model leveraging the rich data and providing actionable insights. Lastly, further research is needed to determine whether our findings generalize to other settings. Because we focused on quantifying marketing effectiveness, the motivations behind consumers' observed behavior remain an important area for future research.

Our paper is a step toward fully understanding the opportunities the Internet offers to marketers in a digital world. So far the Internet has most often been conceptualized as either a new advertising medium or a new distribution channel. The former has often generated research focused on the effectiveness of online advertising (be it banner or search engine advertising) alone without taking into account interaction with other marketing mix activities of the firm. Digital media combine the advertising and distribution channel functions of the Internet, allowing for immediate consumption with nearly perfect availability of even the most obscure, "long-tail" media products, and for sampling a wide variety of music (at home or a similarly convenient location) before purchase. It also allows for impulse purchasing. For example, one can buy a song from a commercial just seen on TV, recommended by a friend on a social network site such as Facebook, or mentioned in a music blog. Traditionally, one would need the record store to be open, would need to get there and hope that the song in question would be available — and then would have to hope to enjoy the other songs that would come bundled on the CD with the desired song.

These differences make the Internet more than a mere channel, and future research is needed to understand the changes in purchasing behavior that come from the combination of the Internet with digital media products. Our findings already highlight some of the differences; they stand in stark contrast to accepted "marketing lore" regarding marketing mix instruments.

## Appendix A

We assign the remaining customers (i.e., the customers not in the estimation sample) to segments by using the following procedure:

Step 1 Based on the estimated segment-level parameters from the latent-class choice model with $K$ segments, $\{\beta_1, \ldots, \beta_K\}$, we calculate the utility for purchase occasion $t$ and customer $i$ across all segments $k = 1, \ldots, K$ as $u_{it}^k = \beta_{ok} + x_t'\beta_k$.

Step 2 For segments $k = 1, \ldots, K$ we calculate for purchase occasion $t$ and customer $i$ the purchase probability $P_{it}^k = \exp(u_{it}^k)/(1 + \exp(u_{it}^k))$ and corresponding individual-level segment log likelihood $LL0_i^k = \sum\left(\log\left(P_{it}^k\right)I(y_{it}) + \log\left(1-P_{it}^k\right)\left(1-I(y_{it})\right)\right)$, where $I(y_{it})$ is an indicator function that is 1 if customer $i$ purchased at time $t$ and zero otherwise.

Step 3 For each customer $i$ we calculate $K$ posterior segment probabilities as $\Pr(i,k) = \pi_k \exp\left(LL0_i^k\right) / \left(\sum_{s=1}^{K} \pi_s \exp\left(LL0_i^s\right)\right)$, where $\pi_k$ are the segment sizes and $\sum_{k=1}^{K} \pi_k = 1$. We assign customers to the segment with the highest probability.

## References


Babin, Barry J., William R. Darden, and Mitch Griffin (1994), "Work and/or Fun: Measuring Hedonic and Utilitarian Shopping Value," *Journal of Consumer Research*, 20, 4, 644–56.

Bodapati, Anand (2008), "Recommendation Systems With Purchase Data," *Journal of Marketing Research*, 45, 1, 77–93.

Brynjolfsson, Erik and Michael D. Smith (2000), "Frictionless Commerce? A Comparison of Internet and Conventional Retailers," *Management Science*, 46, 4, 563–85.

Choudhury, Vivek and Elena Karahanna (2008), "The Relative Advantage of Electronic Channels: A Multidimensional View," *MIS Quarterly*, 32, 1, 179–200.

Dekimpe, Marnik G. and Dominique M. Hanssens (1999), "Sustained Spending and Persistent Response: A New Look at Long-term Marketing Profitability," *Journal of Marketing Research*, 36, 4, 397–412.

Diehl, Kristin, Laura J. Kornish, and John G. Lynch (2003), "Smart Agents: When Lower Search Costs for Quality Information Increase Price Sensitivity," *Journal of Consumer Research*, 30, 1, 56–71.

Dufft, Nicole, Andreas Stiehler, Danny Vogeley, and Thorsten Wichmann (2005), "Digital Music and DRM, Results from a European Consumer Survey," *INDICARE*, May 2005.

Edell, Julie A. and Kevin Lane Keller (1989), "The Information Processing of Coordinated Media Campaigns," *Journal of Marketing Research*, 26, 2, 149–63.

Elberse, Anita and Felix Oberholzer-Gee (2007), "Superstars and Underdogs: An Examination of the Long Tail Phenomenon in Video Sales," *MSI Reports: Working Paper Series,* 4, 49–72.

——— (2010), "Bye Bye Bundles: The Unbundling of Music in Digital Channels," *Journal of Marketing*, 74, 3, 107–23.

Enders, Walter (2010), Applied Econometric Time Series. New York, N.Y.: John Wiley

Fader, Peter S., Bruce G.S. Hardie, and Ka Lok Lee (2005), "Counting Your Customers the Easy Way: An Alternative to the Pareto/NBD Model," *Marketing Science*, 24, 2, 275–84.

——— and ——— (2009), "Probability Models for Customer-base Analysis," *Journal of Interactive Marketing*, 23, 1, 61–9.

Fallows, Deborah (2004), "The Internet and Daily Live," *PEW Internet & American Life Project.*

Fan, Ming, Subodha Kumar, and Andrew B. Whinston (2007), "Selling or Advertising: Strategies for Providing Digital Media Online," *Journal of Management Information Systems*, 24, 3, 143–66.

Franses, Philip-Hans (2005), "On the use of econometric models for policy simulation in marketing," *Journal of Marketing Research*, 42, 1, 1–14.

Ghose, Anindya and Sha Yang (2009), "An Empirical Analysis of Search Engine Advertising: Sponsored Search in Electronic Markets," *Management Science*, 55, 10, 1605–22.

Gollijan, R. (2013), "iTunes Turns 10: How Apple Music Store killed the Music Industry," http://www.nbcnews.com/technology/technolog/itunes-turns-10-how-apple-music-store-killed-old-music-6C9633923.

Google (2011), "Winning the Zero Moment of Truth," http://www.zeromomentoftruth.com/.

Granger, C.W.J. (1969), "Investigating Causal Relations by Error-correction Models and Cross-spectral Methods," *Econometrica*, 37, 3, 424–38.

Hanssens, Dominique M. (2009), "Advertising Impact Generalizations in a Marketing Mix Context," *Journal of Advertising Research*, 49, 2, 127–9.

Holbrook, Morris B. and Elizabeth C. Hirschman (1982), "The Experiential Aspects of Consumption: Consumers' Fantasies, Feelings and Fun," *Journal of Marketing*, 9, 2, 132–40.

Jagpal, Harsharanjeet S. (1981), "Measuring Joint Advertising Effects in Multiproduct Firms," *Journal of Advertising Research*, 21, 1, 65–9.

Jamhouri, Oscar and Marek L. Winiarz (2009), "The Enduring Influence of TV Advertising and Communications Clout Patterns in the Global Marketplace," *Journal of Advertising Research*, 49, 2, 227–35.

Johansen, Soren, Rocco Mosconi, and Bent Nielsen (2000), "Cointegration Analysis in the Presence of Structural Breaks in the Deterministic Trend," *Econometrics Journal*, 3, 2, 1–34.

Kamakura, Wagner A. and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, 26, 4, 379–90.

Kim, W. Chan and Renee Mauborgne (2005), *Blue Ocean Strategy: How to Create Uncontested Market Space and Make Competition Irrelevant.* Harvard Business Press.

Lacher, Kathleen T. (1989), "Hedonic Consumption: Music as a Product," *Advances in Consumer Research*, 16, 367–73.

Lim, Jooseop, Imran S. Currim, and Rick L. Andrews (2005), "Consumer Heterogeneity in the Longer-term Effects of Price Promotions," *International Journal of Research in Marketing*, 22, 4, 441–57.

Lütkepohl, H. (1993), *Introduction to Multiple Time Series Analysis.* NY: Springer-Verlag.

Manchanda, Puneet, Jean-Pierre Dubé, Khim Yong Goh, and Pradeep K. Chintagunta (2006), "The Effects of Banner Advertising on Internet Purchasing," *Journal of Marketing Research*, 43, 1, 98–108.

McKinsey (2009), "The Consumer Decision Process," http://www.mckinseyquarterly.com/The_consumer_decision_journey_2373.

Moe, Wendy W. and Peter S. Fader (2001), "Modeling Hedonic Portfolio Products: A Joint Segmentation Analysis of Music Compact Disc Sales," *Journal of Marketing Research*, 38, 3, 376–85.

Musalem, Andrés, Eric T. Bradlow, and Jagmohan S. Raju (2009), "Bayesian Estimation of Random-coefficients Choice Models Using Aggregate Data," *Journal of Applied Econometrics*, 24, 3, 490–516.

Naik, Prasad A. and Kalyan Raman (2003), "A Hierarchical Marketing Communications Model of Online and Offline Media Synergies," *Journal of Interactive Marketing*, 23, 4, 288–99.

——— and Kay Peters (2009), "Understanding the Impact of Synergy in Multimedia Communications," *Journal of Marketing Research*, 34, 2, 248–61.

Neslin, Scott A., Caroline Henderson, and John Quelch (1985), "Consumer Promotions and the Acceleration of Product Purchases," *Marketing Science*, 4, 2, 147–65.

———, Sunil Gupta, Wagner Kamakura, Juxiang Lu, and Charlotte H. Mason (2006), "Defection Detection: Measuring and Understanding the Predictive Accuracy of Customer Churn Models," *Journal of Marketing Research*, 43, 2, 204–11.

NielsenWire (2010), http://blog.nielsen.com/nielsenwire/online_mobile/nielsen-and-abcs-innovative-ipad-app-connects-new-generation-of-viewers/.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, and Dominique M. Hanssens (2001), "The Category–Demand Effects of Price Promotions," *Marketing Science*, 20, 1, 1–22.

Pauwels, Koen H., Dominique M. Hanssens, and Sivaramakrishnan Siddarth (2002), "The Long-term Effect of Price Promotions on Category Incidence, Brand Choice and Purchase Quality," *Journal of Marketing Research*, 39, 4, 421–39.

——— (2004), "How Dynamic Consumer Response, Competitor Response, Company Support and Company Inertia Shape Long-term Marketing Effectiveness," *Marketing Science*, 23, 4, 596–610.

——— (2007), "How Retailer and Competitor Decisions Drive the Long-term Effectiveness of Manufacturer Promotions for Fast-moving Consumer Goods," *Journal of Retailing*, 83, 3, 297–308.

———, Peter Leeflang, Marije Teerling, and Eelko Huizingh (2011), "Does Online Information Drive Offline Revenues? Only for Specific Products and Consumer Segments," *Journal of Retailing*, 87, 1, 1–17.

Ratchford, Brian T., Myung-Soo Lee, and Debabrata Talukdar (2003), "The Impact of the Internet on Information Search for Automobiles," *Journal of Marketing Research*, 40, 2, 193–209.

Reichheld, Frederick and Earl Sasser (1990), "Zero Defects: Quality Comes to Services," *Harvard Business Review*, 05–111 (Sept–Oct).

Reinartz, Werner J. and V. Kumar (2000), "On the Profitability of Long-life Customers in a Noncontractual Setting: An Empirical Investigation and Implications for Marketing," *Journal of Marketing*, 64, 4, 17–35.

Rubinson, Joel (2009), "Empirical Evidence of TV Advertising Effectiveness," *Journal of Advertising Research*, 49, 2, 220–6.

Sharp, Byron, Virginia Beal, and Martin Collins (2009), "Television: Back to the Future," *Journal of Advertising Research*, 49, 2, 211–9.

——— and Yoram (Jerry) Wind (2009), "Today's Advertising Laws: Will They Survive the Digital Revolution?" *Journal of Advertising Research*, 49, 2, 120–6.

Simester, Duncan, Peng Sun, and John Tsitsiklis (2006), "Dynamic Catalog Mailing Policies," *Management Science*, 52, 5, 683–96.

Srinivasan, Shuba, Koen Pauwels, Dominique M. Hanssens, and Marnik Dekimpe (2004), "Do Promotions Benefit Retailers, Manufacturers, or Both?" *Management Science*, 50, 5, 617–29.

Steenkamp, Jan-Benedict E.M., Vincent R. Nijs, Dominique M. Hanssens, and Marnik G. Dekimpe (2005), "Competitive Reactions to Advertising and Promotion Attacks," *Marketing Science*, 24, 1, 35–54.

Tellis, Gerard J. (2009), "Generalizations About Advertising Effectiveness in Markets," *Journal of Advertising Research*, 49, 2, 240–5.

Trusov, Michael, Randolph E. Bucklin, and Koen H. Pauwels (2009), "Effects of Word of Mouth versus Traditional Marketing: Findings for an Internet Social Networking Site," *Journal of Marketing*, 73, 5, 90–102.

Wiesel, Thorsten, Koen H. Pauwels, and Joep Arts (2011), "Practice-prize Paper: Marketing's Profit Impact: Quantifying Online and Offline Funnel Progression," *Marketing Science*, 30, 4, 604–11.

Zhang, Jie and Michel Wedel (2009), "The Effectiveness of Customized Promotions in Online and Offline Stores," *Journal of Marketing Research*, 46, 2, 190–206.

Zivot, Eric and Donald W.K. Andrews (1992), "Further Evidence on the Great Crash, the Oil-price Shock, and the Unit-root Hypothesis," *Journal of Business and Economic Statistics*, 10, 3, 251–70.