Information Technology and Online Content Distribution: Empirical Investigations and Implications for the Marketing of Entertainment Products

Cumulative Dissertation

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Submitted by

Dipl.-Kfm. Nils Wlömert
Poststraße 11
27383 Scheeßel
nils.wloemert@gmx.net

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Approved by:

Prof. Dr. Michel Clement (advisor & first referee)
Faculty of Business, University of Hamburg

Prof. Dr. Karen Gedenk (second referee)
Faculty of Business, University of Hamburg

Prof. Dr. Armin Rott (third referee)
Department of Economics, University of Hamburg

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I. Synopsis

Information Technology and Online Content Distribution: Empirical Investigations and Implications for the Marketing of Entertainment Products

by Nils Wlömert

Introduction

Information technology has brought substantial and enduring changes to many markets, notably to those markets in which products are exchanged digitally. Media industries are particularly affected by the ongoing digital transformation process because their business models are based on managing products that are well-suited for digitalization, such as music, books and films. In these industries, digitalization radically transformed virtually all stages of the value creation process, i.e., the ways in which the content is created, produced, marketed, distributed, and consumed. With the rise of new digital platforms, devices and applications, consumers are provided ever-increasing possibilities for enjoying content, while media companies are increasingly confronted with shifting competitive conditions, forcing them to adapt.

The transition toward a digital content economy provides opportunities and challenges for media companies at the same time. On the one hand, the near-zero marginal costs for reproducing digital goods in conjunction with a large decrease in the costs associated with content distribution have made (legitimate) online channels (e.g., streaming services like Spotify and Netflix) an attractive addition to the relatively costly production and distribution of physical media products (e.g., music CDs and movie DVDs) (Bakos and Brynjolfsson 1999; 2000; Shapiro and Varian 1999). On the other hand, adding new online channels to the distribution mix entails several risks for media companies, most importantly, the risk of the cannibalization of other distribution channels (Gentzkow 2007). This situation deteriorates through digitalization because the characteristics of digital products facilitate the illegal exchange of content among consumers at a global scale on the Internet (e.g., via file-sharing networks and file-hosting services) so that firms operating with digital products in online markets not only compete against each other but also with (illegitimate) piracy channels through which unauthorized copies of their products are available free of charge (Bhattacharjee et al. 2007; Danaher et al. 2010; Liebowitz 2008; Oberholzer-Gee and Strumpf 2007).

The consequences of the digital transformation process are clearly visible in virtually all media industries. One prominent example is the music industry, in which the rise of digital distribution channels has been paralleled by a sharp decline in physical album sales, and as a result, global revenues from recorded music have declined by almost 50% over the past 15 years (IFPI 2013). Efficient compression techniques (e.g., MP3), the early availability of compatible media players and hardware (e.g., Apple's iTunes and iPod), as well as the easy transmission of music files over the Internet due to small file sizes are among the factors that have led consumers to embrace online channels relatively early in the digitalization process as a means of music consumption compared with other entertainment products, such as movies or books (IFPI 2012). The decline in sales is evidence of the disruptive influence of new technologies on the music market, particularly the detrimental effect of Internet piracy (Danaher, Smith, and Telang 2013). Music-sharing networks, which have emerged since the late 1990s, enabled consumers to take on crucial functions in the value creation process that have traditionally been controlled by industry players (e.g., reproduction and distribution). In addition, with the introduction of legitimate online stores (e.g., iTunes), new intermediaries whose core business is typically outside the music industry (e.g., selling hardware in the case of Apple) have entered the market. As a consequence, the content that has generated premium prices in the past is more and more commoditized in an increasingly digitized world.

Media companies therefore face the challenge of developing consumer-oriented marketing strategies and legitimate content offers in order to strengthen their position in the value chain and to regain control over music distribution. One important challenge that media companies face is the issue of Internet piracy. (To what extent) do illegal piracy channels cannibalize legitimate demand? What are the motives underlying pirating behavior, and how should companies address pirates? Should providers of paid content offers adjust their prices in order to compete with free offers? These are some of the most important questions that marketers in the music industry face. The latest phase of the upheaval in the music industry saw the introduction of (free) streaming services in an attempt to address the legitimate demand for online music and to tackle the problem of music piracy. Content owners, however, are confronted with various uncertainties in this respect. How should digital music services be configured in order to provide attractive alternatives to piracy channels? What is the market potential of streaming services? How do new music services impact the demand through existing distribution channels? The next section discusses how the present dissertation contributes to answering these questions.

Objectives and overview of dissertation projects

The overarching objective of the present cumulative dissertation is to investigate the different ways in which recent advances in information technology and the transition to online channels for content distribution affect the marketing of entertainment products. By systematically analyzing the demand-side factors that influence the consumption of media content in six empirical research projects, implications regarding the value creation potential and the challenges arising from the transition to a digital marketplace for entertainment media industries are derived. This dissertation focuses on the music industry. However, because the effects of digitization on the music industry are typically visible earlier compared to other entertainment industries, the implications are also relevant for adjacent entertainment industries, such as the movie or book industry, in which similar developments are likely to occur with a certain delay (Elberse 2010; IFPI 2012; Smith and Telang 2010).

Table 1 provides an overview of the dissertation projects. As can be seen, the cumulative dissertation is based on a wide range of methods and makes empirical as well as methodological contributions to the literature. Furthermore, the analyses are conducted at different levels of analysis, i.e., at the consumer level (projects 1, 3, 4 and 5), the market level (project 2), and the product level (project 6). With respect to the substantive focus, each research project addresses specific aspects of the overarching research objective. Projects 1 and 2 focus on the issue of Internet piracy and how it should be addressed at the individual level (project 1) and at the country level (project 2). Projects 3 and 4 are concerned with the questions about how legal music services should be configured in order to provide attractive alternatives to piracy channels and how free advertising-based streaming services impact the demand through existing distribution channels and illegitimate piracy channels. The studies build upon and complement each other by analyzing cross-sectional survey data from a time when most consumers had no experience with free advertising-based streaming services (project 3), as well as longitudinal survey data from a time when the streaming market had gained momentum in our target market (project 4). Project 5 is concerned with the prediction of the market potential of on-demand music streaming services and compares different methods regarding their predictive accuracy. Lastly, project 6 analyzes the implications of the new competitive environment for the pricing of digital content offers.

In sum, the present cumulative dissertation presents the results from six strongly intertwined research projects, each providing in-depth empirical analyses of specific aspects related to the ongoing digital transformation process in the media industry. Taken together, the findings provide strategic implications regarding the opportunities and challenges that entertainment media companies face as a result of the emergence of online channels for content distribution. The substantive focus and the key findings of each research project as well as how the projects relate to each other will be discussed next in more detail.

Table 1: Overview of dissertation projects

Project	Authors	Status	Research objective	Sample	Methods	Key findings
1	Wlömert, Fox, and Clement (2013)	Working paper, submitted to *Information Systems Research* (under review, first round)	Ascertain the relationship between piracy and purchase intentions; investigate the determinants of consumer music piracy and purchase intentions; control for socially desirable responding and endogeneity bias	N1 = 1,601, N2 = 3,246, and N3 = 1,652 music consumers	Multivariate item randomized response theory model; Bayesian inference; simulation study	Piracy negatively influences purchases; socially desirable responding and endogeneity bias systematically affect results; in addition to legal and economic measures, the industry should employ moral arguments to leverage its antipiracy efforts
2	Wlömert (2014)	Working Paper, destined for submission to *Management Information Systems Quarterly*	Investigate how country characteristics moderate the effect of Internet piracy on music sales	Music sales and various control variables for N = 38 countries and T = 15 years (1996-2010)	Fixed-effects panel data model; endogeneity correction using copulas; moderator analysis	Piracy negatively influences sales; cannibalization effect is weaker in countries with sound economic policies and stronger in highly globalized and urbanized countries
3	Papies, Eggers, and Wlömert (2011)	Published in *Journal of the Academy of Marketing Science*	Investigate how free ad-funded business models affect consumer choice in the digital music market	N = 2,540 music consumers	Latent-class choice-based conjoint analysis	Ad-funded offers may expand the music market but cannot (yet) threaten the dominance of the download model; prices of subscription services are unattractive to most consumers
4	Wlömert and Papies (2014)	Working Paper, destined for submission to the *International Journal of Research in Marketing*	Investigate how the adoption and usage of a free music-streaming service affects the purchasing and illegal downloading behavior of music consumers	Music purchases and various control variables for N = 2,756 music consumers and T = 9 observations over a period of 13 months	Difference-in-difference estimator	Consumers cut their music expenditures by 10% after adopting a free streaming service; higher cannibalization rates for higher usage levels; piracy is reduced for consumers who intensively use the service
5	Wlömert and Eggers (2013)	Submitted to *Marketing Letters* (revise and resubmit, first round)	Predict the market potential of streaming services; compare the external predictive validity of the standard (hypothetical, single stage) conjoint approach with incentive-aligned and dual response choice designs	Stated preferences of N = 2,679 music consumers; observed adoption behavior of N = 1,827 music consumers	(1) Choice-based conjoint (CBC), (2) incentive-aligned (IA) - CBC, (3) dual response (DR) - CBC, (4) incentive-aligned dual-response (IA-DR) - CBC	Predicted adoption rates vary between 12% (IA-DR-CBC) and 28% (CBC), the IA-CBC and DR-CBC procedures increase the predictive accuracy to a similar extent; the overall best results are generated by the IA-DR-CBC procedure
6	Papies, Clement, Spann, and Wlömert (2013)	Submitted to *International Journal of Research in Marketing* (reject and resubmit, first round)	Compute price elasticities for music album downloads	N1 = 190 albums, T1 = 52 weeks, S1 = 1 store; N2 = 100 albums, T2 = 226 weeks, S2 = 5 stores; N3 = 7 albums, T3 = 9 weeks, S3 = 1 store	Fixed-effects panel data model; non-experimental price variation (studies 1 and 2) and experimental price variation (study 3)	Price elasticities are surprisingly small (between –1.26 and –1.68) despite theoretical evidence (e.g., the availability of pirated copies, low search costs) that suggests that demand should be highly price elastic

Project 1: Wlömert, Nils, Jean-Paul Fox, and Michel Clement (2013): Investigating the Antecedents and Consequences of Consumer Music Piracy and Purchase Intentions: A Multivariate Item Randomized Response Analysis

One important challenge that media companies face in the digital economy is the competition from (illegitimate) piracy channels through which unauthorized copies are available to consumers at no monetary cost. This issue raises many important questions for marketers, particularly whether piracy cannibalizes the legitimate demand for music products and how to most effectively shift consumer preferences away from piracy toward commercial distribution channels. Providing answers to these questions is the goal of this research project. Unfortunately, research on these questions is significantly complicated by two methodological challenges: (1) socially desirable responding (SDR) might bias the results of surveys because piracy is a legally and socially sensitive topic (Kwan, So, and Tam 2010); and (2) endogeneity problems may lead to inaccurate estimates in determining the relationship between piracy and purchases if uncontrolled variables exist that influence both piracy and purchases (Danaher, Smith, and Telang 2013). For example, one might expect music enthusiasts to download more music illegally and also purchase larger numbers of music products, making it seem that there is a positive relationship between piracy and purchases. As a consequence, due to the uncontrolled factor of "interest in music," the results will underestimate the effect of piracy on purchases.

To address these issues, we present and validate a multivariate item randomized response model that controls for SDR and attenuates endogeneity bias through the joint modeling of the piracy and purchase variables. We demonstrate the performance of the proposed method in a simulation study and via three large-scale empirical studies. Building upon extant research and utility theory, a behavioral model of the determinants and consequences of piracy and purchase intentions is proposed and empirically tested on a sample of 3,246 music consumers.

Methodologically, our results demonstrate that SDR may not only lead researchers to underestimate the true extent of piracy, but it may also systematically affect the coefficients in structural models, which may lead to fallacies and misguided managerial decision making. Furthermore, we find that endogeneity problems exert a systematic influence on the effect of piracy on purchase variables, with the (negative) effect reinforced when our proposed model is applied. Empirically, the study findings suggest a cannibalistic relation between piracy and purchases and provide managers with strategic directions on how to address the problem of music piracy. In particular, our findings reveal that while legal measures (e.g., stricter laws) deter piracy and the availability of legitimate alternatives stimulates purchases, the reverse is not true. Thus, we suggest that marketing management should complement its strategies with alternative measures, such as moral arguments, to leverage its antipiracy efforts.

Project 2: Wlömert, Nils (2014): Investigating the Influence of Country Characteristics on the Relationship between Internet Piracy and Music Sales: Evidence from a Longitudinal Cross-Country Study

In project 1, the focus is on the factors that explain the variation in piracy intentions at the consumer level. However, considering that unauthorized copying takes place on a global scale, it is likely that piracy behavior is also influenced by country characteristics, such as policy efforts and cultural backgrounds. The role of such country-level factors is analyzed in research project 2.

Global music sales have declined by almost 50% over the past 15 years, and Internet piracy has been identified as one cause for this decline (Danaher, Smith, and Telang 2013). While a large body of research has analyzed the effect of Internet piracy on the legitimate demand for media products, not much is known about the factors that can explain the large differences that we observe between countries with respect to the sales development since Internet piracy became available. How can we explain the fact that music sales experienced a much steeper decline in some countries than in other countries (IFPI 2013)? Despite the generally recognized relevance of this question, empirical research that is systematically focused on explaining the cross-country variation in the effect of Internet piracy on music sales is scarce.

To address this research gap, I compile a longitudinal dataset at the macro-level, comprising recorded music sales and various control variables from a sample of 38 countries over a period of 15 years (from 1996 to 2010). Based on this dataset, I first investigate the effect of Internet piracy on music sales and estimate that in 2010, the sales decline due to Internet piracy amounted to 36%. Using moderator analyses, I then identify country characteristics that can explain the cross-country differences in displacement rates due to piracy. Specifically, the results demonstrate that the degree of cannibalization is lower in countries with sound economic policies that aim to improve the functioning of the legal system, market access, and regulatory efficiency. Furthermore, I find a country's global connectedness to be a double-edged sword for the music industry because the emergence of a global consumer culture is conducive to the music industry's global brand positioning strategy, while simultaneously leading to stronger cannibalization effects due to piracy. Finally, the results provide evidence of stronger cannibalization effects in countries that exhibit a high degree of openness to change, as well as in highly urbanized countries in which the penetration potential of file-sharing networks is high. From these findings, I derive strategic implications of how managers and policymakers should address the problem of Internet piracy.

The results of both projects 1 and 2 suggest a negative (i.e., cannibalistic) relationship between Internet piracy and the legitimate demand for music content. Against this background, marketers are interested in identifying and implementing viable business models to address the legitimate demand for online music and to tackle the problem of music piracy (Danaher et al. 2010; Schlereth and Skiera 2012; Sinha and Mandel 2008). One business model that is strongly associated with such hopes is the on-demand streaming model, which grants subscription users access to a comprehensive online music library. This business model deviates from the music industry's traditional business model in that it allows customers to temporarily access the music rather than purchasing it (e.g., CDs or downloads). Once the subscription ends, users can no longer access the content. Streaming service providers (e.g., Spotify, Deezer) earn revenue either by charging a monthly flat fee to consumers (e.g., US$ 10) or by offering the service free of charge to consumers and generating revenue through advertising instead. In particular, the consequences of adding a free streaming channel to the music industry's distribution mix are unclear and represent a topic of ongoing debate (e.g., Luckerson 2014). This issue is investigated in research projects 3 and 4.

Project 3: Papies, Dominik, Felix Eggers, and Nils Wlömert (2011): Music for Free? How Free Ad-funded Downloads Affect Consumer Choice

Being free of charge, ad-funded streaming services may attract consumers who would otherwise refrain from commercial downloading, making such offerings a potential instrument for decreasing illegal file-sharing and increasing overall market size, i.e., generating a "lift" in the number of customers. Although there is some precedent for providing content whose production is costly online without charging for it—e.g., magazines and newspapers offer their content online for free (Gentzkow 2007)—this strategy entails several risks (Geyskens, Gielens, and Dekimpe 2002), notably the risk of cannibalization of other distribution channels, i.e., generating a "shift" in demand. Thus, management and researchers are left with two important questions that constitute the motivation for this research project. Are free advertising-based models a viable alternative to competing models that operate on a pay basis? On which combination of business models should the music industry rely to provide attractive alternatives to illegal file-sharing options?

Using a latent class choice-based conjoint approach, we analyze the attractiveness of these business models from the consumer's perspective. Our findings indicate that advertising-based models have the potential to attract consumers who would otherwise refrain from commercial downloading, that they cannot (yet) threaten the dominance of the download model (e.g., iTunes), and that market prices for subscription services are unattractive to most consumers.

Project 4: Wlömert, Nils and Dominik Papies (2014): Friend or Foe? Assessing the Impact of Free Streaming Services on Music Purchases and Piracy

Research project 3 relies on stated preferences measured at a time when most consumers had no experience with free ad-based services. The German on-demand streaming market gained momentum in March 2012, when the largest worldwide on-demand music streaming service provider entered the market. Until then, only a small number of consumers used free streaming services, and revenues from streaming services only accounted for a small fraction of the overall revenues from recorded music in Germany (BVMI 2012). Thus, this market entry is a unique quasi-experimental shock to the market that makes it more likely that consumers adopt a free streaming service. For research project 4, we timed our empirical study around this event in order to analyze the following two central research questions: (1) What is the effect of the adoption of a free streaming service on the purchasing behavior of individuals, and does this effect vary with usage intensity; and (2) what is the effect of free streaming service adoption on illegitimate demand (i.e., piracy)?

One important challenge arises when one seeks to empirically identify the cannibalization effects of streaming services on the consumer level. It is difficult to distinguish a true cannibalization effect from a spurious correlation that may arise if the purchase behavior of adopters is compared to that of non-adopters (Gentzkow 2007). Similar to project 1, one might expect consumers with a strong affinity for music to have a higher probability of both spending money on music *and* adopting a free streaming service, making it appear that there was a positive relationship between streaming and purchasing. Therefore, in this study, we constructed a research design that avoids this problem by relying on longitudinal variation. That is, we obtained access to a large-scale panel of more than 2,000 music consumers in the German market and repeatedly interviewed these music consumers over a period of 13 months regarding their music expenditures as well as their piracy and listening behavior. We then employed a difference-in-difference estimator, which eliminates individual-specific unobserved effects, to estimate the effect of the adoption of a free streaming service on music purchases and piracy. That is, our analysis assesses the changes in consumers' behavior after the adoption compared to the pre-adoption time and relative to those respondents who did not adopt.

Our results show that the adoption of a free streaming service reduces music expenditures by approximately 10% and that this effect increases with the usage intensity of the service. In a similar vein, our results suggest that the adoption of a free streaming service reduces piracy for those consumers who intensively use the service. This dual effect highlights the ambiguous situation of managers in the music industry, i.e., the reduction of piracy for one group of consumers comes at the cost of a significant reduction of music expenditures for other consumers. However, cannibalization effects do not occur for every type of streaming service. While we find that consumers cut their expenditures after the adoption of a paid streaming service, their monthly subscription fees overcompensate for this reduction. Thus, we suggest that marketing managers should focus on business models that directly generate income and meaningfully differentiate the free tier of the service from the premium tier to trigger the conversion to paid subscriptions.

Project 5: Wlömert, Nils and Felix Eggers (2013): Predicting New Service Adoption with Conjoint Analysis: External Validity of Incentive-Aligned and Dual Response Choice Designs

Research projects 3 and 4 are concerned with the consequences of adding a free on-demand streaming channel to the music industry's mix of distribution channels. Most on-demand music streaming services that are available on the market (e.g., Spotify, Deezer) rely on a two-tiered business model in which a baseline version of a service is provided free of charge to consumers and income is generated through advertising (i.e., free tier), but money is charged for an advertising-free version of the service with advanced features and functionality (i.e., premium tier). This type of business model, featuring a free version and a paid premium version, is commonly used in the Internet economy (e.g., by services such as Dropbox or Skype) and is referred to as the "Freemium" model (Anderson 2010; Oestreicher-Singer and Zalmanson 2013). For companies that rely on this business model, it is vital to maintain a profitable balance between paying premium subscribers and users of the free service because the former customer segment often subsidizes the latter. Consequently, accurate predictions with respect to the market potential of the different service variants are of crucial importance to service providers. Predicting the market potential of on-demand streaming services in the German market is the goal of this research project.

One popular method to predict market outcomes under different market settings is choice-based conjoint (CBC) analysis (e.g., Louviere and Woodworth 1983). Recently, two extensions of this method have been proposed that aim to increase its predictive accuracy, i.e., incentive-aligned (IA-CBC; Ding 2007) and dual response (DR-CBC; Brazell et al. 2006) choice designs. In this research project, we compare the standard (i.e., hypothetical, single-response) CBC approach with incentive-aligned IA-CBC and DR-CBC choice designs in terms of their external predictive validity and their ability to accurately capture consumers' willingness to pay. In addition, we test a combination of both conjoint procedures, i.e., an incentive-aligned dual response (IA-DR-CBC) procedure.

Our empirical study features a sample of 2,679 music consumers who were randomly assigned to the experimental conditions and participated in a conjoint choice experiment prior to the entry of a new music streaming service into the German market. To judge the methods' predictive accuracy, we contacted the same respondents again five months after the launch and compared the predictions with the actual adoption decisions. The results demonstrate that the predicted adoption rates vary considerably between 12% using the IA-DR-CBC procedure and 28% using traditional CBC analysis. Furthermore, we find that the IA-CBC and DR-CBC procedures increase the predictive accuracy to a similar extent. This result is promising because IA-CBC is not applicable to every research context, so that DR-CBC provides a viable alternative. The overall best results are generated by the IA-DR-CBC procedure, which inherits the conceptual benefits of IA-CBC and DR-CBC choice designs.

The discussion so far has made it clear that the transition to digital distribution channels provides consumers with the opportunity to consume music via different channels at no monetary cost (e.g., via free streaming channels or piracy channels). One important question arising from this discussion is to what extent this new competitive environment affects the sensitivity with which consumers react to changes in the prices that are charged for paid digital content offers. For example, should providers of paid content offers lower their prices in order to compete with free offers? This question is analyzed in the next research project.

Project 6: Papies, Dominik, Michel Clement, Martin Spann, and Nils Wlömert (2013): Price Elasticities for Music Downloads: Experimental and Non-Experimental Findings

Arguably, one of the most important marketing variables that may affect the sales of any product is price (e.g., Bijmolt, van Heerde, and Pieters 2005). Retailers selling digital products online often compete in terms of largely homogenous products (e.g., music, movies, or e-book downloads) in a market that allows consumers to easily identify the cheapest price of a given product within seconds (Brynjolfsson and Smith 2000; Granados, Gupta, and Kauffman 2010). In addition, the ready availability of unauthorized copies through piracy channels represents a unique characteristic of digital products, enabling consumers to obtain the product for free if they are unsatisfied with the price they have to pay for legal offers (Danaher, Smith, and Telang 2013). These factors suggest that consumers should react sensitively to price changes in the digital marketplace (i.e., that the price elasticity should be high).

Although information technologies turned the Internet into a marketplace for digital products more than a decade ago, our knowledge about price elasticities for digital products is surprisingly incomplete. In this research project, we therefore estimate the price elasticities for digital music downloads using three large and unique datasets from the German market, comprising two panel datasets with non-experimental price variation as well as data from a field experiment. Across all three studies, we consistently find that the demand is surprisingly price inelastic, with price elasticities between –1.26 and –1.68. This finding as well as the low cross-price elasticity across stores suggests that consumers rarely compare prices. Rather, content providers (e.g., iTunes) have been successful in creating strong lock-in effects through hardware–software combinations with barely permeable boundaries and high perceived switching costs that tie consumers to a particular trusted store. Furthermore, we do not find evidence that piracy puts strong pressure on the price elasticity because the elasticity is lower here than in many markets in which piracy is not prevalent (e.g., Bijmolt, van Heerde, and Pieters 2005). This finding suggests that higher prices do not drive the existing customers of download stores away toward pirated products. However, it also indicates that it is difficult to attract demand from piracy channels towards legal outlets by reducing the prices of paid digital music services.

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II. Self-declaration

Table 2: Self-declaration

Project	Authors	Title	Conception	Execution	Reporting
1	Wlömert, Fox, and Clement (2013)	Investigating the Antecedents and Consequences of Consumer Music Piracy and Purchase Intentions: A Multivariate Item Randomized Response Analysis	Literature review, identification of the research gap, development of the conceptual framework, the research design and the questionnaire design	Establish contact with cooperation partners, questionnaire programming, data collection, and preparation, participation in the development of the analytical model, data analysis, and interpretation of the results	Participation in the preparation of the first and the revised versions of the manuscript, reporting to cooperation partners
3	Papies, Eggers, and Wlömert (2011)	Music for Free? How Free Ad-funded Downloads Affect Consumer Choice	Participation in the literature review, the identification of the research gap, the development of the conceptual framework, the research design and the questionnaire design	Establish contacts with cooperation partner, questionnaire programming, data collection and preparation, participation in the data analysis and interpretation	Participation in the preparation of all versions of the manuscript, reporting to cooperation partner
4	Wlömert and Papies (2014)	Friend or Foe? Assessing the Impact of Free Streaming Services on Music Purchases and Piracy	Participation in the literature review, the identification of the research gap, the development of the conceptual framework, the research design and the questionnaire design	Establish contacts with cooperation partners, questionnaire programming, data collection and preparation, participation in the data analysis and interpretation	Participation in the preparation of the first version of the manuscript, reporting to cooperation partners
5	Wlömert and Eggers (2013)	Predicting New Service Adoption with Conjoint Analysis: External Validity of Incentive-Aligned and Dual Response Choice Designs	Participation in the literature review, the identification of the research gap, the development of the conceptual framework, the research design and the questionnaire design	Establish contacts with cooperation partners, questionnaire programming, data collection and preparation, participation in the data analysis and interpretation	Participation in the preparation of the first version of the manuscript, reporting to cooperation partners
6	Papies, Clement, Spann, and Wlömert (2013)	Price Elasticities for Music Downloads: Experimental and Non-Experimental Findings	Participation in the development of the research design (study 2)	Establish contact with cooperation partner (study 2), participation in data collection, preparation, analysis and interpretation (study 2)	Participation in the preparation of the revised version of the manuscript, reporting to cooperation partner (study 2)

III. Doctoral seminars and colloquia, practice transfer, scientific conferences, research stays, grants, teaching

Doctoral seminars and colloquia, practice transfer, scientific conferences, research stays, grants, teaching

Doctoral seminars and colloquia

11/2013	Presentation: “Illegal Copying of Media Content – The Influence of Piracy on the Legitimate Demand for Media Products” at the discussion event “Repeat, Remix, Remediate: Modes and Norms of Digital Media Repurposing” of the Research Center for Media and Communication, University of Hamburg
10/2013	Presentation: “Investigating the Antecedents and Consequences of Consumer Music Piracy and Purchase Intentions: A Multivariate Item Randomized Response Analysis” at the research seminar of the School of Communication, Journalism and Marketing, Massey University, Auckland, New Zealand
06/2013	Presentation: “Assessing the Impact of Free Streaming Services on Music Purchases and Piracy” at the doctoral colloquium of the Graduate School of Media and Communication, University of Hamburg
10/2012	PhD course: “Bayesian Item Response Modeling,” Prof. Dr. Cees Glas and Prof. Dr. Jean-Paul Fox, Department of Research Methodology, Measurement, and Data Analysis, University of Twente, Enschede, Netherlands
07/2012	Presentation: “How Accurate are Self-Stated Piracy Measures? An Investigation into the Antecedents and Consequences of Digital Music Piracy Using Item Randomized Response Theory” at the doctoral colloquium of the Graduate School of Media and Communication, University of Hamburg
07/2011	Presentation: “A Global Investigation into the Causes and Consequences of International Digital Music Piracy” at the doctoral seminar “Quantitative Marketing,” Prof. Dr. Henrik Sattler, University of Hamburg
05/2011	Presentation: “A Global Investigation into the Causes and Consequences of International Digital Music Piracy” at the doctoral colloquium of the Graduate School of Media and Communication, University of Hamburg
01/2011	PhD course: “Marketing Models,” Prof. Dr. Karen Gedenk, University of Hamburg; Presentation: “The No-Choice Option in Choice-based Conjoint Analysis”

12/2010 PhD course: "Research Methods," Graduate School of Media and Communication, University of Hamburg

10/2010 PhD course: "Research Theories," Graduate School of Media and Communication, University of Hamburg

Practice transfer

05/2013 Presentation: "Assessing the Impact of Free Streaming Services on Music Purchases and Piracy" at Universal Music Group, Berlin

07/2012 Presentation: "Music Streaming Services – Market Potential and Cannibalization in the German Market" at the IFPI's annual business forecast meeting, Berlin

03/2011 Presentation of the research proposal: "A Global Investigation into the Causes and Consequences of International Digital Music Piracy" at the IFPI's European office, Brussels, Belgium

01/2011 Presentation of the research proposal: "A Global Investigation into the Causes and Consequences of International Digital Music Piracy" at the IFPI's German office, Berlin

Scientific conferences

12/2012 Marketing Camp, University of Cologne

06/2012 Marketing Science Conference and Doctoral Consortium, Boston University, USA

12/2011 Marketing Camp, University of Hamburg

01/2011 Marketing Camp, University of Hamburg

12/2010 SALTY 13. Conference "Quantitative Marketing," University of Mannheim

Research stays

10/2013 Visiting researcher at Massey University, Auckland, New Zealand,
Prof. Dr. Harald van Heerde, School of Communication, Journalism and Marketing

06/2013 – 09/2013	Visiting researcher at the University of Technology, Sydney, Australia, Dr. Christine Eckert, Marketing Discipline Group
04/2013	Visiting researcher at the University of Tuebingen, Prof. Dr. Dominik Papies, School of Business and Economics, Chair of Marketing
01/2012 – 02/2012	Visiting researcher at the University of Twente, Enschede, Netherlands, Prof. Dr. Jean-Paul Fox, Department of Research Methodology, Measurement and Data Analysis

Grants

- 2013: Grant for international research stays at the University of Technology, Sydney, Australia and Massey University, Auckland, New Zealand by the German Academic Exchange Service (granted for 4 months; 6,600 EUR)
- 2013: Grant for international piracy research project by the German ZEIT foundation (granted for 4 months; 4,600 EUR)
- 2010: PhD scholarship by the Hamburg State Excellence Initiative (granted for 31 months; 35,650 EUR)

Teaching

- Supervisor of the undergraduate course: “Media Management” (WS 2011/12)
- Supervisor of the undergraduate course: “Management in China” (SS 2011)
- Bachelor’s and Master’s thesis supervision (including empirical research supervision)

IV. Dissertation projects

1. Investigating the Antecedents and Consequences of Consumer Music Piracy and Purchase Intentions: A Multivariate Item Randomized Response Analysis

Authors:

Nils Wlömert, Jean-Paul Fox, and Michel Clement

Year:

2013

Status:

Submitted to *Information Systems Research* (under review, first round)

Investigating the Antecedents and Consequences of Consumer Music Piracy and Purchase Intentions: A Multivariate Item Randomized Response Analysis

Nils Wlömert

Jean-Paul Fox

Michel Clement

Submitted to

Information Systems Research

(under review, first round)

November 2013

Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

Jean-Paul Fox, Professor of Measurement and Data Analysis, Department of Research Methodology, Measurement, and Data Analysis, University of Twente, Netherlands. E-mail: j.p.fox@utwente.nl, URL: www.Jean-PaulFox.com.

Michel Clement, Professor of Marketing and Media Management, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: michel.clement@uni-hamburg.de, URL: www.imm.uni-hamburg.de

1. Introduction

Since the rise of digital distribution channels in the late 1990s and the subsequent sharp decline in the music industry's worldwide sales, digital piracy has been identified as a major threat to the legitimate demand for media products. Considering that, for example, global revenues from recorded music nearly halved from $27 billion in 2000 to $15 billion in 2010 (IFPI 2013b), it is not surprising that this field of research has received increasing attention from academics, media industry executives and policy decision makers in the recent past. Two of the most important questions raised by this development are (1) what is the motivational structure underlying piracy behavior, and how can it be manipulated to curb piracy; and (2) how does piracy affect the purchasing behavior of individuals?

To answer these questions, researchers frequently rely on survey-data when information on actual piracy and purchase behavior is not available (e.g., Andersen and Frenz 2010; Hennig-Thurau, Henning, and Sattler 2007; Rob and Waldfogel 2006; Rob and Waldfogel 2007; Taylor, Ishida, and Wallace 2009). Notwithstanding the ready availability of survey-data, there are two main methodological challenges, threatening the validity of results in such applications.

First, because piracy is an illegal activity, it can be considered a "dark side variable" (Mick 1996). When asked about their behavior, respondents may not answer truthfully, but rather in a way that they perceive as socially and legally accepted. This form of dishonesty is considered one of the most pervasive sources of common method bias in survey-based research and is referred to as socially desirable responding (SDR) (Mick 1996). Importantly, SDR may not only impact the mean level of a sensitive construct (e.g., the true extent of piracy), but it may also produce spurious relationships between the construct and important predictor and outcome variables, which may lead to fallacies and misguided managerial and policy decision making (Ganster, Hennessey, and Luthans 1983; Podsakoff et al. 2003). The relevance of SDR for survey-based IS research has recently been demonstrated by Kwan, So, and Tam (2010).

Second, a prominent challenge when linking piracy behavior to purchases in cross-sectional analyses arises from unobserved factors that drive both piracy and purchases. For example, one might expect music enthusiasts to download more music illegally and also purchase larger numbers of music products, making it look like there is a positive relationship between piracy and purchases. In this case, the omitted variable pertaining to the interest in music affects both the levels of piracy and purchases. The unobserved heterogeneity with respect to the interest in music is problematic because it induces correlation between the explanatory piracy variable and the structural error term in the regression of purchases on piracy. This regressor-error correlation is well known to produce biased regression coefficients and is commonly referred to as the endogeneity problem (Park and Gupta 2012).[1]

Unfortunately, these challenges present a serious drawback for researchers. As a result, the relationship between piracy and purchases remains a controversial topic and academic research does not provide sound evidence on how to most effectively dissuade consumers from piracy and shift preferences toward commercial distribution channels. Consequently, the aim of this article is twofold: (1) to develop and validate a method that controls for SDR and endogeneity bias in cross-sectional studies of piracy and purchases, and (2) to apply this method to empirically test a behavioral model of the determinants and consequences of engaging in music piracy and purchasing.

To meet these challenges, we build upon a state-of-the-art approach to control for SDR that integrates randomized response (RR) techniques (Fox and Tracy 1986; Lensvelt-Mulders et al. 2005) for data collection with item response theory (IRT) (Lord and Novick 1968) for

[1] In addition, a third interpretation challenge with individual-level data pertains to the choice of sample and the fact that most studies use convenience samples, typically students, to test their models. The use of convenience samples, however, limits the generalizability of the results.

data analysis in Item Randomized Response Theory (IRRT) (De Jong, Pieters, and Fox 2010; De Jong, Pieters, and Stremersch 2012; Fox 2005; Fox and Wyrick 2008). To address the endogeneity problem, we extend this literature in a multivariate way by jointly modeling the latent piracy and purchase variables. Specifically, the endogenous regressor piracy is jointly modeled with the distribution of purchases given piracy, while controlling for within-person correlated errors. The proposed method is shown to correct for endogeneity bias from both measurement error of the explanatory piracy variable and uncontrolled confounding variables.

We demonstrate the performance of the proposed method in a simulation study and via three large-scale controlled empirical studies. Our first study involves an experiment in which we query 1,601 music consumers about their piracy intentions to investigate the influence of SDR on piracy self-reports, the motives for SDR and the functioning of IRRT. In our main study of 3,246 music consumers, we shed light on the determinants and consequences of piracy and purchase intentions. Our behavioral model is rooted in expected utility theory (EUT) and jointly analyzes the individual motives that lead to the formation of piracy and purchase intentions based on the utility and costs associated with piracy. Our model extends previous research as it is, to our knowledge, the first integrative model to simultaneously test the determinants of piracy *and* purchase intentions while accounting for within-subject dependencies. Thus, besides investigating the drivers of music piracy, we also address the hitherto less researched, albeit equally important question, how these factors influence the purchase probability of individuals. Subsequent to the second survey, we conduct a controlled longitudinal panel study in which we collect data on actual music purchases from a sub-sample of 1,652 respondents to test the effect of piracy intentions on purchase behavior.

Our findings contribute to the literature as follows. First, our analyses reveal that self-stated piracy measures are subject to a considerable degree of under-reporting and that IRRT effectively attenuates the influence of SDR. In addition, we show that the coefficients in our structural model are systematically influenced by SDR. Crucially, the diminishing effect of piracy intentions on purchase intentions is only uncovered when the IRRT method is used. Second, we propose and validate an instrument-free, IRT-based approach to mitigate endogeneity bias from unobserved heterogeneity and measurement error in cross-sectional studies. Our results suggest a cannibalistic relation between piracy and purchases and show that unobserved factors exert a systematic influence on the relation between piracy and purchase variables, with the effect reinforced when our proposed model is applied. Third, our results provide managerial guidance on how to address the problem of music piracy. An intriguing finding is revealed by our multivariate analyses: while legal measures (e.g., stricter laws) deter piracy and the availability of legitimate alternatives stimulates purchases, the reverse is not true. Thus, we suggest that marketing management should complement its strategies with alternative measures, such as moral arguments, to leverage its antipiracy efforts.

2. Conceptual framework

Figure 1 displays our conceptual framework. In this section, we will develop and explain our conceptual rationale for the direction of the expected effects based on the theoretical and empirical literature.

With respect to our focal constructs, we define consumer piracy as the illegitimate obtainment or dissemination of unauthorized copies of copyrighted recorded music products (e.g., tracks or albums). We deliberately choose this rather broad definition because it is not limited to a specific format (e.g., digital vs. physical) or channel that might be used to obtain unauthorized music products (e.g., file sharing networks). Rather, this definition reflect recent trends of consumers away from file sharing networks toward other sources to obtain unauthorized copies (e.g., file-hosting services, stream-ripping) (GFK 2012; IFPI 2013a).

Similarly, our conceptualization of consumer music purchases includes various commercial channels (e.g., digital, physical) and business models (e.g., sell-through, streaming) that are available on the market. Our model seeks to examine the antecedents and consequences of music piracy and purchase *intentions*, defined as consumer's decisions and motivations to perform a certain behavior (Sheeran 2002). We focus on intentions based on social psychology theories, which consider intentions to be the key determinant of a person's volitional behaviors as well as a mediator of the influence of central behavioral predictors (e.g., Ajzen 1991). Moreover, there is considerable evidence for a causal relation between behavioral intentions and actual behaviors (Webb and Sheeran 2006).

With respect to the antecedents and consequences, we follow previous work and derive our behavioral model from EUT (e.g., Chellappa and Shivendu 2005; Hennig-Thurau, Henning, and Sattler 2007). Although the underlying theoretical foundation is similar, we refine and extend the existing models in a newly arranged framework of antecedents grouped into three building blocks: costs of piracy, the utility of piracy, and control variables. Applied to our research context, we argue that a rational consumer mentally weighs the costs of committing music piracy against the utility he or she derives from it and decides to pirate a song or an album, chooses a commercial channel, or opts to forgo the opportunity to obtain it, depending on which choice offers the highest expected net utility. Since the influential articles by Becker (1968) and Ehrlich (1981), this utility maximization perspective has been one of the major paradigms in models of individual decision making related to illegitimate activities.

>>> Figure 1 about here <<<

2.1. Antecedents to piracy and purchase intentions

Following the EUT line of argumentation, in which consumers' choice among alternatives is determined by their expected utility, we propose that common factors influence the relative attractiveness of illegal and legal distribution channels and lead to the formation of piracy and purchase intentions.

2.1.1. Costs of piracy. Considering that music files obtained from illegal and legal sources share the same characteristics with regard to quality, choice, and compatibility, one may wonder why consumers would purchase music via commercial channels rather than obtaining it through piracy, which is free. Building upon theoretical arguments provided by Danaher et al. (2010) and previous empirical work (Hennig-Thurau, Henning, and Sattler 2007), we expect that there are non-financial costs to piracy that decrease (increase) the relative attractiveness of illegitimate (legitimate) channels and that exert a negative (positive) impact on piracy (purchase) intentions. These perceived costs comprise, respectively, legal costs (i.e., fear of legal sanctions), moral costs (i.e., moral concerns about piracy), technical costs (i.e., the danger of a personal computer becoming infected with viruses), learning costs (i.e., the perceived difficulty), as well as search costs (i.e., finding music files of acceptable quality).

2.1.2. Utility of piracy. Furthermore, we expect that there are factors that increase (decrease) the relative attractiveness of illegitimate (legitimate) channels and that will positively (negatively) influence piracy (purchase) intentions:

(i) Social utility: It is well understood that individuals' behavior is influenced by their links to relevant others (e.g., Ajzen 1991). Consumers may derive a benefit from interacting with their peers in the same network, where a sense of community and mutuality is present and where they can demonstrate their expertise and receive recognition and status.

(ii) Anti-industry utility*:* The music industry has been subject to fierce criticism because of its hard stance toward piracy. It is possible that some consumers view piracy as a means of revenge and derive utility from this (Hennig-Thurau, Henning, and Sattler 2007).

(iii) Economic utility: Because music files can be obtained free of charge via illegitimate channels, we expect that individuals derive utility from accrued monetary savings compared with purchasing via commercial channels.

(iv) Devaluation utility: Recorded music, once digitized, can be copied instantly with almost no loss at marginal costs. As a result, some consumers may assign lower value to digital music. Further, because digital music has been available for free for over a decade via illegitimate online channels, some consumers may have become accustomed to obtaining music for free, suggesting an inverse relation between piracy and the (collector's) value.

(v) Lack of legitimate alternatives: Although some consumers may generally prefer legitimate alternatives, they may feel compelled to obtain music through illegal channels if legal alternatives are perceived as inferior (e.g., with respect to convenience).

(vi) Price of legitimate alternatives: Similarly, individuals may derive utility from piracy if the prices of legitimate products and services exceed their willingness to pay.

(vii) Sampling utility: Music is an experience good whose true utility is only revealed to the consumer after it has been consumed. However, the degree of uncertainty about the product's quality is reduced after a work has been consumed. It has been argued that the reduced level of uncertainty may lead consumers to update their a priori utility expectation, which may induce "sampling," meaning that consumers buy music they have previously discovered via illegal channels (Chellappa and Shivendu 2005). Consequently, as an exception among the utility variables, we expect this variable to be positively related to both piracy and purchase intentions.

2.1.3. Control variables. Although our primary focus is on cost and utility variables, we control for consumer characteristics with respect to age, gender, income, and taste in music (mainstream versus independent), for which we do not formulate specific expectations.

2.2. Consequences of piracy intentions

In addition to the analysis of the antecedents of piracy and purchase intentions, we investigate the effect of piracy intentions on purchase intentions and purchase behaviors. Regarding the direction of these effects, the theoretical literature offers two opposing views: (1) the single-stage decision model of the EUT posits that a person chooses between buying, pirating, or forgoing the opportunity to obtain an album or a song and that the individual ultimately opts for the alternative with the highest expected net utility. Based on this rationale, the *displacement effect* states that unauthorized copies substitute for legitimate demand, suggesting a negative effect of piracy on sales. Conversely, (2) the *sampling effect* postulates that piracy may stimulate legitimate demand because it reduces uncertainty about the utility of an album or a song. That is, after opting to pirate a song or an album in the first stage of the EUT model, consumers may update their a priori utility expectations in favor of purchasing via legal channels. This two-stage model suggests that there can also be a positive relation between piracy and commercial channels (Chellappa and Shivendu 2005).[2]

Because theory does not make clear predictions about which of these effects is prevalent, we turn to evidence provided by extant empirical studies to derive our expectations. Two recently conducted literature reviews by Danaher, Smith, and Telang (2013) and Oberholzer-Gee and Strumpf (2010) conclude that that the majority of empirical studies provides support for the existence of a negative (i.e., cannibalistic) effect of piracy on purchases. Indeed, in the domain of music content, the majority of studies published in the peer-reviewed academic journals consistently reports at least some evidence for sales displacements as a consequence of piracy (e.g., Bhattacharjee et al. 2007; Liebowitz 2008; Rob and Waldfogel 2006), and only two sets of authors report insignificant results (Andersen and Frenz 2010; Oberholzer-

[2] We acknowledge that apart from sampling, analytical articles have identified further conditions under which piracy is not necessarily harmful to the publisher's profits. For example, piracy may accelerate the diffusion of the legal product version, induce network effects, and/or reduce price competition among higher customer types by serving as a price discrimination device (see Tunca and Wu 2013 for a review of the analytic literature).

Gee and Strumpf 2007). Similarly, in the domain of movie and TV content, only one study that focuses on movies in a later stage of the product life-cycle (i.e., when movies are shown on free TV) does not find evidence for either of the two effects (Smith and Telang 2009), whereas all other studies consistently report evidence for the displacement effect (e.g., Danaher et al. 2010; Hennig-Thurau, Henning, and Sattler 2007; Rob and Waldfogel 2007).[3] It should be noted, however, that, despite the empirical support for the displacement effect, there is still considerable discussion about the existence and magnitude of this effect. This ongoing debate is primarily triggered by the methodological challenges faced by researchers, such as endogeneity and SDR (e.g., Oberholzer-Gee and Strumpf 2010).

With respect to the endogeneity problem, the main challenge in identifying cannibalization effects is to rule out concerns that the estimated effects are confounded by a mere correlation in preferences that is due to an unobserved variable that influences both piracy and purchases. Specifically, we expect that persons with a high interest in music products are more likely to engage in piracy *and* to purchase more music products. As a consequence, due to the uncontrolled factor "interest in music," the results will underestimate the effect of piracy on purchases, i.e., the effect should be more negative than the estimates suggest. For example, the survey-based findings by Andersen and Frenz (2010) of an insignificant effect of piracy on purchases have been contested because the authors fail to adequately control for unobserved correlations in consumer preferences (Barker and Maloney 2012).

With respect to SDR, despite the generally recognized relevance of this issue, no research to date has investigated the influence of inaccurate piracy self-reports on the relationship between piracy and purchase variables. Theoretically, given that piracy is illegal, there is a risk that SDR might act as a "suppressor," which have been shown to mask the true relationships

[3] We note that the reviewed studies differ widely with respect to the method of identification, choice of sample, and type of data that is used. Because an in-depth analysis is beyond the scope of this article, we refer readers to the comprehensive reviews by Danaher, Smith, and Telang (2013) and Oberholzer-Gee and Strumpf (2010).

between variables (Ganster, Hennessey, and Luthans 1983). In our case, if the piracy variable is contaminated by SDR, the SDR component, which has nothing to do with purchasing, may cause the real relation with purchases to remain undetected. Specifically, we expect that the results will underestimate the effect of piracy on purchases because of the systematically decreased variance in the piracy variable that is due to under-reporting.

In summary, the ongoing discussion notwithstanding, the prevalent empirical support for the displacement effect and the absence of empirical evidence for the sampling effect leads us to anticipate a negative relation between piracy intentions and purchases. However, for the reasons outlined above, we expect this negative effect to be stronger when the two challenges of endogeneity and SDR are controlled for. We will elaborate how our model targets at these challenges in the next section.

3. Methods

3.1. Data

To empirically test our research framework, we collected data from an online survey conducted in November 2011 in Germany, one of the four largest market for recorded music worldwide (IFPI 2013b). Respondents were recruited through an online access panel, which is administered by a major worldwide media distributor with the aim of monitoring consumer preferences with respect to the consumption of media content. A comparison between our sample and secondary market research data representing the entire German music buyer population (BVMI 2012) shows a good match, although younger consumers (sample mean: 36 years, German music market mean: 38 years) and female consumers (our sample: 49%, German music market: 41%) were slightly over-represented in our sample. In total, 3,246 usable cases were obtained. The main study was preceded by a pre-study with a random sample of 1,601 panel members in April 2011 with the aim of validating the applicability of IRRT for our research context. Subsequent to the main survey, we conducted a longitudinal field study between January and June 2012 in which we queried the same respondents about their music spending behavior on a monthly level over a period of six consecutive months. To avoid bias, the connection of the longitudinal survey to the previous study was not revealed to the respondents. In total, 1,652 panel members completed all six questionnaires.

3.2. Measurement and experimental design

In accordance with our definition of piracy, we developed a multi-item scale to measure an individual's piracy intention. This scale was designed to capture various aspects of piracy. Based on insights we gained from interviews with industry experts and a review of public press articles we identified 16 behavioral intentions that were consistently mentioned.[4] These items comprise the exchange of music files with distant others over the Internet, downloads from unauthorized Web sites, the use of stream ripping software, online and offline exchange within a social environment, the use of special privacy protection software, and the purchase or sale of unlicensed music products. The composition of the scale aims to reflect the severity of piracy intentions by assuming that respondents endorsing more difficult items (e.g., sharing music files via file-sharing networks) should have a higher probability of endorsing easier items (e.g., sharing music files offline).

For each item, respondents were asked to indicate their intention to make use of the respective channel within the next six months on a five-point rating scale. Survey participants were randomly assigned to one of two experimental groups and were either instructed to follow the RR procedure for increased privacy protection (n = 2,426) or were interviewed using direct questioning (DQ), without the RR procedure (n = 820). This between-subject design enables us to investigate the effect of the RR method. The flow of the randomization proce-

[4] Please refer to Appendix 1 for a full list of questionnaire items, descriptive statistics and the instructions that were used in the questionnaire.

dure is depicted in Figure 2. For the RR group, a virtual animated die was programmed and displayed before every sensitive question in the online questionnaire. After every virtual die roll, a short instruction appeared on the monitor.

>>> Figure 2 about here <<<

We developed a nine-item scale to measure consumers' purchase intentions. The scale aimed to capture the inclination of consumers toward commercial (paid) consumption aggregated over various distribution channels. The items reflect the expected likelihood and frequency of purchases via these channels as well as their expected usage share for the purpose of music consumption over the next six months. In addition, the measure includes self-estimates of planned spending compared to other people, as a share of disposable income, as well as in terms of absolute monetary value.

We measured purchase behaviors subsequent to the main study using a short standardized online questionnaire, which was made available monthly over a period of six months. Every month, participants indicated how much money they had spent on recorded music products so that every monthly observation constitutes an item of our purchase behavior measure.

To measure antecedents, we rely on previously validated scales, where available. Exceptions are the six variables of learning costs, sampling utility, economic utility, anti-industry utility, lack of legitimate alternatives, and price of legitimate alternatives, for which we developed new scales.

3.3. Analytical procedure

3.3.1. Multivariate IRT model. We develop a multivariate IRT model to simultaneously model the expected utility an individual derives from pirating and purchasing recorded music products. For each item k (k = 1, …, K) of the multi-item scale j (1 = piracy intentions, 2 =

purchase intentions), the IRT model relates person i's (i = 1, …, N) probability of endorsing a specific response category c (c = 1, …, C) on a rating scale to an underlying continuously valued unobservable (latent) trait level $\boldsymbol{\theta}_i$ and item parameters (Lord and Novick 1968). Note that in our multivariate context, $\boldsymbol{\theta}_i$ represents the latent scores of person i with the elements θ_{1i} and θ_{2i}, denoting the individual-level piracy and purchase parameters, which are jointly modeled (i.e., θ_{ji}). The utility respondent i derives from a response in category c to item k of scale j can be written as

$$U_{jikc} = a_{jk}\theta_{ji} - \tau_{jkc} + \varepsilon_{jikc}, \tag{1}$$

where α_k denotes the scale- and item-specific discrimination parameter reflecting the strength of the relationship between an item and the latent construct similar to a factor loading, τ_{kc} is the scale-, item- and category-specific "threshold" parameter reflecting the frequency with which items are endorsed, and ε_{jikc} is a random error.[5] We propose that respondent i chooses category c on item k of scale j if this choice provides the highest expected utility compared with all remaining categories for the respective item:

$$Y_{jik} = c \; if \; U_{jikc} > U_{jikv} \; for \; v = 1,\ldots,c-1,c+1,\ldots,C, \tag{2}$$

where Y_{jik} is respondent i's observed category response on item k belonging to scale j. Because we obtain responses to polytomous items that have C = 5 ordered response options, we apply Samejima's (1969) graded response model. In the graded response model, a person's conditional probability of a response in a specific category is modeled by the probability of responding in (or above) this category minus the probability of responding in (or above) the next category. The normal ogive version of the proposed multivariate graded response model has the mathematical representation

[5] Our model represents a generalization of the non-compensatory multidimensional Rasch model for binary randomized response data proposed by Böckenholt and Van der Heijden (2007).

$$\pi_{jikc} = P\left(Y_{jik} = c \,\middle|\, \theta_{ji}, \alpha_{jk}, \tau_{jkc-1,} \tau_{jkc}\right) = \Phi\left(\alpha_{jk}\theta_{ji} - \tau_{jkc-1}\right) - \Phi\left(\alpha_{jk}\theta_{ji} - \tau_{jkc}\right), \tag{3}$$

where π_{jikc} is the probability of respondent i's response in category c on item k of scale j, and $\Phi(.)$ denotes the standard normal cumulative distribution function. The boundaries between the response categories within an item are governed by an ordered vector of thresholds τ with the constraint $\tau_{jkc-1} < \tau_{jkc} < \tau_{jkc+1}$. The thresholds are measured on the same scale as the latent traits θ_{ji} and are often referred to as "difficulty" parameters because they determine the difficulty of responding above a certain category c on item k. Technically, they correspond to the value on the latent scale where the probability of a response above a value c is 0.5 for $c = 1, ..., C - 1$.

Plotting a person's category response probabilities for an item against the θ_{ji} values yields an item's category response functions (CRF). For illustration, the CRFs for items 1 ("Downloading files via BitTorrent") and 10 ("Obtaining files via instant messaging & email") of the piracy scale are depicted in Figure 3 based on the posterior mean item parameter values (α_k, τ_{k1}, τ_{k2}, τ_{k3}, τ_{k4}) = (1.61, 0.13, 0.75, 1.30, 1.85) for Item 1 and (1.02, –0.84, –0.14, 0.74, 1.75) for Item 10 as well as the latent trait $\theta_{1i} \sim N(\mu, \sigma^2)$ with $\mu = -0.88$ and $\sigma^2 = 0.85$.

>>> Figure 3 about here <<<

Piracy is illegal, and survey data are therefore prone to SDR. To address this issue, we apply a RR model to measure piracy intentions (see Figure 2). The basic idea underlying RR methodologies is to provide confidentiality to respondents by randomizing each response before it is observed. Thus, under RR, $\tilde{Y}_{1ik}$ refers to the unobserved "latent" response because it is randomized before observation. According to the known probability distribution of the RR mechanism, a probabilistic relationship can be defined between the observed item randomized response and the latent item response:

$$
\begin{aligned}
P\left(Y_{1ik}=c\,|\,\theta_{1i},a_{1k},\tau_{1kc},\tau_{1kc-1}\right) &= p_1 P\left(\tilde{Y}_{1ik}=c\,|\,\theta_{1i},a_{1k},\tau_{1kc},\tau_{1kc-1}\right)+\left(1-p_1\right)p_{2c} \\
&= p_1\pi_{1ikc}+\left(1-p_1\right)p_{2c}
\end{aligned}, \quad (4)
$$

where p_1 is the probability that the respondent is instructed to provide an honest response and p_{2c} is the probability of a forced response in category c (see Figure 4; De Jong, Pieters, and Fox 2010). It is a salient advantage of IRRT over previous approaches (e.g., Kwan, So, and Tam 2010) that it allows for individual level inferences at the level of the latent construct by relating the intercorrelated randomized item responses. Other important advantages of our model include that it does not assume a linear relationship between the categorical item responses and the continuous construct scores and that not all items are assumed to measure the construct in the same way, which is not realistic. Moreover, it is possible to control for respondents who do not adhere to the procedural instructions. Because we obtain responses to multiple items per person, non-adherence can be dealt with in a natural way by specifying a latent class structure, in which respondents belong to a non-adherence class with a certain probability κ and to an adherence class with probability $1 - \kappa$ (Böckenholt and Van der Heijden 2007; De Jong, Pieters, and Fox 2010). Then, π_{jikc} is modeled according the normal ogive graded response model.

>>> Figure 4 about here <<<

3.3.2. Joint model of piracy intentions and purchase intentions. In the previous section we developed our measurement model. Next, we need to model the latent piracy and purchase intention variables in a multivariate context, in which the latent variables are nested within individuals. This yields the following multivariate normal distribution:

$$
\begin{pmatrix}\theta_{1i}\\ \theta_{2i}\end{pmatrix} \sim MVN\left(\begin{matrix}\mu_{1i}\\ \mu_{2i}\end{matrix}, \begin{pmatrix}\sigma_1^2 & \rho\\ \rho & \sigma_2^2\end{pmatrix}\right), \quad (5)
$$

where ρ denotes the common within-person covariance between the two latent variables. Our theorizing further posits that the behavioral intention scores are predictably related to the characteristics of the respondents. Therefore, we consider the following multivariate normal regression model:

$$\theta_{1i} = \beta_{0,1} + \beta_1 X_i + \delta RR_i + \varepsilon_{1i} \text{ , and} \tag{6}$$

$$\theta_{2i} = \beta_{0,2} + \beta_2 X_i + \varepsilon_{2i} \text{ ,} \tag{7}$$

where X_i is a vector of observed respondent characteristics exerting an influence on piracy and purchase intentions, i.e., the cost and utility variables and control variables, and ε_{1i} and ε_{2i} are error terms, which we allow to be correlated through a bivariate normal structure to account for within-subject dependencies. In addition, to examine the impact of the questioning technique, we simultaneously estimate the IRRT model for the DQ and RR experimental groups and include an indicator variable as a predictor in equation (6) that equals 1 if a respondent is in the RR condition and 0 otherwise. Thus, δ captures the effect of the questioning technique on the individual piracy intention scores.

In a next step, interest is focused on the effect of piracy intentions on purchase intentions, which merits special attention. To investigate this effect, we include the latent piracy intention variable as a predictor of purchase intentions in equation (7), such that

$$\theta_{1i} = \beta_{0,1} + \beta_1 X_i + \delta RR_i + \varepsilon_{1i} \text{ , and} \tag{8}$$

$$\theta_{2i} = \beta_{0,2} + \beta_2 X_i + \gamma\theta_{1i} + \varepsilon_{2i} \text{ ,} \tag{9}$$

where γ now captures the effect of piracy intentions on purchase intentions. One prominent challenge when determining the effect of piracy on purchases is that the explanatory piracy variable is endogenous. Recall that we argued in the previous section that the unobserved factor pertaining to the interest in music may contaminate the estimates because it drives both piracy and purchases. When this confounding variable is not properly controlled for, it is absorbed by the error terms and the predictor θ_{1i} will be correlated with ε_{2i}, thereby inducing an endogeneity problem (Park and Gupta 2012). To see this, we can rewrite equation (9), such that

$$\theta_{2i} = \beta_{0,2} + \beta_2 X_i + \gamma\mu_{1i} + \gamma\varepsilon_{1i} + \varepsilon_{2i}\,, \tag{10}$$

where μ_{1i} denotes the structural mean component associated with the endogenous predictor of piracy intentions, i.e., $\beta_{0,1} + \beta_1 X_i + \delta RR_i$, and ε_{1i} is the corresponding person-specific random component, which is correlated with the structural error ε_{2i} because it captures the unobserved interest in music. As a result, the estimates will be inconsistent.

Furthermore, the piracy intention variable is measured with error, which further contributes to the endogeneity problem because the measurement error of the predictor θ_{1i} is likely be correlated with the structural error term ε_{2i}. For illustration, we can rewrite equation (9), such that

$$\theta_{2i} = \beta_{0,2} + \beta_2 X_i + \gamma(\theta_{2i} - \upsilon_i) + \varepsilon_{2i} = \beta_{0,2} + \beta_2 X_i + \gamma\tilde{\theta}_{2i} + u_i\,, \tag{11}$$

where υ_i is the measurement error and $u_i = \varepsilon_{2i} - \gamma\upsilon_i$. Because u_i and $\tilde{\theta}_{2i}$ depend on υ_i, they are correlated. This further complicates the estimation of the regression effects since the variability in purchase intentions given piracy intentions cannot be assumed to be independently and identically distributed.

Our modeling approach targets at these challenges in two ways. First, we model the error in θ_{1i} using IRT, which is a person-specific measurement error distribution because it is based on the individual response pattern. That is, the measurement error associated with the explanatory piracy variable is explicitly modeled and is not included in the regression error term ε_{2i} in equation (8). By purifying the error terms in equations (8) and (9) from measurement error, we avoid endogeneity bias from measurement error in the estimation of the predictor effects (Fox and Glas 2003).

Second, we address the endogeneity problem from unobserved heterogeneity by explicitly modeling the joint distribution of the errors in θ_{1i} and θ_{2i}. Our methodological approach is related to the analyses of Park and Gupta (2012), who explicitly model the joint distribution of the endogenous regressor and the structural error. In the present framework, ε_{1i} and the structural error ε_{2i} in equations (8) and (9) are jointly modeled. This implies that the errors in the conditional distribution of purchase intentions given piracy intentions are not independently distributed. Instead, they are allowed to correlate with the error in the distribution of piracy. It is straightforward to assume that the corresponding errors are correlated to some degree, because the latent variables are nested within individuals. The introduced correlation term is assumed to capture unobserved correlations in consumer preferences. The modeling of unobserved heterogeneity through the residual correlation means that the strength of the relationship between the purchase variables and piracy intentions can be adjusted in a linear way, such that a positive (negative) correlation stimulates (weakens) the strength.

Note that the proposed model represents an alternative to instrumental variable (IV) estimation, which provides another means to mitigate endogeneity bias if exogenous variables exist, that are (1) correlated with the piracy variable and (2) uncorrelated with the error term (e.g., Rob and Waldfogel 2006). We did not use this approach, because valid IVs are typically difficult to obtain in the present research context.[6] Moreover, even if a theoretically valid IV is available, this approach may lead to erroneous conclusions when the two requirements for valid IVs are not met, and (2) (i.e., the "exclusion restriction") cannot be tested directly because the error is unobserved (Park and Gupta 2012).

3.3.3. Joint model of piracy intentions and purchase behavior. We model purchase behaviors similar to the piracy and purchase intention constructs. However, because the data format of the spending construct is not categorical but continuous (Euro amounts), we specify T_{ik} as the log-transformed spending amount of person i in month k:

$$\log(spend_{ik}) = T_{ik} = \alpha_k \theta_{2i}^B - b_k + \varepsilon_{ik}, \tag{12}$$

[6] For example, instruments related to consumers' Internet skills are vulnerable to concerns that they may proxy not only for piracy but also for other forms of online entertainment and legitimate online music consumption.

where α_k is the month-specific discrimination parameter, θ_{2i}^B is the latent purchase behavior parameter, b_k constitutes a monthly adjustment for underlying trends in purchasing, and $\varepsilon_{ik} \sim N(0, \sigma^2)$. Note that by correcting the time-varying purchase parameter θ_{2i}^B for monthly effects, we obtain the underlying time-invariant measure of purchase behavior. We apply a normal model for T_{ik} with a mean depending on how much money a person spends on music products (θ_{2i}^B) and the monthly correction term (b_k). Following the distribution of our data, we define a mixture model in which respondents either belong to a latent class that did not spend a significant real amount of money on music products within the six-month observation period (i.e., overall spending equal or close to zero) with probability λ or to a second latent class for which the reverse was true with probability 1- λ, such that [7]

$$\log(spend_{ik}) = T_{ik} = \begin{cases} N\left(\alpha_k \theta_{2i}^B - b_k, \sigma_2^2\right) \text{ with probability } 1 - \lambda \\ N\left(0, \sigma_1^2\right) \text{with probability } \lambda \end{cases}.$$

We consider piracy intentions a predictor for the class of purchasers only, since there is not enough variability to be explained in the class of non-purchasers. To investigate if non-purchasers exhibit a higher tendency to engage in piracy, we include the realization of the random variable λ_i (i.e., $\lambda_i = P(G_i = 1)$), as a predictor in the regression equation on piracy, such that

$$\theta_{1i} = \beta_{0,1} + \delta RR_i + \beta_{NP} G_i + \varepsilon_{1i} \text{ , and} \tag{13}$$

$$\theta_{2i}^B = \beta_{0,2} + \gamma \theta_{1i} + \varepsilon_{2i} \text{ ,} \tag{14}$$

[7] We noticed that the purchase observations are potentially zero-inflated and right-truncated because some persons did not spend any money on music products over the observation period. Following the mixture modeling approach, we did not define a mean structure as in equation (12) for the non-purchasers because this would seriously bias the results. Note, however, that the mixture modeling approach treats the observations as random variables. Therefore, zero spending means that there is a high probability that no money was spend on music but the item observations remain indicators for measuring the latent variable of purchase behavior.

where $G_i = 1$ means that person i belongs to the class of non-purchasers, and $G = 0$ otherwise. The modeling of these equations then follows the same procedure as discussed in the previous section.

3.4. Estimation

We use Markov Chain Monte Carlo methods to estimate all model parameters simultaneously (e.g., Gelman et al. 2004) and obtain the posterior distributions of the unknown parameters by successively sampling from their full conditional distribution. We opt for Bayesian inference techniques because they can flexibly handle such complex model structures, and the MCMC method enables the estimation of individual-level parameters while accounting for background differences. For estimation, we rely on the public domain software WinBUGS (Lunn et al. 2000). Within the Bayesian routine, we complete 20,000 iterations and discarded the first half to make sure the process converged.

3.5. Establishing validity

3.5.1. Social desirability. We pre-tested our piracy intention measure in April 2011 using a ten-item subscale on a randomly drawn sample of 1,601 panel members. Participants were randomly assigned to a condition of a two-group experimental design, including a RR condition that followed the randomization procedure (n = 825) and a DQ condition without this mechanism (n = 776).

We argue that in the domain of intellectual property theft, response distortions may arise from two different motivations that are either extrinsic or intrinsic: first, because piracy is illegal, the risk of legal sanctions may provide an extrinsic motivation for dishonest responding. Second, another distorting influence may stem from intrinsic motivations if the behavior under study is personal to respondents. More precisely, respondents may provide dishonest answers to prevent threats to their self-esteem or image and to maintain a positive self-concept both toward themselves and others (Barkan et al. 2012; Mazar, Amir, and Ariely 2008). Barkan and colleagues (2012) recently demonstrated in a series of experiments that the inconsistency between a person's need to maintain a moral self-concept and his or her own past unethical behavior may cause ethical dissonance, which can be resolved by engaging in deliberate impression management (IM), i.e., giving a false, overly positive presentation of one's self. At the same time, although people typically value honesty and attempt to comply with their internal standards for it, they may cheat (e.g., over- or under-report) within a certain range without negatively affecting their self-concept (Mazar, Amir, and Ariely 2008).

To test our expectations, we included a ten-item version of the IM scale of Paulhus's balanced inventory of desirable responding (Paulhus 1991), a three-item scale measuring the perceived social undesirability of piracy, and a two-item scale measuring the perceived legal risk associated with piracy as validation constructs. We estimated the piracy intention and IM latent scores based on the graded IRT model. The unstandardized coefficients are presented in Table 1. Regressing the latent piracy score on the group indicator (RR = 1) in Model 1 reveals that higher piracy scores are obtained in the RR condition ($\delta = 0.575$, $p < 0.05$)[8], as expected. In Model 2, we test whether the posterior IM scores are related to reported piracy intentions while controlling for basic sociodemographic characteristics. If the IM measure is related to piracy intentions, the data are likely to be impacted by deliberate IM. Our results show that reported piracy intentions are indeed significantly lower when respondents are high on the IM scale ($\beta_{IM} = -0.332$, $p < 0.05$). If RR is an appropriate tool to counter the influence of SDR, it should reduce the impact of IM. In support of our expectations, the interaction effect with the question technique indicator reveals that under RR, reported piracy intentions are significantly higher for respondents who are high on the IM scale ($\beta_{RR,\ IM} = 0.162$, $p <$

[8] For better readability, throughout the paper, we interpret a parameter to be significant at the 5% level in frequentist terms (i.e., $p < 0.05$) if 0 is not included in the 95% posterior credible interval.

0.05). Note that under RR, the effect size of the β_{IM}-parameter is reduced to –0.179 (p < 0.05), below the |0.2| cutoff recommended by Steenkamp, De Jong, and Baumgartner (2010).[9]

Similarly, Model 3 shows that the perceived social undesirability construct is negatively related to piracy intentions (β_{SD} = –0.620, p < 0.05) and that under RR, significantly higher scores are obtained for persons who perceive piracy to be a socially undesirable activity ($\beta_{RR, SD}$ = 0.273, p < 0.05). Finally, Model 4 provides evidence that the perceived risk of legal prosecution is negatively related to reported piracy intentions (β_{risk} = –0.287, p < 0.05) and that under RR, higher scores are obtained for persons who perceive piracy to be a legally risky activity ($\beta_{RR, risk}$ = 0.192, p < 0.05).

In summary, the pre-study results demonstrate that respondents under-report their piracy intentions for intrinsic and extrinsic motivations and that IRRT effectively attenuates both types of SDR. We report additional results regarding the wording and randomizing device in Appendix 2.

>>> Table 1 about here <<<

3.5.2. Endogeneity. In this section, we describe a Monte Carlo simulation experiment that is designed to demonstrate the benefits of the joint modeling of the latent piracy and purchase variables while controlling for within-subject correlations. We generate data according to the following model

$$\begin{gathered} \begin{pmatrix} \theta_{1i} \\ \theta_{2i} \end{pmatrix} \sim MVN\left(\begin{bmatrix} \mu_{1i} \\ \mu_{2i} \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \\ \mu_{1i} = \beta_{0,1} + \beta_{1,1} X_i \\ \mu_{2i} = \beta_{0,2} + \beta_{1,2} X_i + \gamma \theta_{1i} \end{gathered}, \tag{15}$$

[9] We calculate the standardized effect size by dividing the unstandardized regression coefficient by the standard deviation of the dependent variable, as suggested by Greenwald, Hedges, and Laine (1996).

which resembles the model specified in equations (8) and (9), excluding the RR component, for 1,000 subjects with the parameter values ($\beta_{0,1}$, $\beta_{0,2}$, $\beta_{1,1}$, $\beta_{1,2}$, γ) = (0, 0, 0.50, 0.30, –0.50), assuming that we know the true values of θ_{1i} and θ_{2i} and assuming a scale variance of one for both components. On a standard scale, we chose moderate effect sizes to avoid scenarios where floor and ceiling effects might interfere with the analysis. We set the intercept values to zero because they are of no interest. The error component of θ_{1i} is person-specific and allowed to be correlated with the structural error in the regression of θ_{2i} on θ_{1i}. Thus, the endogeneity problem is characterized by the correlation between the errors of the distribution of piracy and the conditional distribution of purchases given piracy. Once this correlation is properly controlled for, the model does not suffer from the endogeneity problem, and consistent estimates for the model parameters can be obtained.

In our simulation study, we vary the within-individual correlation (ρ), representing different settings of unobserved heterogeneity in consumer preferences, and investigate the recovery of the true model parameters. As a baseline model, we estimate a naïve model, which assumes independence between the errors (i.e., ρ = 0) (please refer to Appendix 3 for details). A total of 100 data sets are generated as replicates. We compute the mean values of the posterior estimates of the model parameters as well as their corresponding root mean squared error (RMSE) over the 100 runs.

The results are summarized in Table 2. It can be seen that the proposed model outperforms the baseline model in terms of parameter recovery with increasing correlation values. Furthermore, it can be seen that the γ-parameter exhibits the expected downward bias, when the correlation between the two latent constructs is not accounted for. We conclude that the proposed method effectively attenuates endogeneity bias from unobserved heterogeneity.

>>> Table 2 about here <<<

4. Results

In the previous section we presented and validated our methodological approach. In this section, we will discuss the results of our main study (see Figure 1).

4.1. Model fit

To assess model fit, we first examine the posterior estimates of the item parameters presented in Table 3. To ensure that the items are sufficiently linked to (i.e., "load on") the underlying construct they are meant to measure, the discrimination parameters should be significant and have a value of > 0.5 (De Jong, Pieters, and Stremersch 2012). As shown in Table 3, all discriminations of our multivariate measure are well above the cutoff, with an average of 1.31 (1.36) on the piracy (purchase) scale. Further, the 95% confidence interval of the discrimination parameters always excludes zero. Therefore, all items are useful to measure the piracy and purchase intention constructs. Inspection of the thresholds reveals that the items differ significantly with respect to the frequency with which they are endorsed. Consider, for example, the third threshold (τ_{k3}), which reflects the "difficulty" of a response in category $c > 3$ on an item (i.e., an affirmative response). The relative size of the values within the range between 0.056 for the easiest item ("Obtaining files via media storage devices") and 1.852 for the most difficult item ("Selling unlicensed music for a profit") on the piracy intention scale suggest high face validity. In addition, factor analysis on the items confirmed the unidimensionality of the piracy and purchase constructs (details can be found in Appendix 4).

>> Table 3 about here <<

We further assess model fit by means of posterior predictive checks. If the model fits the data, we should be able to predict the actual category responses from the posterior estimates. To test this, we estimate the percentage of respondents in the DQ condition that provided an affirmative response to each piracy item, i.e., $c > 3$, according to equation (3) and compare this to the observed actual percentages. The results are reported in Table 4. It can be seen that the estimated percentages closely match the observed percentages. As a measure of the accuracy of the predictions, we compute the “hit rate,” i.e., the percentage of correct individual level predictions across all 16 items. The results show that 93.3% of all piracy intentions are predicted correctly, which we consider satisfactory.

In the last column of Table 4, we report the predicted shares for respondents in the RR condition. The numbers clearly show that there are large differences between the experimental groups, pointing to a considerable degree of under-reporting. For example, under DQ, 4.6% of the respondents admit their intention to obtain music files via sharehoster or FTP servers, whereas under RR, the predicted share is 7.2%, an increase of approximately 36%. On average, our estimates even show an increase in reported piracy intentions of approximately 48% through the application of the RR technique.

Finally, we compare the percentage of affirmative responses obtained under DQ to external market research data to investigate the external validity of our data. While data on channel-specific usage levels is not available, we could identify two figures for comparison. First, we compare our data to a survey, which revealed that 4% of German Internet users had used peer-to-peer networks in 2011 (Karaganis and Renkema 2013). This percentage is mirrored well by our sample with a share of 3.4% of respondents who indicated their intentions to make use of the respective channels (i.e., Items 1, 2 and/or 3). Second, the observation that 18% of Germans had shared files via storage devices in 2011 reported by the GFK (2012) compares well to our observation that 20% of the respondents intended to do so (i.e., Item 11). We conclude that our dataset exhibits a sufficient degree of external validity.

>>> Table 4 about here <<<

4.2. Investigating the antecedents of piracy and purchase intentions

4.2.1. Main effects. We report the unstandardized regression coefficients resulting from the simultaneous estimation of equations (6) and (7) in Table 5. Model 1 presents the SDR-corrected parameters. The large effect size of the experimental group indicator confirms that the RR-technique effectively protects the privacy of respondents and that in this group substantially higher piracy scores are obtained (δ =0.401, p < 0.05).[10] Of the 16 remaining predictors, 13 have significant impacts on the piracy or purchase intention constructs and show the expected signs, as we will discuss subsequently.

>>> Table 5 about here <<<

With respect to the group of sociodemographic control variables, only age is significantly related to piracy intentions, with younger consumers scoring higher on the piracy intention scale ($\beta_{1,1}$ = –0.008, p < 0.05). Although this result is not unexpected, the finding that piracy is unrelated to gender and income is surprising because it runs counter to the common perceptions that piracy is prevalent among male and low-income consumers. In the purchase intention model, in contrast, all control variables exert a significant influence, drawing a clear sociodemographic profile with the latent scores significantly related to age (young) ($\beta_{1,2}$ = –0.012, p < 0.05), gender (male) ($\beta_{2,2}$ = –0.314, p < 0.05), income (high) ($\beta_{3,2}$ = 0.096, p < 0.05), and music taste (independent) ($\beta_{4,2}$ = 0.142, p < 0.05).

Investigating the coefficients of the cost of piracy variables reveals that the risk of legal prosecution is negatively related to piracy intentions ($\beta_{5,1}$ = –0.075, p < 0.05) but unrelated to purchase intentions. This finding contrasts with previous findings of an insignificant effect of legal risk on piracy behavior in the movie industry (Hennig-Thurau, Henning, and Sattler

[10] Different from the first study, category responses were selected automatically in the main study if a forced answer was instructed to increase the controllability of non-adherence. We took thorough precautions to ensure that pre-selecting the forced responses did no impact the perceived degree of privacy protection. Importantly, a between-subjects comparison revealed no effect of this adjustment on reported piracy intentions.

2007) and informs the ongoing debate about the effectiveness of legal measures in the fight against piracy. Our model predicts that increasing the risk of legal prosecution (e.g., stricter enforcement of anti-piracy laws) will dissuade consumers from using illegal services but is unlikely to convert them to paying customers.[11] Moral considerations, in contrast, are negatively related to piracy intentions ($\beta_{6,1}$ = –0.185, $p < 0.05$) and are positively related to purchase intentions ($\beta_{6,2}$ = 0.231, $p < 0.05$). Our results further show that the search cost of finding music files of acceptable quality via illegitimate channels is positively related to purchase intentions ($\beta_{7,2}$ = 0.049, $p < 0.05$) but is unrelated to piracy intentions in support of the general notion that piracy is prevalent in a young, "time rich" segment. Similarly, technical costs and learning costs do not represent serious obstacles for consumers in obtaining unauthorized copies.

In terms of the utility of piracy, we find support for our expectation that the variable of social utility is positively related to piracy intentions ($\beta_{10,1}$ = 0.293, $p < 0.05$), emphasizing the importance of social elements of piracy, such as normative influences and interaction with relevant others. Confirming previous research, our results show that piracy is motivated by an anti-industry attitude, making it a retaliatory action against the industry's practices ($\beta_{11,1}$ = 0.158, $p < 0.05$). Surprisingly, the variable of economic utility is unrelated to piracy intentions, indicating that monetary considerations are not among the motives for consumers to engage in piracy. Although people do not seem to pirate for monetary gain, we find that a low valuation of recorded music products is positively related to piracy intentions ($\beta_{13,1}$ = 0.065, $p < 0.05$) and negatively related to purchase intentions ($\beta_{13,2}$ = –0.318, $p < 0.05$). Adding to this, the perception of the prices of existing legitimate services as too high remains an important factor that keeps consumers from using these services ($\beta_{14,2}$ = –0.105, $p < 0.05$).

[11] Danaher, Smith, and Telang (2013a) find that increasing the risk of legal prosecution positively influenced the sales of one major distributor of digital music (iTunes) in another market (France). Unfortunately, we cannot test this based on our aggregate level measure, which refers to all (paid) channels.

Similarly, despite the availability of various commercial offers, the lack of adequate legitimate alternatives represents a major drawback for consumers ($\beta_{15,2} = -0.155$, $p < 0.05$).

Our findings also provide insights into the largely unresolved role of music sampling and show that the perception of piracy as way to discover and subsequently purchase music facilitates the formation of piracy intentions ($\beta_{16,1} = 0.224$, $p < 0.05$), as expected. Interestingly, this does not translate into a positive relation between the variables of sampling utility and purchase intentions, which advocates the single-stage EUT decision model and raises concerns that the sampling argument may only be an internal justification mechanism for people engaging in piracy.

4.2.2. Influence of social desirability on coefficients. So far, we have summarized the managerially relevant results that arise from our model. In a next step, we investigate the difference in the magnitude of the coefficients between the RR and DQ groups by consecutively adding interaction terms between the experimental group indicator and piracy antecedents in equation (6). Significant interactions indicate that the respective coefficient is likely to be biased as a result of response distortions in the criterion variable. We arrive at our final model by keeping only the significant interactions.[12] The results are presented in Table 5, Model 2.

As the positive interaction with age indicates, under RR, significantly more consumers belonging to older age groups admit their intentions to engage in piracy. That is, under DQ, the effect of age (young) is overestimated ($\beta_{RR,\ age} = 0.008$, $p < 0.05$), thereby weakening the conclusion that piracy is prevalent among young consumers. Further, without the RR technique, the results suggest a significant relation between taste in music (independent) and piracy intentions, whereas under RR, this effect vanishes as significantly more consumers listening to mainstream music disclose their true piracy intentions ($\beta_{RR,\ taste} = -0.135$, $p < 0.05$).

[12] It is not feasible to include all possible interactions at once because partitioning the data too much makes it difficult to draw objective inferences due to capitalization on chance, sampling error, and multicollinearity.

In addition, individuals whose relevant others are unlikely to engage in piracy and consider this behavior unadvisable obtain significantly higher scores on the piracy scale under RR ($\beta_{RR,\ social} = -0.137$, $p < 0.05$). Confirming our pre-study results, this finding suggests that the RR technique leads respondents whose social environment does not endorse such activities to provide more accurate answers. Lastly, our results reveal that respondents who perceive piracy as a way to discover and subsequently purchase new music are more open to admitting their piracy intentions under DQ. Conversely, when RR is applied, the effect diminishes as respondents who do not utilize this justification strategy provide more accurate responses ($\beta_{RR,\ sampling} = -0.135$, $p < 0.05$).

In summary, these results suggest that under-reporting is systematically related to the perception that piracy is a socially undesirable activity and to the inability of respondents to internally justify this behavior. Although this finding is new, it is supported by previous research, which has shown that people may cheat (here: under-report) in a systematic way in order to maintain a positive self-concept both towards themselves and others (Barkan et al. 2012; Mazar, Amir, and Ariely 2008).

4.3. Investigating the consequences of piracy intentions

4.3.1. Effect of piracy intentions on purchase intentions. We investigate the effect of piracy intentions on purchase intentions through the joint estimation of equations (8) and (9). The posterior mean estimates are reported in Table 6, Models 1 and 2. As a baseline model, we estimate a model that does not account for the residual correlation between equations (8) and (9) and infer the difference in magnitude of the piracy intention main effect (γ) by including its interaction effect with the question technique indicator in equation (9).

>>> Table 6 about here <<<

As can be observed from Model 1, the impact of piracy intentions on purchase intentions in the baseline model is negative ($\gamma = -0.107$, $p < 0.05$), in line with our expectations. Note, however, that there is a significant interaction between the question technique indicator and the piracy main effect, indicating that under DQ, the effect size is diminished by 0.090 ($p < 0.05$) and rendered insignificant. In support of our expectation, this finding reveals that that SDR acts as a suppressor that masks the true relationship between piracy and purchases. Additionally, taking the residual correlation into account yields an even larger coefficient, as seen in Model 2 ($\gamma = -0.171$, $p < 0.05$). Confirming the results of our simulation study, this finding provides empirical evidence that unobserved correlations in consumer preferences induce a downward bias in the explanatory piracy variable and that our proposed model effectively controls for this bias. The associated effect size shows that neglecting the correlation would lead us to underestimate the magnitude of the effect by approximately 40%.

4.3.2. Effect of piracy intentions on purchase behavior. To further test the relationship between piracy intentions and purchases and to exclude the risk of potential single source bias, we relate the latent piracy intention variable to the purchase behavior variable in equations (13) and (14). The results are presented in Table 6, Models 3 and 4. [13] [14] As can be inferred from Model 3, the effect of piracy intentions on purchase behavior is negative ($\gamma = -0.083$, $p < 0.05$), sustaining our previous results. In further support of our previous findings, accounting for endogeneity reinforces the effect size, resulting in a posterior mean estimate of $\gamma = -0.120$ ($p < 0.05$), which represents an increase in magnitude of approximately 30%. Furthermore, the number of respondents that did not spend any or a very small amount of money on music products is fairly small (posterior mean $\lambda = 10.1\%$). Note, however, that the

[13] The posterior mean estimates of the item parameters are as expected and are provided in Appendix 1. As another validity check, we test the effect of purchase intentions on purchase behavior by fitting the multivariate IRT model. The large effect size of $\gamma = 0.579$ ($p < 0.05$) and the high degree of correlation between the latent scores of $r = 0.650$ ($p < 0.01$) indicate that intentions are good predictors for behaviors in our model.

[14] To rule out an effect of the experimental measurement on the subsequent behavior, we additionally queried 217 respondents about their purchase behavior, who did not participate in the piracy study. Our analyses did not reveal systematic differences in reported spending behavior.

latent class membership is positively related to piracy intentions, suggesting that people with low spending levels exhibit a higher tendency to engage in piracy ($\beta_{NP} = 0.223$, $p < 0.05$).

In contrast to our previous results, we do not observe a significant interaction between the question technique indicator and the piracy variable. One likely explanation is related to differences in the sample composition due to panel attrition. Because we only consider respondents of the longitudinal study, this leaves 1,652 cases for estimation (346 of which belong to the DQ condition). We test whether this group systematically differs from the dropped cases by defining an indicator variable for these participants in the full data set. In a regression of purchase intentions on piracy intentions we find that these participants exhibit an overall lower tendency to pirate ($\beta = -0.172$, $p < 0.05$) as well as a weaker interaction effect between the questioning technique and the explanatory piracy intention variable ($\beta = -0.212$, $p < 0.05$), suggesting a lower degree of systematic under-reporting.

5. Discussion

5.1. Implications for research

To investigate the accuracy of our self-stated piracy measure, we apply an IRRT model, which corrects for social desirability bias – an issue of general relevance when sensitive topics are addressed in IS-research (e.g., the motives of hackers). Building upon recent empirical findings in marketing and psychology, we provide empirical evidence that individuals engage in deliberate impression management for intrinsic and extrinsic motivations and that IRRT is an adequate instrument to control for both types of SDR. In our main study among a sample of 3,246 consumers, our estimates show a 48% increase in reported piracy intentions when the RR mechanism for increased privacy protection is used. In addition, our results provide evidence that people under-report their piracy intentions in a systematic way, such that this under-reporting may obfuscate the true relationships between the piracy construct and important predictor and outcome variables in structural models. With respect to the former, we find that of 16 tested relationships, four are significantly biased as a result of SDR. Particularly, our results demonstrate that, besides sociodemographic variables, relationships with constructs pertaining to the individuals' self-concept are prone to be impacted by SDR. Thus, caution is warranted when interpreting the corresponding coefficients in structural models.

With respect to the effect of piracy on purchases, our results suggest a cannibalistic relation. Although the majority of existing studies support this finding to varying degrees, there is still considerable discussion about the existence and magnitude this effect triggered by the methodological challenges faced by researchers. Against this background, our analyses provide a more thorough understanding of the influence of the two main methodological challenges associated with survey-based research in this field, namely SDR and endogeneity. Specifically, we show that the diminishing effect of piracy intentions on purchase intentions is only uncovered when the IRRT model is used to account for SDR. Another distorting influence that may cause researchers to underestimate the effect of piracy on purchase variables is the disregard for unobserved correlations in consumer preferences. We propose an instrument-free, IRT-based approach that corrects for this type of endogeneity bias and find that ignoring the endogeneity problem would lead us to underestimate the effect of piracy intentions on purchase intentions (behavior) by approximately 40% (30%).

In view of the systematic impact of SDR and endogeneity on our results, we consider it important for researchers to establish the accuracy of their piracy measures, particularly when cross-sectional data are used to infer the relation between piracy and purchases. To that end, we provide the code we used to estimate our model in Appendix 5 of this paper.

5.2. Implications for management

Confronted with decreasing sales volumes, music industry associations have constantly proclaimed that a substantial portion of the industry's worldwide sales decline is attributable to digital piracy since the advent of digital sharing technologies. Our empirical study examines this claim and shows that piracy intentions cause consumers to forgo purchases. Therefore, decreasing consumers' intentions to engage in piracy while increasing their purchase intentions appears to be a promising strategy to address the problem of music piracy.

With respect to the strategic responses to piracy, the perspective taken herein moves beyond existing approaches by jointly analyzing the factors that influence piracy and purchase intentions. We summarize our findings in terms of both the direction and the significance of the effects in Table 7. Effective anti-piracy strategies aim to increase (decrease) the costs (the utility) associated with piracy.

>>> Table 7 about here <<<

One major finding of our analyses is that while legal measures deter piracy and the availability of legitimate alternatives stimulates purchases, the reverse is not true. Notwithstanding this finding, according to our results, current efforts of the music industry to strike a balance between "negative incentives" (i.e., stricter laws), that aim to discourage piracy, and "positive incentives" (i.e., provision of commercial offers), that aim to provide incentives for commercial usage, constitute important prerequisites for addressing the problem of music piracy (see also Sinha and Mandel 2008). However, our results suggest that the impacts of these measures are limited because they only address one side of the problem, i.e., they either decrease piracy intentions or increase purchase intentions. Focusing on the moral aspects of piracy (e.g., the consequences on society), in contrast, may prove to be a rewarding strategy in the fight against piracy because moral considerations are the single most important cost to piracy that prevents people from pirating and positively impacts the purchase probability. For such measures to effectively convert existing pirates, recent research in psychology suggests that granting amnesty to pirates may effectively underpin efforts to reset their ”moral compass” (Ariely 2012). Interestingly, some new cloud services (e.g., iTunes match) allow consumers to match their entire music libraries against an online database and to legitimately access the database for a flat fee regardless of the source from which the files were originally obtained, which may lead to purchases in the long term. Moreover, this strategy may offer an additional advantage, because such measures may counteract the effect of an anti-industry attitude, which we find to increase piracy intentions.

Furthermore, we identify social factors as an important driver of piracy intentions. This finding underlines the vital role of normative influences in the formation of piracy intentions and reveals the risk associated with the broad perception of piracy as a common behavior. In view of the relative popularity of certain illegitimate channels (e.g., stream ripping software), the music industry should continue to invest in efforts to prevent a situation in which increasing social proof will negatively impact the understanding of the legitimacy of piracy and the value assigned to recorded music products. This appears even more important considering that, according to our findings, a low (high) valuation of music products is positively related to piracy (purchase) intentions.

Surprisingly, we do not find monetary considerations to increase piracy intentions. Thus, attributing the causes of piracy solely to consumers’ “for-free mentality” falls short of the truth. Similarly, the perceived prices of legitimate music products are unrelated to piracy intentions. Hence, addressing piracy by lowering prices is unlikely to be successful and is not recommended. Given the homogeneous nature of music products this strategy also entails the risk of increasing price competition among paying customers. That is, piracy may serve as a price discrimination device through which firms only compete over less price-sensitive consumers, which may increase profits in the long-run (Jain 2008).

Finally, our results show that although the utility derived from music sampling increases piracy intentions, it is unrelated to purchase intentions. Thus, obtaining unauthorized copies of an album or a song is unlikely to translate into purchases. Considering that unauthorized copying takes place at a global scale, it is advisable that music companies should adopt a global release scheme rather than a sequential release strategy by geographical markets and should synchronize promotional activities (e.g., video releases) with release timings as precautionary measures against pre-release piracy.

5.3. Limitations and future research

Similar to most empirical studies, our research is subject to limitations that represent departure points for future research. Two limitations are of particular interest. First, our empirical research was conducted in the German market, which is one of the four largest markets for recorded music worldwide. Although we do not expect our findings to deviate substantially from other Western markets, piracy behavior is likely to be influenced by country characteristics, such as the existence and enforcement of anti-piracy legislation, economic indicators, and cultural variables. Therefore, it would be interesting to compare our results to other countries or even to extend the framework to explicitly account for country characteristics using a multi-level framework. Second, although we have shown that moral aspects play a crucial role in the formation of piracy and purchase intentions, our research does not provide an in-depth analysis of how moral and emotional appeals can be utilized most effectively, which qualifies as an avenue for future research.

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Tables and figures

Table 1

Pre-study results

Predictors	*Influence on Piracy Intention*			
	Model 1	*Model 2*	*Model 3*	*Model 4*
Structural parameters				
Intercept (β_0)	**–0.708**	**–1.130**	**–1.037**	**–1.283**
Questioning technique (RR=1) (δ)	**0.575**	**0.567**	**0.625**	**0.595**
Main effects				
Age (in years) (β_{age})		**–0.030**	**–0.030**	**–0.032**
Gender (female=1) (β_{gender})		–0.127	–0.113	0.083
Impression management (β_{IM})		**–0.332**		
Perceived social undesirability (β_{SD})			**–0.620**	
Perceived legal risk (β_{risk})				**–0.287**
Interaction effects				
RR x Impression management ($\beta_{RR,\ IM}$)		**0.162**		
RR x Perceived social undesirability ($\beta_{RR,\ SD}$)			**0.273**	
RR x Perceived legal risk ($\beta_{RR,\ risk}$)				**0.192**
Latent class probability (κ)				
Non-adherence (%)	**12.0**	**11.8**	**11.8**	**11.8**

Notes. Estimates in bold do not contain 0 in their 95% credible interval. All tests are two-sided tests. All predictors are mean-centered. n = 1,601.

Table 2

Simulation study results

Simulated covariance (ρ)	*Parameters*	*True values*	*Baseline model*			*Proposed model*		
			Mean	*SD*	*RMSE*	*Mean*	*SD*	*RMSE*
0.000	γ	–0.500	–0.503	0.032	0.028	–0.496	0.156	0.046
	$\beta_{1,2}$	0.300	0.304	0.035	0.152	0.301	0.084	0.154
	ρ	0.000	—	—	—	–0.007	0.153	0.034
0.200	γ	–0.500	–0.305	0.032	0.197	–0.486	0.089	0.076
	$\beta_{1,2}$	0.300	0.196	0.035	0.202	0.287	0.055	0.158
	ρ	0.200	—	—	—	0.179	0.084	0.070
0.500	γ	–0.500	–0.003	0.032	0.498	–0.493	0.046	0.048
	$\beta_{1,2}$	0.300	0.052	0.035	0.274	0.297	0.039	0.153
	ρ	0.500	—	—	—	0.489	0.036	0.036
0.800	γ	–0.500	0.303	0.032	0.803	–0.496	0.022	0.022
	$\beta_{1,2}$	0.300	–0.101	0.035	0.351	0.297	0.033	0.155
	ρ	0.800	—	—	—	0.797	0.010	0.010
1.000	γ	–0.500	0.501	0.032	1.001	–0.500	0.000	0.000
	$\beta_{1,2}$	0.300	–0.200	0.035	0.400	0.292	0.021	0.160
	ρ	1.000	—	—	—	1.000	0.000	0.000

Table 3

Item characteristics of piracy and purchase intention items

Intention Items	*Discriminations* α_k	*Thresholds* $\tau_{k,1}$	$\tau_{k,2}$	$\tau_{k,3}$	$\tau_{k,4}$
Piracy Intention Items (θ_{1i})					
Item 1: Download files via BitTorrent	1.611	0.127	0.752	1.302	1.848
Item 2: Download files via other P2P-networks	1.942	0.094	0.722	1.330	1.649
Item 3: Upload/share files via file-sharing networks	2.357	0.141	0.740	1.334	1.708
Item 4: Download files via newsgroups/Usenet	1.933	–0.036	0.631	1.283	1.706
Item 5: Download files via sharehoster or FTP server	1.428	–0.273	0.360	0.955	1.577
Item 6: Upload/share files via sharehoster or FTP server	2.011	0.069	0.682	1.282	1.640
Item 7: Download files via blogs or forums	1.442	–0.182	0.510	1.232	1.750
Item 8: Rip files from audio streams	0.827	–0.530	0.238	1.192	2.279
Item 9: Rip files from video streams	0.826	–1.054	–0.373	0.586	1.609
Item 10: Obtain files via instant messaging or email	1.024	–0.835	–0.143	0.741	1.745
Item 11: Obtain files via media storage devices	0.820	–1.993	–1.268	0.056	1.245
Item 12: Share files via instant messaging, email or storage devices	0.885	–1.595	–0.902	0.240	1.396
Item 13: Use VPN services for privacy protection	1.081	–0.359	0.427	1.316	2.059
Item 14: Purchase counterfeit CDs	0.743	–0.035	0.772	1.827	3.134
Item 15: Purchase unlicensed MP3s	0.847	–0.437	0.445	1.489	2.465
Item 16: Sell unlicensed music for a profit	1.144	0.578	1.270	1.852	2.677
Purchase Intention Items (θ_{2i})					
Item 1: Purchase likelihood	1.928	–1.519	–1.144	0.583	0.138
Item 2: Purchase frequency	1.813	–1.319	–0.642	0.045	0.756
Item 3: Usage of paid channels for music consumption	0.820	–1.479	–0.752	0.090	1.045
Item 4: Usage share of paid channels (most music consumption)	1.484	–1.158	–0.592	0.002	0.784
Item 5: Usage share of paid channels (all music consumption)	1.190	–0.874	–0.273	0.392	1.054
Item 6: Spending intention	1.965	–1.572	–1.150	–0.423	0.394
Item 7: Spending intention compared with others	1.326	–0.908	–0.120	0.645	1.265
Item 8: Spending intention as part of disposable income	0.884	–0.647	0.593	1.582	2.361
Item 9: Spending amount (planned)	0.795	–1.224	–0.479	0.352	1.304

n = 3,246

Table 4

Posterior predictive check and agreement with piracy items under DQ and RR

	Percentage Agreement		
Piracy Intention Items	*obs. DQ*	*est. DQ*	*est. RR*
Item 1: Download files via BitTorrent	2.2%	2.1%	3.0%
Item 2: Download files via other P2P-networks	1.2%	1.5%	2.3%
Item 3: Upload/share files via file-sharing networks	1.3%	1.1%	1.8%
Item 4: Download files via newsgroups/Usenet	2.0%	1.7%	2.6%
Item 5: Download files via sharehoster or FTP server	4.6%	5.0%	7.2%
Item 6: Upload/share files via sharehoster or FTP server	2.0%	1.3%	2.4%
Item 7: Download files via blogs or forums	3.0%	2.9%	4.3%
Item 8: Rip files from audio streams	6.8%	7.5%	10.3%
Item 9: Rip files from video streams	12.8%	14.3%	19.4%
Item 10: Obtain files via instant messaging or email	9.0%	9.9%	13.7%
Item 11: Obtain files via media storage devices	20.0%	22.9%	30.3%
Item 12: Share files via instant messaging, email or storage devices	17.3%	18.8%	25.3%
Item 13: Use VPN services for privacy protection	3.5%	4.1%	5.8%
Item 14: Purchase counterfeit CDs	3.7%	4.3%	5.9%
Item 15: Purchase unlicensed MP3s	4.3%	5.0%	6.9%
Item 16: Sell unlicensed music for a profit	1.7%	1.4%	2.0%

Notes. Agreement are responses 4: "agree" or 5: "strongly agree". Obs. DQ = observed percentage in the direct questioning group, est. DQ/est. RR = estimated percentage under the proposed model in the direct questioning and randomized response group, respectively. n = 3,246

Table 5

Posterior mean estimates of the antecedents of piracy and purchase intentions

Predictor	*Model 1* Piracy Intention	*Model 1* Purchase Intention	*Model 2* Piracy Intention	*Model 2* Purchase Intention
Structural Parameters				
Intercept (β_0)	**–1.109**	**0.288**	**–1.041**	**0.467**
Question technique (RR = 1) (δ)	**0.401**		**0.426**	
Control variables				
Age (in years) (β_1)	**–0.008**	**–0.012**	**–0.015**	**–0.012**
Gender (female = 1) (β_2)	0.070	**–0.314**	0.075	**–0.317**
Income (β_3)	–0.017	**0.096**	–0.016	**0.096**
Music taste (independent) (β_4)	0.010	**0.142**	**0.106**	**0.141**
Costs of piracy				
Legal costs (β_5)	**–0.075**	–0.037	**–0.084**	–0.037
Moral costs (β_6)	**–0.185**	**0.231**	**–0.179**	**0.230**
Search costs (β_7)	0.041	**0.049**	0.038	**0.049**
Technical costs (β_8)	–0.025	0.007	–0.025	0.007
Learning costs (β_9)	0.030	0.003	0.023	0.003
Utility of piracy				
Social utility (β_{10})	**0.293**	–0.014	**0.387**	–0.014
Anti-industry utility (β_{11})	**0.158**	0.013	**0.164**	0.012
Economic utility (β_{12})	0.003	0.019	0.002	0.020
Devaluation utility (β_{13})	**0.065**	**–0.318**	**0.064**	**–0.317**
Price of legitimate alternatives (β_{14})	–0.032	**–0.105**	–0.033	**–0.105**
Lack of legitimate alternatives (β_{15})	0.017	**–0.155**	0.016	**–0.155**
Sampling utility (β_{16})	**0.224**	0.003	**0.315**	0.002
Question technique interactions				
RR x Age ($\beta_{RR,\ age}$)			**0.008**	
RR x Music taste ($\beta_{RR,\ taste}$)			**–0.135**	
RR x Social utility ($\beta_{RR,\ social}$)			**–0.137**	
RR x Sampling utility ($\beta_{RR,\ sampling}$)			**–0.127**	

Notes. Estimates in bold do not contain 0 in their 95% credible interval. All tests are two-sided tests. All predictors are mean-centered. The prior variances of θ_{1i} and θ_{2i} are set equal to 1 to fix the scale. n = 3,246.

Table 6

Influence of piracy intentions on purchase intentions and purchase behaviors

	Influence on Purchase Intentions[a] *(n = 3,246)*				*Influence on Purchase Behaviors (n = 1,652)*			
	Model 1		*Model 2*		*Model 3*		*Model 4*	
Predictor	*Piracy Intention*	*Purchase Intention*	*Piracy Intention*	*Purchase Intention*	*Piracy Intention*	*Purchase Behavior*	*Piracy Intention*	*Purchase Behavior*
Controlling for …								
social desirability?[b]	yes		yes		yes		yes	
endogeneity?[c]	no		yes		no		yes	
Structural Parameters								
Intercept (β_0)	**–0.947**	–.0269	**–0.923**	0.080	**–0.534**	**1.601**	**–0.786**	**1.753**
Question technique (δ)	**0.407**		**0.409**		**0.495**		**0.491**	
Piracy Intention								
Main effect (γ)		**–0.107**		**–0.171**		**–0.084**		**–0.120**
Interaction effect ($\beta_{DQ,\ piracy}$)[b]		**0.090**		**0.151**		0.007		0.029
Latent class probability (λ)								
Main effect (β_{NP})					**0.219**		**0.223**	
Non-purchasers (%)						**10.1**		**10.1**

[a] We only report coefficients that are related to the effect of piracy intentions on purchase intentions because the remaining predictor effects exhibit a high degree of stability across models.
[b] The difference in magnitude of the γ-parameter between the experimental groups is inferred by including an interaction term between the group indicator (DQ = 1) and the piracy intention main effect in the purchase regression equations. For example, the effect size of 0.090 in Model 1 indicates that $\gamma = -0.017$ under DQ**.**
[c] In models 1 and 3 with uncorrelated errors, we specify independent normal priors for the piracy and purchase constructs and define another independent predictor variable for piracy intentions.
Notes. Estimates in bold do not contain 0 in their 95% credible interval. All tests are two-sided tests. All predictors are mean-centered.

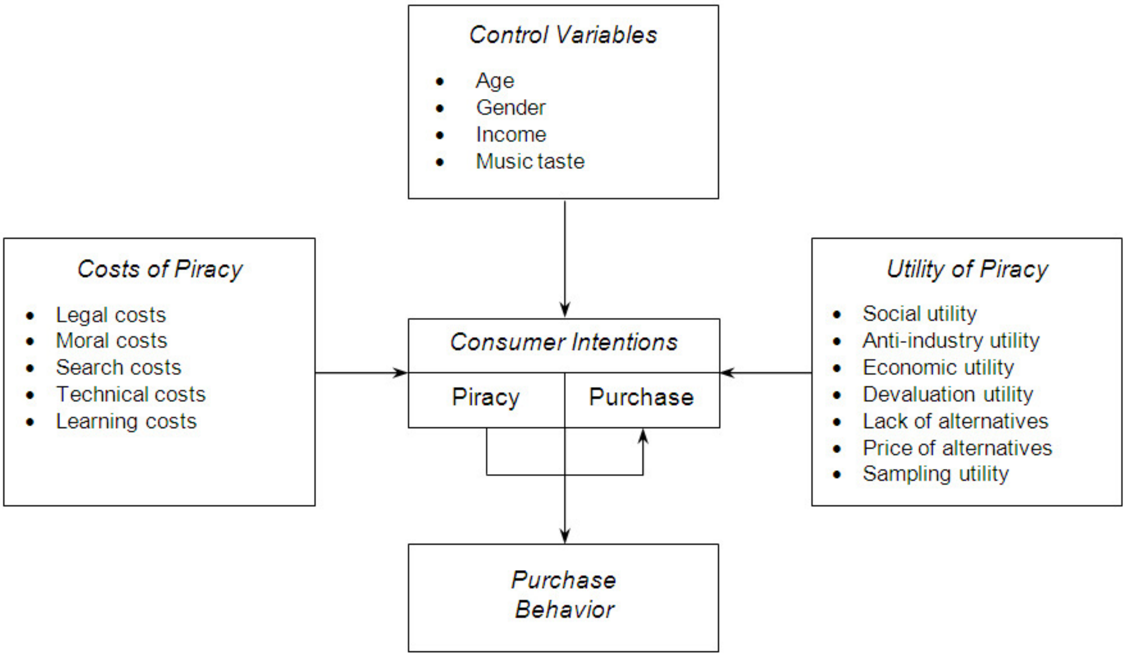
Table 7

Summary of effects

Purchase intentions	**Piracy intentions: Negative effect**	**Piracy intentions: No effect**	**Piracy intentions: Positive effect**
Positive effect	• Moral costs	• Search costs • Income • Music taste (independent)	
No effect	• Legal costs	• Technical costs • Learning costs • Economic utility	• Social utility • Anti-industry utility • Sampling utility
Negative effect	• Age	• Price of alternatives • Lack of alternatives • Gender (female)	• Devaluation utility

Figure 1

Framework of the antecedents and consequences of piracy and purchase intentions



Notes. Piracy intentions are measured with direct questioning and randomized response using a between-subjects design. The effect of consumer intentions on purchase behavior is tested on a sub-sample using data from a longitudinal survey that was conducted subsequent to the main study.

Figure 2

Randomized response mechanism

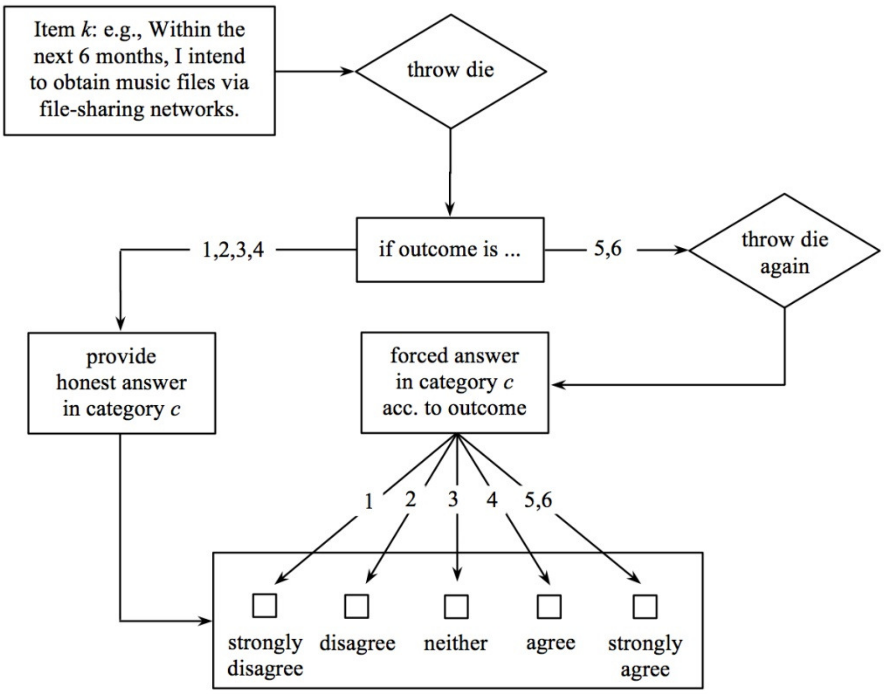
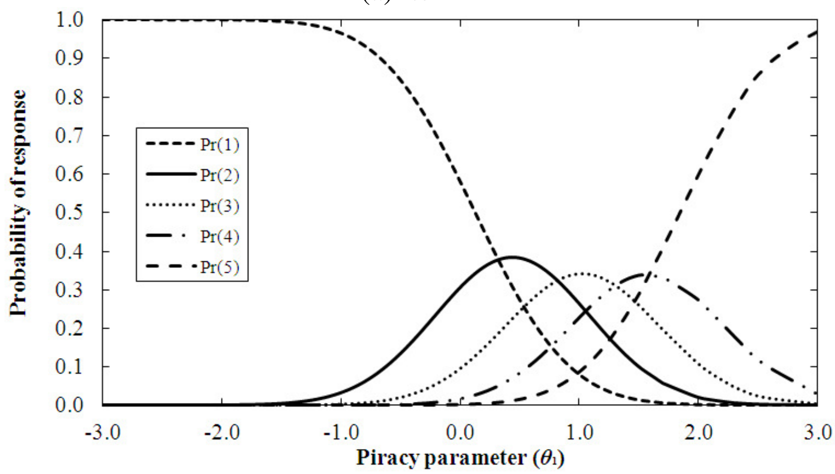


Figure 3

Category response functions

(a) Item 1



(b) Item 10

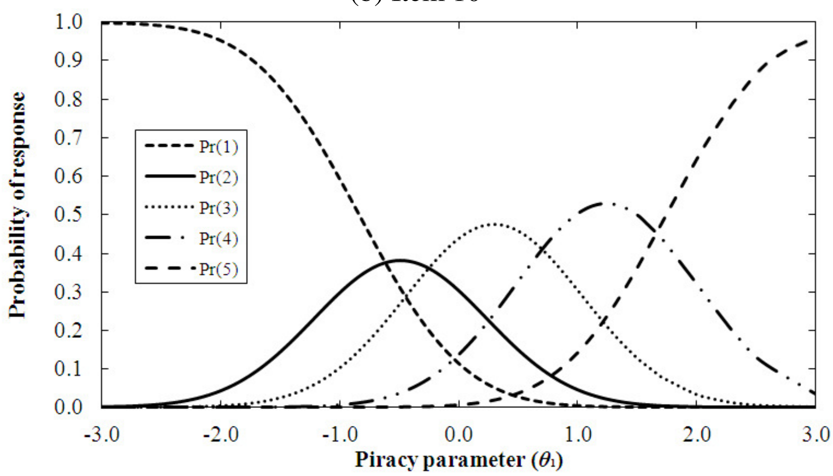
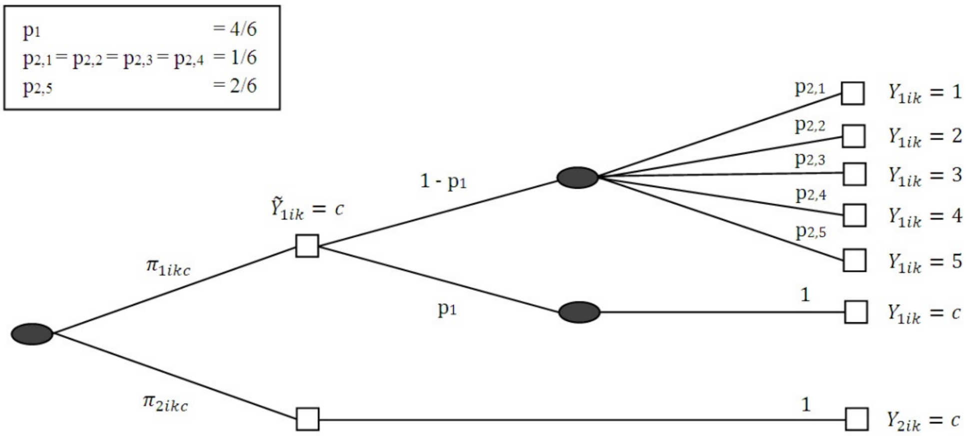


Figure 4

Probability distribution under proposed randomized response scheme



Note. The randomization device does not have to produce outcomes that are uniformly distributed, since the sampling design is integrated in the model. For example, when more forced "strongly agree" responses are instructed, the model will expect on average more "strongly agree" responses

Appendix

Appendix 1: Survey items, descriptive statistics and procedural instructions

Table A.1.1

Survey items

Construct / Items		M	SD
Piracy intention items (α = 0.91 (computed based on DQ answers only), measured with randomized response and direct questioning using a between-subjects design; randomized item order) *To what extent do you disagree/agree with the following statements? Within the next six months, I intend to …* [1 = strongly disagree—5 = strongly agree]			
1. Download music files via BitTorrent-tracker (e.g., The Pirate Bay, IsoHunt, Btjunkie, Torrentz.com) and -programs (e.g., Vuze, µTorrent, BitTorrent)[a]	DQ:	1.26	0.68
	**RR:	2.05	1.43
2. Download music files via peer-to-peer-networks [excluding BitTorrent] (e.g., eMule, Soulseek, Gnutella)[a]	DQ:	1.25	0.62
	**RR:	2.04	1.44
3. Upload/share music files via file-sharing networks [e.g., BitTorrent or other peer-to-peer networks]	DQ:	1.22	0.61
	**RR:	1.97	1.39
4. Download music files via Usenet-/newsgroup-services (e.g., Firstload, UseNeXT, GigaNews, overnext, EasyNews)[a]	DQ:	1.29	0.68
	**RR:	2.07	1.42
5. Download music files via sharehoster/cyberlocker (e.g., Rapidshare, Megaupload, Mediafire, Hotfile, Dropbox) or FTP servers[a]	DQ:	1.46	0.89
	**RR:	2.29	1.48
6. Upload/share music files via sharehoster/cyberlocker (e.g., Rapidshare, Megaupload, Mediafire, Hotfile, Dropbox) or FTP servers	DQ:	1.28	0.69
	**RR:	1.98	1.37
7. Download music files via non-official blogs or forums (e.g., websites where songs and albums are available before their official release date)[a]	DQ:	1.37	0.80
	**RR:	2.18	1.43
8. Record/convert audio-streams to mp3 files via stream-ripping software (e.g., Radio.fx, Streamripper, Audiojack, Winamp)[a]	DQ:	1.62	0.99
	**RR:	2.40	1.46
9. Record/convert video-streams to mp3 files via stream-ripping software (e.g., YouTube MP3 Converter, Videoloader, Video 2 mp3)[a]	DQ:	1.94	1.20
	**RR:	2.69	1.47
10. Obtain music files via instant messaging programs (e.g., Skype, ICQ) or email[a]	DQ:	1.76	1.09
	**RR:	2.51	1.43
11. Obtain music files via media storage devices (e.g., burned CD-Rs, hard disk, USB sticks, mobile phones)[a]	DQ:	2.39	1.25
	**RR:	3.11	1.35
12. Pass on/share music files via instant messaging programs (e.g., Skype, ICQ), email or media storage devices (e.g., burned CD-Rs, hard disk, USB sticks, mobile phones)	DQ:	2.20	1.25
	**RR:	2.94	1.40
13. Use special services that protect your privacy while sharing music files on the internet (e.g., VPN services)	DQ:	1.47	0.85
	**RR:	2.22	1.42
14. Purchase counterfeit CDs (e.g., on a holiday) or unauthorized digital music files (e.g., burned to a CD-R)[a]	DQ:	1.54	0.89
	**RR:	2.33	1.44
15. Purchase conspicuously low-priced music files on the Internet (e.g., MP3 flatrates from vendors such as ZEEZEE, Flatster, Musicmonster)	DQ:	1.44	0.84
	**RR:	2.18	1.44
16. Sell unauthorized music files for a profit (e.g., burned to CD-Rs or stored on other media storage devices)	DQ:	1.21	0.60
	**RR:	1.88	1.38
Purchase intention items[b] (α = 0.89, randomized item order) *To what extent do you intend to use one or more of the following commercial channels to obtain or consume recorded music products within the next six months?* [1 = strongly disagree—5 = strongly agree]			
• *Purchase original music on CDs/LPs/DVDs in brick-and-mortar record stores*			
• *Order original music on CDs/LPs/DVDs from online retailers (e.g., Amazon)*			
• *Commercial download stores (e.g., iTunes, Musicload, Amazon MP3)*			
• *Commercial (paid) music streaming services (e.g., Napster, Simfy, Musicload Nonstop)*			
1. It is likely that I will purchase music products via these channels.		4.10	1.20

2. I intend to purchase music products via one or more of these channels frequently.	3.53	1.29
3. It is likely that I will make use of these channels for the purpose of music consumption.	3.39	1.39
4. I plan to use these channels for most of my music consumption.	3.48	1.36
5. I intend to use these channels for all my music consumption.	3.12	1.46
6. I intend to spend money on recorded music products.	3.96	1.17
7. Compared with other people, I will spend more money on recorded music products.	2.96	1.36
8. I will spend a large share of my disposable income on recorded music products.	2.36	1.20
9. How much money do you intend to spend on recorded music products (CDs/LPs/DVDs), music downloads, and digital music subscriptions within the next six months? [stated Euro amounts were categorized: 1=0-20, 2: 21-40, 3: 41-60, 4: 60-100, 5: >100]	3.17	1.43
Impression management scale[a] (α = 0.70, adapted from Paulhus 1991)		
1. I have received too much change from a salesperson without telling him or her.[c]	2.93	1.32
2. I sometimes tell lies if I have to.[c]	2.86	1.04
3. When I was young, I sometimes stole things.[c]	1.97	1.19
4. I have done things that I don't tell other people about.[c]	2.98	1.31
5. I have said something bad about a friend behind his/her back.[c]	3.04	1.12
6. When I hear people talking privately, I avoid listening.	3.40	0.97
7. I never cover up my mistakes.	2.91	0.97
8. I always obey laws, even if I'm unlikely to get caught.	2.47	1.01
9. I never take things that don't belong to me.	2.21	1.21
10. I don't gossip about other people's business.	2.88	1.06
Perceived social undesirability of unauthorized obtainment[a] (α = 0.78, own scale) *In my opinion, using these channels to obtain music products in Germany is ...* [five-point bipolar scale]		
1. ... uncommon—common[c]	2.97	1.15
2. ... socially inacceptable—socially acceptable[c]	2.41	1.11
3. ... socially undesirable—socially desirable[c]	2.19	1.05
Legal costs[a] (α = 0.77, adapted from Chiang and Assane 2002)		
1. The danger of being punished for obtaining music files via these channels is high.	3.61	1.07
2. Sharing music files via these channels is legally risky.	4.10	0.93
Moral costs (α = .88, adapted from Huang 2005)		
1. Using these channels to obtain music files is unfair to the artists.	3.97	1.01
2. Sharing music files via these channels is unethical.	3.71	1.07
3. When you use these channels to obtain music files, you do harm to someone.	3.55	1.11
Technical costs (adapted from Hennig-Thurau, Henning, and Sattler 2007)		
The danger of my personal computer becoming infected with computer viruses when obtaining music files via these sources is high.	3.55	1.11
Search costs (adapted from Hennig-Thurau, Henning, and Sattler 2007)		
It is cumbersome to find music files of acceptable quality via these channels.	3.05	1.06
Learning costs (own scale)		
Obtaining music files via these sources will be difficult.	2.69	1.16
Social utility (α = 0.86, adapted from Papies, Eggers, and Wlömert 2011)		
1. My friends would think that it is advisable to obtain music files via these sources.	2.75	1.11
2. Many people in my social environment would obtain music files via these sources.	2.75	1.11
Sampling utility (own scale)		
These sources of recorded music products provide a good opportunity for me to discover new music that I will subsequently purchase.	3.01	1.19
Anti-industry utility (α = 0.73, own scale based on Hennig-Thurau, Henning, and Sattler 2007)		
1. By obtaining music files via these sources you can “get back” at the music companies and media corporations for their unfair practices.	2.75	1.15
2. If anything, by obtaining music files through these sources, you do harm to the large media corporations, at most, but certainly to not the artists.	2.43	1.08

3. The music industry is responsible for the widespread use of these sources (e.g., because there are no adequate legitimate alternatives).			3.22	1.06
4. The crisis of the music industry is self-inflicted (e.g., because the industry has not appropriately reacted to technological developments).			3.31	1.06
Economic utility (own scale)				
By obtaining music files via these sources, you can save money.			3.53	1.12
Devaluation utility (adapted from Hennig-Thurau, Henning, and Sattler 2007)				
For me, recorded music products have a high collector's value.[c]			3.58	1.28
Lack of legitimate alternatives (own scale)				
In your opinion, are there other sources that are better or equally well suited to obtaining recorded music products? [1 = there are none—5 = there are many] [c]			3.52	1.08
Price of legitimate alternatives (own scale)				
In my opinion, the prices of recorded music products are generally too high.			3.33	0.98
Sociodemographics				
Age (in years) [a]			36.2	12.86
Sex (1 = female) [a]			49%	0.50
Income [1 = "<500 EUR"—8 = ">3.000" in increments of 500 EUR]			3.42	2.31
Music taste [1 = only mainstream—5 = only independent]			3.22	0.84
Music purchase behavior items (the first two columns report the posterior mean estimates of the monthly adjustment terms "b_k" and the item discrimination parameters "α_k")				
Within the last 30 days, how much money have you spent on recorded music products via the following channels? [monthly questionnaire; stated Euro amounts were aggregated across channels at monthly level]				
• *Purchase original music CDs/LPs/DVDs (brick-and-mortar stores or online)*				
• *Commercial download stores (e.g., iTunes, Musicload, Amazon MP3)*				
• *Commercial (paid) music streaming-services (e.g., Napster, Simfy, Musicload Nonstop)*				
1. January	b_1: –0.404	α_1: 1.01	42.30	58.13
2. February	b_2: 0.714	α_2: 1.24	31.16	49.90
3. March	b_3: 0.959	α_3: 1.27	28.16	53.54
4. April	b_4: 1.12	α_4: 1.28	25.66	49.49
5. May	b_5: 1.24	α_5: 1.31	25.38	47.64
6. June	b_6: 1.15	α_6: 1.27	24.44	45.81

Notes. Variables measured on a five-point scale unless otherwise stated. (1 = strongly disagree—5 = strongly agree)
[a] Denotes items/constructs that were (also) included in the pre-study
[b] To avoid that respondents intentionally obfuscate the relation between purchase and piracy intentions by answering the purchase intention items dishonestly, the respective questions were placed at the beginning of the questionnaire, before the questions pertaining to the piracy intentions.
[c] Scale reverted for measurement
[**] Mean difference between RR and DQ significant at $p < 0.001$

Table A.1.2

Means, standard deviations and correlations among constructs

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Piracy intention	–0.88	0.92	1																	
2. Purchase intention	0.18	0.98	**–0.25**	1																
3. Age	36.2	12.9	**–0.21**	**0.04**	1															
4. Gender	1.48	0.50	**0.07**	**–0.17**	**–0.38**	1														
5. Income	3.43	2.31	**–0.16**	**0.20**	**0.51**	**–0.38**	1													
6. Music taste	3.22	0.84	0.03	**0.12**	–0.01	**–0.06**	–0.00	1												
7. Legal costs	3.86	0.90	**–0.21**	**0.07**	**0.11**	**0.05**	0.03	**–0.08**	1											
8. Moral costs	3.74	0.96	**–0.33**	**0.28**	**0.14**	–0.03	**0.12**	**–0.04**	**0.44**	1										
9. Technical costs	3.56	1.07	**–0.14**	**0.06**	0.02	**0.06**	–0.03	**–0.08**	**0.43**	**0.27**	1									
11. Search costs	3.05	1.06	–0.01	**0.08**	0.01	0.02	0.01	–0.00	**0.12**	**0.11**	**0.23**	1								
10. Learning costs	2.69	1.16	–0.02	0.02	0.02	**0.05**	0.01	**–0.05**	**0.11**	**0.07**	**0.14**	**0.21**	1							
12. Social utility	2.61	1.02	**–0.37**	**–0.05**	**–0.25**	0.02	**–0.15**	**0.04**	**–0.19**	**–0.24**	**–0.13**	**–0.09**	–0.00	1						
13. Sampling utility	3.08	1.19	**0.36**	**–0.06**	**–0.19**	0.01	**–0.11**	**0.09**	**–0.21**	**–0.35**	**–0.18**	**–0.04**	**–0.04**	**0.38**	1					
14. Anti-industry utility	2.93	0.81	**0.28**	**–0.14**	**–0.10**	**–0.05**	**–0.08**	**0.05**	**–0.19**	**–0.45**	**–0.13**	–0.02	–0.00	**0.24**	**0.37**	1				
15. Economic utility	3.53	1.12	**0.19**	–0.00	**–0.22**	0.03	**–0.10**	0.03	**–0.09**	**–0.11**	**–0.12**	–0.02	–0.01	**0.35**	**0.39**	**0.23**	1			
16. Devaluation utility	3.58	1.28	**–0.11**	**0.39**	**–0.08**	–0.03	–0.01	**0.09**	**0.06**	**0.19**	**0.09**	0.02	**0.07**	0.02	0.03	**–0.08**	0.02	1		
17. Lack of alternatives	2.48	1.08	**0.12**	**–0.23**	**–0.13**	**0.06**	**–0.11**	0.01	**–0.09**	**–0.19**	**–0.06**	–0.03	**–0.05**	**0.09**	**0.09**	**0.19**	0.00	**–0.15**	1	
18. Price of alternatives	3.33	0.98	**0.12**	**–0.12**	**–0.11**	0.01	**–0.09**	–0.00	**–0.04**	**–0.21**	–0.03	0.01	0.00	**0.13**	**0.19**	**0.39**	**0.20**	**0.05**	**0.13**	1

Notes. Means and standard deviations are calculated for the sum of construct items.
Correlation coefficients in bold are significant at $p < 0.05$ or less. n = 3,246

Appendix 1.3.: Procedural instructions

<u>Important privacy notice</u>

The following pages of this online questionnaire include questions regarding your music consumption via different channels. Previous studies have revealed that despite anonymous questioning, some participants have concerns regarding disclosing information about their true behavior with respect the usage of certain channels (e.g., peer-to-peer networks or Cyberlockers) because of potential interference with their privacy as well as fear of undesirable consequences. Therefore, we have developed a method designed to fully protect your privacy that allows you to be completely honest when answering the questions. The method guarantees complete confidentiality and anonymity. Even if you find this technique with the dice a bit strange, it is fun to use and it is useful since it guarantees your privacy. On the following pages, we will explain how this works.

<u>Randomized response mechanism</u>

*) The flow chart of the RR mechanism was provided as a visual aid on this page

1. For every question with the die symbol displayed before it, please roll the virtual die by clicking with your mouse pointer on it. Only you know the outcome of the die roll!
2. If the die shows a 1, 2, 3, or 4, please answer the respective question completely honestly.
3. If the die shows a 5 or 6, please roll the die again by clicking on it a second time. The response category will now be selected randomly according to the outcome of the second throw. If the outcome of the second throw yields a ...
    - ... 1, the first category will be selected ("strongly disagree")
    - ... 2, the second category will be selected ("disagree")
    - ... 3, the third category will be selected ("neither")
    - ... 4, the fourth category will be selected ("agree")
    - ... 5 or 6, the fifth category will be selected ("strongly agree")

Please repeat steps 1 to 3 for every question with the die symbol displayed before it.

<u>Because nobody but you knows the outcome of the die rolls, nobody can know why you answered a question in a certain category. Therefore your true answer remains completely confidential.</u>

Your answers are still useful for us because we can still make inferences at an aggregate level, but not at the level of the individual questions. Please do not worry about answering questions incorrectly or even dishonestly if the die tells you so. With this method you are being honest when you answer according to the rules, like in a game.

As an exercise, please first answer the following three example questions to acquaint yourself with his method. To what extent do you disagree/agree with the following statements? Hint: after every die roll, a short instruction will appear on your monitor [scale: 1 = strongly disagree—5 = strongly agree]

- I sometimes use public transport without a valid ticket.
- When I receive too much change at the supermarket checkout, I usually keep it.
- When I am in a hurry, I sometimes cross the road despite a red light.

Because only you know the outcome of the die rolls, no one can know why you answered a question in a specific category—it may either be a true or a random answer. If, for example, you answered one of the example questions in category 4 (“agree”), it may either be that the outcome of the first roll of the die was a 1, 2, 3, or 4 and you provided an honest answer or that the outcome of the first roll of the die was a 5 or a 6 and the outcome of the second throw was a 4—<u>only you know the truth</u>!

<u>We guarantee you that there is no way for anyone to know the outcome of the die rolls, except for you. Thus, your privacy is fully protected.</u>

Appendix 2: Pre-study results - effects of instructions and randomization device

We pre-tested our piracy measure using a ten-item sub-scale. Respondents indicated their piracy intentions on a five-point rating scale ranging from "never" to "very often". We estimated the latent piracy scores based on the graded IRRT model proposed by De Jong, Pieters, and Fox (2010). Table A.2.1 presents the posterior means of the item parameters.

Table A.2.1

Item characteristics of the piracy intention items

	Discriminations	***Thresholds***			
Piracy Intention Items	α_k	$\tau_{k,1}$	$\tau_{k,2}$	$\tau_{k,3}$	$\tau_{k,4}$
Item 1: Download files via BitTorrent	1.462	1.408	2.000	2.448	2.857
Item 2: Download files via other P2P-networks	1.349	1.560	2.061	2.634	3.159
Item 3: Download files via newsgroups/Usenet	0.971	1.593	2.323	3.024	4.034
Item 4: Download files via sharehoster & FTP server	1.400	0.995	1.552	2.007	2.668
Item 5: Download files via blogs & forums	1.598	1.005	1.613	2.213	2.777
Item 6: Rip files from audio streams	0.838	1.217	2.085	2.794	3.240
Item 7: Rip files from video streams	0.823	0.311	1.213	2.175	2.942
Item 8: Obtain files via instant messaging & email	1.126	0.833	1.687	2.358	3.144
Item 9: Obtain files via media storage devices	1.039	-0.443	0.599	1.781	2.647
Item 10: Purchase counterfeit CDs	0.869	1.090	2.117	3.212	4.037

n = 1,601

Participants (total n = 1,601) were randomly assigned to a condition of a two-group experimental design, including one group that followed the Randomized Response (RR) procedure (n = 825) and one control group that was queried directly (n = 776). We sub-divided participants in the direct questioning (DQ) condition into two subgroups to test for differences between the standard and extended instructions (38 words (n = 379) and 97 words (n = 397)). The extended version additionally stressed the importance of truthful answers to gain relevant new insights and explicitly guaranteed confidentiality to respondents, which may serve as a signal that privacy concerns are taken seriously. We further sub-divided participants in the RR condition into two subgroups to test for differences between a physical randomization device (n = 382) and a virtual randomization device (n = 443). In the former group, respondents were contacted prior to the survey and asked to obtain a die before completing the online questionnaire at their PC. The physical die may provide an increased level of privacy protection because respondents may suspect that the outcomes of the virtual die may be stored and traced. The results are presented in Table A.2.2.

Table A.2.2

Influence of instructions and randomization device

	Influence on Piracy Intention		
Predictors	*Model 1*	*Model 2*	*Model 3*
Structural parameters			
Intercept (β_0)	**–0.708**	**–1.153**	–0.442
Questioning technique (RR = 1) (β_{RR})	**0.575**		**0.475**
Questioning technique (DQ = 1) (β_{DQ})		**–0.602**	
Questioning technique interactions			
DQ x Extended wording ($\beta_{DQ,\ extended}$)		0.035	
RR x Physical die ($\beta_{RR,\ phsical}$)			**0.217**
Latent class probability (κ)			
Non-compliance (%)	**12.0**	**12.0**	**11.9**

Notes. Estimates in bold do not contain 0 in their 95% credible interval. All tests are two-sided tests. n = 1,601.

Model 1 presents the baseline model with the group membership as the sole predictor and shows that higher piracy scores are obtained under RR (β_{RR} = 0.575, $p < 0.05$). Model 2 includes an additional indicator for participants in the extended wording condition. Because we do not find a significant differences with respect to reported piracy intentions ($\beta_{DQ,\ extended}$ = 0.035, $p > 0.05$), we conclude that differences between the DQ and RR groups are not merely caused by the extended wording used in the RR group. Finally, Model 3 tests the effect of using a physical versus an electronic randomization device. Although both devices yield significantly higher scores compared to DQ, it can be seen that the physical die leads to even higher scores ($\beta_{RR,\ physical}$ = 0.218, $p < 0.05$). This finding suggests a trade-off between an increase in the perceived level of privacy protection and practical considerations (e.g., controllability of non-adherence, costs). Because both devices yield acceptable results, we follow previous studies (e.g., Böckenholt and Van der Heijden 2007; De Jong, Pieters, and Stremersch 2012) and opt for the electronic die in our main study for practical considerations.

Appendix 3: Simulation study

In the simulation study, we simulate data for the two latent variables θ_{1i} and θ_{2i} in our model, assuming that we know their true values and assuming a scale variance of one for each component. When additionally imposing structural models onto the means of the latent constructs, the model can be specified as

$$\begin{gathered}\begin{pmatrix}\theta_{1i}\\ \theta_{2i}\end{pmatrix} \sim MVN\left(\begin{bmatrix}\mu_{1i}\\ \mu_{2i}\end{bmatrix}, \begin{bmatrix}1 & \rho\\ \rho & 1\end{bmatrix}\right)\\ \mu_{1i} = \beta_{0,1} + \beta_{1,1}X_i \qquad ,\\ \mu_{2i} = \beta_{0,2} + \beta_{1,2}X_i + \gamma\theta_{1i}\end{gathered} \tag{A.3.1}$$

such that the expected mean of θ_2 depends on θ_1. The random error component of θ_1 is allowed to correlate with the structural error in the regression of θ_2 on θ_1, which represents the regressor-error correlation with θ_{1i}, an endogenous predictor. In the proposed modeling framework, the within-subject correlation can absorb such a regressor-error correlation.

We can rewrite the equation A.3.1, by using the mean term of θ_1 as the manifest predictor for θ_{2i} such that the random error component of θ_1 is included in the structural error term. It follows that,

$$\begin{gathered}\begin{pmatrix}\theta_{1i}\\ \theta_{2i}\end{pmatrix} \sim MVN\left(\begin{bmatrix}\mu_{1i}\\ \mu_{2i}\end{bmatrix}, \begin{bmatrix}1 & \gamma+\rho\\ \gamma+\rho & 1+\gamma^2+2\gamma\rho\end{bmatrix}\right)\\ \mu_{1i} = \beta_{0,1} + \beta_{1,1}X_i \qquad ,\\ \mu_{2i} = \beta_{0,2} + \beta_{1,2}X_i + \gamma\left(\beta_{0,1} + \beta_{1,1}X_i\right)\end{gathered} \tag{A.3.2}$$

such that parameters γ and ρ are included in the covariance between both latent variables.

When ignoring the within-subject correlation, the model is unable to control for the defined regressor-error correlation. This restricted model is represented by

$$\begin{pmatrix} \theta_{1i} \\ \theta_{2i} \end{pmatrix} \sim MVN\left(\begin{bmatrix} \mu_{1i} \\ \mu_{2i} \end{bmatrix}, \begin{bmatrix} 1 & \gamma \\ \gamma & 1+\gamma^2 \end{bmatrix} \right)$$
$$\mu_{1i} = \beta_{0,1} + \beta_{1,1} X_i \quad . \tag{A.3.3}$$
$$\mu_{2i} = \beta_{0,2} + \beta_{1,2} X_i + \gamma\left(\beta_{0,1} + \beta_{1,1} X_i\right)$$

The model captures the effect of the mean term of the endogenous predictor on θ_2, since a covariance term of γ is specified and a variance component of γ^2 is added, but it fails to include the effect of the person-specific random component of θ_1. To demonstrate the benefits of the proposed simultaneous modeling approach, we compare the results of the proposed model to this naïve model, which does not account for the within-subject residual correlation (equation A.3.3). We refer to this model as the baseline model.

Appendix 4: Test of unidimensionality

To assess whether multiple factors underlie the manifest piracy and purchase items, we fitted the multidimensional randomized item response (MRIRT) model as suggested by Fox, Klein Entink, and Avetisyan (2013). The MRIRT model assumes that more factors can explain the item responses in a compensatory or non-compensatory way. Therefore, let $\boldsymbol{\theta}_i$ denote the latent factors of subject *i*, and $\mathbf{A}_k$ the factor loadings of item *k*. The probability of a randomized response *c* to item *k* of subject *i* is given by

$$P\left(Y_{ik}=c \middle| \boldsymbol{\theta}_i,\mathbf{A}_k,b_k\right)=p_1\left[\Phi\left(\mathbf{A}_k^t\boldsymbol{\theta}_i-\tau_{kc-1}\right)-\Phi\left(\mathbf{A}_k^t\boldsymbol{\theta}_i-\tau_{kc}\right)\right]+\left(1-p_1\right)p_2, \qquad \text{(A.4.1)}$$

where a multivariate normal model is assumed for the latent factors. For the direct-questioning responses, p_1 was set to one. The complete specification of the model and the estimation method can be found in Fox, Klein Entink, and Avetisyan (2013).

We fitted a two-factor MRIRT model to investigate whether a single factor underlies the piracy and the purchase item responses. We identified the factors by fixing two item loadings of each scale to one. The estimated factor loadings were standardized by dividing each loading with the average item loading. The estimated standardized factor loadings are presented in Table A.4.1. The results show that the piracy intention items relate to the first factor and purchase intention items to the second factor. We conclude that the MRIRT analysis confirms the unidimensionality of both scales. The estimated correlation between both factors is approximately 0.28:

$$Cov(\mathbf{A}^t)=\begin{pmatrix}0.92 & 0.28\\ 0.28 & 0.99\end{pmatrix}$$

Table A.4.1

Factor loadings of the Piracy and Purchase Intention Items

Measurement items	$\mathbf{A}_k^1$	$\mathbf{A}_k^2$
Piracy Intention Items		
Item 1: Download files via BitTorrent	0.999	0.017
Item 2: Download files via other P2P-networks	0.997	0.075
Item 3: Upload/share files via file-sharing networks	0.999	0.032
Item 4: Download files via newsgroups/Usenet	0.995	0.101
Item 5: Download files via sharehoster or FTP server	0.994	0.104
Item 6: Upload/share files via sharehoster or FTP server	0.999	0.046
Item 7: Download files via blogs or forums	0.997	0.072
Item 8: Rip files from audio streams	0.996	0.088
Item 9: Rip files from video streams	0.999	0.039
Item 10: Obtain files via instant messaging or email	0.999	0.005
Item 11: Obtain files via media storage devices	0.995	0.097
Item 12: Share files via instant messaging, email or storage devices	0.990	0.140
Item 13: Use VPN services for privacy protection	1.000	0.000
Item 14: Purchase counterfeit CDs	0.999	–0.011
Item 15: Purchase unlicensed MP3s	0.995	0.102
Item 16: Sell unlicensed music for a profit	1.000	0.000
Purchase Intention Items		
Item 1: Purchase likelihood	0.000	1.000
Item 2: Purchase frequency	0.000	1.000
Item 3: Usage of paid channels for music consumption	0.039	0.999
Item 4: Usage share of paid channels (most music consumption)	–0.076	0.997
Item 5: Usage share of paid channels (all music consumption)	–0.181	0.983
Item 6: Spending intention	–0.039	0.999
Item 7: Spending intention compared with others	0.163	0.986
Item 8: Spending intention as part of disposable income	0.246	0.969
Item 9: Spending amount (planned)	0.052	0.999

n = 3,246

Appendix 5: WinBUGS code multivariate IRRT

```
######  WinBUGS code for multivariate IRRT model
######  theta[i, j] = person-specific piracy and purchase parameters
######  tau[k, c] = scale-, item- and category-specific discrimination parameters
######  a[k] = scale- and item-specific discrimination parameters
######  p1 = probability that respondents are instructed to give an honest answer
######  p2 = probability of a forced response
######  p3 = latent class probability to identify structural non-adherence (if applicable)
######  delta = effect of randomized response technique
######  gamma = effect of piracy intentions on purchase intentions
######  beta1[] = vector of predictor effects on piracy intentions
######  beta2[] = vector of predictor effects on purchase intentions
######  beta01 = intercept in the regression on piracy intentions
######  beta02 = intercept in the regression on purchase intentions
######  p[i, k, c] = probability of a response to item k in category c in the graded IRT model

######  Specification of interdependent person-specific piracy and purchase parameters with structural models
######  imposed on their means
model
        {
        for(i in 1:(N1+N2)){
                theta[i,1]  ~ dnorm(mvu1[i], 1)
                theta[i,2]  ~ dnorm(mvu2[i], rho)
                mvu1[i] <- beta01 + delta*RR[i] + inprod(cov[i,],beta1[])
                mvu2[i] <- beta02 + gamma*(theta[i,1] - mvu1[i]) + inprod(cov[i,],beta2[])
                }
######  Specification of graded IRT model for the DQ group (piracy items)
        for (i in 1:N1){
                for (k in 1:16) {
                        for (c in 1 : (C-1)) {
                                Q[i, k, c] <- phi( a[k]*( tau[k, c] - theta[i,1] ) )
                        }
                p[i, k,1] <- Q[i, k,1]
                p[i, k,2] <- Q[i, k,2] -Q[i, k,1]
                p[i, k,3] <- Q[i, k,3] -Q[i, k,2]
                p[i, k,4] <- Q[i, k,4] -Q[i, k,3]
                p[i, k,5] <-  1-Q[i, k,4]

                Y[i, k]~dcat(p[i, k,])
                }
######  Specification of graded IRT model for the DQ group (purchase items)
                for (k in  17:K) {
                        for (c in 1 : (C-1)) {
                                Q[i, k, c] <- phi( a[k]*( tau[k, c] - theta[i,2] ) )
                        }
                p[i, k,1] <- Q[i, k,1]
                p[i, k,2] <- Q[i, k,2] -Q[i, k,1]
                p[i, k,3] <- Q[i, k,3] -Q[i, k,2]
                p[i, k,4] <- Q[i, k,4] -Q[i, k,3]
                p[i, k,5] <- 1-Q[i, k,4]

                Y[i, k]~dcat(p[i, k,])
                        }
                }
```

```
###### Specification of graded IRT model for the RR group (piracy items)
        for (i in (N1+1):(N1+N2)) {
                for (k in 1:16) {
                        for (c in 1 : (C-1)) {
                                Q[i, k, c] <- phi( a[k]*( tau[k, c] - theta[i,1] ))
                                }
                p[i, k,1] <- mem[i] + (1-mem[i])*(p1 * Q[i, k,1] + p2 * 0.16)
                p[i, k,2] <- (1-mem[i])*(p1 * (Q[i, k,2] -Q[i, k,1]) + p2 * 0.16)
                p[i, k,3] <- (1-mem[i])*(p1 * (Q[i, k,3] -Q[i, k,2])  + p2 * 0.16)
                p[i, k,4] <- (1-mem[i])*(p1 * (Q[i, k,4] -Q[i, k,3]) + p2 * 0.16)
                p[i, k,5] <- (1-mem[i])*(p1 * (1-Q[i, k,4]) + p2 * 0.36)

                Y[i, k]~dcat(p[i, k,])
                }
###### Specification of graded IRT model for the RR group (purchase items)
                for (k in 17:K) {
                        for (c in 1 : (C-1)) {
                                Q[i, k, c] <- phi( a[k]*( tau[k, c] - theta[i,2] ))
                        }
                p[i, k,1] <- Q[i, k,1]
                p[i, k,2] <- Q[i, k,2] -Q[i, k,1]
                p[i, k,3] <- Q[i, k,3] -Q[i, k,2]
                p[i, k,4] <- Q[i, k,4] -Q[i, k,3]
                p[i, k,5] <-  1-Q[i, k,4]

                Y[i, k]~dcat(p[i, k,])
                        }
                mem[i] ~ dbern(p3)
                }

###### Prior specification
        for (k in 1:K) {
        al[k]~dnorm(0,1)
        a[k]<- exp(al[k])
        tau[k,1] <- mu[k]
        tau[k,2] <- tau[k,1] + exp(mu2[k])
        tau[k,3] <- tau[k,2] + exp(mu3[k])
        tau[k,4] <- tau[k,3] + exp(mu4[k])
        mu[k] ~ dnorm(-1,0.1)
        mu2[k] ~ dnorm(0,.5)
        mu3[k] ~ dnorm(0,.5)
        mu4[k] ~ dnorm(0,.5)
        }
p3 ~ dbeta(1,1)
beta01 ~ dnorm(0,1.0E-1)
beta02 ~ dnorm(0,1.0E-1)
delta ~ dnorm(0,1.0E-1)
gamma ~ dunif(-1,1)
rho <- 1/(1-pow(gamma,2))
for(k in 1:16)  {beta1[k] ~ dnorm(0,.5)}
for(k in 1:16)  {beta2[k] ~ dnorm(0,.5)}
}

###### Initial values
list(mu2=c(0, 0, 0, 0, 0, 0, 0, 0, 0, 0,0, 0, 0, 0, 0, 0,0,0,0,0,0,0,0,0,0,0), mu3=c(0, 0, 0, 0, 0, 0, 0, 0, 0, 0,0, 0, 0, 0, 0,
0,0,0,0,0,0,0,0,0,0,0), mu4=c(0, 0, 0, 0, 0, 0, 0, 0, 0, 0,0, 0, 0, 0, 0, 0,0,0,0,0,0,0,0,0,0,0), mu=c(0, 0, 0, 0, 0, 0, 0, 0,
0, 0,0, 0, 0, 0, 0, 0,0,0,0,0,0,0,0,0,0,0), al=c(0, 0, 0, 0, 0, 0, 0, 0, 0, 0,0, 0, 0, 0, 0, 0,0,0,0,0,0,0,0,0,0,0), delta =
0,beta1=c(0, 0, 0,0,0, 0, 0,0,0, 0, 0,0,0, 0, 0,0), beta2=c(0, 0, 0,0,0, 0, 0,0,0, 0, 0,0,0, 0, 0,0),  gamma=0, be-
ta01=0, beta02=0)
```

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2. Investigating the Influence of Country Characteristics on the Relationship between Internet Piracy and Music Sales: Evidence from a Longitudinal Cross-Country Study

Author:

Nils Wlömert

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Nils Wlömert

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Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

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1. Introduction

Since the rise of digital channels for media distribution toward the end of the last century, the global content industry has undergone a major transformation process. On the one hand, the near-zero marginal costs for reproducing digital goods in conjunction with a large decrease of the costs associated with content distribution have made (legitimate) online channels (e.g., music download services like Apple's iTunes) an attractive addition to the relatively costly production and distribution of physical media products (e.g., music CDs). On the other hand, the same characteristics of digital products have facilitated the illegal exchange of content among consumers at a global scale on the Internet (e.g., via file-sharing networks and file-hosting services) so that firms operating with digital products in online markets not only compete against each other but also with (illegitimate) piracy channels through which unauthorized copies are available free of charge (Bhattacharjee et al. 2007; Danaher et al. 2010; Liebowitz 2008; Oberholzer-Gee and Strumpf 2007).

Given this ambiguous situation for content owners, it is not surprising that academic and managerial interest has evolved around the two central questions (1) what is the effect of digital distribution channels – and illegitimate piracy channels in particular – on the legitimate demand for media products; and (2) what factors determine the relationship between piracy channels and legitimate distribution channels, and what measures should be taken to address the problem of Internet piracy most effectively?

One prominent example is the music industry, in which the rise of digital distribution channels has been paralleled by a sharp decline in physical album sales (IFPI 2013). The questions, how much of this decline is attributable to digital piracy and how sales would have developed in the absence of piracy have been studied widely over the past decade. The main conclusion that can be drawn from this literature is that Internet piracy represents a major threat to recorded music sales. That is, although the results are not fully consistent (e.g., Oberholzer-Gee and Strumpf (2007) do not find a significant effect), the majority of empirical studies supports the notion that piracy channels negatively affect the demand from legitimate distribution channels (see Danaher, Smith, and Telang (2013b) for a detailed discussion of the existing literature). With respect to the moderators of this cannibalization effect, extant research is less conclusive. In particular, existing research is largely focused on surveys of convenience samples, typically college students, in an attempt to explain the variation in piracy intentions at the individual level (e.g., Miyazaki, Aguirre Rodriguez, and Langenderfer 2009; Sinha, Machado, and Sellman 2010; Sinha and Mandel 2008; Taylor, Ishida, and Wallace 2009). However, considering that unauthorized copying takes place at a global scale, it is likely that piracy behavior is influenced by country characteristics, such as policy efforts and cultural backgrounds. For example, how can we explain the fact that music sales experienced a much steeper decline in some countries than in other countries (IFPI 2013)? Because Internet piracy is a global phenomenon, it is not obvious why piracy effects should be different across countries. Despite the generally recognized relevance of this question, existing research at the country level is almost exclusively focused on main-effects relationships but is not systematically focused on explaining the cross-country variation in Internet piracy's impact on music sales (e.g., Hui and Png 2003; Peitz and Waelbroeck 2004; Zentner 2005).

To address this research gap, we compile a longitudinal dataset at the macro level, comprising recorded music sales from a sample of 38 countries over a period of 15 years (from 1996 to 2010). Using Internet adoption and the speed of the Internet connection as proxies for Internet piracy, we rely on a fixed-effects panel data estimator to assess the effect of Internet piracy on music sales. Our main interest is to investigate how country characteristics can explain the variation in the piracy effect across countries. To that end, we collect an additional set of country-level variables, which we expect to moderate the effect of piracy on sales. These variables broadly map into four building blocks: (1) policy, (2) global connectedness, (3) infrastructure and interpersonal communication, and (4) social norms. We then perform moderator analyses to ascertain the influence of these country characteristics on the relationship between piracy and music sales.

Within the domain of piracy research our study is most closely related to the body of literature that investigates the effect of Internet piracy on media sales aggregated at the market level (e.g., Hui and Png 2003; Liebowitz 2008; Smith and Telang 2010; Zentner 2005; Zentner 2009). Our research makes three important contributions to this literature. First, and most importantly, we indentify factors that can explain cross-country variation in cannibalization effects due to Internet piracy. In particular, our results demonstrate that the degree of cannibalization is lower in countries with sound economic policies that aim to improve the functioning of the legal system, market access, and regulatory efficiency. We further find a country's global connectedness to be a double-edged sword for the music industry because the emergence of a global consumer culture is conducive to the music industry's global brand positioning strategy, while simultaneously leading to stronger cannibalization effects due to piracy. Moreover, our results provide evidence of stronger cannibalization effects in countries that exhibit a high degree of openness to change, as well as in highly urbanized countries in which the penetration potential of file-sharing networks is high. Second, our dataset is one of the first to include sales from both physical formats (i.e., CDs, LPs, MCs) and digital formats (i.e., track- and album-downloads) in the dependent variable. In contrast, previous research has mostly focused on a time when no legitimate digital sales channels were available (e.g., Hui and Png 2003; Peitz and Waelbroeck 2004). However, since then, the industry has introduced several legitimate online content offers (e.g., iTunes, Amazon MP3) in an attempt to provide alternatives to illegal file-sharing so that in order to determine the net effect of Internet piracy on music sales it is important to control for legitimate downloads in the dependent variable. Third, another important characteristic of our comprehensive dataset is that it allows us to include various important control variables, which is crucial to identify the effect of piracy on sales. For example, we find that, besides illegal piracy, the unbundling of music products via legitimate download services (i.e., consumer purchasing single tracks rather than full albums; Elberse 2010) has had a substantial negative effect on overall music sales. When accounting for the various control variables, our estimates suggest that the sales decline due to Internet piracy amounted to 36% in 2010.

The results of our analyses provide important insights for policymakers and managers in the music industry in order to judge the effectiveness of anti-piracy measures. However, because the effects of digitization on the music industry are typically visible earlier compared to other industries, the results are also relevant for managers in adjacent industries, such as the movie or book industry, in which similar developments are likely to occur with a certain delay (IFPI 2012; Langenderfer and Cook 2001; Smith and Telang 2010).

We structure the remainder of this article as follows. In the next section, we will discuss our conceptual model and provide an overview of the relevant existing literature. In section 3 we describe our dataset, which is followed by the explanation of our empirical approach in section 4. We summarize the results from our analyses in section 5 and conclude with a discussion of the results and implications in section 6.

2. Theoretical background, related literature and research contribution

Figure 1 displays our conceptual framework. In this section, we will develop and explain our conceptual rationale for the direction of the expected effects based on the theoretical and empirical literature.

>>> Figure 1 about here <<<

2.1. The impact of piracy on music sales

Theoretically, piracy may either negatively or positively influence the legitimate demand for recorded music products. This is because on the one hand illegal downloads represent a close substitute for a largely homogenous product at zero monetary costs, suggesting that there should be a negative (i.e., cannibalistic) relation between piracy and sales. On the other hand, music is an experience good, and digital piracy may stimulate legitimate demand because it helps to reduce uncertainty about the quality of an album or a song before purchasing (Chellappa and Shivendu 2005). Since theory does not make clear predictions about which of these effects is prevalent, the question of how digital piracy affects music sales must be addressed empirically.

Existing empirical research examined this question using three different identification strategies, i.e., (1) by relying on individual-level (survey) data, (2) by exploiting exogenous shocks to the demand at the product level, or (3) by analyzing variation in demand aggregated at the country or market level. Across the different identification strategies, the majority of studies consistently report at least some evidence for a negative effect of piracy on sales, although no consensus has yet been achieved regarding the magnitude of this effect (Danaher, Smith, and Telang 2013b). Because the focus of our analysis is on cross-country heterogeneity, the identification strategy pursued herein relies on (3), i.e., cross-country variation. Relying on aggregate sales of recorded music products as the unit of analysis has the advantage that it alleviates potential endogeneity problems associated with product-level analysis, i.e., the time-varying unobserved popularity of an artist may influence both piracy *and* sales. Using actual sales data also avoids the difficulties that are inherent to cross-cultural survey research (e.g., De Jong, Steenkamp, and Fox 2007; De Jong, Steenkamp, and Veldkamp 2009), especially with respect to socially desirable responding, which may induce bias because piracy is a socially and legally sensitive topic (De Jong, Pieters, and Stremersch 2012; Kwan, So, and Tam 2010; Steenkamp, De Jong, and Baumgartner 2010). Table 1 summarizes the results of the existing published peer-reviewed studies that fall into category (3).

>>> Table 1 about here <<<

With respect to the dependent variable, all existing published studies analyze the effect of piracy on physical media products. Furthermore, all listed studies focus on the music market (i.e., music CDs) with the exception of Smith and Telang (2010), who focus on the market for motion pictures (i.e., movie DVDs). As can be seen, the present study accounts for both the various available physical music formats (i.e., CDs, LPs, MCs, CD-singles) *and* digital sales formats (i.e., digital track and album downloads).[1] Accounting for digital sales in the dependent variable is important to establish the net effect of digital piracy on sales, because legitimate downloads and physical music purchases are likely to be substitutes. That is, if digital sales were excluded from the analyses, the results would overestimate the effect of piracy on sales to the extent that legitimate downloads replace demand from other distribution channels.

The sample size of the existing studies varies from 16 to 28 countries, with two studies focusing on a set of "designated metropolitan areas" (DMAs) within one country, i.e., Liebowitz (2008) and Smith and Telang (2010) each analyze sales from 99 DMAs in the U.S.. The observation period ranges from three years to seven years. Within these periods Peitz and Waelbroeck (2004), Liebowitz (2008) and Zentner (2005) each consider a regression equation in differences in order to analyze the changes in sales between a period before and after the existence of file-sharing[2], i.e., they analyze the difference between the years 2002 and 1998, the years 2003 and 1998 and the sum of sales in the years 2001 and 2002 and

[1] Besides the present study, Zentner (2009) in his working paper uses the overall sales volume (i.e., including digital formats) as the dependent variable.

[2] The first file-sharing network (i.e., Napster) was introduced in 1998. Since then, new technologies that further facilitated the exchange of content among Internet users have emerged, such as BitTorrent and sharehoster.

the sum of sales in the year 1997 and 1998, respectively. In contrast, Hui and Png (2003) and Pons and García (2008) use a fixed-effects panel data model to investigate the relationship between piracy and sales and Smith and Telang (2010) use a model in first differences to validate the findings from a fixed-effects specification. Investigating the observation periods reveals that most studies use data from a time before the existence of legitimate digital distribution channels (iTunes was launched in 2003 in the U.S.) and in the case of Hui and Png (2003) even before the advent of file-sharing networks. Table 1 makes it clear that our dataset comprises information both from the time before the introduction of the first file-sharing network in 1998 as well as from the time after the industry introduced legitimate digital music services in an attempt to address the legitimate demand for digital music products and to provide alternatives to illegal file-sharing.

With respect to the measurement of piracy, researchers have pursued different strategies. Hui and Png (2003) use CD piracy rates published by the IFPI as a measure of piracy. To circumvent endogeneity problems, the authors use instrumental variable techniques with piracy rates from the markets for music cassettes and software serving as exogenous instruments. Peitz and Waelbroeck (2004) use information regarding "the percentage of adult Internet users who downloaded music files in MP3 format from the Internet at least once," obtained from a 2002 cross-national survey as a proxy for file-sharing. The underlying assumption is that file-sharing was essentially not existent before 1998 so that the observation in levels represents a valid proxy for the variable in first differences. Given the unavailability of industry-specific Internet piracy rates, all remaining studies either use Internet or broadband Internet penetration as a proxy for file-sharing. Similar to an experiment, these studies assess the changes in sales after an increase in (broadband) Internet adoption compared to the time before the increase occurred and relative to those countries, in which there was no change in Internet adoption. Because (broadband) Internet adoption and music sales are unlikely to be influenced by common unobserved factors, this approach circumvents potential endogeneity concerns that may arise when direct measures of pirated quantities are used. One possible limitation of this approach, however, is that broadband penetration may of course also proxy for other forms of online entertainment, which would lead researchers to overestimate the impact of piracy on sales. Of the reviewed studies listed in Table 1 only Liebowitz (2008) accounts for this possibility by estimating the "entertainment-diversion" impact of the Internet on an activity that is assumed to be related to music purchasing (i.e., television viewing) and uses this estimate as a proxy for the portion of sales that has been substituted by the Internet as a new entertainment medium, rather than file-sharing. In the present study, we follow Zentner (2009) and account for this possibility by using broadband Internet penetration as a proxy for Internet piracy, while conditioning on dial-up Internet penetration (see Zentner (2009) for a discussion of this approach). The underlying assumption is that while sharing large quantities of music files requires high bandwidth (i.e., broadband access), other entertainment activities on the web (e.g., web-browsing, emailing, social networking) require less bandwidth (i.e., dial-up access).

Table 1 also reports the percentage reduction in sales due to Internet piracy based on the reported estimates for the respective observation periods. As can be seen, all studies that focus on the music market find a negative effect of piracy on sales. In contrast, Smith and Telang (2010) find a positive effect of broadband penetration in the market for movie DVDs, which the authors attribute to the fact that their study focuses on a time when it was technically difficult to download large media files (e.g., motion pictures) from the Internet; i.e., during that time the Internet appears to have rather had a promotional effect on sales. The results from the music market further provide support for notion that the piracy effect was reinforced after file sharing networks became available, i.e., Hui and Png (2003) report a sales decline of 7% due to piracy in the four years before the existence of file-sharing platforms, whereas the other studies estimate higher percentage declines in the time after 1998. Considering that music sales continued to decline until 2010, it appears logical that the estimated overall cannibalization effect is larger in the present study compared to most existing studies.

In summary, the reviewed macro-level empirical studies consistently report a negative effect of piracy on music sales. Thus, we expect a negative (i.e., cannibalistic) relation between Internet piracy (via broadband Internet penetration) and sales.

2.2. Control variables

For the identification of the piracy effect it is vital that the analyses include as many control variables as possible to rule out alternative explanations for the changes in sales over time. As Figure 1 shows, we group the control variables into four categories, i.e., (1) information and communication technology (ICT) diffusion, (2) marketing, (3) economy, and (4) policy.

2.2.1. ICT diffusion. One important factor that is likely to influence the cross-country variation in music sales is the substitution from other forms of entertainment. For example, Peitz and Waelbroeck (2004) include a measure of DVD player diffusion and Pons and García (2008) include a measure of videogame console penetration as controls in their analyses, while Liebowitz (2008) accounts for the entertainment-diversion impact of the Internet. To account for potential substitution of sales through the Internet as a new entertainment medium, we follow Zentner (2009) and include country-specific Internet penetration rates that include dial-up Internet access in addition to the broadband Internet penetration in our analyses. Furthermore, we control for cell phone subscriptions that may also represent a substitute for music purchases (Zentner 2009). Because we assume that these alternative entertainment options compete for the consumer's limited time and entertainment budget, we expect the Internet and cell phone variables to be negatively related to music sales.

2.2.2. Marketing. Arguably, one of the most important marketing variables that may affect the sales of any product is price (e.g., Bijmolt, van Heerde, and Pieters 2005). Consequently, the price of legitimate music products will be considered as a control variable in our analyses. Surprisingly, as Table 1 shows, only two previous macro-level studies control for the variation in prices over time. In both studies, price was found to be significantly (negatively) related to music sales. Thus, we expect a negative relation between price and sales. Another important factor, which has been shown to negatively affect the overall sales volume, is the unbundling of music products, i.e., consumers purchasing single tracks rather than whole albums via digital distribution channels. For example, Elberse (2010) in her analyses of product-level data finds that approximately one-third of the reduction in music sales between January 2005 and April 2007 in the U.S. is attributable to the unbundling of music in online channels. Thus, we expect the unbundling of music products to negatively affect overall music sales. This variable has not been considered as a control variable in previous macro-level research.

2.2.3. Economy. Economic indicators are likely to exert an influence on sales levels over time. Following previous research, we include income as an explanatory variable in our model, which we expect to be positively related to music sales. It is further likely that the effect of income on sales also depends on the income level. More precisely, we expect that the income effect will be stronger (positive) for lower income levels compared to higher income levels. To account for such non-linear effects, we additionally include the squared income as an explanatory variable in our analyses. Furthermore, we include a measure of unemployment in an attempt to control for additional developments in the economic environment. Because economic hardship due to unemployment is likely to reduce consumers' budget for entertainment products, we expect that unemployment is negatively related to music sales.

2.2.4. Policy. Finally, political indicators may play a role in explaining variations in music sales over time. Specifically, we expect that (1) sound economic policies, and (2) the continuity of policy efforts to positively influence music sales. The rationale for this expectation is that economic policy efforts that aim to create a sound business environment, e.g., by reducing trade barriers, improving market access, and strengthening the functioning of the legal system, are an important characteristic for market participants – especially in industries that heavily rely on the exploitation of international copyrights (as it is the case in the music industry; IFPI 2013). The policy continuity is an essential component of a country's legal framework, which reduces risk for market participants and ensures stability. These control variables have not been considered by previous research.

2.3. Moderator effects

Because the negative effect of piracy on sales has been established before, the main focus of our analyses is on the heterogeneity in the piracy effect across countries. As Table 1 shows, only one of the reviewed studies includes moderator analyses, i.e., Pons and García (2008) test the moderating effect of a country's legal origin and find that the substitution effect is weaker in common law countries compared with civil law countries. However, further empirical evidence regarding managerially relevant factors that can explain cross-country differences in the piracy effect remains scarce. Thus, we will derive our expectation regarding the moderator effects based on findings from adjacent research areas.

2.3.1. Policy. With respect to the group of political indicators, we expect that (1) the existence of sound economic policy efforts, and (2) the continuity of policy efforts will moderate the effect of piracy on music sales.

We expect (1) to be an important factor for two main reasons. First, policy efforts that aim to strengthen IP protection laws and improve the enforcement of such laws should make the misuse of the Internet as a source for unauthorized copies relatively less attractive compared with legitimate distribution channels. This expectation is in line with the utility maximization perceptive on decision making in the context of illegal activities, which suggests that a rational person weighs the costs of committing piracy against the utility s/he derives from it, i.e., increasing the risk of getting punished will decrease the utility of piracy (Becker 1968; Ehrlich 1981). In support of this notion, Danaher, Smith, and Telang (2013a) find that a country which increased the level of IP protection by means of a new legislation subsequently experienced a larger increase in digital music sales compared to a group of control countries. The authors attribute this finding to a shift in demand from illegal toward legal distribution channels. Second, we expect that economic policy efforts that aim to improve market access, the functioning of the legal system, and the regulatory efficiency will provide incentives for providers of legitimate digital music services (e.g., iTunes) to enter a given market. The existence of attractive legal alternatives in turn has been shown to make illegitimate piracy channels relatively less attractive (Danaher et al. 2010; Sinha and Mandel 2008). Thus, we expect that sound economic policies will attenuate the effect of piracy on sales, i.e., the effect will be weaker in countries with effective economic policies.

Furthermore, we expect that factor (2), i.e., the continuity of policy efforts, will attenuate the piracy effect in a similar way for two main reasons. First, the transmission of IP policy changes to the society requires time because people need to get accustomed to the changes. We propose that countries with a high degree of continuity in its policy efforts will adapt quicker to changes that may be necessary due to current regulatory objectives and provide clearer guidance with respect to the legitimacy of certain activities. Second, a high degree of continuity in a country’s policies creates trust among investors and reduces risk for market participants, which in turn should foster the emergence of an efficient market for legitimate digital music. Thus, we expect that the effect of piracy on sales will be weaker in countries that exhibit a high degree of continuity in its policy efforts.

2.3.2. Global connectedness. With respect to a country's global connectedness, we consider two variables in our analyses, i.e., (1) social globalization, and (2) internet restrictions. Social globalization refers to the social-cultural dimension of globalization in terms of (i) personal contacts among people living in different countries, (ii) information flows between people from different countries, as well as (iii) the degree of cultural proximity (Dreher, Gaston, and Martens 2008; Martens, Dreher, and Gaston 2010). We expect this variable to be an important factor for two main reasons.

First, we argue that a high degree of social globalization facilitates the diffusion of innovations in a society, because the above conceptualization directly pertains to the cross-national transmission of information, which has been identified as a key driver of a country's innovativeness (e.g., Gatignon, Eliashberg, and Robertson 1989; Talukdar, Sudhir, and Ainslie 2002). Gatignon, Eliashberg, and Robertson (1989) use the related term "cosmopolitanism," while Talukdar, Sudhir, and Ainslie (2002) in their cross-national diffusion analysis consider various related variables grouped under the category "consumer's access to product related information". All these conceptualizations have in common that they refer to the extent to which information about innovations are transmitted across national boundaries, which is associated with a higher propensity to innovate. Because the peer-to-peer technology represented an innovation when it was first introduced in 1998, we propose that socially globalized countries will exhibit a higher propensity to switch to file-sharing networks as an alternative source of music consumption, i.e., we expect that the effect of piracy on sales will be stronger in countries that exhibit a high degree of social globalization.

A second possible explanation comes from the globalization literature. The globalization of the marketplace and the homogenization of consumer preferences across countries have been discussed in the marketing literature since the early 1980s (Levitt 1983). Some researchers argue that, e.g., through the pervasiveness of global mass media and developments in ICT, globalization leads to the convergence of consumer preferences around the world to a "global consumer culture" and marketers increasingly address global demand through standardized products and brands (Alden, Steenkamp, and Batra 1999). The music industry traditionally operates in this way by investing in the development of superstars (i.e., "brands"), which are then marketed at a global level (Rosen 1981). As a result, the international exploitation of copyrights, primarily from the West, plays a crucial role in virtually all music markets around the globe (IFPI 2013).[3] The construct of "global consumption orientation" has been introduced as a measure of consumer preferences for global (versus local) products (Alden, Steenkamp, and Batra 2006), and consumers from different countries differ considerably in this respect (Steenkamp and De Jong 2010). We propose that the concept of social globalization reflects a country's global consumption orientation because the characteristics of a socially globalized society (e.g., easy access to international television programs and newspapers, a high degree of cultural proximity, many interpersonal contacts with foreigners) should facilitate the emergence of a global consumer culture.[4] Applied to our research context we argue that the music industry's global brand positioning strategy together with a country's global consumption orientation will lead to a higher degree of file-sharing, i.e., the more similar the tastes across borders, the higher the file-sharing propensity and consequently, the higher the potential for the cannibalization of legitimate demand. Thus, also from this perspective, we expect the negative effect of piracy on sales to be stronger in socially globalized societies.

[3] 48 of the Top 50 global best seller albums in 2010 were from western artists and more than 50% of the global music industry's revenue was from international repertoire (IFPI 2011b).
[4] The analyses of Steenkamp and De Jong (2010, p. 26) provide support for this proposition by showing that global consumption orientation is positively associated with the consumption of foreign mass media, social contacts with foreigners, as well as the interest in foreign lifestyles.

Following a similar line of argumentation we propose that factor (2), i.e., restricting information flows between countries, will (i) restrict an important source of external information that fosters the diffusion of innovation (i.e., file-sharing networks), and (ii) limit the opportunities for consumers to share music files over the internet, despite possible cross-country similarities in taste. With respect to the latter, Danaher and Smith (2014) find that restricting access to illegal material (via the shutdown of one major file-hosting service) has had a positive influence on the digital revenue of two major movie studios. Therefore, we expect that the effect of Internet piracy on sales will be weaker in countries in which restrictions are imposed on cross-country information flows.

2.3.3. Infrastructure and interpersonal communication. Previous research has established a link between the diffusion of innovations and the degree of interpersonal communication as well as the infrastructure development in a country (e.g., Gatignon, Eliashberg, and Robertson 1989; Talukdar, Sudhir, and Ainslie 2002). That is, the decision to adopt a new product or service depends on the interpersonal transmission of relevant information about the innovation as well as the penetration potential, which may be limited by infrastructural conditions. Because both factors are intertwined to some degree, we will discuss them here together. Specifically, we consider three variables in this group, which we assume to moderate the influence of piracy on sales, i.e., (1) urbanization, (2) mobility, and (3) female labor participation.

Regarding (1), we propose that the degree of urbanization, i.e., the percentage of the population living in urban agglomerations, is an important factor for two main reasons. First, we suggest that urban environments promote interpersonal communication due to the higher population density and that cosmopolitanism is more likely to be present in large cities. Therefore (cross-national) information will transmit quicker. Second, the penetration potential of file-sharing networks is likely to be higher in urban areas due to the superior infrastructural conditions (Talukdar, Sudhir, and Ainslie 2002). This should accelerate the diffusion file-sharing technologies as an alternative to existing distribution channels, also among the group of imitators, and reinforce the displacement of legitimate demand. Thus, we expect that the piracy effect will be stronger in countries that are characterized by a high degree of urbanization.

With regard to (2), it has been shown that a lack of mobility represents a barrier to the diffusion of innovations because it limits the degree of interpersonal communication (Gatignon, Eliashberg, and Robertson 1989). In contrast, the transmission of information about competing alternatives to existing distribution channels will be easier in countries which exhibit a high degree of mobility. Therefore, the displacement rate should be higher in these countries.

Finally, we consider the female labor participation rate, i.e., the share of women who are economically active, as a potential moderator for two reasons. First, this variable captures a country's openness to change with respect to key roles in a society that determine its economic success. This may proxy for a country's openness to change at a more general level. Second, we assume that this variable also proxies for the level of "heterophilous" influence within a society, i.e., influence that is transmitted among dissimilar people (Gatignon, Eliashberg, and Robertson 1989). The underlying assumption is that the diffusion of new services and competing alternatives to existing distribution channels requires persuasion and information, and this information is more likely to be transmitted through heterophilous influence. This proposition is in line with the notion that individuals are often influenced by contacts outside their personal network (i.e., "weak ties"), and that such less personal communication can have a stronger impact on information dissemination than communication within the personal network (i.e., strong ties; Goldenberg, Libai, and Muller 2001;

Granovetter 1973). Thus, we expect that the effect of piracy on sales will be stronger in countries with a high female labor participation rate.

2.3.4. Social norms. Finally, the role of social norms may help us to better understand the variation in piracy effects across countries. Previous research suggests a connection between the degree of individualism (versus collectivism) and the prevalence of piracy in a society (Gopal and Sanders 1998; Marron and Steel 2000; Shin et al. 2004; Yang et al. 2009). Hofstede (2001, p. 209) defines individualism as “a preference for a loosely-knit social framework in which individuals are expected to take care of their immediate families,” whereas collectivism “represents a preference for a tightly-knit framework in a society in which individuals can expect their relatives or members of a particular in-group to look after them”. According to Gopal and Sanders (1998), piracy represents a group activity in which individuals make copies available to all group members. Shin et al. (2004) propose that in collectivistic societies the sharing of resources with others is regarded as a social norm with which individuals comply in order to increase the overall welfare of the group. In addition, it has been suggested that individualism encourages social institutions that protect individual rights, whereas collectivism encourages institutions that emphasize recourse sharing (Marron and Steel 2000). Finally, there is considerable empirical evidence for a positive relationship between the degree of collectivism and piracy in a society (see Yang et al. 2009 for an overview). Based on these findings and because the sharing of unauthorized copies is largely facilitated by the characteristics of digital goods (i.e., low costs of reproduction and distribution), we expect that the effect of Internet piracy on sales will be weaker (stronger) in individualistic (collectivistic) countries.

3. Data, operationalization and sample

3.1. Data and operationalization

To operationalize the previously discussed variables, we combine data from various sources. Descriptive statistics and correlations for our model variables for the observation period from 1996 to 2010 and our sample of 38 countries are summarized in Tables 2 and 3.

>>> Table 2 about here <<<

>>> Table 3 about here <<<

3.1.1. Sales. We obtain data on recorded music sales from various issues of the IFPI's Recorded Industry in Numbers report. In these reports, the IFPI provides annual market information with respect to the sales of recorded music products in terms of both revenue and units for 49 countries.[5] The reported sales are subdivided into the various available formats (e.g., albums, singles) and also include sales of digital formats (i.e., digital album- and track-downloads) since 2004. To reflect the overall market development we consider the sales volume of all the available formats, i.e., including digital channels, which together accounted for 29% of the global sales volume in 2010 (IFPI 2011a). Thus, besides physical sales, our dependent variable includes information regarding legitimate downloads (e.g., iTunes), which enables us to estimate the net effect of Internet piracy on sales. Recall that accounting for digital sales is important so as not to overestimate the effect of piracy on sales because legitimate downloads and physical sales are likely to be substitutes. Furthermore, we focus on units, rather than revenue, because this measure is less likely to be influenced by exchange rate fluctuations of the local currencies against the US dollar over time. In addition, we compute the sales per capita by dividing the overall sales volume by the countries' population count for each year to account for changes in market size over time. Finally, taking the various different sales formats into account requires the standardization of the measurement

[5] We had to restrict our estimation sample to 38 of these countries due to missing data as we will discuss below.

units. Therefore, we assign weights to the formats in the following way. Every sold music album is assigned a weight of 1 (i.e., CD-, MC-, LP-, and digital albums). We follow the IFPI's official reporting practice and convert physical singles to album units by assigning a weight of 1/3 to every sold unit (i.e., 3 singles = 1 album; IFPI 2005). Following the same underlying logic, we convert digital track downloads to album units by assigning a weight of 1/10 to every downloaded track (i.e., 10 tracks = 1 album). By summing up the weighted units across the different formats we obtain the focal dependent variables for our analyses: the per capita music sales of country i in year t. The mean of this variable across countries and years is 1.28 units. Over the observation period, per capita sales decayed by 55% from 1.66 units in 1996 to .75 units in 2010. The sales development for the 38 analyzed countries is graphically depicted in Figure 2.

>>> Figure 2 about here <<<

3.1.2. Internet piracy. Because data on Internet music piracy rates is not available, we follow previous research and rely on Internet penetration as a proxy for file-sharing (e.g., Liebowitz 2008). Specifically, we use broadband Internet penetration as a proxy for piracy, while conditioning on dial-up Internet penetration, i.e., the speed of the Internet connection serves as the proxy for Internet piracy (see Zentner 2009). Information on broadband Internet penetration was collected from the World Bank's world development indicators databank. The variable is defined as the number of fixed broadband Internet subscribers per 100 people. The numbers are derived based on insights from the International Telecommunication Union, the World Telecommunication/ICT Development report and database, as well as World Bank estimates. The mean broadband Internet penetration over the observation period was 8.30%. Broadband penetration was zero in 1996 and 1997 and increased from 1% in 1998 to 21% in 2010 (see Figure 2).

3.1.3. ICT diffusion. Data on Internet penetration rates that include dial-up access and data regarding mobile cellular subscriptions were also collected from the World Bank's world development indicators databank. The definition and data sources are analogous to the broadband variable. The mean Internet (cell phone) penetration over the observation period was 35% (62%). Internet penetration increased from 4.05% in 1996 to 62.48% in 2010 (see Figure 2). The cell phone penetration was 9% in 1996 and increased to 110% in 2010.[6]

3.1.4. Marketing. Because we observe annual music sales in terms of both units and revenues, we are able to compute the average price per unit.[7] To do this, the revenue variable, which is measured in local currencies at current retail prices, is first inflation-adjusted using the country-level consumer price index from the World Bank with 2010 serving as the base year so that a comparison across years is possible. These inflation-adjusted values are then converted to US dollars at the official exchange rate for the year 2010 from the World Bank. The country- and year-specific retail revenue is then divided by the sold units. This yields the average retail price in constant 2010 US dollars of a sold unit in country *i* in year *t*. The mean price of a music album across countries and years was US$ 15.01. The average retail price has declined by approximately 28% over the observation period from US$ 16.78 in 1996 to US$ 12.14 in 2010, which appears realistic, considering the lower retail prices of digital music albums (e.g., 9.99 US$) compared to physical music products and the possibility that music companies adjusted prices in response to piracy (Hui and Png 2003).

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[6] The cell phone penetration rate may exceed 100% if consumers in a given country on average own more than one device.

[7] Note that revenues are reported in retail value before 2001, in retail and trade value from 2001 to 2005 and in trade value since 2006. The trade value "refers to record companies revenue, net of discounts, net of returns, net of taxes," whereas the retail value represents an "estimate of the final value paid by the consumer for the purchase of a music product, inclusive of relevant sales taxes and retailer markup" (IFPI 2005).We opt for retail values in our analyses to better reflect the prices that had to be paid by the consumer. To allow for a comparison across years, we convert the trade values for the years after 2005 to retail values using the country-specific average ratio between retail and trade value from 2001 to 2005 as the conversion factor. This ratio is highly consistent across years within countries with an overall mean of 1.55 and a mean absolute deviation of .043.

To control for the fact that an increasing level of single purchases may influence overall sales levels, we compute the share of single format sales in country *i* in year *t* as follows:

$$Unbundling_{it} = \frac{Single\ sales_{it}}{Overall\ sales_{it}}, \qquad (1)$$

where $Single\ sales_{it}$ refers to the single format sales volume (i.e., CD-singles and digital track downloads) and $Overall\ sales_{it}$ refers to the overall sales volume in country *i* in year *t*.

3.1.5. Economy. Data on per capita gross domestic product (GDP) and unemployment were collected from the World Bank's world development indicator databank. The GDP serves as a proxy for per capita income and is measured in '000 constant PPP adjusted 2005 US dollars. We opt for a PPP-based measure to allow for a more realistic comparison of the countries' income development over time relative to the other countries.[8]

3.1.6. Policy. In the previous section we formulated our expectations that economic policies will be relevant to our research context because they proxy for both the level of IP protection as well as the existence of a sound business environment. Thus, we needed a measure which covers both of these aspects and which is available for the whole observation period. The Economic Freedom Index is compiled annually by The Heritage Foundation in cooperation with The Wall Street Journal based on 10 quantitative and qualitative factors, grouped into the four categories (1) rule of law (i.e., property rights, freedom from corruption), (2) open markets, (3) regulatory efficiency, and (4) limited government (please see The Heritage

[8] We follow Talukdar, Sudhir, and Ainslie (2002) and rely on a PPP adjusted income measure to account for differences in prices across countries. This approach captures the true differences in purchasing potential of income across countries, especially when analyzing a diverse group of countries as it is the case here (The World Bank 1993; United Nations 1990). For example, if the value of a given domestic currency devalues by 50% against the US dollar, this country's GDP measured in US dollars will also decrease by halve. However, this does not necessarily mean that individuals in this country are worse off by 50% if the income and prices measured in domestic currency remain stable and imported goods are not crucial to the quality of life. We also estimate the model with other routine GDP measures (e.g., in constant US dollars using national deflators), which does not alter the conclusions.

Foundation (2014) for details). Thus, this measure represents a good candidate for our purposes.[9]

We validate whether this measure represents a valid proxy for the level of IP protection based on two alternative indices that both aim to capture the level of IP protection, but that are not available for the full observation period. First, the World Economic Forum's (WEF) annual survey of 15,000 executives from 138 countries includes a question pertaining to the IP protection under the second pillar "Political and Regulatory Environment" as part of its "Global Information Technology Report" (Dutta and Mia 2011). The question reads "How would you rate the intellectual property protection, including anti-counterfeiting measures, in your country? [1 = very weak; 7 = very strong]". This variable is available since 2002 and is positively correlated with the Economic Freedom Index ($r = .73$; $p < .001$; n = 342). Second, the Intellectual Property Rights Index (IPRI) is constructed annually based on secondary data from various sources and, besides IP rights, also captures physical property rights as well as the legal and political environment (Jackson 2011). The IPRI is available from 2006 and ranges from 0 to 10, with 10 indicating the strongest level of property rights protection. The high degree of correlation between the IPRI and the economic freedom measure of $r = .83$ ($p < .001$; n = 183) again indicates that the Economic Freedom Index constitutes a reasonable proxy for the level of IP protection.

As a measure of policy continuity, we used the Political Constraints Index proposed by Henisz (2000), which measures the feasibility of policy change in a country (please refer to Henisz (2000) for details). For example, Henisz (2002) shows that political environments that limit the feasibility of policy change, i.e., that exhibit a high degree of policy continuity, are an important driver of infrastructure investments.

9 An alternative measure of economic freedom is available from the Fraser Institute. Unfortunately, this measure is not available prior to the year 2000 on an annual basis, which is why we rely on the measure provided by The Heritage Foundation. However, we find that the indices are highly correlated ($r = .87$; $p < .001$; n = 418).

3.1.7. Global connectedness. We use the KOF index of social globalization as the first measure of a country's global connectedness (Dreher 2006; Dreher, Gaston, and Martens 2008; KOF 2014). The measure comprises various indicators that are grouped into three categories: (1) data on personal contacts (i.e., telephone traffic, transfers, international tourism, foreign population, and international mail), (2) data on information flows (i.e., internet, television, and newspapers), and (3) data on cultural proximity (i.e., number of McDonald's restaurants, number of Ikea shops, and trade in books) (please refer to Dreher, Gaston, and Martens (2008) for details). Moreover, we use the Freedom of the Press Index compiled by Freedom House to control for the degree to which a country's government imposes restrictions on information flows (see Freedom House (2014) for details).

3.1.8. Infrastructure and interpersonal communication. We operationalize the degree of urbanization, using data regarding "the population in urban agglomerations of more than 1 million," which is provided by The World Bank. Furthermore, we collect information regarding the "road sector energy consumption" and the "female labor participation rate," which were also retrieved from The World Bank, as proxies for the degree of mobility, as well as a country's openness to change and the level of heterophilous influence, respectively.

3.1.9. Individualism. Finally, we obtain our measure of the degree of individualism versus collectivism in a society from Hofstede (2014).

3.2. Sample

Overall, the IFPI reports contain data regarding the music sales of 49 countries. To ensure the validity of our results, we restrict our analyses to 38 countries for which we could obtain sufficient data with respect to the aforementioned variables during our observation period (i.e., 1996 - 2010). The time series of 11 countries exhibited gaps of 1/3 (i.e., 5 years) or more so that we discarded these countries from the analyses. Note, however, that the excluded countries are rather small music markets.[10] Based on the 2010 trade value, the 38 countries in our sample include the 20 largest music markets worldwide and together account for more than 95% of the global music industry's revenue (IFPI 2011b). Table 4 reports the mean per capita sales of the 38 countries over the observation period.

>>> Table 4 about here <<<

4. Model

To investigate the impact of piracy (via broadband Internet adoption) on music sales, we are interested in estimating the following regression model:

$$Sales_{it} = \delta Broadband_{it} + \beta X_{it} + \phi_t + u_{it}, \qquad (2)$$

where $Sales_{it}$ denotes the per capita sales of country i in year t, δ captures the effect of Internet piracy, β is a parameter vector capturing the effects of the country-specific time-varying controls, ϕ_t are time-specific fixed-effects (i.e., period dummies) controlling for common developments in sales over time, and $u_{it} = \eta_i + \varepsilon_{it}$, i.e., the error term consists of a country-specific component, η_i, and the idiosyncratic error, ε_{it}.

The first goal of our study is to obtain a consistent estimate for δ. One potential problem that may arise from estimating Equation (2) is that time-invariant unobserved country characteristics (fixed-effects), such as geography, culture and country specific demand shocks, which are contained in the country-specific error component, η_i, may be correlated with the explanatory variables. For example, if there were unobserved characteristics that drive both music sales and (broadband) Internet adoption the results would underestimate the effect of (broadband) Internet adoption on sales.

[10] The excluded countries are Bulgaria, Croatia, Ecuador, Hong Kong, Peru, Russia, Slovakia, Taiwan, Turkey, Uruguay, and Venezuela. Missing values are due to missing sales data (units and/or revenue). For Taiwan and Hong Kong, data on some of the independent variables were also missing.

One popular way to address this issue is to draw the country-specific fixed-effect, η_i, out of the error term similar to the time-specific effects through the inclusion of a dummy variable for each country, such that

$$Sales_{it} = \delta Broadband_{it} + \beta X_{it} + \phi_t + \eta_i + u_{it}. \tag{3}$$

Using this fixed-effects (or "within groups") estimator, we now explicitly control for time-invariant unobserved country effects. The fixed-effects estimator is a standard procedure to assess the effect of policy changes (e.g., Wooldridge 2002, pp. 265).[11]

Another issue that may cause the estimates obtained from Equation (3) to be inconsistent is that the price and unbundling variables may be endogenously determined. To account for this possibility, but also because we could not identify any convincing candidates that could serve as exogenous instruments for these variables, we rely on an instrument-free method to correct for endogeneity bias using copulas, which has recently been shown to perform well (Park and Gupta 2012). This approach models the correlation between the endogenous explanatory variables and the structural error term, ε_{it}, in Equation (3). As suggested by Park and Gupta (2012), we include two additional regressors in Equation (3), $Price^*_{it}$ and $Unbundling^*_{it}$:

$$Price^*_{it} = \Phi^{-1}\big(H_{Price}(Price_{it})\big), \text{ and} \tag{4}$$

$$Unbundling^*_{it} = \Phi^{-1}\left(H_{Unbundling}(Unbundling_{it})\right), \tag{5}$$

where Φ^{-1} is the inverse of the normal cumulative distribution function, and $H_{Price}(\cdot)$ and $H_{Unbundling}(\cdot)$ are the empirical distributions of the $Price_{it}$ and $Unbundling_{it}$ variables, respectively. For identification, it is required that $Price_{it}$ and $Unbundling_{it}$ are non-

[11] We follow previous research and estimate a linear regression model (e.g., Hui and Png 2003; Liebowitz 2008; Smith and Telang 2010; Zentner 2009).

normally distributed, which a Shapiro-Wilk test confirms (W_{Price} = .9851, p < .001; $W_{Unbundling}$ = .8559, p < .001).[12]

Our theorizing further posits that the piracy effect is predictably related to specific country characteristics, which we assume to moderate the effect. We test our expectations by introducing a vector of (grand-mean centered) moderator variables, M_{it}, and interact these variables with the broadband variable, such that

$$Sales_{it} = \delta Broadband_{it} + \beta X_{it} + \gamma M_{it} + \lambda M_{it} * Broadband_{it} + \phi_t + \eta_i + \varepsilon_{it}, \quad (6)$$

where γ is a parameter vector capturing the main effects of the country-specific time-varying moderator variables and λ captures their interaction with the broadband variable.[13]

5. Results

We report the results from the estimation of Equations (3) and (6) in Table 5. We summarize our findings in sections 5.1. and 5.2., respectively.

>>> Table 5 about here <<<

5.1. The effect of Internet piracy on music sales

Model 1 presents the results from the estimation of Equation (3), i.e., without the interaction effects. As can be seen, the broadband coefficient is negative and highly significant. The associated effect size suggests that a 1 percentage point increase in broadband Internet penetration on average reduces per capita sales by .0300 units. In 2010 the average broadband Internet penetration was approximately 20%. This means that file-sharing (via broadband Internet penetration) overall accounts for a decline in sales of approximately .60 units per capita over the observation period (i.e., 20*(–.0300)). Given that the actual sales decline was about .91

[12] As a validity check, we test whether any of the other explanatory variables in our model are endogeneous, which is not the case (i.e., the coefficients of the correction terms were insignificant).

[13] As an exception among the moderator variables, individualism is time-invariant, i.e., this moderator only carries the subscript *i*.

units per capita, this corresponds to a share of 66% of the overall sales decline (i.e., .60/.91). Another interpretation is that 36% of the sales volume in 1996 (1.66 units per capita) has been cannibalized by Internet piracy (i.e., .60/1.66).

5.2. The effects of control variables on music sales

Investigating the coefficients of the control variables reveals that (dial-up) Internet adoption is negatively related to music sales. This finding provides support for our expectation that the Internets function as a new entertainment medium causes music sales to decline, albeit not as severely as the displacement effect due to Internet piracy (i.e., broadband adoption). The magnitude of this effect suggests that a 1 percentage point increase in Internet penetration on average reduces sales by .0069 units per capita. In contrast, although the coefficient shows the expected sign, cell phone penetration does not have a significant influence on music sales.

Turning to the product related covariates we find that the price variable is negatively related to music sales. This finding shows that increasing prices are associated with decreasing demand and vice versa, as expected. Recall that the average retail price declined by approximately 28% over the observation period. Thus, lowering prices has positively impacted sales during this period. Note that the associated endogeneity correction parameter is insignificant, suggesting that after controlling for country- and time-specific fixed-effects, the degree of remaining intertemporal price endogeneity is rather low, which might also be explained by the high aggregation level of our data.

Moreover our results provide evidence that the unbundling of music albums via legitimate digital sales channels negatively influences overall music sales. Consumers appear to increasingly replace music album purchases with single track downloads – a finding that is in line with previous micro-level research (Elberse 2010). The magnitude of the coefficient suggests that a 1 percentage point increase in the sales share of single music formats decreases the overall sales volume by .0280 units per capita. The single share of sales in our sample in 2010 was 4.4%, up from 2.5% before the first legitimate digital download store was introduced in 2003. Thus, unbundling on average accounted for a sales decline of approximately .05 units per capita over the observation period (i.e., 1.9*(–.0280)). While the overall magnitude of this effect may appear low, the results demonstrate the high cannibalization potential of unbundling as the adoption of digital download stores progresses. Also for this variable we find the correction factor to be insignificant, indicating that intertemporal endogeneity is no reason for concern.

With respect to the economic indicators, we find support for previous findings that income is positively related to music sales. Our results further provide evidence for the existence of a non-linear effect of income on sales, suggesting that the positive effect of income is diminishing with higher income levels, in line with our expectations. However, we find the turning point to be at a rather high income level; more precisely, we find the turning point to be at approximately 46,000 US dollars (i.e., .1476/(2*(–.0016)); Wooldridge 2002, p. 459). Moreover, our results show that unemployment has the anticipated negative effect.

Finally, the policy indicators do not have a significant influence on music sales. This finding suggests that policy decision making cannot directly explain variations in demand over time, contrary to our expectations. However, it is possible that these variables have a positive indirect effect on sales by attenuating the negative effect of piracy on sales. We will investigate if this is the case in the next section.[14]

[14] Note that of the non-hypothesized relationships, only the variable “Internet restrictions” is significantly related to music sales, suggesting that Information restrictions exert a negative influence on sales.

5.3. Moderating effects of country characteristics

Besides investigating the effect of Internet piracy on sales, it is the main goal of our research to identify factors that can explain the cross-country variation in this effect. Model 2 presents the results from the estimation of Equation (6), i.e., including the interaction effects.

With respect to the policy indicators our results reveal that the economic policy variable indeed shows the expected positive interaction with the broadband variable. This finding provides support for our expectation that the detrimental effect of Internet piracy on sales is less severe in countries which are characterized by a high degree of IP protection and a sound business environment (via economic freedom). Thus, effective economic policies play a central role as a countermeasure against Internet piracy because they (i) reduce piracy thorough an increased level of IP protection, and (ii) promote the emergence of an efficient market for legal downloads. Although we cannot disentangle these two possible effects, we speculate that they are highly intertwined and therefore interpret the significant interaction as their net effect. Similarly, the positive interaction between the broadband variable and the policy continuity variable indicates that a high degree of policy continuity reduces the effect of Internet piracy on sales.

Our findings also shed light on the largely unresolved role of globalization and Internet restrictions in the context of Internet piracy. As the significant interaction effects reveal, social globalization and Internet restrictions indeed exert a significant influence on the relationship between piracy and music sales, in line with our expectations. More precisely, the effect is stronger in highly globalized countries, where a global consumption orientation is likely to be present and cross-national information about innovations transmits quicker. In further support of this finding, our results show that restricting international information flows mitigates the piracy effect, as the strong positive interaction with the Internet restrictions variable reveals.

With respect to the group of covariates pertaining to the infrastructure and interpersonal communication, we find that the piracy effect is significantly stronger in urbanized environments, where (cross-national) information about innovations transmits quicker and where the penetration potential is higher due to the superior infrastructure. Furthermore, we find support for our expectation that the piracy effect is stronger in countries with a high female labor participation rate, i.e., countries in which the openness to change and the level of heterophilous influence is high. In contrast, mobility cannot explain the cross-country variation in the effect of Internet piracy. We speculate that this finding may be due to the shifting role of interpersonal communication for the diffusion of innovations in digital environments, where face-to-face communication is likely to be less relevant. Similarly, although the coefficient shows the expected sign, we do not find support for our expectation that a higher degree of collectivism is associated with a significantly stronger effect of piracy on sales.

To further shed light on the identified interaction effects, we performed simple slopes analyses, i.e., we calculate the simple slopes at one standard deviation below and above the overall mean of the moderator variable in each interaction. We visually depict the interactions that are significant in the full regression model in Figure 3. In addition, we report their spotlight analysis (Fitzsimons 2008) in Table 6, i.e., we shifted the overall mean level of the moderator variable up and down by one standard deviation, and then conducted significance tests for the individual slopes (Aiken and West 1991).

>>> Figure 3 about here <<<

>>> Table 6 about here <<<

As panel (a) shows, Internet piracy still negatively influences sales when the level of IP protection and economic openness is high, but to a lesser degree compared to countries in which the degree of IP protection and economic openness is low (i.e., both slopes are significant as shown in Table 6, but there is a positive interaction). A similar effect can be observed for the degree of policy continuity, as depicted in panel (b). Moreover, countries which exhibit a high degree of social globalization are more affected by Internet piracy compared to less socially globalized countries, as seen in panel (c). In addition, panel (d) depicts the interaction between Internet piracy and Internet restrictions. In line with our expectations, the effect of Internet piracy is stronger if information flows are not restricted. Table 6 shows that the corresponding slope of the Internet piracy variable is insignificant for high levels of Internet restrictions and highly significant for low levels of Internet restrictions. Finally, panels (e) and (f) show that the effect of Internet piracy is reinforced with increasing levels of urbanization and female labor participation.

6. Discussion and implications

Since the rise of file-sharing networks in the late 1990s, the effect of Internet piracy on the media industry has been a topic of much debate in both academic research and marketing practice. While a large body of research has analyzed the effect of piracy on the legitimate demand for media products, less is known about the factors that may explain the large differences that we observe between countries with respect to the sales development since Internet piracy became available, i.e., some countries experienced a steeper decline than others. Using the music industry as the research object, our study takes a first step towards understanding these cross-country variations by investigating the country characteristics that moderate the extent to which music sales are cannibalized by illegal file-sharing. Understanding these moderating effects is important for marketing managers and policymakers in order to judge the effectiveness of anti-piracy measures.

In the first part of our study, we investigate the factors that explain the country-level variation in music sales over a period of 15 years from 1996 to 2010. Consistent with the majority of previous studies, we find that piracy has a negative effect on music sales. More precisely, our results suggest that Internet piracy is responsible for a sales decline of about 36% since 1996, or about 66% of the overall decline in global sales. This finding informs the ongoing debate about the magnitude of the substitution effect, which has not yet reached a final conclusion with existing estimates ranging from 0% (Oberholzer-Gee and Strumpf 2007) to more than 100% (Liebowitz 2008). The magnitude of our estimates lies between these extreme effect sizes and is comparable to displacement rates reported by previous researchers (see Table 1; Zentner 2009; Danaher, Smith, and Telang 2013b).

Furthermore, our research sheds light on alternative factors that might have contributed to the sales decline. Particularly, we find that, besides illegal piracy, the emergence of legal download stores has had a negative influence on overall sales levels because consumers increasingly purchase single track downloads instead of music albums. Thus, marketing managers in the music industry should continue to invest in efforts that aim to increase the relative attractiveness of product bundles. One way this could be achieved is through tiered pricing strategies, e.g., by raising single track prices to increase the relatively attractiveness of album bundles (Danaher et al. 2014). Another promising way to address this issue is through product bundling in the form of "all you can eat" access bundles that grant subscription users access to a comprehensive music library, e.g., for a monthly flat fee (Papies, Eggers, and Wlömert 2011). For example, Bakos and Brynjolfsson (1999; 2000) show that the profits from bundling of digital products increase with the size of the bundle due to negligible marginal and bundling costs.

The second part of our study focuses on the country-level moderators of the effect of Internet piracy on music sales. Investigating the interaction effects revealed that variables from three domains are important predictors of the country-level cannibalization rates: (1) policy indicators, (2) global connectedness, as well as (3) infrastructure and interpersonal communication. With respect to (1) our results show that sound economic policies that aim to create a sound business environment constitute an important factor that attenuates the piracy effect on sales. Thus, we suggest that policymakers should target piracy through a combination of negative incentives that aim to increase the costs of piracy (e.g., by strengthening IP protection laws and law enforcement) and positive incentives that aim to promote the emergence of attractive legitimate alternatives (e.g., simplification of cross-country licensing procedures). In view of the increasingly globalized music market, the focus should be on the design of cross-border policies that aim to establish uniform standards across countries. For example, the first commercial music service, which addressed the legitimate demand for recorded music products (i.e. iTunes), was introduced in the U.S. in 2003 – some five years after the introduction of the first file-sharing network (i.e., Napster) in 1998. Despite the subsequent expansion to many other markets, the service was still not available in 17 of the 38 analyzed countries in 2010. One major obstacle that service providers face is the often cumbersome process of obtaining licenses. Efforts that aim to simplify the cross-border licensing procedures are a promising way to foster the emergence of an efficient legitimate digital music market (e.g., European Parliament 2014). The continuity of policy efforts is another important factor, which we find to mitigate sales cannibalization due to piracy. Unstable and risky political environments appear to provide a fertile breeding ground for illegal piracy. This finding strengthens the call for international policies and conventions in which common standards are agreed upon by all member states, which reduces the feasibility of policy changes in single countries.

With respect to (2), globalization appears to be a double-edged sword for the music industry. On the one hand the emergence of a global consumer culture is a development which is conducive to the music industry's global brand positioning strategy and its business model, which is heavily reliant on the international exploitation of copyrights. On the other hand, our results suggest that consumers' global consumption orientation also reinforces the cannibalization effect of piracy on sales due to similarities in tastes and quicker transmission of information across borders. In view of these findings and the fact that unauthorized copying takes place at a global scale, it is advisable (i) that music companies should adopt a global release scheme rather than a sequential release strategy by geographical markets to ensure that the material is available via legitimate channels, and (ii) that promotional activities (e.g., video and radio releases) should be synchronized with release timings as precautionary measures against pre-release piracy. Furthermore, we find that restricting information flows attenuates the impact of piracy on music sales. This finding underlines the vital role of removing copyright infringing material from the respective websites. For example, many sites offer copyright holders the option to issue takedown notices in case of copyright infringements. However, given the notoriously difficult task of removing content from the Internet once it has became available, this finding also calls for technological advancements regarding the underlying takedown procedures.

Finally, with respect to (3), we find urbanization to increase the losses due to piracy. One likely reason for this finding is the high penetration potential of file-sharing networks because of the superior infrastructure in highly urbanized environments. However, the superior infrastructural conditions also provide the music industry with an opportunity because they facilitate the adoption of legitimate digital music services. For example, in order for streaming services to unfold their true potential, high network coverage is essential. To leverage the advantages of high network coverage in urban environments digital music service providers could strike deals with network operators, e.g., by bundling mobile phone subscriptions with music subscription services. Moreover, we find a society's openness to change and the presence of heterophilous influence in a society (via female labor participation) to reinforce the piracy effect. This finding highlights the importance of providing innovative and convenient legal content offers to consumers as an alternative to illegal file-sharing early in the digitalization process. This is particularly important in countries that exhibit the above characteristics (i.e., openness to change, heterophilous influence) because consumers in these countries are likely to switch to digital channels for music consumption relatively early compared with consumers in other countries. Consider, for example, Sweden, a country with a high female labor participation rate, which was once considered a major hub for pirated content, and which – through a steep growth in revenues from new legal music services – managed to reverse the downward trend in overall revenues from recorded music (Grundberg 2014).

Similar to most empirical studies, our research is subject to limitations that represent departing points for future research. First, our analyses only focus on the music market. While we believe that our findings are largely transferable to other media industries (e.g., the movie and book industry) future research should investigate in how far our results can be replicated based on sales data from adjacent industries. Second, because a direct measure of file-sharing is not available we rely on broadband Internet penetration as a proxy variable. We tried to address potential concerns of this procedure by conditioning on dial-up Internet penetration to control for the entertainment-diversion impact of the Internet on music sales, as well as by including as many control variables as possible that may provide alternative explanations for the decline in sales (e.g., unbundling). However, we cannot rule out that the broadband Internet penetration still also proxies for other forms of online entertainment (e.g., YouTube). Therefore, the estimate of the broadband variable should be regarded as an upper bound of the effect of Internet piracy on sales.

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Tables and figures

Table 1

Comparison of the present study with existing macro-level studies published in peer-reviewed journals

Author(s) (year)	*Dependent variable*			*Empirical basis*			*Piracy*		*Control variables*					*Moderator analysis*
	Physical sales	Digital sales	Measure, context	No. of countries	No. of years	Observation period	Measure	Effect lower/upper	ICT	Price	Unbundling	Economy	Policy	
Hui/Png (2003)	✓		Music CDs	28	5	1994-1998	Piracy rate	–7%	✓	✓		✓		
Peitz/Waelbroeck (2004)	✓		Music CDs	16	5	1998-2002	Survey	–20%	✓			✓		
Zentner (2005)	✓		Music CDs	16	5	1998-2002	Internet	–6%/–24%				✓		
Liebowitz (2008)	✓		Music CDs	1 (US)	6	1998-2003	Internet	–20%/–56%[a]	✓			✓		
Pons/Garcia (2008)	✓		Music CDs	16	7	1999-2005	Broadband	–25%/–27%[b]	✓	✓		✓		✓
Smith and Telang (2010)	✓		Movie DVDs	1 (US)	3	2000-2003	Broadband	+9%	✓			✓		
This study	✓	✓	All music formats	39	15	1996-2010	Internet & Broadband	–36%	✓	✓	✓	✓	✓	✓

[a] The author reports .57/1.65 as the lower-/upper-bound values of the net reduction in per capita sales due to file-sharing. Compared to the reported mean value of 2.90 units per capita in 1998, this represents a reduction in sales of –20%/–56%. It should be noted, however, that the true reduction in sales over the observation period was only .58 units so that even the lower-bound value would imply that file-sharing accounted for the whole decline in sales.

[b] The authors report elasticities of –1.76 and –1.90 for the broadband variable. The broadband Internet penetration in the 16 analyzed countries was 14% in 2005. Thus, the lower-/upper-bound piracy effect for the observation period corresponds to 14*(–1.76)% and 14*(–1.9)%, respectively.

Table 2

Descriptive statistics

Variable	*Operationalization*	*Source*	*Mean*	*SD*	*Min*	*Max*
Sales	Number of recorded music products (CDs, MCs, LPs, digital downloads) sold per capita in market *i* in year *t* (standardized to album level)	IFPI	1.28	1.03	.003	4.09
Broadband	Broadband Internet users in market *i* in year *t* (% of total population)	The World Bank	7.91	10.56	.00	38.10
Internet	Internet users in market *i* in year *t* (% of total population)	The World Bank	35.02	28.18	.01	93.39
Cell phone	Mobile cellular subscribers in market *i* in year *t* (% of total population)	The World Bank	62.24	40.96	.03	156.40
Price	Average retail price per sold unit in market *i* in year *t* (in 2010 constant US dollars; standardized to album level)	IFPI; own calculation	15.01	6.65	1.58	33.54
Unbundling	Single format sales (i.e., CD-singles, digital track downloads) in market *i* in year *t* (single sales as a share of overall sales volume)	IFPI; own calculation	2.92	3.73	.00	24.97
GDP per capita	PPP adjusted GDP per capita in market *i* in year *t* (in '000 2005 constant US dollars)	The World Bank	22.37	12.31	1.50	52.31
Economic policy	Economic Freedom Index in market *i* in year *t*	The Heritage Foundation	67.86	8.66	47.40	88.90
Policy continuity	Political Constraints Index in market *i* in year *t*	Henisz	.41	.16	.00	.72
Social globalization	KOF Social Globalization Index in market *i* in year *t*	KOF	68.16	19.62	20.35	93.28
Internet restrictions	Freedom of the Press Index in market *i* in year *t*	Freedom House	28.02	18.72	5.00	85.00
Urbanization	Population in urban agglomerations of more than 1 million in market *i* in year *t* (% of population)	The World Bank	26.42	18.03	.00	100.00
Mobility	Road sector energy consumption in market *i* in year *t* (% of total energy consumption)	The World Bank	17.00	5.61	.00	30.78
Female labor partic-ipation	Female labor force participation rate in market *i* in year *t* (% of female population ages 15-64)	The World Bank	60.81	11.21	30.20	84.80
Individualism	Degree of individualism in market *i* (as opposed to collectivism)	Hofstede	53.63	24.03	13.00	91.00

Notes. The observation period spans 15 years from 1996 to 2010.
Number of observations = 570. Statistics for Price are based on 565 observations due to missing values for 5 countries for the year 1996.

Table 3

Correlations among variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Sales per capita	1															
2	Broadband	.05	1														
3	Internet	**.28**	**.87**	1													
4	Cell phone	.03	**.73**	**.81**	1												
5	Price	**.67**	**.17**	**.34**	**.21**	1											
6	Unbundling	**.59**	**.28**	**.32**	**.19**	**.76**	1										
7	GDP	**.72**	**.55**	**.71**	**.53**	**.72**	**.56**	1									
8	Unemployment	**–.24**	**–.20**	**–.28**	**–.14**	–.06	**–.10**	**–.28**	1								
9	Economic policy	**.52**	**.40**	**.56**	**.35**	**.44**	**.38**	**.70**	**–.25**	1							
10	Policy continuity	**.30**	**.11**	**.12**	.03	**.40**	**.30**	**.24**	.04	.11	1						
11	Social globalization	**.62**	**.40**	**.58**	**.48**	**.65**	**.43**	**.83**	**–.15**	**.59**	**.24**	1					
12	Internet restrictions	**–.66**	**–.27**	**–.40**	**–.24**	**–.64**	**–.46**	**–.59**	–.06	**–.40**	**–.58**	**–.56**	1				
13	Urbanization	.02	.08	**.10**	.05	**.09**	.06	**.22**	–.02	**.45**	**–.27**	.05	**.19**	1			
14	Mobility	**.14**	.03	.08	**.13**	**.21**	**.15**	**.13**	–.05	**.27**	**.14**	**.14**	**–.18**	**.11**	1		
15	Female labor participation	**.56**	**.41**	**.54**	**.33**	**.38**	**.32**	**.57**	**–.31**	**.39**	.08	**.52**	**–.40**	**–.09**	–.05	1	
16	Individualism	**.67**	**.27**	**.41**	**.25**	**.58**	**.54**	**.61**	.06	**.39**	**.35**	**.64**	**–.73**	**–.16**	.05	**.43**	1

Notes. Correlation coefficients in bold are significant at $p < .05$ or less (two-tailed).

Table 4

Analyzed countries and per capita sales

Country	Sales p.c.[a]	Country	Sales p.c.[a]
Argentina	.41	Italy	.65
Australia	2.32	Japan	2.12
Austria	1.86	Malaysia	.30
Belgium	1.83	Mexico	.50
Brazil	.38	New Zealand	1.88
Canada	2.00	Netherlands	1.88
Chile	.38	Norway	2.78
China	.04	Philippines	.09
Colombia	.26	Poland	.51
Czech Republic	.66	Portugal	1.16
Denmark	2.45	Singapore	1.02
Finland	1.75	South Africa	.45
France	1.88	South Korea	.54
Germany	2.30	Spain	1.12
Greece	.68	Sweden	2.30
Hungary	.57	Switzerland	2.65
India	.11	Thailand	.54
Indonesia	.18	UK	3.25
Ireland	2.10	USA	2.87

[a] Refers to the mean value of the dependent sales variable over the observation period from 1996-2010. The 38 analyzed countries represented more than 95% of the global recorded music industry revenue in 2010 (IFPI 2011b).

Table 5

Estimation results

Independent variables	*Expected effect*	*Model 1* Coeff.	SE	*p*	*Model 2* Coeff.	SE	*p*
Main effects							
Broadband	–	**–.0300**	**.0045**	**< .001**	**–.0177**	**.0043**	**< .001**
Internet	–	**–.0069**	**.0023**	**.005**	**–.0070**	**.0019**	**< .001**
Cell phone	–	–.0021	.0015	.178	–.0018	.0012	.135
Price	–	**–.0426**	**.0075**	**< .001**	**–.0455**	**.0078**	**< .001**
Unbundling	–	**–.0280**	**.0072**	**< .001**	**–.0272**	**.0069**	**< .001**
GDP	+	**.1476**	**.0365**	**< .001**	**.1050**	**.0279**	**< .001**
GDP^2	–	**–.0016**	**.0004**	**< .001**	**–.0011**	**.0003**	**< .001**
Unemployment	–	**–.0297**	**.0083**	**< .001**	**–.0315**	**.0086**	**< .001**
Economic policy	+	–.0032	.0048	.510	.0047	.0048	.336
Policy continuity	+	–.0391	.0863	.654	.0199	.0875	.821
Social globalization		.0041	.0049	.405	.0052	.0042	.222
Internet restrictions		**–.0079**	**.0032**	**.018**	–.0042	.0029	.156
Urbanization		–.0249	.0225	.276	–.0113	.0189	.554
Mobility		–.0041	.0069	.555	.0012	.0063	.851
Female labor participation		–.0043	.0053	.427	–.0075	.0061	.222
Intercept		1.7693	.9299	.065	.7142	.5285	.185
Endogeneity correction using copulas							
Price		.0347	.0452	.448	.0113	.0536	834
Unbundling		.0066	.0224	.769	.0255	.0197	.204
Interaction effects							
Broadband x Economic policy	+				**.0007**	**.0002**	**.009**
Broadband x Policy continuity	+				**.0207**	**.0090**	**.027**
Broadband x Social globalization	–				**–.0003**	**.0001**	**.022**
Broadband x Internet restrictions	+				**.0006**	**.0002**	**.003**
Broadband x Urbanization	–				**–.0003**	**.0001**	**.006**
Broadband x Mobility	–				–.0003	.0004	.431
Broadband x Female labor participation	–				**–.0044**	**.0003**	**.044**
Broadband x Individualism	+				.0040	.0086	.644
No. of observations			565			565	
R-squared (within)			.89			.91	

Notes. Variables in bold are significant at the $p < .05$ level (two-tailed test). All regressions include a set of year and country dummies, which we do not report in the interest of brevity. Standard errors are robust to disturbances that are heteroskedastic and autocorrelated. All interaction variables in Model 2 are grand-mean centered. The number of observations is 565 (and not 570) because we lack price information for 5 countries for the year 1996 (i.e., 5 cases are missing).

Table 6

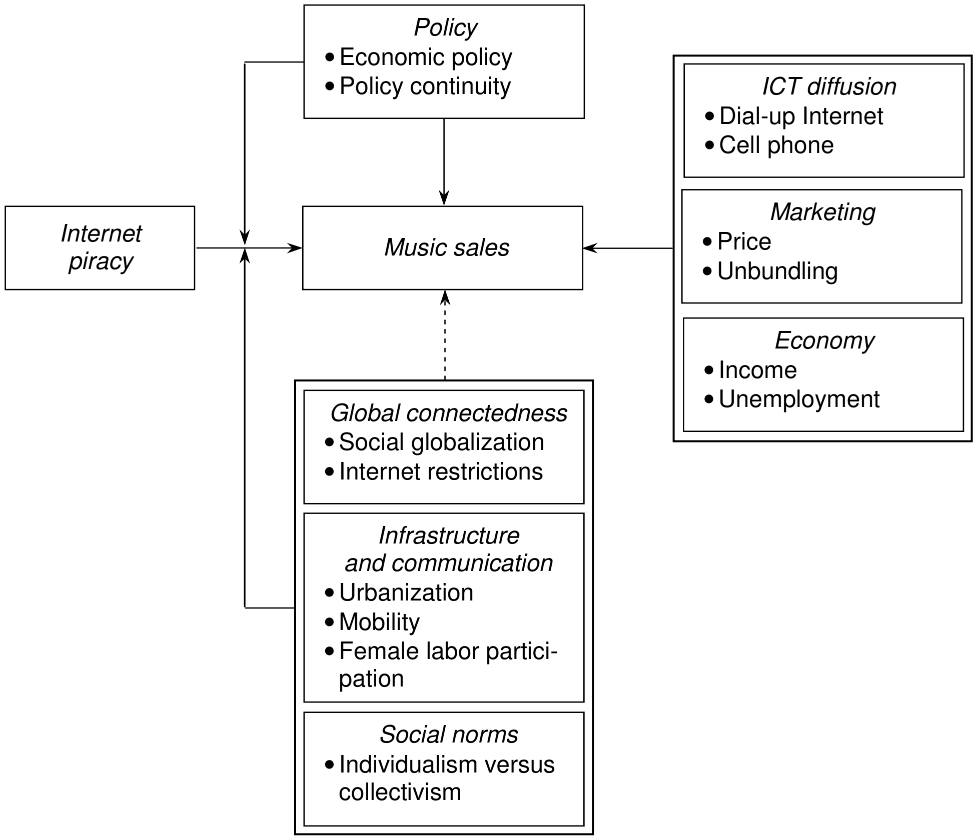
Spotlight analyses

Effect of Broadband if …		*Influence on music sales* Coeff.	SE	*z*	*p*
Economic policy	High	**–.0111**	**.0046**	**–2.39**	**.017**
Economic policy	Low	**–.0236**	**.0052**	**–4.53**	**< .001**
Policy continuity	High	**–.0139**	**.0045**	**–3.06**	**.002**
Policy continuity	Low	**–.0206**	**.0047**	**–4.43**	**< .001**
Social globalization	High	**–.0236**	**.0048**	**–4.90**	**< .001**
Social globalization	Low	**–.0109**	**.0054**	**–2.02**	**.043**
Internet restrictions	High	–.0052	.0068	–.76	.445
Internet restrictions	Low	**–.0291**	**.0045**	**–6.41**	**< .001**
Urbanization	High	**–.0253**	**.0046**	**–5.54**	**< .001**
Urbanization	Low	**–.0107**	**.0053**	**–2.02**	**.044**
Female labor participation	High	**–.0231**	**.0049**	**–4.72**	**< .001**
Female labor participation	Low	**–.0113**	**.0055**	**–2.05**	**.040**

Notes. Variables in bold are significant at the $p < .05$ level (two-tailed test). The terms "high" and "low" refer to values one standard deviation above and below the mean of the respective variables.

Figure 1

Conceptual framework



Note. The dotted arrow refers to relationships that are estimated but not hypothesized due to a lack of theoretical substantiation.

Figure 2

Developments of music sales and (broadband) Internet adoption in the 38 analyzed countries

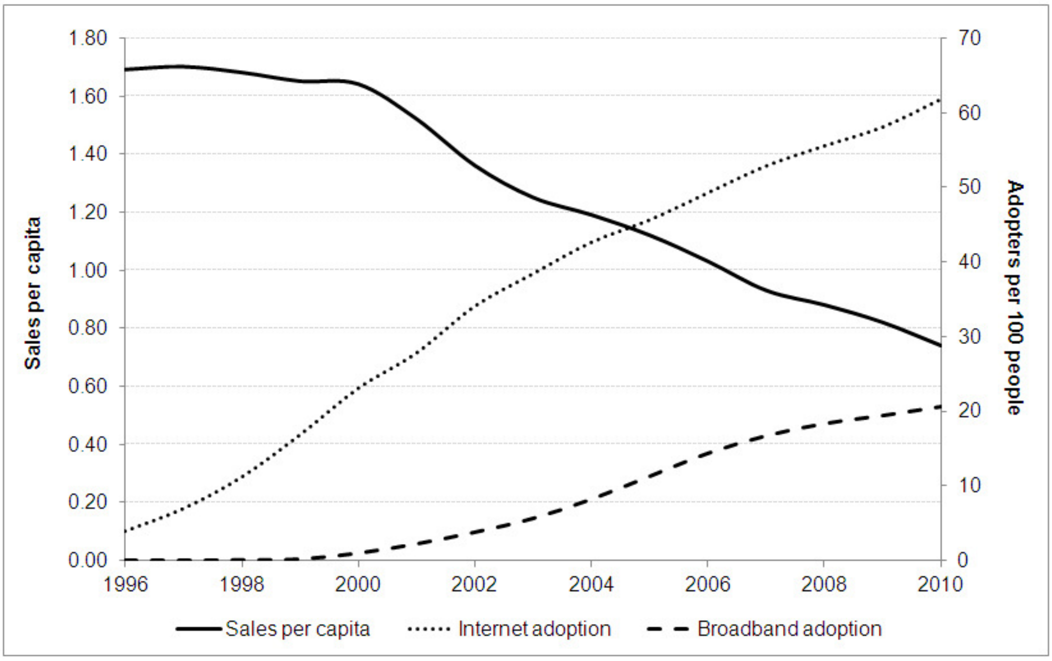
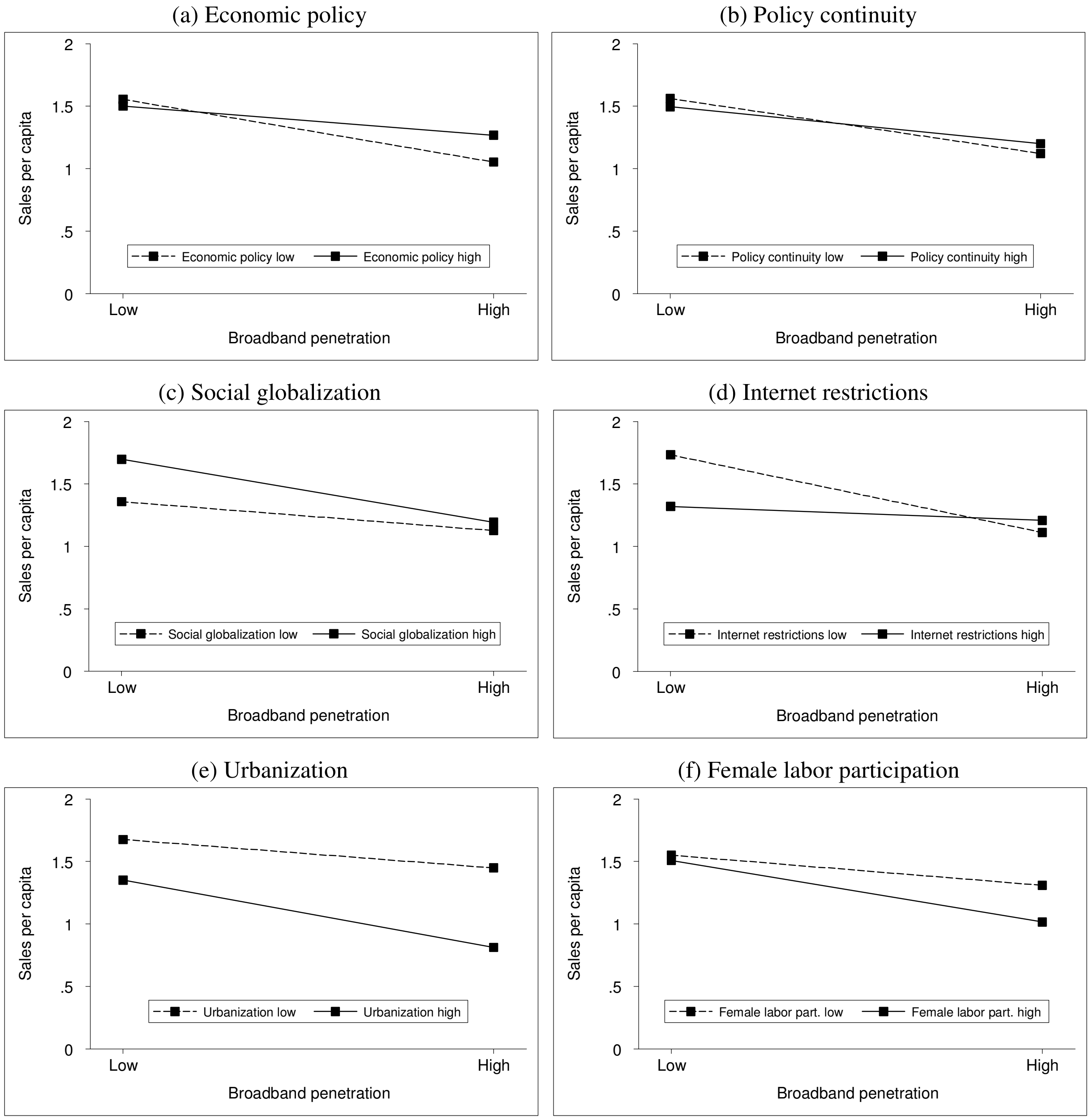


Figure 3

Simple slopes analyses results



Notes. The terms “high” and “low” refer to values one standard deviation above and below the mean of the respective variables.

3. Music for Free? How Free Ad-funded Downloads Affect Consumer Choice

Authors:

Dominik Papies, Felix Eggers, and Nils Wlömert

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Dominik Papies, Professor of Marketing, School of Business and Economics, University of Tuebingen, Nauklerstr. 47, 72074 Tuebingen, Germany. E-mail: dominik.papies@uni-tuebingen.de, URL: www.wiwi.uni-tuebingen.de.

Felix Eggers, Assistant professor, Department of Marketing, Faculty of Economics and Business, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands.
E-mail: f.eggers@rug.nl, URL: www.rug.nl/feb/marketing.

Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

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"Ad funded downloads are the way to provide free music to the consumer without depriving musicians of their livelihood." (Peter Gabriel)

1. Introduction

The content industry is still struggling to establish successful online business models. One popular example is the market for music downloads, which has been characterized by a sharp decline in physical album sales since the late 1990s, while a substantial portion of sales volume has been cannibalized by free, illegal downloads offered on file-sharing networks. Despite the promising launch of iTunes and those of some successful followers, illegal downloads are still a key player in the market for music downloads (Elberse 2010; Gopal, Bhattacharjee, and Sanders 2006; IFPI 2009; Peitz and Waelbroeck 2005; Sinha and Mandel 2008). To address the demand for music downloads and to tackle illegal music downloads, three legal, online alternatives are available. (1) The established way relies on the principle of digital sell through (DST) and offers individual titles or bundles on a download-to-own basis (e.g., iTunes). (2) Some services (e.g., Napster 2.0) are offering their customers unlimited access to a comprehensive online library of titles but restricting access and the usability of the titles to the period of membership, i.e., allowing customers to rent music rather than buy it (subscription model). (3) Some recent entrants into the market for digital music rely on advertising as a revenue source (e.g., Spotify or We7) and offer their customers a free membership with restrictions on usage similar to those of the subscription models (ad-based model).

Being free of charge, ad-funded downloads may attract consumers who would otherwise refrain from commercial downloading, making such offerings a potential instrument for decreasing illegal file-sharing and increasing overall market size, i.e., generating a "lift" in the number of customers. Although there is some precedent for providing content whose production is costly online without charging for it—e.g., magazines and newspapers offer their content online for free (Gentzkow 2007)—this strategy entails several risks (Geyskens, Gielens, and Dekimpe 2002), most importantly the risk of cannibalization of other distribution channels, i.e., generating a "shift" in demand. Thus, management and researchers are left with two important questions that constitute the motivation for this research. Are free advertising-based models a viable alternative to competing models that operate on a pay basis? On which combination of business models should the music industry rely to provide attractive alternatives to illegal file-sharing options?

Despite the importance of these questions for marketing management, academic research does not make a clear prediction about the sustainability of either business model or whether the addition of a free download service is a favorable decision. Most research that is related to music downloading has piracy issues and file-sharing as the common nucleus (e.g., Bhattacharjee et al. 2007) or is not focused on systematically eliciting consumer preferences (e.g., Peitz and Waelbroeck 2005; Sundararajan 2004). Recent research started analyzing consumer preferences for content downloads (Sinha, Machado, and Sellman 2010; Sinha and Mandel 2008). One major implication is that consumers should be treated with a carrot-and-stick strategy that discourages illegal file-sharing while providing positive incentives for commercial downloads, e.g., through attractive download stores. However, it remains an unresolved question how attractive download stores should be configured. Further, all available analyses focus on a single business model (DST models, such as iTunes or Amazon) and do not take into account that the market offers different business models (e.g., subscription-based). Most importantly, no research empirically analyzes consumer reaction to the introduction of a free, ad-based download model and the implications an introduction may have on other download channels.

We therefore contribute to the literature by empirically analyzing the effect of a free online channel on consumer choice for a music download service. Based on the theoretical framework for the analysis of channel additions by Geyskens, Gielens, and Dekimpe (2002), we examine the attractiveness of multiple business models, i.e., DST, subscription model, and ad-based model, and predict choices for download stores and the level of competition between the channels using a latent-class choice-based conjoint approach (Desarbo, Ramaswamy, and Cohen 1995). By analyzing segments, we shed light on consumer preferences in the music download market and show how the identified segments differ in their choice behavior and willingness-to-pay. Moreover, by comparing segments, we are able to explain different types of consumer behavior, which we base on behavioral factors that we derived from extant research.

Based on the empirical results, we show that content owners should have a strong interest in adding free, advertising-based outlets to their distribution chains because they attract new customers rather than cannibalizing incumbent business models. These findings are relevant for (1) content owners in the music industry and other branches of the creative industries looking to decide which content distributors are the most promising with which to contract and which prices and DRM restrictions should be the aim. They are also essential findings for (2) content distributors, who can use these implications to allocate their resources to the most promising business models, improve the configuration of their download stores and the pricing they offer. Further, the findings can be used to anticipate the results of competitive actions.

In the next section, we derive behavioral factors that make predictions about consumer reactions to the introduction of a free, ad-based outlet. We then describe the model we used to identify the favorability of the addition of a free channel before we present our estimation and discuss the results. We conclude with implications and remarks regarding generalization and limitations.

2. A conceptual framework of providing content for free

When firms (e.g., content owners) consider the addition of an online distribution channel that offers products free of charge that are sold elsewhere in the online market, they face a trade-off between potential opportunities and threats. As we will outline below, extant theories that can be used to make predictions about consumer behavior in the presence of free alternatives do not provide unequivocal predictions about the favorability of the addition of a free online channel. The situation is complicated by the fact that attractive features of a free, ad-based download store might, on the one hand, attract new customers who would otherwise refrain from commercial downloading (create a "lift" in the total number of consumers). On the other hand, it might encourage consumers to abandon the use of incumbent download stores in favor of a free, ad-based service (create a "shift"; Geyskens, Gielens, and Dekimpe 2002). To shed light on factors that characterize consumer behavior in online marketplaces when free alternatives are introduced, we derive several behavioral factors from extant theories that are likely to shape consumer choice for a music download service. These behavioral factors may motivate users to (1) remain with their previous choice, keeping the number of adopters for an ad-based service low, (2) switch to an ad-based download service, or (3) adopt an ad-based service without having used a commercial download service before. We elaborate on each of these below and follow Geyskens, Gielens, and Dekimpe (2002), who distinguish between those factors that increase demand by creating a "lift" versus those that create a "shift" in demand (Figure 1). Because we model choice for a specific business model we cannot equate demand for a given business model and demand for music because we do not analyze the amount of music obtained through a given business model. We therefore define "lift" as a total increase of users who adopt a commercial downloading service and "shift" as users adopting an ad-based service while abandoning the use of incumbent services.[1]

>>> Figure 1 about here <<<

2.1. Factors that suggest low attractiveness of ad-based services

Consumers may find a free, ad-based download service unattractive for several reasons, which would create neither a shift nor a lift but would keep the number of adopters of an ad-based service low.

2.1.1. Signaling of low product quality. It is likely that consumers will make inferences about the reasons why a company offers its products for free when being confronted with a free download service. Consumers may use the price of zero as a signal of inferior product quality, which may result in a lower valuation and reduced preference for the product, making the product less attractive and keeping the number of adopters of ad-based services low, both among new and existing customers of incumbent business models (Campbell 1999; Kamins, Folkes, and Fedorikhin 2009).

2.1.2. Dislike of advertisements. Although the ad-based models offer music free of charge, consumers in return have to "pay" by devoting some of their attention to advertisements. It can be assumed that consumers prefer download stores without advertisements over those that use advertisements (Prasad, Mahajan, and Bronnenberg 2003). People may dislike ad-based stores because they do not want to be exposed to ads and might view ads as intrusive. Consumers will therefore balance the utility they derive from free downloads against their dislike for advertisements. If a dislike for advertising is prevalent, the number of adopters of an ad-based service will be low, both among new and existing consumers of incumbent services.

[1] We thank an anonymous reviewer for pointing out these distinctions.

2.2. Factors that suggest high attractiveness of ad-based services

Other behavioral factors suggest that ad-funded models may be attractive for consumers. It is likely that the importance of these factors varies between previously inactive consumers (or those who have used illegal file-sharing) and those consumers who have purchased music downloads on the Internet before.

2.2.1. Justification of illegal file-sharing. One major source for consumers who want to download music for free is file-sharing networks, where a broad variety of content is offered free of charge but, in most cases, illegally. As long as no free, ad-based services operate in the market, consumers can internally and externally justify their decision to use file-sharing networks, e.g., because they might not be able to afford the prices demanded by commercial download ventures, such as iTunes or Napster 2.0. If, however, free *and* legal options are available, it will be more difficult to justify the use of illegal file-sharing. Continuing to use p2p networks might cause cognitive dissonance (Festinger 1957), which can be resolved by either developing a negative attitude towards ad-based models, or by refraining from illegal downloading and adopting a free, ad-based offer. If these considerations are operant when consumers evaluate the benefits of different business models, it is likely to increase the total number of customers using commercial downloading services by creating a "lift."

2.2.2. Risk of illegal file-sharing. Similar reasoning can be used for the legal consequences of file sharing. Consumers who engage in the illegal use of p2p networks are exposed to risks of lawsuits (Bhattacharjee et al. 2007) and possibly files that contain malicious software. If a consumer can avoid these risks at no costs, he or she may adopt a free, ad-based service, again, creating a "lift".

2.2.3. Low reference price and WTP. Previous research suggests that consumers form reference prices and price expectations based on previous encounters with price information

(Winer 1986). If consumers incorporate the content available for free through file-sharing networks into the computation of their reference price, this will result in reference prices of close to zero for these consumers. As reference prices are an important driver of willingness to pay, consumers who are characterized by these reference prices can be attracted to legal business models only if they are offered free of charge. This will make an ad-based model a potentially attractive candidate for consumers with low reference prices and low WTP. This will primarily concern consumers who have previously refrained from using commercial download stores, therefore creating a "lift" in total number of adopters.

2.2.4. Positive Affect. Frequently, consumers value free products disproportionately higher than products offered at a low price. Possible explanations include the positive affect that consumers associate with free alternatives. Furthermore, a free option relieves consumers of the burden of actively evaluating costs and benefits (Shampanier, Mazar, and Ariely 2007). Hence, this positive affect may attract customers towards the free, ad-based business model. If this effect is strong, it will both attract new consumers as well as consumers who have previously been paying for content downloads.

2.2.5. Reducing WTP. Consumers who are confronted with a free download service are likely to define their valuation for an incumbent business model that requires payments (e.g., iTunes, Napster 2.0) against the utility they derive from using a free, ad-based service. The presence of a free alternative might therefore negatively affect their WTP for those services that charge consumers for downloading music. If this effect is strong, it will create a shift in the number of adopters in favor of ad-based models.

2.3. Net effect

Although one can draw upon several behavioral theories to make predictions about the favorability of a free, ad-based download service, it is *a priori* unclear which effect will dominate and whether the net effect will be positive or negative. Content owners will only be able to use a free, ad-based model as a tool to reach previously inactive consumers and, thereby, effectively segment the market if those factors that will create a lift will dominate over the other factors. An ad-based service will only work as a market segmentation tool if it is capable of attracting users who have not been using commercial download services before. If factors that will shift preferences towards ad-based services (e.g., a positive affect and a reduced WTP for incumbents) dominate consumer decision-making and a majority of consumers feel that they can maximize their rent in an ad-funded store, ad-based services will cannibalize customers from incumbents. Assuming that utility-maximizing consumers take into account the behavioral factors discussed, the degree to which a shift occurs will depend on the degree of substitutability between an ad-based service and the incumbent offers. If the two types of business models (pay vs. free models) are too close in their intrinsic value, consumers who had previously been paying for downloading music will abandon the incumbent in favor of the ad-based model. Therefore, the effect of the factors that might shift consumer choice will depend on the degree of substitutability.

Although it would be of interest to test the effect of each of the factors discussed above separately, it is of foremost importance to empirically identify the net effect of those factors that create a lift or shift in the total number of adopters of commercial download offers, respectively, as theory does not provide unambiguous predictions about the magnitude of the effects.

3. Eliciting consumer preferences in the presence of free alternatives

To analyze consumer preferences in the market for digital music, we rely on choice-based conjoint analysis (CBC)—a procedure that has gained wide acceptance in marketing research for eliciting consumer preferences (Hennig-Thurau et al. 2007; Louviere and Woodworth

1983). CBC mimics real purchase situations more accurately than do traditional rating- or ranking-based conjoint approaches, leading to the assumption that CBC provides more accurate responses (Toubia, Hauser, and Simester 2004). An example that was used in our application to the music market is displayed in Figure 2.

>>> Figure 2 about here <<<

Because the level of analysis is not an individual track or album but is, rather, the business model, the choice tasks required the respondents to indicate what *type of download store* would be most preferable. Within one choice set this does not allow for modeling the possibility that some consumers might choose to make purchases using different types of business models or to purchase CDs as well. Although we view it as a reasonable assumption that, in general, consumers focus on one type of store or business model, our model also accommodates the consideration of multiple business models across several consecutive choice sets.

3.1. Attributes and attribute levels

We decompose music download services and their respective business models into their main characteristics, which we assume to be price, advertising intensity, restrictions through DRM, and catalog size (Table 1). The selection of attributes and levels is based on insights we gained from three sources. (1) We conducted interviews with focus groups prior to the main data collection process that dealt with issues of legally downloading music from the Internet to gain qualitative insights into consumer preferences. (2) We interviewed experts from the industry to learn about the attributes that the managers perceive to be important. (3) To ensure that no major facet was omitted, we reviewed articles in the popular press and comments that were posted by users in the online versions of relevant articles.

>>> Table 1 about here <<<

3.1.1. Price. The research question requires special consideration of the price variable in the design and estimation of the model. The subscription model, on the one hand, is associated with a monthly subscription fee that is not related to individual titles and does not entitle consumers to permanently keep any tracks that were downloaded through the service. The DST model, on the other hand, charges a fee for every track purchased. Thus, the interpretation of a price variable depends on the respective business model. We therefore introduce an alternative-specific variable for price that we term $price_{sub}$ ($price_{dst}$) for the subscription model (DST model). $Price_{sub}$ ($price_{dst}$) is only shown to the respondent if it occurs for an alternative that represents the subscription model (DST model). The specific valuation of a respondent for either business model is thus captured in the corresponding price coefficient. The five levels for the respective price variables (Table 1) enclose the price range that can be observed in the market. To accommodate advertising-funded offerings that are free of charge, the price of € 0 is included as the minimum level.

3.1.2. Advertising. To capture consumer preferences with regard to advertising, we use four attribute levels: no advertising, banner on the site, banner and obligatory disclosure of preferences and personal information, and advertising embedded in music files. These attribute levels capture the options that are generally available for content distributors.

3.1.3. Digital rights management. Due to the fact that restrictions imposed by DRM strongly affect the utility of a music download (Sinha, Machado, and Sellman 2010; Sundararajan 2004), we include DRM and adapt this attribute to the specific requirements of the respective business models. For the DST model, we incorporate DRM on four different attribute levels. In the case of a subscription-based service, downloads without DRM are not an option because this would render a sustainable business model infeasible due to potential arbitrage. Thus, the attribute level with the highest utility is that at which downloads can be played on all current devices.

3.1.4. Catalog size. The utility that consumers associate with a download store is likely to depend on the number of different titles offered by that particular store (Sinha and Mandel 2008). This assumption follows the rationale that consumers do not want to cover their demand for music downloads at several different download shops but instead prefer a one-stop-shop that provides a comprehensive selection of artists and titles. We thus include a variable that captures the perceived size of the catalog on four levels (small, medium, large, comprehensive).

Based on these attributes and attribute levels, we constructed conjoint choice sets consisting of three stimuli and a no-choice-option; we used a randomized computer-generated design that accounts for minimal overlap, level balance, and orthogonality (Huber and Zwerina 1996). So as not to overstrain the respondents' cognitive resources, we assigned eight choice sets to each respondent. Seven of these were used for estimation; one hold-out set (Figure 2) was deployed to test the predictive validity of our model.

3.2. Covariates

Several covariates were included to help characterize respondents and the resulting segments because the estimation is enriched with information that is not directly contained in the choice behavior. The questionnaire covered aspects that relate primarily to three conceptual domains. (1) The "theory of planned behavior" has proven powerful in explaining and helping us to understand future behavior, including the adoption of innovations (Ajzen 1991; Taylor and Todd 1995)—hence, the theory's constructs attitude (towards DST and subscription models, respectively), perceived behavioral control, and subjective norm (to adopt any commercial download store) are included. (2) Rogers (2004) identified several product characteristics that determine whether an innovation is likely to be adopted. Based on previous research (Taylor and Todd 1995), we include these innovation criteria as the perceived degree of relative advantage, complexity, and compatibility of commercial downloads. Note that these variables do not pertain to specific download stores but rather to the concept of obtaining music from commercial download stores. We extend these variables via constructs that pertain to the perceived risk of adopting a download service, the perceived critical mass (Van Slyke et al. 2007), and consumers' price sensitivity (Ofir 2004). (3) We control for music usage habits by asking respondents to indicate, for example, how much time they spend on listening to music, their budget for music purchases, and how important they view the opportunity to permanently keep the tracks. Because the choice of a legal download service will probably be affected by the likelihood of an individual's engaging in illegal file-sharing that, however, is hard to measure, we computed a measure that relates the number of files stored on a computer to the annual downloading budget. We use this measure as a proxy of the inclination to use the computer to consume music that was obtained from other sources. These may include illegitimate file-sharing as well as files copied from previously purchased CDs. A list of all items can be found in the Appendix.

4. Data

We collected our data using an online questionnaire that was made available in Germany in April 2008. To avoid the severe bias that a student-only sample would represent, respondents were recruited through an online-access panel that was launched by a major European media distributor to keep track of developments with regard to consumer preferences for the consumption of media products in one of the largest markets for music worldwide. The structure of the panel is designed to represent the market for recorded music in Germany, so we are confident that the composition and magnitude of the panel are well-suited to measuring consumer preferences and represent a strong potential for high external validity. Respondents received "panel points" for their participation, and a prize drawing for 100 CDs was held among all respondents who completed the questionnaire. In total, 2,540 usable cases were obtained.

A comparison of sample characteristics with market research data that represent the entire online music market suggests that the allocation of demographic variables reported in other publications matches the composition of our study quite well, although younger people are still slightly over-represented (GFK 2009). The ages in our sample range from 12 to 73 years, with a mean of 29 years and a median of 27 years. Approximately 52% of the respondents were male. Furthermore, a large fraction (44%) had no experience downloading and paying for music from legal download shops, whereas 13% report weekly or more frequent usage. These numbers indicate that the sample is comprised of both experienced and inexperienced users who do not already experience lock-in effects because they have not yet chosen a particular download shop. Hence, we trust that the online target group of the music industry is well represented here.

5. Estimation and results

5.1. Utility estimates

We use the multinomial logit (MNL) model for the estimation of consumer preferences for the music download characteristics. MNL models preferences β in terms of choice probabilities *p*. For example, if a music service *i* has been chosen from a set of *J* download alternatives, this choice would be integrated into a likelihood function given by (1):

$$p(i \mid J) = \frac{\exp(\beta \cdot X_i)}{\sum_{j=1}^{J} \exp(\beta \cdot X_j)}, \qquad (1)$$

with X_j being a vector that describes the specific characteristics of the download service *j*, e.g., being a free, ad-based model with a large catalog size (for details see Desarbo, Ramaswamy, and Cohen 1995). To obtain results that facilitate managerial implementation, we estimate preferences not on an individual level but, rather, based on segments using latent-class analysis. Latent-class analysis assumes that respondents belong to a discrete but *a priori* unknown number of homogenous segments. The method clusters respondents based on the similarity of their choice behavior. As a result each segment contains consumers with similar preferences (Desarbo, Ramaswamy, and Cohen 1995). All respondents who chose the no-choice-option in all choice sets (n = 221) were *a priori* assembled into one segment and discarded from the estimation because their choice behavior does not contain additional information.

With latent class analysis the optimal number of segments is *a priori* unknown. We therefore computed solutions for up to seven segments and used information criteria (AIC, BIC, CAIC; Andrews and Currim 2003) as well as a measure of entropy, which assesses the degree of fuzziness in separation (Ramaswamy et al. 1993), to determine the adequate number of segments. The model selection criteria are reported in Table 2 for the number of segments from $k = 1$ to $k = 7$.

>>> Table 2 about here <<<

The information criteria use the model's log likelihood that is maximized in the estimation and the number of parameters that were used for estimation to compute goodness-of-fit measures that indicate a better fit for lower values (Andrews and Currim 2003). BIC and CAIC impose a stronger penalty on the number of parameters to be estimated, and thus these criteria lean toward the more parsimonious models. BIC and CAIC indicate the optimum for the six-segment solution. The entropy-based measure (EN) does not clearly lean toward a particular number of segments but suggests a good separation between segments for all solutions. Thus, we rely on BIC and CAIC and focus on the six-segment solution (Table 2).

5.2. Validity

To test the validity of the solution, we compare the observed choices in the hold-out set (see Figure 2) with the predicted choices based on the utility estimates within the logit model. We use the mean absolute error (MAE) and the hit rate as measures to assess the prediction accuracy (Huber et al. 1993; Moore, Gray-Lee, and Louviere 1998). The MAE considers the absolute difference between predicted and actual choice shares of each identified segment across the four alternatives in the hold-out set. The six segment solution exhibits an MAE of 4.61%, indicating that predicted shares differ from actual behavior by less than 5 percentage points. By using the first-choice rule for prediction (i.e., assuming that the alternative with the highest utility will be chosen) the prediction can be enhanced to an MAE of only 1.69%. We further compute the hit rate, which assesses if the predicted alternative matches the actual choice on an individual level. To derive individual-level values from the segment-specific estimates, the estimates are weighted by each individual's segment membership probability. A hit rate of 55.9% indicates a good degree of predictive validity compared to a hit rate of 25% using a random prediction model.[2]

To provide an additional measure of validity we use the model to predict the share of respondents who would not adopt any commercial download store and compare it to the share of respondents who did not use commercial downloading in the past. Given a configuration of business models that was typical for the German market in 2008 our model predicts that between 36.5% and 49.6% (depending on the price of a single download) of all respondents would not choose any commercial download offer. Using the average price of a music download in 2008 (€ 1.13; GFK 2009) our choice model predicts that 43% of all respondents

[2] As another benchmark for the validity assessment, we estimated utilities by means of a hierarchical Bayes procedure (Rossi and Allenby 1993; Rossi, Allenby, and McCulloch 2005; Rossi and McCulloch 2006), which resulted in comparable validity measures, i.e., a hit rate of 59.2% and MAE values of 3.85 (logit) and 2.75 (first-choice). We rely on the segment-level approach here because it generates more managerially relevant information.

would choose not to adopt. This finding correspondents well to the observation that 44% of the respondents have no experience with commercial music downloading and suggests a reasonable degree of convergent validity. We therefore conclude that strategic choice behavior or compliance to potentially perceived social pressures is unlikely to severely compromise our results.

5.3. Predicted shares and scenarios

We use the conjoint data to simulate different market scenarios to predict how consumers decide when confronted with competing business models. Marketers can use these analyses to focus on those product features that have the strongest positive impact on market share. The *status quo* at the time the survey was conducted was a DST model offering DRM-protected tracks with a reference price of € .99 and competing against a subscription model priced at € 14.99 that could be used in combination with selected mobile devices. Competitive ad-based models were virtually absent from the market.

The predicted shares based on the logit model are displayed in Table 3[3]. While more than 20% of the respondents would not choose any commercial downloading option at all, roughly half of the market would opt for the DST model, with only a minority inclined to adopt the subscription model (scenario 1). However, about 20% would opt for a free, ad-based store, suggesting considerable market potential for this business model. One major change in the industry's strategy was the decision to remove DRM from DST downloads in 2008 (scenario 2). Comparing scenarios 1 and 2, we can observe that this decision has had a strong, positive effect on DST market shares. It barely taps the market potential for ad-based services but has the potential to increase overall market size by reducing the share of consumers who prefer not to purchase to 18%. However, the simultaneous move toward higher prices has a strong,

[3] The choice shares implicitly consider that a choice for a given business model may not be exclusive. Rather, they can indicate a usage ratio between generally acceptable business models.

detrimental effect on the DST models' market share, increasing the percentage of consumers who do not purchase to 27%. The advertising-based model substantially gains in market share due to customers in the segment moving from DST to the ad-based model.

>>> Table 3 about here <<<

We suggested earlier that ad-based models potentially attract consumers if they provide utility to their customers that is close to that of the incumbents. One way of increasing the utility of the service is by increasing the catalog size. As indicated by scenario 4, a major improvement to this product attribute, featuring the introduction of a catalog comparable to that of the market leader, would indeed attract a considerable number of new customers—of whom most would not choose any other option for commercial downloading. Increasing catalog size does not seem to have a strong effect on the competing business models; their market share is barely decreased (scenario 4). This does not only suggest that the advertising-based model has the potential to increase market size and attract consumers who would otherwise refrain from commercial downloading (mainly segment 4). It also implies that the dislike for advertising is strong while the valuation of free, ad-based services is low in segments 1, 5, and 6, and the degree of cannibalization only marginally depends on the substitutability expressed in terms of catalog size.

Comparing scenarios 3 and 5, we see that when ad-based providers disappear from the market, almost half of their customers leave the market and refrain from commercial downloading, whereas a minor portion switches to subscription models. Hence, the music industry should have some interest in preserving ad-based downloading services to avoid market size shrinkage. For companies that offer both an ad-funded basic service and a paid-for premium service, it is advisable to maintain a free component because most users would otherwise leave the market (as opposed to becoming paying customers).

5.4. Segment characteristics

The segments we derived above not only differ with regard to their choice behavior but also in those characteristics that are captured in the covariates. In the interest of readability, Table 4 indicates whether the segment-specific mean for a given variable significantly differs from the mean across all other segments. Based on the most distinctive characteristics and the segments' main preference we labeled the segments column accordingly.

>>> Table 4 about here <<<

One key finding is that the respondents who only selected the no-choice option (assembled in segment 7) exhibit a negative attitude towards music downloading and associate a high degree of complexity and low degree of compatibility with music downloading. These consumers prefer to consume music via CDs and therefore refrain from music downloading. Consumers from this potentially profitable "offline" segment are not attracted by free, ad-based models and are therefore not subject to a shift in choice for business models.

Segment 4, which is also skeptical of adopting a pay model, appears to have different motives. Consumers in this segment use their computer for consuming music, but they do not rely on CDs or purchase music on the Internet. Rather, they believe that music on the Internet should be offered free of charge. It is therefore advisable to address this segment with free, ad-funded models, as this segment would not choose any other legal download offer, and the inclination to use illegitimate download sources is likely to be strong in this segment. Noteworthy are also the characteristics of segment 3. Their enthusiasm for music downloading is not only reflected in a positive attitude towards DST and subscription models, but they also accept the limitations that are imposed on music files in terms of usability and durability.

These segment characteristics suggest that those segments that can be attracted by the ad-based model are less likely to be CD buyers. Hence, the danger of cannibalizing profitable CD customers with the ad-based model appears to be low.

6. Willingness-to-pay

6.1. Calculation of willingness-to-pay-measures

We transform the utility estimates we derived above into WTP measures. This has several advantages. (1) Although ad-based models are usually offered free of charge, it is also conceivable for these services to charge fees. In determining reservation prices for ad-based services, WTP measures are useful. (2) The monetary value of the different product attributes can be assessed. (3) WTP measures allow one to evaluate to what degree the presence of free alternatives affects the monetary valuation of other business models.

The calculation of WTP measures can generally be achieved by dividing the utility function by the price vector, which yields the incremental monetary value of the respective attributes (Srinivasan 1982). However, this measure has at least four shortcomings: (1) it requires a linear relationship between price and utility, (2) it is highly sensitive to the scale of the parameter estimates and often yields extreme values (e.g., when the price coefficient approaches zero) or misleading results, (e.g., when the price coefficient is positive; Ofek and Srinivasan 2002), (3) the incremental value leaves the question of the absolute magnitude of the monetary value of a product unresolved, and (4) competitive market offerings are not considered explicitly.

Several methods have been proposed as ways to overcome these shortcomings. Ofek and Srinivasan (2002) address the problem of outlier values and the integration of competing products; they propose weighting WTP estimates according to a consumer's probability of choosing a product in a specific competitive market scenario (Ofek and Srinivasan 2002).

Similarly, Sonnier, Ainslie, and Otter (2007) try to avoid outlier values and suggest a parameterization of the likelihood function that directly incorporates a WTP measure and thus can affect its prior distribution in hierarchical Bayes analyses.

However, Ofek and Srinivasan (2002) focus on the incremental value of attribute improvement and use a linear price coefficient in their demonstration. Similarly, the WTP measure of Sonnier, Ainslie, and Otter (2007) is based on a linear price vector and requires hierarchical Bayes analysis. The alternative that we propose in our approach is not limited to a specific analysis technique and yields absolute WTP. The approach does not rely on a linear price function because we estimate price preferences with a part-worth model. Moreover, competition can be considered explicitly because our measure is based on the reservation price that makes a respondent indifferent between the choice of a specific alternative and the no-choice option (Jedidi and Zhang 2002). This follows the rationale that because a consumer does not merely have the option of choosing vs. not choosing a product, competition from other offers should be taken into account (Ofek and Srinivasan 2002). Assuming a utility-maximizing agent, it is likely that the consumer's WTP depends on the utility she or he obtains by choosing a different option—e.g., the WTP for a track from the DST store depends on the utility a consumer derives from the net utility of an ad-based download store. We, therefore, differentiate our findings and report two different WTP measures: (1) WTP compared to the no-choice option (consideration WTP) and (2) WTP compared to the next-best market option (competition WTP).

We calculate the WTP by comparing the utility u_i^* of the benchmark alternative with a specific alternative *t*. The alternative *t* is only chosen if its utility exceeds that of the benchmark alternative. This benchmark alternative can either be the no-choice option (consideration WTP) or a relevant competitor (competition WTP). The maximum WTP for alternative *t* can thus be set such that the utility of alternative *t* plus the (negative) utility for the price still exceeds the utility of the benchmark alternative:

$$u_{i,t|\sim p} + u_i\left(p\right) = u_i^* + \varepsilon \tag{2}$$

where $u_{i,t|\sim p}$ represents the utility of alternative *t* without the utility for price, and ε is a small positive value (Kohli and Mahajan 1991). Figure 3 shows this idea in an example, where the x-axis represents the price for a focal offer, and the y-axis represents the utility associated with different price levels of the focal offer.

>>> Figure 3 about here <<<

Because both price attributes include € 0.00 as a level, this automatically sets the lower boundary of WTP. The upper boundary is given by the highest price level that is included for the different attributes—i.e., € 19.99 for the subscription model and 1.69 Euro for the DST model. Thus, if an offer is still preferable even though it exhibits the highest price levels, we can only state that its WTP is exceeding this price.

6.2. Willingness-to-pay-measures

All WTP measures are initially computed for the products that were displayed in the holdout set that thus serves as the *status quo* scenario (Table 5, scenario 1). The largest segment, segment 1, appears to be quite skeptical with regard to music download offers; only a DST store offering mp3 files results in a moderate WTP that is close to current market prices. As is the case for most segments, the decision for consumers in this segment is not between different business models but rather between a DST model (e.g., iTunes or Amazon) and no commercial music downloading at all. This can be seen in the information on the respective "closest competitor" that captures which offer exhibits the next highest utility. The closest competitor for all DST offers is the no-choice-option in 4 out of 6 segments. This implies that these consumers would rather refrain from commercial downloading than make use of subscription or ad-based services, indicating a small degree of cannibalization given the available configuration of ad-based services. Segments 2 and 3 are the only segments in which substitution between the advertising and the DST model might occur, and ad-based services should therefore focus on these segments. The competition WTP indicates that typical prices in DST stores above € 1.15 per track would decrease the utility of a DST store, making an ad-based service the most preferable alternative. Segment 3, which can be termed the "enthusiast" segment (these consumers display remarkably high consideration WTP for all offers, almost regardless of the product configuration), even exhibits high consideration WTP for an advertising-based service. However, taking into account the competition by other business models, we see that no segment has a WTP for advertising-based services.

>>> Table 5 about here <<<

This implies that almost all segments show a rather clear preference for one of the business models. Competition for customers and fear of cannibalization is likely to focus on segments 2 and 3 because these consumers do not have a strong preference for a specific business model. Segment 3 is the only segment whose members exhibit a notable competition WTP for a subscription-based download service. In a market where no downloads without DRM are available, the mean WTP in this segment approaches € 14, which is close to the current market price of € 15, the closest competitor being an advertising-based service. In this segment, we can observe the effect of the recent policy change of removing DRM restrictions from DST downloads on the potential success of competing business models: the WTP for a subscription-based service is reduced from € 13.62 in a setting without DRM-free downloads (scenario 1) to € 9.71, where the subscription service has to compete against mp3 downloads without DRM (scenario 2). This deterioration of WTP for a subscription service captures how a download service that offers mp3 files without DRM becomes relatively more attractive than a subscription service. These findings not only suggest that subscription-based services will have to revise their offer if they are to have a chance of success and provide a sustainable business model after the industry's move to offer mp3 downloads, but they also offer an explanation for why they have so far failed to attract a sufficient number of customers, although the music industry's expectations associated with this business model are high (IFPI 2009).

The two smallest segments, 5 and 6, are characterized by a strong preference for a DST model; the WTP for all other options is negligible. The closest competitor is always the no-choice option, such that these consumers would choose no downloading service at all rather than rely on a subscription or advertising-based service. These two segments are the target segments that any DST downloading service should seek to address; cannibalization by ad-based services is unlikely.

7. Elasticities

To provide an even more condensed picture of the market reaction to firms' and competitors' actions, it is useful to rely on elasticities—i.e., the relative change in market share in relation to the relative change in price.[4] The elasticities displayed in Table 6 are considerably lower than for most consumer goods (Bijmolt, van Heerde, and Pieters 2005). A likely reason for this finding might be that these market-share elasticities capture whether a consumer decides to purchase or not to purchase but do not cover to what extent consumers adapt the quantity of songs purchased as a reaction to changes in price. Overall, a 1% increase in price is usually associated with a less than 1% decrease in market share; the lowest elasticity can be observed for the DST model.

>>> Table 6 about here <<<

[4] Elasticities are computed as the relative change in market share divided by the relative change in price on all attribute levels for price compared to a medium price level of € 0.99 for DST and € 9.99 for subscription models.

Looking at the cross-price elasticities, we observe three remarkable points. (1) Most cross-elasticities are rather low, indicating a low degree of competition and substitutability between the different business models. (2) Both subscription-based models can profit from price increases conducted by DST models. In particular, the advertising-based models gain market share as a 1% increase in DST prices expands their market share by .58%. (3) The degree of price interaction between subscription- and advertising-based models is low, suggesting that these two business models do not directly compete but, rather, serve two distinct segments. Although generally low, the competitive relationship is asymmetric. Whereas advertising-based models can gain some customers when subscription providers increase prices, the opposite is not true; if advertising-based models raise prices, most customers will leave the market instead of switching to other business models.

8. Conclusion

Our empirical analysis takes a first step toward analyzing the effect of free downloads on established business models and represents a first approach to answer the previously unaddressed, albeit important, question of how to properly approach consumers in the download market. The findings can be summarized as four main points. (1) Given an attractive configuration, the advertising-based model has the potential to attract new customers who previously did not engage in commercial downloading, thus increasing market size. The results suggest that the danger of severe cannibalization and channel conflicts is low and will most likely focus on segments 2 and 3. This indicates that those behavioral factors that induce a lift in the number of adopters dominate those that create a shift. Hence, it appears to be the case that consumers with low WTP and those consumers that cannot justify the use of illegal p2p networks would primarily be attracted by free, ad-based services. The free, ad-based services do not create a positive affect that dominates the apparent dislike of advertising present in most segments. Content owners should therefore ensure that free, ad-based services can establish themselves in the market because, in combination with incumbent business models, free, ad-based services can be used to segment the market; consumers willing to pay are served with DST and subscription models, consumers with low WTP are offered free, ad-based services. This market segmentation is possible because ad-based services barely cannibalize existing demand. One way of fostering ad-based services might be granting attractive royalty payments when negotiating licensing contracts to ensure the take-off of these services. (2) The subscription model, with its current pricing strategy, is unattractive for most consumers. This is unlikely to change even when product features, such as catalog size, are improved. Thus, our data do not provide any support for the optimism associated with the subscription-based model in the music industry. (3) Despite recent decisions to increase prices for a part of the single catalog above € .99, the DST model is likely to dominate tomorrow's market for music downloads. (4) Dislike for advertising appears to strongly impact consumer preferences not only in segments 1, 5, and 6 but also for those consumers who selected only the no-choice option. At first glance one could assume that any alternative with a free, ad-based model dominates the no-choice option because it enables consumers to obtain music at no cost and should therefore be more attractive than the no-choice option. The fact, however, that a substantial portion of consumers selected only the no-choice option indicates that the dislike for advertising is strong enough to let these respondents refrain from commercial downloading completely.

The developments in the market for other digital downloads (e.g., movies, books) are usually delayed compared to those in the music industry. This gives companies in adjacent industries the opportunity to learn from experiences in the music industry. At least two key conclusions can be drawn: (1) Free, ad-funded downloads can be a powerful tool to increase market size and segment the market. Hence, they should be taken into consideration to maximize market size when cannibalization is low. (2) Restricting downloads through severe DRM systems will hinder the spread of commercial downloading and exclude many consumers from the market. This becomes evident in the high sensitivity respondents exhibit with regard to the DRM attribute in the present analysis. In the case of movie downloads, comparable preferences can be expected. Marketers in the movie industry should therefore try to avoid severe restrictions through DRM.

Like most empirical studies, our analysis is subject to limitations. First, in this study, the consumer reactions to attribute changes reveal whether consumers would change their minds in favor of a specific business model. Knowledge about this choice behavior is necessary but not sufficient to derive profit implications. What is necessary to estimate the impact on profits is the individual choice regarding the *number of units purchased* or *downloaded* and hence should be the subject of future research. Second, our study was conducted in the German music download market, which is the third largest market for music worldwide. We do not expect preferences to differ substantially from those seen in other Western markets, but a study with a larger sample and an international focus incorporating several countries might confirm or strengthen the generalizability of our results. Third, a choice-based conjoint experiment is a hypothetical experiment that is not incentive-compatible such that the respondents have an incentive to reveal their true preferences (e.g., by being obliged to buy; Völckner 2006). Thus, we cannot exclude the possibility of a hypothetical bias that leads to an overestimation of WTP. Experiments that involve a buying obligation and that are incentive-compatible (Ding 2007), or real market experiments that overcome this limitation, are likely to be a rewarding avenue for further research. Similarly, conjoint experiments are limited in the number of attributes that are subject to variation. So, it could be possible that for some consumers other or additional attributes than the ones we integrated are important drivers for choice that our predictions cannot account for. Fourth, given the finding that a substantial number of consumers find ad-based download offers attractive, future research should address the question of under which circumstances ad-based services will be successful in generating sufficient advertising revenues to be profitable.

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Tables and figures

Table 1

Attributes and attribute levels

Attribute	*Levels*				
$Price_{sub}$ (per month)	0.00 €	4.99 €	9.99 €	14.99 €	19.99 €
$Price_{dst}$ (per title)	0.00 €	0.49 €	0.99 €	1.29 €	1.69 €
Advertising	Free	Banner	Banner & Personal Information	Embedded in file	
DRM_{sub}	PC & Mobile All Devices	PC & Mobile Selected Devices	PC Download / Stream	PC Stream	
DRM_{dst}	DRM free	Watermark	Selected Devices	Selected Devices Copy Protection	
Catalog size	Comprehensive	Large	Medium	Small	

Table 2

Model selection

No. of segments	*Log likelihood*	*AIC*	*AIC3*	*BIC*	*CAIC*	*EN*	*$R^2(0)$*	*Class. Error*
1	-19000.719	38043.438	38064.438	38164.165	38185.165	1	0.165	0.000
2	-16898.739	33925.478	33989.478	34293.407	34357.407	0.837	0.271	0.043
3	-16239.201	32692.402	32799.402	33307.533	33414.533	0.804	0.329	0.105
4	-15716.424	31728.847	31876.847	32579.683	32727.683	0.783	0.386	0.122
5	-15322.124	31024.249	31214.249	32116.538	32306.538	0.774	0.421	0.142
6	-15044.313	30550.626	30781.626	31878.620	32109.620	0.779	0.459	0.151
7	-14912.803	30371.606	30644.606	31941.054	32214.054	0.777	0.471	0.164

Table 3

Predicted shares in different scenarios

	Segments						
	1	2	3	4	5	6	Aggregate
Scenario 1: DRM on DST downloads							
Subscription	0.84%	1.28%	30.45%	3.50%	0.55%	0.80%	7.13%
DST	65.27%	59.76%	29.58%	3.37%	80.93%	90.92%	50.38%
Advertising	0.89%	28.45%	32.71%	38.77%	2.74%	2.47%	19.79%
None	33.01%	10.52%	7.26%	54.36%	15.78%	5.81%	22.69%
Scenario 2: mp3 in DST downloads							
Subscription	0.48%	1.12%	27.63%	3.49%	0.30%	0.60%	6.43%
DST	80.27%	64.55%	36.10%	3.62%	89.61%	93.18%	57.10%
Advertising	0.51%	25.06%	29.68%	38.67%	1.49%	1.86%	18.22%
None	18.75%	9.27%	6.59%	54.22%	8.60%	4.36%	18.25%
Scenario 3: Price increase to € 1.29 per download							
Subscription	1.15%	2.23%	30.85%	3.49%	0.47%	1.56%	7.54%
DST	52.38%	29.51%	28.65%	3.62%	83.71%	82.38%	40.62%
Advertising	1.22%	49.83%	33.14%	38.67%	2.34%	4.79%	24.50%
None	45.25%	18.42%	7.36%	54.22%	13.48%	11.27%	27.33%
Scenario 4: Comprehensive catalog in Advertising-based model							
Subscription	1.14%	1.73%	28.56%	2.55%	0.47%	1.49%	6.82%
DST*	51.83%	22.87%	26.52%	2.64%	83.29%	79.10%	38.18%
Advertising	2.26%	61.11%	38.12%	55.27%	2.84%	8.58%	31.39%
None	44.77%	14.28%	6.81%	39.55%	13.41%	10.82%	23.61%
Scenario 5: Advertising-based models leave the market							
Subscription	1.16%	4.45%	46.14%	5.69%	0.48%	1.64%	11.38%
DST*	53.03%	58.82%	42.85%	5.90%	85.72%	86.53%	50.56%
Advertising							
None	45.80%	36.72%	11.00%	88.41%	13.80%	11.84%	38.06%

Note. All business models are configured according to the hold-out choice set (cf. Figure 2) unless otherwise stated.
* DST model configured as in scenario 3.

Table 4

Segment characteristics

	Segments						
	1	2	3	4	5	6	7*
Covariates	Skeptics	Advertising	Enthusiasts	None	DST	DST	None
Theory of Planned Behavior (Ajzen 1991; Taylor/Todd 1995)							
Attitude$_{DST}$	---**	+++	+++	-	+++	--	---
Attitude$_{SUB}$	---	0	+++	+++	0	--	---
Subjective norm	0	0	++	---	++	+++	---
Perc. beh. contr.	0	+++	0	--	++	0	-
Diffusion of Innovation Theory (Rogers 2003)							
Relative adv.	--	+++	+++	---	+++	+++	---
Compatibility	---	+++	+++	---	+++	0	---
Complexity	+++	---	--	+++	---	0	+++
Financial risk	--	0	---	+++	0	0	0
Usage risk	0	0	---	+++	0	++	0
Perc. critical mass	---	0	+++	---	+++	+++	---
Price sensitivity	0	0	0	0	-	0	0
Usage habits / demographic variables							
Files stored on PC	+++	---	---	+++	0	0	+++
CD preference	0	---	---	0	0	0	+++
Accept. of DRM	---	0	+++	0	0	0	0
Accept. of perish.	---	--	+++	0	-	0	0
PC usage (music)	++	--	0	+	+	0	---
Credit card usage	0	+++	0	---	0	++	--
Music free	0	0	0	+++	0	--	---
Music listening	0	---	+++	0	0	0	++
Internet usage	0	---	0	+++	--	0	0
Age (in years)	+++	0	--	--	---	0	+++
Sex (1=male)	0	0	+	---	+++	0	0
Digital music exp.	0	0	+++	---	+	0	---
CD expenditures	+++	-	-	0	0	0	+++

Notes.
* Only no choice option.
** To be read as follows: attitude towards DST model is significantly less positive in this segment compared to the mean of all other segments.
Mean of each segment is tested for significant difference against mean of all other segments;
+++ / --- = $p < 0.01$, ++ / -- = $p < 0.05$, + / - = $p < 0.1$, 0 = not significant

Table 5

Segment-specific WTP measures (in Euro)

	Segments					
	1	2	3	4	5	6
Segment size	22%	20%	19%	18%	10%	10%
	Skeptics	Advertising	Enthusiast	None	Only DST	Only DST
Consideration Willingness-to-pay						
Subscription	0.00	3.72	>19.99	1.58	0.00	2.54
DSTmp3	1.29	1.30	>1.69	0.45	>1.69	>1.69
DST	1.15	1.29	>1.69	0.44	>1.69	>1.69
Advertising	0.00	2.33	>19.99	0.00	0.00	0.00
Advertising (comp. catalog)	0.00	3.41	>19.99	0.77	0.00	0.00
Scenario 1: Competition Willingness-to-pay (DRM)						
Subscription	0.00	0.00	13.62	1.58	0.00	0.00
Closest Competitor	DST	DST	Advertising	None	DST	DST
Advertising	0.00	0.00	1.44	0.00	0.00	0.00
Closest Competitor	DST	DST	Subscription	None	DST	DST
DST	1.15	1.14	0.57	0.44	>1.69	>1.69
Closest Competitor	None	Advertising	Advertising	None	None	None
Scenario 2: Competition Willingness-to-pay (mp3 in DST downloads)						
Subscription	0.00	0.00	9.71	1.58	0.00	0.00
Closest Competitor	DST	DST	DST	None	DST	DST
Advertising	0.00	0.00	0.00	0.00	0.00	0.00
Closest Competitor	DST	DST	DST	None	DST	DST
DST (DRM free)	1.29	1.18	1.16	0.45	>1.69	>1.69
Closest Competitor	None	Advertising	Advertising	None	None	None
Scenario 4: Competition Willingness-to-pay (Comprehensive catalog in Advertising based models)						
Subscription	0.00	0.00	8.83	0.81	0.00	0.00
Closest Competitor	DST	DST	Advertising	Advertising	DST	DST
Advertising (Comp. Catalog)	0.00	0.00	0.43	0.77	0.00	0.00
Closest Competitor	DST	DST	DST	None	DST	DST
DST (DRM free)	1.29	1.09	0.90	0.38	>1.69	>1.69
Closest Competitor	None	Advertising	Advertising	Advertising	None	None
Scenario 5: Competition Willingness-to-pay (Advertising-based models leave the market)						
Subscription	0.00	0.00	9.71	1.58	0.00	0.00
Closest Competitor	DST	DST	DST	None	DST	DST
DST (DRM free)	1.29	1.30	1.22	0.45	>1.69	>1.69
Closest Competitor	None	None	Subscription	None	None	None

Note. All business models are configured according to the hold-out choice set (cf. Figure 2) unless otherwise stated.

Table 6

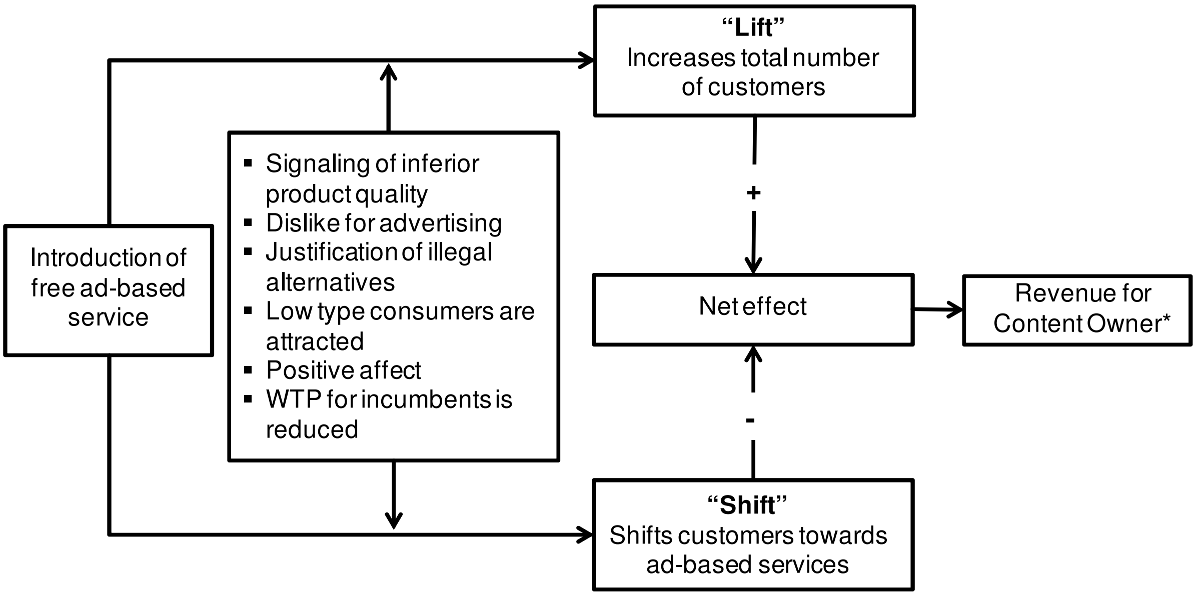
Elasticities

	Price elasticities			Cross-price elasticities					
				Subscription		DST		Advertising	
	Sub.	DST	Adv.*	DST	Adv.	Sub.	Adv.	Sub.	DST
Lowest Price level	-2.12	-0.39	-2.42	0.24	0.13	0.11	0.09	0.32	0.55
Price level below mean	-0.57	-0.35	-0.61	0.17	0.06	0.03	0.03	0.09	0.50
Price level above mean	-0.44	-0.95	-0.44	0.57	0.09	0.03	0.02	0.12	0.69
Highest Price level	-0.28	-0.85	-0.28	0.35	0.05	0.02	0.01	0.06	0.60
Mean elasticity	-0.85	-0.64	-0.94	0.33	0.08	0.05	0.04	0.15	0.58

* *Note.* Ad-based models are typically offered free of charge. However, this is not a necessary condition and the CBC contained choice sets with ad-based models that had a non-zero price. We therefore computed elasticities in the same manner as for the subscription model but focus the interpretation on the other models and the cross-elasticities respectively.

Figure 1

Conceptual framework



Note. Revenue is not analyzed in this study.

Figure 2

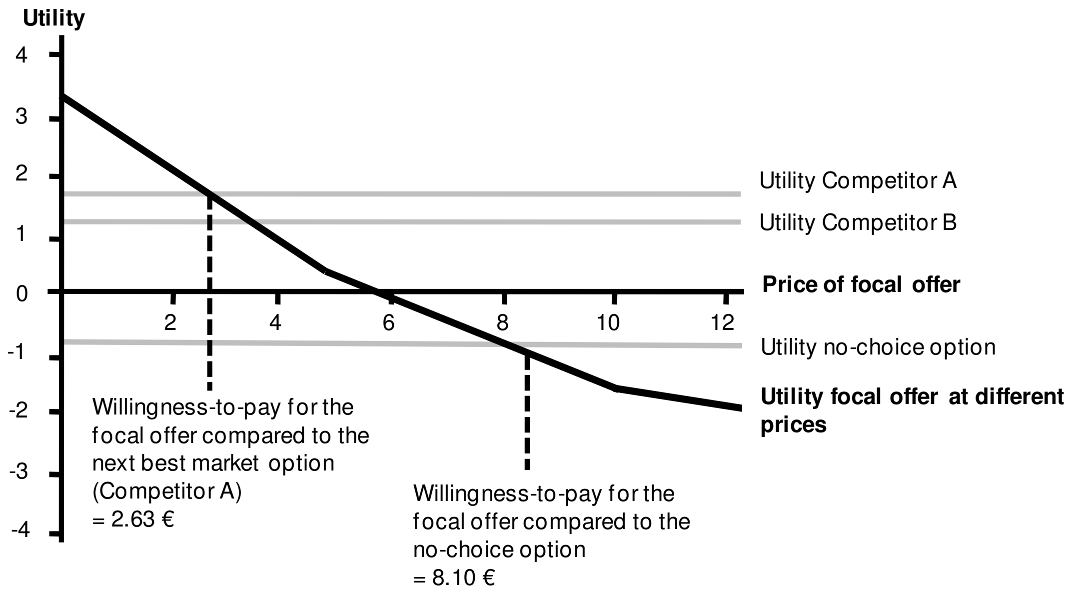
Choice set example[5]

Please select the offer you would prefer.				
	1	2	3	
Price	14.99 € per month	0.99 € per title	0.00 € per month	I would choose none of these.
DRM	PC & mobile devices; selected devices; no burning rights	PC & mobile devices; selected devices; unlimited burning rights	PC & mobile devices; selected devices; no burning rights	
Advertisement	No ads	No ads	Disclosure of personal information, banner ads	
Catalog	Large catalog	Comprehensive catalog	Medium catalog	

[5] The choice set was adapted from the original German questionnaire.

Figure 3

Hypothetical example of relationship between consideration and competition WTP



Appendix

Table A1

Survey items

Attributes/Levels	M	SD
Theory of Planned Behavior (Ajzen 1991) [adapted from Taylor/Todd 1995]		
Attitude$_{DST}$ Attitude towards Digital Sell Through offers: - Payment: per track / „Download-to-Own" - Catalogue size: large. - Usage: PC & selected mobile devices - Copy protection: 10 CD-Burns	2.847	1.045
Attitude$_{SUB}$ - Payment: monthly flat fee (unlimited use of the available catalogue) - Catalogue size: large - Usage: PC & selected mobile devices - Copy protection: no burning rights / music files will be only be usable during time of membership - Membership can be terminated on a monthly basis	4.081	1.038
1 Using this download service for buying music is a good idea.		
2 Using this download service for buying music is a foolish idea.*		
3 I like the idea of using this download service for buying music.		
4 Using this download service for buying music would be pleasant.		
Subjective norm	3.239	0.966
1 People who influence my behavior would think that it is advisable to pay for music on the Internet.		
2 People who influence my behavior would pay for music on the Internet.		
Perceived behavioral control	1.898	0.853
1 I would be able to use (legitimate) music download services on the Internet.		
2 Downloading music over the Internet (legitimate sources) is entirely within my control.		
3 I have the resources (e.g., time, money, or technical equipment) *and* the knowledge *and* the ability to use (legitimate) music download services.		
Diffusion of Innovation Theory (Rogers 2003)		
Relative advantage [adapted from Taylor/Todd (1995)]	3.038	1.113
1 The use of music download services will be beneficial.		
2 Overall, using a music download service will be advantageous.		
Compatibility [adapted from Taylor/Todd 1995]	3.123	1.075
1 Using digital music services on the Internet fits well with the way I like to consume music.		
2 Using the Internet for buying music fits well with my lifestyle.		
Complexity (Ease of Use) [adapted from Moore/Benbasat 1991]	2.049	0.806
1 It will be easy to learn how to use a music download service.		
2 My interaction with music download services is clear and understandable.		
3 The usage rights of digital music files obtained from legitimate download services are easy to understand (e.g., burning, copying, range of devices).		
4 Overall, I believe that music download services are easy to use.		
Risk		
Financial Risk: To what extent do you fear that downloading music is not financially viable, e.g., because you have to purchase new hardware or because music files will not be usable in the future? [1=high risk – 5=no risk]	2.775	1.089
Usage Risk: To what extent do you fear that music files will not be compatible with you technical equipment due to proprietary formats? [1=high risk – 5=no risk]	2.734	1.171
Perceived critical mass [adapted from van Slyke et al. 2007]	3.290	1.012
1 A lot of my friends already use legitimate music download services.		
2 Of the people I frequently exchange music with, many use legitimate music download services.		
3 Many of the people I frequently exchange music with will continue to use legitimate music download services in the future.		
Price sensitivity [adapted from Ofir 2004]	2.348	0.997
1 To find the cheapest price, I frequently compare the prices of several websites before I buy something on the Internet.		

2	It is worthwhile to search for the cheapest price on the Internet because it saves money.		
Usage habits / demographic variables			
Files stored on PC: digital music spending (€) / no. of tracks saved on hard drive – ratio (Scale: 1-10)		5.546	2.826
CD preference: I generally rather buy CDs than digital music on the Internet.		2.084	1.186
Acceptance of DRM: It is sufficient if I can only use digital music files on a limited range of devices (e.g., only iPod or WMA-compatible devices).		4.377	0.981
Acceptance of perishability: It is sufficient if I can only use music files during the time of membership.		4.331	0.979
Usage of PC for music listening: 7-point-scale [1 = daily – 7 = never]		1.963	1.264
Usage of credit card on the web: 7-point-scale [1 = daily – 7 = never]		5.275	1.456
Music Free: Music on the Internet should generally be available free of charge.		2.526	1.256
Music listening time (hours per day)		4.694	2.313
Internet usage time (hours per day)		4.106	2.276
Age (in years)		29.255	10.735
Sex (1=male, 2=female)		1.487	0.500

Note. Variables are measured on a 5-point scale unless otherwise stated. [1= fully agree – 5 = not at all]
* Scale reverted for measurement

Table A2

Estimation results[6]

	Segments									
	1	2	3	4	5	6				
Segment size	*22%*	*20%*	*19%*	*18%*	*10%*	*10%*				
Attribute/Level	*Coefficients*						*W*	*p*	*W=*	*p*
Price$_{sub}$							800.405	0.000	359.369	0.000
0.00	1.582	3.856	0.374	2.458	2.380	1.444				
4.99	0.080	1.727	0.127	0.302	1.251	0.369				
9.99	-0.246	0.160	0.007	-0.393	1.215	0.369				
14.99	-0.505	0.160	-0.254	-0.968	0.073	-1.083				
19.99	-0.912	-5.903	-0.254	-1.399	-4.920	-1.098				
Price$_{dst}$							1405.057	0.000	1405.057	0.000
0.00	5.895	6.113	0.443	3.311	0.370	0.450				
0.49	5.895	5.457	0.150	1.069	0.174	0.450				
0.99	5.451	4.661	0.030	-1.460	0.174	0.450				
1.29	4.143	3.191	-0.312	-1.460	-0.343	-0.622				
1.69	-21.384	-19.423	-0.312	-1.460	-0.375	-0.727				
Catalog size							749.273	0.000	75.317	0.000
Small	-0.858	-0.860	-0.448	-0.380	-0.683	-0.995				
Medium	-0.152	0.010	-0.009	-0.291	0.070	-0.056				
Large	0.534	0.380	0.249	0.289	0.346	0.482				
Comprehensive	0.476	0.469	0.208	0.382	0.267	0.568				
DRM$_{sub}$							236.404	0.000	62.502	0.000
PC&all dev.	1.514	0.996	0.278	0.592	1.256	3.131				
PC&sel. dev.	1.762	0.725	0.155	0.128	0.058	2.906				
PC	-4.073	-0.466	-0.133	-0.063	-0.526	-1.517				
Stream	0.797	-1.255	-0.300	-0.656	-0.788	-4.520				
DRM$_{dst}$							389.161	0.000	167.609	0.000
Free	0.992	0.186	0.179	0.563	5.740	6.328				
Watermark	-0.470	0.096	0.108	-0.584	5.302	-17.654				
Sel. Dev.	0.219	-0.018	-0.118	0.490	5.031	6.018				
Copy Protection	-0.741	-0.264	-0.169	-0.469	-16.074	5.308				
Advertising							602.556	0.000	146.782	0.000
Free	1.074	0.307	0.245	0.395	0.434	0.746				
Banner	0.352	0.141	0.051	0.154	0.050	0.370				
Banner&Info	-0.268	0.086	-0.054	-0.047	0.013	-0.119				
Embedded	-1.158	-0.534	-0.242	-0.502	-0.496	-0.997				
No-choice-option							1034.488	0.000	1031.526	0.000
0	-3.269	-1.841	0.520	-1.293	-2.135	-2.515				
1	3.269	1.841	-0.520	1.293	2.135	2.515				

[6] Latent Gold Choice 4.0 was used for estimation (Vermunt and Magidson 2005).

Table A3

Covariate estimates

	Segments							
	1	2	3	4	5	6		
Segment size	*22%*	*20%*	*19%*	*18%*	*10%*	*10%*		
Covariates	β	β	β	β	β	β	W	p
Attitude_{DST}	0.275	-0.417	-0.282	0.462	0.395	-0.432	126.612	0.000
Attitude_{SUB}	0.529	0.021	-0.386	-0.305	0.097	0.045	93.385	0.000
Subjective norm	-0.112	0.089	-0.009	0.117	-0.145	0.060	3.838	0.570
PBC	0.034	-0.109	0.169	-0.157	0.004	0.059	6.303	0.280
Relative advantage	0.006	-0.028	-0.029	0.377	-0.207	-0.120	20.140	0.001
Complexity	0.223	0.041	-0.113	0.133	-0.080	-0.204	9.641	0.086
Compatibility	0.070	-0.068	0.026	0.014	-0.007	-0.035	1.652	0.890
Financial risk	0.146	-0.066	0.143	-0.151	-0.026	-0.046	14.876	0.011
Usage risk	-0.011	0.072	-0.042	0.102	-0.118	-0.003	6.580	0.250
Perc. critical mass	0.044	0.139	-0.185	0.052	-0.068	0.016	6.226	0.280
Files stored on PC	-0.042	0.040	0.064	-0.044	-0.039	0.020	15.076	0.010
Price sensitivity	-0.012	-0.053	-0.021	-0.012	-0.039	0.137	3.742	0.590
CD preference	0.027	0.053	-0.054	0.155	-0.047	-0.134	9.185	0.100
Acceptance of DRM	0.085	0.057	-0.113	-0.007	-0.092	0.071	6.246	0.280
Acceptance of perishability	0.153	0.084	-0.114	-0.193	-0.027	0.097	12.251	0.032
Usage of PC (Music)	-0.180	0.043	0.039	0.035	0.058	0.006	9.968	0.076
Credit card usage	0.035	-0.067	0.044	0.046	-0.054	-0.004	5.801	0.330
Music Free	0.043	-0.033	0.026	-0.199	0.111	0.052	13.663	0.018
Listening time	-0.011	-0.076	0.066	-0.043	0.050	0.014	16.492	0.006
Internet Usage	0.009	-0.014	-0.017	0.103	-0.030	-0.052	13.032	0.023
Age (in years)	0.041	-0.007	-0.013	0.007	0.009	-0.038	46.745	0.000
Sex	0.275	-0.005	-0.019	-0.463	0.174	0.039	13.983	0.016

4. Friend or Foe? Assessing the Impact of Free Streaming Services on Music Purchases and Piracy

Authors:
Nils Wlömert and Dominik Papies

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Nils Wlömert

Dominik Papies

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Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

Dominik Papies, Professor of Marketing, School of Business and Economics, University of Tuebingen, Nauklerstr. 47, 72074 Tuebingen, Germany. E-mail: dominik.papies@uni-tuebingen.de, URL: www.wiwi.uni-tuebingen.de.

1. Introduction

Since the rise of digital channels for media distribution toward the end of the last century the music industry has undergone a major transformation process, wherein a substantial portion of the physical sales volume has been displaced by illegal piracy (Danaher, Smith, and Telang 2013). Recent figures show that although sales from digital channels accounted for 39% of the music industry's global revenues in 2013, digital revenues can still not compensate for the continuing losses in the physical segment (IFPI 2014). Against this background, marketers are interested to identify and implement viable business models to address the legitimate demand for online music and to tackle the problem of music piracy (Papies, Eggers, and Wlömert 2011; Schlereth and Skiera 2012; Sinha and Mandel 2008).

Many industry representatives pin their hopes on the on-demand streaming model, which grants subscription users access to a comprehensive online music library (IFPI 2014). This business model deviates from the music industry's traditional business model in that it allows customers to temporarily access the music rather than purchasing it (e.g., CDs or downloads). Once the subscription ends, users can no longer access the content. Streaming service providers (e.g., Spotify, Deezer) earn revenue either by charging a monthly flat fee to consumers (e.g., USD 10) or by offering the service free of charge to consumers and generating revenue through advertising instead. In particular, this free streaming service (FSS) has gained a lot of public attention recently (e.g., Luckerson 2014).

The consequences of adding a free streaming channel to the music industry's distribution mix are unclear and a topic of ongoing debate. On the one hand, this new channel could attract new customers who were inactive before or who obtained music primarily via illegitimate channels. Accordingly, some industry representatives believe that "the presence of access services can expand the whole market" (IFPI 2012). This notion is line with the call to offer consumers attractive legal alternatives to illegal file sharing (Sinha and Mandel 2008), and free streaming services could be such an alternative. Further, music is an experience good that consumers typically want to sample before they purchase in order to reduce the uncertainty associated with the unobservable product quality (Dewan and Ramaprasad 2012; Nelson 1970; Peitz and Waelbroeck 2006). In this context, free streaming services can play an important role by offering consumers a convenient sampling device.

On the other hand, free streaming services may appeal to existing customers who then turn to the streaming service and reduce their expenditures for existing channels of obtaining music. This cannibalization will be harmful to the publisher's profits if consumers generate less revenue in the new channel compared to the established channel. Consequently, other industry representatives fear that this will happen. For example, Edgar Bronfman, the former chairman of Warner Music, once stated that "free streaming services are clearly not net positive for the industry" (Youngs 2010).

In sum, it is highly unclear, whether free streaming services are beneficial or harmful for the industry. Previous research on cannibalization effects in the media industry has primarily focused on the effect of piracy on the legitimate demand (e.g., Bhattacharjee et al. 2007; Danaher et al. 2010; Liebowitz 2008; Oberholzer-Gee and Strumpf 2007). Another stream of literature investigates the interplay between free ad-funded and paid content offers on the Internet analytically but does not offer empirical analyses (e.g., Halbheer et al. 2013; Prasad, Mahajan, and Bronnenberg 2003). Deleersnyder et al. (2002), Biyalogorsky and Naik (2003), and Gentzkow (2007) empirically study the addition of the Internet as a distribution channel. However, their findings are inconsistent, as we will outline in the next section. In sum, previous research does not give a clear indication of the effect one should expect, and the inconsistent findings as well as the conflicting voices from the industry suggest that the cannibalizing effects of a channel addition are not well understood. Therefore, it is important that the recent technological developments and their implications for the management of multiple distribution channels are analyzed.

Our research aims at contributing to the literature on channel cannibalization by providing answers to the following two research questions. (1) What is the effect of the adoption of a FSS on the purchasing behavior of individuals, and does this effect vary with usage intensity; and (2) what is the effect of FSS adoption on illegitimate demand (i.e., piracy)?

One important challenge arises when one seeks to empirically identify the cannibalization effects of streaming services on the consumer level. It is difficult to distinguish a true cannibalization effect from a spurious correlation that may arise if, e.g., the purchase behavior of adopters is compared to that of non-adopters (Gentzkow 2007). For instance, the popular press reports that adopters of a free ad-funded streaming service "are much more likely to buy music downloads" compared to non-adopters (Chen 2013). This type of comparison is confounded by the fact that consumers with a strong affinity for music have a higher probability of both spending money on music *and* adopting a free streaming service, i.e., the preferences for the channels are correlated. Therefore, in this study, we constructed a research design that avoids this problem by relying on longitudinal variation. That is, we obtained access to a large-scale panel of music consumers in the German market and repeatedly interviewed these music consumers over a period of 13 months. We then employ a difference-in-difference approach to estimate the effect of the adoption of a FSS on music purchases, i.e., our analysis assesses the changes in consumers' behavior after the adoption compared to the pre-adoption time and relative to those respondents who did not adopt. Our methodological approach is closely related to the analysis of Bronnenberg, Dubé, and Mela (2010) who assess the effect of the adoption of a digital VCR (i.e., Tivo) on purchase behavior using a difference-in-difference estimator. The identifying assumption of this method is that unobserved individual characteristics may be correlated both with the decision to adopt and with the expenditures. The difference-in-difference estimator will remove time-invariant unobserved individual differences. We assume that these individual differences are relatively stable over time, such that the endogeneity of adoption is concentrated in the cross-sectional dimension rather than in the time dimension (Ebbes, Papies, and van Heerde 2011; Leenheer et al. 2007).

Our results demonstrate that consumers who adopt a FSS spend significantly less money on recorded music products after the adoption. This cannibalization effect is consistent across different model specifications. The magnitude of the effect implies that consumers on average cut their spending for CDs and downloads by roughly 10% after the adoption of a FSS with higher cannibalization rates for increasing usage levels. Further, the adoption of a FSS reduces piracy for those consumers who intensively use the FSS. This dual effect highlights the ambiguous situation of managers in the music industry, i.e., the reduction of piracy for one group of consumers comes at the cost of a significant reduction of music expenditures for other consumers. However, these cannibalization effects do not occur for every type of streaming service. While we find that consumers cut their expenditures after the adoption of a *paid* streaming service, their monthly subscription fees overcompensate for this reduction. Thus, we suggest that marketing managers should focus on business models that directly generate income and meaningfully differentiate the free tier of the service from the premium tier to trigger the conversion to paid subscriptions.

Our results contribute to the literature in two important ways. First, previous research has produced conflicting findings regarding the cannibalization effects of channel additions, despite the fact that it is important to understand when the addition of a channel is beneficial or not. Our study contributes to the literature on channel cannibalization effects by analyzing the effect of the addition of free streaming services on expenditures in other channels. This deepens our understanding of the interaction between different distribution channels. Second, our results add to the literature on piracy, which has extensively analyzed the effects of piracy on legitimate demand. Research on how to convert pirates to legitimate customers, however, is scarce. We therefore contribute to the literature by assessing whether a FSS can be a viable alternative that makes piracy relatively less attractive.

We structure the remainder of the paper as follows. In the next section, we describe the relevant literature and the theoretical background. We then discuss our research design in section 3 and the method which we use for estimation in section 4. In section 5, we present our results. Section 6 contains robustness checks. We conclude with a discussion of our findings and implications for future research in section 7.

2. Literature

The ever-increasing opportunities to deliver content to consumers have sparked academic interest in how multiple channels interact, in particular when the online channel became increasingly important for many business models (e.g., retailers, media firms) in the late 1990s. One question that firms faced in that time was whether the addition of the online channel would hurt sales in traditional channels, and most empirical studies on channel cannibalization deal with this question. Findings regarding the cannibalization effects of channel additions, however, are inconsistent.

Both Deleersnyder et al. (2002) and Gentzkow (2007) assess the effect of the online channel addition on offline circulation of daily newspapers. Deleersnyder et al. (2002) use market level circulation and advertising revenue data for a sample of 85 online newspaper introductions and find a low danger of cannibalization. In contrast, Gentzkow (2007) relies on survey data from the Washington D.C. area and finds that online and print newspapers are substitutes (i.e., there is a cannibalization effect) once observed and unobserved heterogeneity are taken into account. Similarly, Simon and Kadiyali (2007) find a cannibalization effect of websites on the print circulation for a sample of US consumer magazines that depends on the type of content that is offered online. The authors show that the closer the online content is to the content in the print version, the stronger the cannibalization effect.

Biyalogorsky and Naik (2003) use data from the media retailer “Tower Records” to assess the relationship between online and offline sales. Their results suggest that there is no cannibalization effect of online sales on the offline channel. Waldfogel (2009) assesses how much, in a cross-sectional sample of 274 college students, the consumption of video content on the web (on YouTube) displaces traditional television viewing. The study finds a small reduction in TV viewing for intensive YouTube users, but YouTube usage is much larger than the reduction in TV consumption.

In sum, previous results regarding the cannibalization effects of channel additions are inconsistent. These different findings may occur because it is likely that the degree of cannibalization depends on the perceived utility of a specific channel or product version relative to the perceived utility of existing channels or product versions. Indeed, Moorthy and Png (1992) demonstrate in an analytical model that firms can reduce cannibalization in a situation when they simultaneously offer two products that are potential substitutes, either by reducing the price of the high-end version (i.e., downloads that consumers pay for, or CD’s) or by lowering the quality of the low-end version (i.e., the free streaming service). This will reduce the relative attractiveness of the low-end version (e.g., the free online version of a newspaper or the free music streaming service) and will make it less likely that consumers will rely on the low-end version only (Moorthy and Png 1992). Riggins (2003) arrives at similar conclusions based on his analytical model of a seller of information products who operates a two-tiered Web site that simultaneously offers a free, ad-based version and a fee-based version. Following this argument, it may seem viable for firms to deliberately reduce the utility of the FSS in order to decrease cannibalization from other paid channels. This can be achieved, for example, through advertising interruptions (Halbheer et al. 2013; Prasad, Mahajan, and Bronnenberg 2003), which represent an additional revenue source for service providers. In the present research context, the specific business model may further reduce the relative attractiveness of free streaming services compared to other channels because consumers cannot keep the music files but only obtain a right to temporarily access the content. This is in contrast to, e.g., pirated music files, which consumers can permanently store on their computers. These arguments suggest that a cannibalization effect is less likely in the case of a FSS compared to piracy channels because consumers may perceive the utility of the FSS to be inferior due to advertising and the inability to keep the files.

In support of the notion that piracy channels indeed represent a close substitute for commercial channels, most studies from a large body of piracy-related research suggest that piracy cannibalizes demand from legitimate channels (e.g., see Danaher, Smith, and Telang (2013) for a detailed discussion of the existing literature). However, it is unclear whether we should expect the same effect in the case of free streaming services, i.e., whether the utility of a FSS is indeed equally close to existing legitimate channels such that cannibalization will occur. As we have discussed above, previous research does not give a clear picture regarding the degree to which the addition of a distribution channel will result in cannibalization of demand from existing channels. We therefore contribute to the literature by estimating the degree of cannibalization between free streaming services and demand from other (paid) music distribution channels.

One important challenge is that keeping the utility of the FSS low to reduce the potential for cannibalization may interfere with the goal to use free streaming services to convert pirates to legal customers. Unfortunately, previous research has rarely assessed whether piracy can be reduced if consumer who use illegal downloads are offered attractive legal alternatives. One exception is the study by Sinha and Mandel (2008) who provide initial evidence that the availability of attractive legal music services may effectively decrease the propensity to pirate. However, their analysis is hypothetical and restricted to a sample of college students, which limits the generalizability of the results. It is unclear whether the results hold in a real market setting and how legal services should be configured. Danaher et al. (2010) use the removal and restoration of the content of one major TV studio (NBC) at one major digital outlet (iTunes) as a source of variation to study how the presence of a (legitimate) digital distribution channel affects demand through the Amazon.com DVD store and BitTorrent piracy channels. The results show that while the demand for NBC's DVD content at Amazon.com was largely unaffected by the presence/absence of the digital alternative, demand for NBC material through piracy channels experienced a significant increase after its removal from iTunes. The authors conclude that illegitimate and legitimate digital sales channels are much closer substitutes than legitimate physical and legitimate digital distribution channels. Based on their findings, one can tentatively conclude that cannibalization between legal channels may not be a major problem, but it is unclear to which extent we can generalize these findings to other industries and business models, such as the on-demand streaming model. Finally, Papies, Eggers, and Wlömert (2011) find that free ad-based music subscription services have the potential to attract consumers who would otherwise use no legal download services. The authors, however, rely on stated preferences measured at a time when most consumers had no experience with free ad-based services. Against this background, we contribute to the literature by analyzing to which degree free streaming services may be a viable tool to attract consumers who would otherwise rely on piracy.

3. Research design

3.1. Data collection

The identification of a substitution or complementary effect between two goods or channels is not straightforward. Empirically, when one observes that the increase in demand from one channel (say, free streaming services) is positively correlated with demand from another channel (say, CD's), one could conclude that these two channels are complements. However, it is not possible to rule out that this correlation is merely a correlation in preferences that is due to an unobserved variable that drives demand in both channels (see Gentzkow (2007) for a detailed discussion). We therefore develop a research design that allows us to utilize the within-person variation to identify the effect of FSS adoption on music purchases and piracy behavior.

To this end, we conducted a panel survey, in which we repeatedly interviewed the same respondents between January 2012 and February 2013 regarding their music expenditures as well as their piracy and listening behavior. To recruit respondents, we gained access to the online consumer panels of three major worldwide media distributers that are active in Germany, one of the four largest markets for recorded music worldwide (IFPI 2013). These online panels are designed to keep track of developments in media consumption of music consumers. In total, we conducted nine surveys during the observation period.

Almost three months after the start of the first survey, a major international music streaming service provider entered into the German market (in March 2012), just before the third survey. Until then, only a small number of consumers used free streaming services, and revenues from streaming services only accounted for a small fraction of the overall revenues from recorded music in Germany (BVMI 2012).[1] Therefore, this market entry is a unique

[1]Overall revenues from streaming services amounted to 1.7% of the music industry's total revenues in 2011 (BVMI 2012).

quasi-experimental shock to the market that makes it more likely that consumers adopt a free streaming service and thus induces variation in our focal independent variable.

The focus of our study is on the individual music expenditures, which serves as the dependent variable. In each of the nine surveys, respondents indicated how much money they had spent, respectively, on physical music products (e.g., CD's or vinyl), downloads from commercial download stores (e.g., Amazon or iTunes), and paid music subscription services (e.g., Napster) over the past 30 days. This approach, asking respondents about their spending behavior, is comparable to the Consumer Expenditure Survey (e.g., Du and Kamakura 2008) and has been used in previous research, e.g., by Lohse, Bellman, and Johnson (2000). To reduce the complexity of this task, we provided explanations for each channel (e.g., the brand names of the most important players in each channel). By summing up across channels per respondent we obtain the focal dependent variables for our analyses: (1) the total spending amount of consumer *i* in month *t* excluding the expenditures for paid subscription services ("net expenditures"), and (2) the total expenditures of consumer *i* in month *t* including the expenditures for paid subscription services ("gross expenditures"). We will use the former variable to infer the effect of the adoption of a streaming service on existing distribution channels, and the latter to investigate the adoption effect on the overall music expenditures. We make this distinction between net and gross expenditures because we assume that free and paid streaming services are direct substitutes.

To gain insights into the respondents' usage behavior, we asked the participants how many hours they had spent listening to music via the various available channels over the past 7 days. These channels included (1) physical formats, (2) digital files, (3) video streaming platforms, (4) free ad-funded on-demand streaming services, (5) paid on-demand streaming services, (6) other free streaming services, and (7) terrestrial radio. This approach, asking respondents about their relative time use, is comparable to the American Time Use Survey and has been used by previous research, e.g., by Luo, Ratchford, and Yang (2013). Again, we took measures to increase the ease of providing accurate answers. We provided explanations for each channel (e.g., the brand names of the most important players in each channel). Furthermore, respondents indicated their weekly usage levels via easy-to-use sliders in increments of 30 minutes. The corresponding weekly and daily average music listening times were displayed automatically at the bottom of the page, enabling respondents to review the accuracy of their responses.

If – in a given survey – a respondent indicated that s/he had used a free streaming service, we count this respondent as an adopter of a free streaming service, i.e., D_{it} = 1. Note that we provided the brand names of all free streaming services that were available in the market during each survey to avoid that consumers provide inaccurate answers.

Several industry representatives expect that free streaming services have the potential to convert pirates (i.e., consumers who were previously unwilling to pay for music and therefore used illegitimate sources). Therefore, we measured whether consumers engaged in piracy. However, because survey data are prone to socially desirable responding since piracy is a legally sensitive topic (Kwan, So, and Tam 2010), we did not ask the respondents directly about their use of specific channels, such as file-sharing networks or file-hosting services. Instead, we asked the participants how many songs they had added to their music libraries via other than the previously mentioned commercial channels over the past 30 days, excluding copies created from their own original CDs. Although it is theoretically possible for consumers to obtain music files free of charge via commercial distribution channels, e.g., during promotional campaigns, our consultation with industry experts in this field revealed that this is only the case for a very small fraction of releases. Thus, we are confident that this variable primarily captures how many music files consumers obtain via non-commercial channels and therefore constitutes a valid proxy for piracy behavior. Clearly, we cannot exclude the possibility that some respondents provide answers that are influenced by a perceived pressure to comply with social norms. We believe, however, that it is reasonable to assume that the susceptibility to comply with social norms will be rather stable over time. Hence, this personality trait will be differenced out by our model and will not bias the results.

3.2. Sample

All members of the respective online access panels were invited to participate in the series of surveys. Respondents who participated in all surveys received a CD of their choice as an incentive at the end of the final survey, and this CD was shipped to the respondents. Further, respondents who completed all surveys participated in a lottery with a chance to win additional prizes, such as home stereos and mobile music players. 2756 respondents completed all nine surveys and constitute the empirical basis for our analyses.[2] To ensure that our results are not contaminated by inaccurate answers we excluded cases based on the following criteria. First, we screened out 27 respondents who answered the surveys in an unrealistic short time, using the fasted 1% centile of the overall response times the cutoff.[3] Second, we deleted 137 respondents, who reported unrealistically high expenditures over the observation period, using the highest 5% centile as the cutoff. After consultation with industry experts, we exclude these as outliers that most likely provided wrong answers or did not purchase for private use. Third, we asked respondents at two different times during the observation period (in the sixth and ninth wave) whether they felt that they had provided accurate answers within the respective periods on a 11-point rating scale from 0% (only random answers) to 100% (always fully accurate). We made it clear that providing fully honest answers to these control questions was vital for the validity of the study results and that the answers would have no influence on the reward, which was provided as an incentive for participating in the survey.

[2] In our robustness checks we will show that panel attrition is not a reason for concern.
[3] We validated with independent test persons whether it was possible to answer the survey in such a short time, which was not the case.

We dropped 124 (82) respondents who stated that their responses were less than 80% accurate in the sixth (ninth) survey. Fourth, we exclude 163 cases with no variation in the dependent variable (i.e., those who never spent during the observation period). Finally, we exclude the 113 respondents, who had already adopted a FSS before the first survey. This is necessary to consistently estimate a treatment effect in a difference-in-difference estimator (Wooldridge 2002, p. 283) because we do not observe the pre-adoption expenditures for these consumers. This leaves us with a valid sample of 2110 respondents.[4]

Table 1 shows that our sample is very similar in terms of key demographic variables compared to the entire German music buyer population (BVMI 2013). However, it shows a somewhat higher affinity for music consumption (time spent listening to music and music expenditures), which is not surprising because the participants were recruited via the media distributors panels, which consist of highly involved music consumers. According to the IFPI, these consumers can be classified as intensive music buyers, who represent the most important consumer group that accounts for almost 50% of the music industry's overall revenue in Germany (BVMI 2014). We provide additional descriptive statistics for our model variables in Table 2.

>>> Table 1 about here <<<

>>> Table 2 about here <<<

3.3. Validation of quasi-experimental approach

Table 3 displays the development of the FSS adoption rate over time. The figures show that almost 30% of all respondents at some point adopted a FSS. This provides a good empirical foundation and ensures sufficient statistical power to identify possible cannibalization effects because the adoption is not restricted to a small sample of respondents.

[4] Note that dropping any of the sample restrictions does not alter the conclusions of our study.

Similar to other field studies (e.g., Bronnenberg, Dubé, and Mela 2010), we could not assign respondents randomly to treatment and control conditions. Rather, some respondents choose to adopt a free streaming service while others do not. To assess whether adopters fundamentally differ from the control group of non-adopters, we compare both groups on several key variables, similar to Bronnenberg, Dubé, and Mela (2010). In our case, we use information from the first survey to compare those who adopt at some later point during the observation period with those who never adopt over the observation period. A comparison of our dependent variable (music expenditures) for adopters and non-adopters (row 1 of Table 4) shows that the mean between the two groups does not differ significantly ($t = .059$). Further, a Wilcoxon rank sum test cannot reject the null hypothesis of equal distributions for adopters and non-adopters. Hence, we can conclude that the two groups on which we will base our analysis later, do not significantly differ in their key dependent variable, which we view as re-assuring.

We further assess differences in how much time consumers spend listening to music. Here, we find that the respondents who later adopt a FSS spend significantly more time listening to music via digital formats than those who do not adopt during the observation period. In addition, a Wilcoxon rank sum test rejects the null hypothesis of equal distributions regarding the music listening time via physical formats between the group of adopters and non-adopters ($p < .10$). This finding suggests that FSS adopters are more inclined to digital music consumption. However, when we follow Bronnenberg, Dubé, and Mela (2010) and take the first difference (between music usage in survey 1 and 2) and compare these between the groups, we again find that there are no significant differences. Hence, also in these variables, taking differences makes the two samples comparable. We therefore rely on first differences throughout our analyses.

>>> Table 3 about here <<<

>>> Table 4 about here <<<

4. Analysis

Our identification strategy exploits the panel structure of our data to identify the effect of FSS adoption on music expenditures. The main identifying assumption is that unobserved preferences that are related to the adoption behavior as well as the spending behavior in other channels are relatively stable, in particular over the time period that we analyze. This means that the panel structure of our data allows us to remove any individual time-invariant consumer effects by taking first differences.

Our point of departure is the following baseline model:

$$Y_{it} = \beta_i + \xi_t + \delta D_{it} + \varepsilon_{it} , \quad (1)$$

where Y_{it} are the expenditures for music products of individual i in period t. β_i and ξ_t are individual and time intercepts, respectively, and ε_{it} is the idiosyncratic error. D_{it} denotes the adoption of a streaming service by respondent i at time t. The main goal of our analyses is to obtain a consistent estimate of δ, which is the effect of the adoption of a streaming service on music spending. We deploy a difference-in-difference estimator that removes the individual intercept by taking the difference for each individual between adjacent periods, such that:

$$\Delta Y_{it} = \xi_t + \delta \Delta D_{it} + \Delta\varepsilon_{it} , \quad (2)$$

where $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$, $\Delta D_{it} = D_{it} - D_{i,t-1}$, and $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$. By removing the individual effects through first differencing, we obtain a consistent estimator under the assumption that there are no time-variant omitted variables contained in the error ε_{it} that are correlated with D_{it}. This means that our model accounts for general individual differences, such as heterogeneous probabilities to adopt, heterogeneous preferences for digital music consumption, or different tastes in music. To ensure that our estimate is robust to time-varying demand shocks that are homogenous across the sample, we include a time-specific intercept ξ_t

(Bronnenberg, Dubé, and Mela 2010; Wooldridge 2002, p. 284). This difference-in-difference estimator is a standard estimator to assess the effect of policy changes (e.g., Wooldridge 2002, p. 283), also in instances when a true experimental manipulation is not feasible.

5. Results

In the previous section, we developed and explained our analytical approach. In this section we will discuss the results of our analyses.

5.1. Free streaming services and music expenditure

5.1.1. Free streaming service adoption. To obtain an estimate for the effect of the adoption of a FSS on music expenditures, we use the log of the monthly music expenditures as the dependent variable. Taking the log has the advantage that δ (the effect of the streaming service adoption) can be interpreted as a percentage change in spending. This implies that for respondents with a high level of spending, the coefficient of the adoption indicator will result in larger absolute Euro value changes compared to respondents with a lower spending level, which is a realistic functional form. In the first step of our analysis, we are interested in estimating the following regression:

$$\Delta Y_{it} = \xi_t + \delta \Delta D_{it}^{FSS} + \Delta \varepsilon_{it} \;, \tag{3}$$

where ΔD_{it}^{FSS}denotes the adoption of a FSS. We estimate two different specifications of Eq. (3). Specifically, Model 1 has the log-transformed sum of the total monthly music expenditures minus expenditures for paid streaming services as the dependent variable (i.e., "net monthly spending"). Model 2 has the log of the sum of the monthly music spending amount as dependent variable, which includes expenditures for paid streaming services (i.e., "gross expenditures"). If paid streaming services and free streaming services are substitutes, the cannibalization effect should be stronger in Model 2. Thus, the coefficient obtained from

Model 1 represents the more conservative estimate. As outlined above, we estimate these models only on those respondents who had not adopted in the first period to ensure that historic adoption decisions do not interfere with our analyses.

Table 5 displays the estimation results of Models 1 and 2. In the interest of brevity, we do not report the coefficients for the time fixed effects. For both models, we see a negative sign and a coefficient of around –.1 for δ. Although the standard errors around the estimate are substantial, the effects are significant at the 5% level (δ_{M1} = –.0988, p < .05, δ_{M2} = –.1034, p < .05). The magnitude of the coefficients implies that the adoption of a FSS reduces the net expenditures for recorded music products from other channels by 9.4% (Model 1) or 9.8% (Model 2) if expenditures for paid streaming services are included.[5] As expected, the effect size is smaller in Model 1, although the difference in magnitude between the coefficients is fairly small.

In conclusion, the above results provide an indication that free streaming services cannibalize demand from other channels because those users who adopt spend significantly less on music products after the adoption compared to the control group of non-adopters.

>>> Table 5 about here <<<

5.1.2. Moderating effect of usage intensity. In the previous section, we identified a negative effect of the adoption of a FSS on the purchasing behavior of individuals. We now assess observed heterogeneity in the effect and investigate whether the cannibalization effect varies with the usage intensity, i.e., whether the negative FSS effect is reinforced with increasing usage levels. To this end, we estimate the following regression:

$$\Delta Y_{it} = \xi_t + \gamma \Delta \left(\frac{INT_{it}^{FSS}}{INT_{it}^{ALL}} \right) + \Delta \varepsilon_{it} \,, \tag{4}$$

[5] The effect is calculated as follows (Halvorsen and Palmquist 1980): the log multiplier –.1034 (–.0988) of δ in the gross (net) expenditure model corresponds to a percentage change of 100*[exp(–.1034) –1] = –9.82% and 100*[exp(–.0988) –1] = –9.41%, respectively.

which resembles the model in Eq. (3) with the only difference that we now use the ratio of the FSS usage intensity, INT_{it}^{FSS}, to the overall usage intensity across all channels a consumer uses to listen to music, INT_{it}^{ALL}, as the focal regressor. Thus, γ captures the effect of the relative usage intensity of the FSS on music spending, and the effect of adoption is contained in the model's intercept (Bronnenberg, Dubé, and Mela 2010). We rely on changes in relative usage intensity because we are interested in changes of how a consumer embraces the FSS relative to other channels. Using the absolute level would confound the measure with changes in music consumption in general. Because we observe usage behavior only for FSS adopters, we estimate Eq. (4) only on respondents who adopted a FSS during the observation period (see Bronnenberg, Dubé, and Mela (2010) for a similar approach). Again, we estimate the effect of the usage intensity on both the net music expenditures and the gross music expenditures. We summarize the results in Table 6.

>>> Table 6 about here <<<

Models 3 and 4 both yield a negative coefficient. The associated effect size ($\gamma_{M3} = -.6826$, $p < .001$) suggests that a 1 percentage point increase in FSS usage decreases net music spending by .6826%. We find similar effects for Model 4 ($\gamma_{M4} = -.7934$, $p < .001$).

The results in this section show that the negative effect of free streaming services on music expenditures is reinforced by usage, i.e., the more consumers use the free streaming service, the more the free streaming service displaces sales in other channels.

5.1.3. Moderating effects of observable consumer characteristics. Our analyses so far revealed a negative effect of the adoption of a FSS on music expenditures. It is therefore important for firms to know whether this effect depends on consumer characteristics that managers can use to tailor free streaming services to consumers segments less prone to cannibalization. To this end, we now investigate whether the FSS effect varies with observable consumer characteristic and interact the FSS effect in Eq. (3) with various demographic and socioeconomic variables, which we collected at different points during the observation period, such that

$$\Delta Y_{it} = \xi_t + \delta \Delta D_{it}^{FSS} + \beta X_i \Delta D_{it}^{FSS} + \Delta \varepsilon_{it} \ , \tag{5}$$

where X_i is a vector of observed respondent characteristics. Specifically, X_i contains a set of set of time-invariant demographic variables, i.e., age, gender, and income, as well as three variables capturing the attitude towards access-based streaming services, the attitude towards advertising-based offers, as well as the self-stated willingness-to-pay for digital music albums.[6]

The results are presented in Table 7. Again, we omit the time fixed effects to conserve space. We specify the age and income variables as indicator variables with the youngest age group (≤ 25 years) and the lowest income group (≤ 1000 EUR) as the reference groups. Model 5 shows the results of the estimation of Eq. (5). The analysis reveals significant interactions between the age group indicators and the FSS adoption indicator, suggesting that the negative FSS effect is significantly stronger in the middle age group (β_1 = –.3456, p < .05) and the oldest age group (β_2 = –.2874, p < .10) compared to the reference group. We view this result as an indication of young consumers being accustomed to consuming music online (in many cases for free) because this age group grew up listening to music via digital services. The introduction of a FSS may be less of a shock to their consumption behavior, hence the cannibalization is lower. This result is promising for the industry because it suggests that free streaming services may be an effective tool to monetize free content usage of a young consumer segment in which budget constraints tend to limit music expenditures. In contrast, we do not find evidence that the cannibalization effect due to the FSS adoption is significantly related to gender and income. Furthermore, we observe a significant interaction effect be-

[6] Please refer to Appendix A for the measurement scales and descriptive statistics.

tween the FSS adoption indicator and the variable attitude towards streaming ($\beta_6 = -.1271$, $p < .05$), suggesting that the cannibalization effect is stronger for persons with a positive attitude towards streaming services. This result suggests that consumers with a low preference for streaming are indeed less likely to replace their music purchases with access-based services. In contrast, the attitude toward ad-funded offers cannot explain the variation in substitution effects across individuals. Finally, our results provide evidence that the cannibalization effect is stronger for consumers with a low willingness-to-pay for digital music products ($\beta_8 = .0120$, $p < .05$) in support of the notion that price sensitive consumers are more likely to replace music purchases with the free ad-funded service.

In summary, the results suggest that the cannibalization effect due to the adoption of a FSS is not the same across individuals, with higher cannibalization rates being significantly related to age (high), a positive attitude toward access-based streaming services, as well as a low willingness-to-pay for digital music products.

>>> Table 7 about here <<<

5.2. Free streaming services and piracy

Our analyses in the previous section revealed an overall negative effect of the adoption of a FSS on music expenditures, and that this effect increases with the intensity with which the service is used. Industry representatives, however, are counting on free streaming services as a measure to attract pirates, i.e., consumers who were previously not willing to pay for music downloads and therefore used illegitimate sources. We therefore assess in a next step how the adoption of a FSS affects the change in piracy behavior of adopters compared to the changes in piracy behavior for non-adopters. As we described above, we measure piracy by asking respondents how many songs they had obtained via the Internet for free in the last month, excluding any paid downloads, streaming, or “ripping” from their own CDs.

To assess the influence of FSS adoption on piracy behavior and the moderating effect of usage intensity, we estimate Eq. (3) and (4) and use the change in the log-transformed number of pirated songs as the dependent variable, i.e., the analysis is the same as above, except for the dependent variable.

Table 8 presents the results of this analysis. Model 6 yields an estimate of the FSS adoption variable that is clearly insignificant, i.e., the adoption of a FSS does not lead to a change in the number of pirated songs compared to the non-adopters (δ_{M6} = .0127, p > .10). This finding is surprising, given that FSS and free illegal services both impose no monetary cost on consumers and therefore could well be substitutes. However, as Model 6 shows, there is observed heterogeneity regarding the effect of FSS adoption on piracy. That is, when we regress the pirated quantity on the FSS usage intensity variable, we find a negative effect, which is marginally significant at the 10% level (γ_{M7} = –.3395, p < .10), i.e., among the group of adopters the degree of piracy is decreasing with increasing usage levels. The associated effect size suggests that a 1 percentage point increase in relative FSS usage decreases the pirated quantity by .3395%. This finding implies that consumers who embrace a free streaming service and use it intensively, rely less on piracy to fulfill their consumption needs.

To sum up, the results presented in this section suggest that the conversion of pirates to customers via free streaming services is not an easy task, as indicated by the insignificant main effect. If, however, a consumer intensively uses the service, s/he will engage less in piracy. This result may be a glimmer of hope for the industry, because, different from illegal channels, free legal streaming services typically generate income for copyright holders through advertising.

>>> Table 8 about here <<<

6. Robustness checks

To ensure that our findings are robust to plausible alternative specifications and estimation approaches, and to rule out alternative explanations, we consider several validations.

6.1. Panel attrition

Panel attrition is potentially worrisome because it may induce bias in the estimate of δ if it is related to the idiosyncratic errors, ε_{it}, (Wooldridge 2002, p. 581).[7] To test whether our estimate of δ is subject to selection bias from panel attrition, we specify a model that corrects for potential attrition bias (see Wooldridge 2002, pp. 585). This procedure involves two steps: (1) compute the "dropout-hazard" (i.e., the inverse Mill's ratio) from each individual cross-section using a probit regression on the full sample (i.e., the dropouts and non-dropouts at time t); and (2) insert these correction terms as explanatory variables in the main equation and estimate this model on the respondents that remain in the survey. The estimate of the adoption effect is subject to selection bias from panel attrition to the extent that the correction terms exhibits an influence on δ.

With respect to (1) we define a selection indicator d_{it} for each period, with $d_{it} = 1$ if D_{it} and Y_{it} are observed and 0 otherwise. For each t, we regress d_{it} on a set of time-varying panel variables observed at $t - 1$ using probit regression. Specifically, we model the probability that a respondent remains in the survey at time t as a function of the adoption of a FSS in $t - 1$, the time that respondents had spent listening to music via physical and digital formats in $t - 1$, the volume of pirated music-files in $t - 1$, as well as the response time in the previous survey. Following Wooldridge (2002, pp. 585) we then compute the "correction factors" (λ_{it}), i.e., the inverse Mill's ratios, using the predicted probability of attrition from the probit model. In step (2) we then include these correction factors as additional predictors in the main model.

[7] Note that if panel attrition is solely a function of time invariant consumers characteristics, these personality traits will be differenced out by our model in first differences.

Our results show that the correction factors do not significantly influence the dependent variable and that the estimate of the main effect in Eq. (3) (i.e., δ) remains virtually unchanged in terms of both magnitude and significance level when we control for the dropout probability in the estimation (δ = –.1008, $p < .05$). Thus, we conclude that our results are insensitive to panel attrition (details are available in Appendix B).

6.2. Effects of the adoption of other free channels

To further validate our estimates regarding the effect of the adoption of a FSS on music expenditures (i.e., Model 1), we re-estimate Eq. (3) using the adoption of related web-based, free music consumption channels as the independent variables. In particular, we consider the adoption of free video streaming services (e.g., Youtube), D_{it}^{Video}, and the adoption of other free audio streaming services (i.e., services that do not operate on an on-demand basis, such as online radios), D_{it}^{Audio}, as validation variables. The intuition behind this analysis is that these services are unlikely to substitute demand from other channels because they are less convenient and offer lower utility. Therefore, the adoption of these channels should not have a negative effect on expenditures in other channels. The estimates indeed show that both, the adoption of video streaming services (δ_{Video} = –.0517, $p > .10$), and the adoption of other audio streaming services (δ_{Audio} = .0242, $p > .10$) are unrelated to music expenditures. Thus, we fail to identify a cannibalistic effect of channels that are comparable to free on-demand streaming services on music expenditures so that this negative effect appears to only occur in the context of on-demand audio streaming services, which increases our confidence in the cannibalistic effect, which we identified in the previous sections.

7. Discussion and conclusion

Free streaming services have received considerable attention lately both from music consumers, who increasingly adopt these services as a new means of music consumption, as well as music industry executives, who view these services as a ray of hope against the background of more than a decade of plummeting revenues. Academic research, however, cannot provide any guidance on whether the addition of the free streaming channel is beneficial for the industry because research on channel cannibalization is scarce and inconclusive. We therefore contribute to the literature by providing evidence on the cannibalization effect of free streaming channels on expenditures in other channels and several moderating effects. To this end, we construct a research design, in which we observe a panel of more than 2000 consumers over more than a year and estimate the effect of FSS adoption on expenditures. Consistently, we find a negative effect, which implies that the adoption of a FSS reduces expenditures by approximately 10%. This effect is stronger for intensive users of the service. Usage intensity is also the key to understanding the effect of FSS adoption on piracy, i.e., the adoption will only reduce piracy for intensive users of FSS.

What do these findings imply for (1) our understanding of how consumers behave in this market, and for (2) managers in this industry?

Our results suggest – in combination with previous research – that advertising as a separation mechanism is not effective in the setting that we studied (e.g., Prasad, Mahajan, and Bronnenberg 2003). Apparently, free streaming services are too attractive for consumers who would otherwise continue to purchase via other channels. Consumers appear to like the way the free streaming services work and do not see the need to make all purchases that they would have made via other channels before the adoption of the streaming service.

Given this significant cannibalization effect, what are the profit implications when one takes into account that a FSS also generates revenue via advertising? Our research design enables us to investigate the monetary effect of the adoption of a FSS on the music labels' revenues. Specifically, we calculate the net effect of the adoption of a FSS on the music labels' revenues by comparing the monetary losses due to the displacement of expenditures with the revenue that the FSS generates. With respect to the losses, our results suggest that on average 9.4% of the monthly music expenditures (mean monthly expenditures: 24.52 EUR, n = 2110) is displaced by the FSS, i.e., a gross loss of approximately 2.30 EUR per customer per month. Assuming a retailer margin of 30%, this equals a net loss for labels of approximately 1.61 EUR. With respect to the FSS revenue, labels are paid on a per stream basis, i.e., every time a customer plays a song, the service provider pays a certain amount to the music label. To obtain an estimate of the monthly FSS label revenue per customer in our sample, we multiply the average monthly number of played songs (353)[8] with an assumed per stream payout rate of .003 EUR[9], amounting to an income of approximately 1.06 EUR per customer per month. This implies that labels make a loss of .55 EUR per FSS adopter, which amounts to 3.2% of the net revenue.

We graphically depict the estimated cannibalization effect for different mean net expenditure levels (i.e., excluding retailer margin) between 0 and one standard deviation above the sample mean in Figure 1. It becomes apparent that – assuming fixed usage levels – free streaming services are particularly worrisome from a label's perspective for consumers with high spending levels (i.e., intensive music buyers), where the cannibalization potential is high. As can be seen, the revenue loss due to the FSS adoption is diminishing with decreasing spending levels and the net effect becomes positive where the two lines intersect (at a mean expenditure level of approximately 11.50 EUR). However, as Figure 1 shows, the cannibali-

[8] The average FSS listening time is approximately 1236 minutes per month. Assuming an average song length of 3.5 minutes, this equals 353 songs per month.

[9] Payout rates are not publicly disclosed and vary by label. The amount of .003 EUR represents an estimate, which is based on publicly available data (e.g., Ingham 2013) and accounts for the fact that ad-funded services typically have lower payout rates than paid services. We acknowledge that actual ad-funded payout rates may be even lower (Dredge 2013) and therefore consider .003 EUR as an upper bound of the ad-funded per stream revenue. Industry sources confirmed that this is a realistic estimate.

zation of expenditures in our sample clearly exceeds the income from free streaming services.[10]

>>> Figure 1 about here <<<

Because of this negative net effect of FSS on revenue, we suggest that managers should increase the utility difference between the FSS and other channels to reduce the cannibalizing effect of the FSS. This may include, e.g., reducing the numbers of hours the service is available for free, limiting the duration of free membership, increasing the amount of advertising, reducing the amount of free content, or making the content available in the ad-funded channel with a time delay through windowing strategies (see Hennig-Thurau et al. 2007 for an analysis of windowing strategies in the movie industry). Managers, however, should proceed with great caution because reducing the utility of the free channel makes the FSS less appropriate to attract pirates, i.e., the FSS will be less effective in reducing piracy if they are made less attractive.

While these implications may look like a very gloomy picture, our research shows possible ways how managers can tackle this dilemma. One possibility arises through the introduction of a premium streaming service (PSS), for which consumers pay a monthly subscription fee and gain access to additional features (e.g., mobile usage). Most on-demand music streaming services that are available on the market (e.g., Spotify, Deezer) offer such an advertising-free version of the service with advanced features and functionality (i.e., a premium tier) in addition to the free tier (Oestreicher-Singer and Zalmanson 2013; Riggins 2003). Our research design also covers the adoption and usage of these premium services. We therefore apply our analyses from the previous sections to assess whether premium streaming services

[10] One factor that might dampen this overall negative effect is the (re-)activation of otherwise inactive customers through the availability of free streaming services. Of the 163 respondents in our sample who did not spend any money on music products over the observation period, 28 (17%) adopted a FSS. However, our research design does not allow us to assess whether these inactive consumers would have purchased music had they not adopted a FSS. Therefore, we cannot quantify this effect.

have equally detrimental effects; i.e., we estimate Eq. (3) and use the adoption of a PSS $\left(\Delta D_{it}^{PSS}\right)$ as the focal regressor.[11] When we use the gross expenditures including PSS subscription fees as the depended variable, we obtain a positive and significant estimate of δ, suggesting that the adoption of a PSS leads to an increase in overall music expenditures (δ_{M9} = .5956, p < .001). Note that premium streaming services do cannibalize expenditures from other channels (i.e., the effect in Model 8 is negative; δ_{M8} = –.2367, p < .10), but the subscription fees exceed the amount that is displaced by PSS such that the total effect is positive.

>>> Table 9 about here <<<

Based on these findings, we therefore suggest that managers focus their attention on attracting consumers into premium streaming services. This finding begs the question of whether there are ways to convert parts of the large installed base of adopters of the *free* streaming services to users of *premium* streaming services. To assess this question, we again estimate different variants of Eq. (3) and (4). In this analysis, we use the log-transformed expenditures for paid streaming services as the dependent variable and lag the independent variables regarding the adoption and usage of free streaming services by one period. These models can answer the following questions: (1) does the adoption of a FSS affect the future expenditures for PSS; and (2) does this effect vary with the relative usage intensity of the FSS? Model 10 (Table 10) shows that the effect of the lagged FSS adoption variable on PSS expenditures is positive and marginally significant at the 10% level (δ_{M10} = .0129, p < .10). Thus, adopting a FSS appears to trigger future expenditures for PSS, albeit to a rather low degree, i.e., adopting a FSS increases future PSS expenditures by 1.30% (i.e., 100

[11] As in our previous analyses, we exclude respondents who had already adopted the focal streaming service in the first period. This leaves 2149 cases for estimation, 105 of which adopted a PSS at some point during the observation period. Considering that 514 participants had adopted a FSS over the observation period, this means that approximately 17% of the overall streaming service adopters opted for the paid version (i.e., 105/619). While this figure represents a realistic ratio of paid to free users in the “freemium” business model, where the average paid user share was found to be 24% across different industries (Mulligan 2013), we acknowledge that the relatively small number of PSS adopters limits the statistical power of our analyses. Therefore, we interpret the findings reported in this section as tentative conclusions, whose validation we leave to future research.

*[exp(.0129) –1]). However, we again find observed heterogeneity in this effect. The effect of the lagged change in the relative FSS usage intensity on the change in PSS expenditures for the group of adopters, as seen in Model 11 (γ_{M11} = .1259, p < .01), is highly significant. Similar to our previous findings from the piracy model, this result suggests that once consumers get accustomed to listening to music via access-based services and change their listening behavior accordingly, the probability that these consumers will convert to paying subscribers of the PSS in the future increases. This finding is in line with previous research in a similar context, which revealed that the decision to subscribe to a paid streaming service is positively influenced by the usage intensity (Oestreicher-Singer and Zalmanson 2013).

>>> Table 10 about here <<<

Taking these analyses together leads to several important implications. Most importantly, firms should be very wary and selective in endorsing free streaming services because they cannibalize demand from other channels. If firms rely on free streaming services, they should use these offers to lock consumers into streaming services and trigger conversions to premium streaming services because – although they cannibalize expenditures from other channels – their total effect on music expenditures is positive. Premium streaming services enable firms to directly generate revenue and to avoid the negative effect of free streaming services. The conversion of free users is more likely to be successful in the case of intensive users. Therefore, to trigger conversion, service providers should positively influence usage levels (e.g., through recommendation engines, social features, and playlists). Increasing the relative usage intensity of on-demand streaming channels may further be beneficial for the industry, because – as our results reveal – it makes piracy channels relatively less attractive while monetizing free usage through the streaming channel, which may increase the overall market size.

In sum, our analyses show that a FSS is a double-edged sword. To make it an effective tool for converting users into paying consumers of premium services and to reduce piracy, firms need to stimulate usage of the service. Stimulating usage, however, makes it more likely that adopters reduce their expenditures in other channels, i.e., cannibalization will be stronger. Hence, for firms to leverage the benefits of free streaming services, it is crucial to ensure that the perceived utility of the FSS compared to paid channels is sufficiently low to prevent cannibalization. Ultimately, it is the key to profitability to attract users into *paid* streaming services, which have the advantage that they generate direct and recurring revenues for the industry. To achieve this goal, firms must meaningfully differentiate the FSS from the PSS to provide incentives for FSS users to convert to users of the PSS. At the same time, the utility of the FSS must be sufficiently high to monetize free usage, e.g., by attracting pirates or consumers who were inactive before. Our results suggest that the utility of the FSS is currently too high. Thus, identifying the optimal utility level of free streaming services (e.g., through field experiments) should be at the top of the music industry's agenda.

By estimating cannibalization effects of free streaming services on other channels, our research makes an important and implementable contribution to the literature. It is, however, subject to limitations that open avenues for future research. First, our analysis looks at one of the largest markets for music, but it only considers one country. It is possible that consumers in other countries differ in their reaction to free streaming services. Second, although our observation period covers more than one year, it is still a short-term analysis. It would be interesting to assess long-term effects that encompass several years. Third, our unit of analysis is the individual consumer and his/her expenditures for recorded music. It may be possible that artists benefit from free streaming services because this music consumption is a way of learning about new music from new artists, which may lead to increased demand in other channels (e.g., for concert tickets). Exploring these spill-over effects would be a fruitful avenue for future research. Fourth, another factor to take into consideration when introducing a free channel is the risk that this channel addition might negatively affect the perceived value of the content (e.g., Brynjolfsson, Hu, and Smith 2003), as well as the reference prices that govern consumers' purchase decision-making (e.g., Winer 1986). While we were able to identify a negative effect of the adoption of a FSS on music expenditures, future research should investigate in more detail how free streaming channels impact the value assigned to recorded music products and reference prices in the long-run. Finally, our identification strategy rests on the assumption that unobserved factors that are related to the adoption variable are relatively stable over time. While we believe that this a realistic assumption, it may be interesting to analyze our research questions in a setting in which this assumption is not necessary. When designing the study we sought to find a way to avoid this assumption by randomly inviting a part of the sample to become a subscriber to the free new streaming service that entered the market. The invitation was made such that there was no visible connection with the questionnaires (i.e., the invitation was sent out two weeks after the last and two week before the next survey). Unfortunately, however, this invitation does not significantly affect the sign-up probability. Therefore, we cannot use this variable as an instrumental variable.

Despite these limitations we believe that our research makes a useful contribution to the literature's understanding of how the music market works and how firms should tailor their products in this difficult market.

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Tables and figures

Table 1

Comparison of sample with population of music buyers

Variable	DE music market	Sample[a]	
		Mean	SD
Age (mean)	38[b]	37	12.02
Gender (male)	60%[b]	57%	.49
Music listening (hours:min per day)	3:42[c]	3:58 (3:12)[d]	3:09
Monthly music expenditures (EUR)	4.66[b]	23.33 (13.00)[d]	32.96

[a] N = 2381. Refers to the valid cases in our sample including the group of non-spenders and participants who adopted a FSS in the first survey.
[b] BVMI 2013
[c] Van Eimeren and Frees 2012; excludes digital music
[d] Number in parentheses is the median

Table 2

Descriptive statistics of model variables

Variable	Description	Mean	SD	Min	Max
$\log(expenditure\_gross_{it})$	log of sum of monthly expenditures including paid subscriptions at time *t* for respondent *i*	2.23	1.68	0	6.14
$\log(expenditure\_net_{it})$	log of sum of monthly expenditures excluding paid subscriptions at time *t* for respondent *i*	2.18	1.69	0	6.14
$\log(expenditure\_PSS_{it})$	log of monthly expenditures for paid streaming services at time *t* for respondent *i*	.03	.27	0	3.24
$\log(piracy_{it})$	log of pirated songs at time *t* for respondent *i*	.85	1.35	0	6.31
$relative\_adusage_{it}$	weekly music listening time (in minutes) via FSS relative to the overall listening time at time *t* for respondent *i*	.01	.06	0	1
D_{it}^{FSS}	= 1 if a FSS is adopted at time *t* by respondent *i*, 0 else	.07	.25	0	1
D_{it}^{PSS}	= 1 if a PSS is adopted at time *t* by respondent *i*, 0 else	.02	.13	0	1

Table 3

Free streaming service adoption rates

	t1	t2	t3	t4	t5	t6	t7	t8	t9
Absolute[a]	4.7%	5.7%	9.3%	8.8%	8.1%	8.0%	10.1%	9.6%	9.9%
Cumulative[b]	4.7%	8.0%	14.1%	16.8%	18.9%	20.7%	24.1%	25.9%	27.5%

[a] Refers to the percentage of respondents that used a streaming service in a given observation.
[b] Refers to the cumulative share of respondents that used a streaming service at least once up to a given observation.
Notes. Percentages are based on all valid cases in our sample including the group of non-spenders and participants who adopted a FSS in the first survey (N = 2381).
.

Table 4

Comparison of adopters with non-adopters

	Adopters		Non-adopters		t-test		Wilcoxon	
Variable	**Mean**	**SD**	**Mean**	**SD**	***t***	***p***	***z***	***p***
Expenditures (Euro per month)	39.24	40.36	39.36	43.12	.059	.953	–.708	.479
Physical Usage (hours per week)	6:56	9:43	7:19	9:47	.794	.428	1.769	.077
ΔPhysical Usage (hours per week)	–.181	10:10	–.585	8:41	–1.464	.143	–1.296	.195
Digital Usage (hours per week)	16:51	17:49	11:33	15:09	–6.600	.000	–7.851	.000
ΔDigital Usage (hours per week)	.029	17:39	–.264	13:28	–.666	.505	–.578	.563

N = 2110

Table 5

Estimation results: free streaming services and expenditures

Model		Coeff.	SE	t	P > | t |	95% Conf. Int.		R^2
M1	Δ Log of net monthly spending							
	Δ FSS adoption	–.0988	.0479	–2.06	.039	–.1929	–.0048	.0126
M2	Δ Log of gross monthly spending							
	Δ FSS adoption	–.1034	.0474	–2.18	.029	–.1963	–.0104	.0128

Notes: Difference-in-Difference estimator, including time period dummies.
N = 2110, Number of observations: 16,880.

Table 6

Estimation results: moderating effect of usage intensity

Model		Coeff.	SE	t	P > | t |	95% Conf. Int.		R^2
M3	Δ Log of net monthly spending							
	Δ FSS usage intensity	–.6826	.2004	–3.41	< .001	–1.0754	–.2898	.0176
M4	Δ Log of gross monthly spending							
	Δ FSS usage intensity	–.7934	.1963	–4.04	< .001	–1.1783	–.4085	.0192

Notes: Difference-in-Difference estimator, including time period dummies.
N = 514, Number of observations: 4112.

Table 7

Estimation results: moderating effect of consumer characteristics

	Δ Log of net monthly spending					
Model	Coefficient	SE	t	P > | t |	95% Confidence Int.	
M5 Influence of FSS adoption and interactions						
ΔFSS adoption (δ)	.1801	.1281	1.41	.160	–.0710	.4312
I(25 < age < 41)[a] x ΔFSS (β_1)	–.3456	.1431	–2.42	.016	–.6025	–.0651
I(age > 40)[a] x ΔFSS (β_2)	–.2874	.1608	–1.79	.074	–.6025	.0277
Gender (female) x ΔFSS (β_3)	–.1266	.1099	–1.15	.249	–.3422	.0888
I(1,001 < income < 2,501)[a] x ΔFSS (β_4)	–.0307	.1321	–.23	.816	–.2896	.2283
I(income > 2,500)[a] x ΔFSS (β_5)	.1461	.1473	.99	.321	–.1427	.4349
Streaming attitude x ΔFSS (β_6)	–.1271	.0500	–2.54	.011	–.2252	–.0292
Advertising attitude x ΔFSS (β_7)	–.0027	.0701	–.04	.970	–.1401	.1348
Willingness-to-pay x ΔFSS (β_8)	.0120	.0089	2.23	.026	.0024	.0375
Model fit (R^2)				.0138		
Number of cases				2110		
Number of observations				16,880		

Notes: Difference-in-Difference estimator, including time period dummies.
[a] The I(·) function is an indicator function that equals 1 if the logical expression in it is true and 0 if otherwise. Thus, I (age > 40) would be 1for age > 40 and 0 for age ≤ 40.

Table 8

Estimation results: free streaming services and piracy

Model		Coeff.	SE	t	P > | t |	95% Conf. Int.		R^2
M6[a]	Δ Log of monthly piracy							
	Δ FSS adoption	.0127	.0373	.34	.733	–.0604	.0858	.0021
M7[b]	Δ Log of monthly piracy							
	Δ FSS usage intensity	–.3395	.1805	–1.88	.060	–.6934	.0143	.0030

Notes: Difference-in-Difference estimator, including time period dummies.
[a] N = 2110, Number of observations: 16,880.
[b] N = 514, Number of observations: 4112.

Table 9

Estimation results: premium streaming services and expenditures

Model		Coeff.	SE	t	P > | t |	95% Conf. Int.		R^2
M8	Δ Log of net monthly spending							
	Δ PSS adoption	–.2367	.1228	–1.93	.054	–.4774	.0041	.0132
M9	Δ Log of gross monthly spending							
	Δ PSS adoption	.5956	.1222	4.87	.000	.3560	.8353	.0144

Notes: Difference-in-Difference estimator, including time period dummies.
N = 2149, Number of observations: 17,192.

Table 10

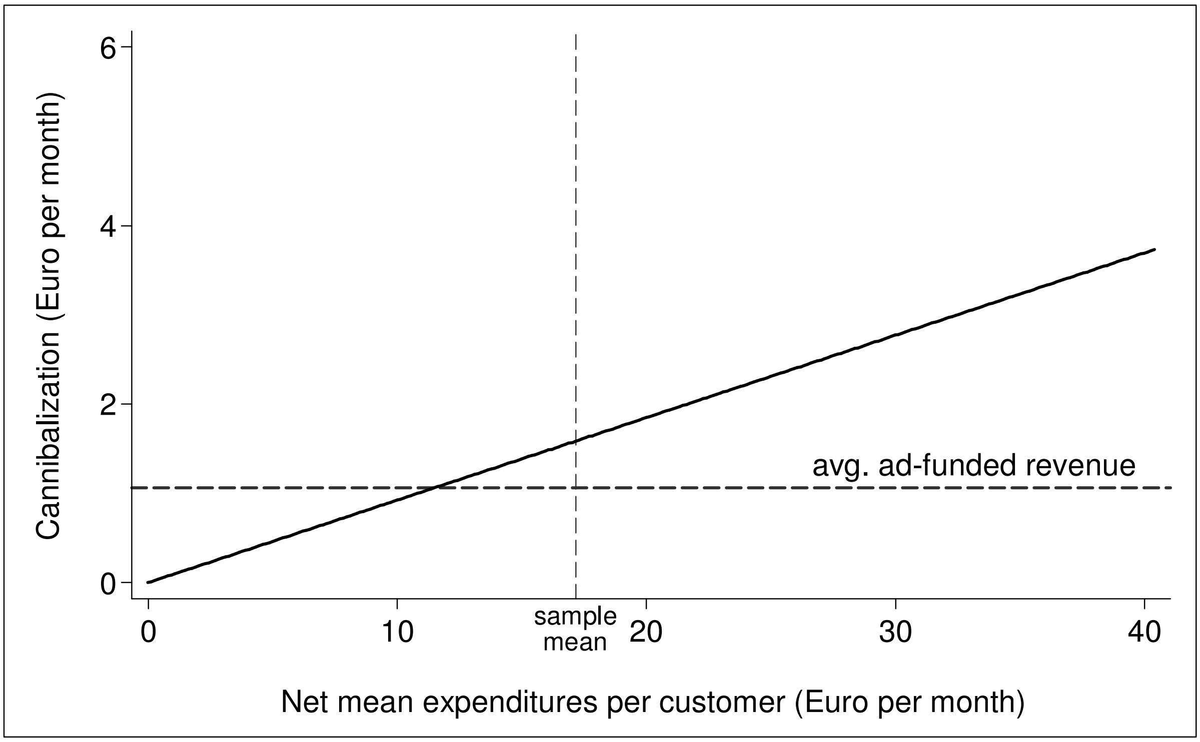
Estimation results: conversion of FSS users to PSS users

Model		Coeff.	SE	t	P > | t |	95% Conf. Int.		R^2
M10[a]	Δ Log of PSS spending							
	Lagged Δ FSS adoption	.0129	.0078	1.66	.097	–.0023	.0282	.0004
M11[b]	Δ Log of PSS spending							
	Lagged Δ FSS usage intensity	.1259	.0483	2.61	.009	.0312	.2205	.0028

Notes: Difference-in-Difference estimator, including time period dummies.
[a] N = 2110, Number of observations: 14,770.
[b] N = 514, Number of observations: 3598.

Figure 1

Cannibalization of expenditures



Appendix

Appendix A. Survey items and descriptive statistics

Table A.1

Measurement scales

Construct/Items	Mean	SD
Attitude towards streaming services (α = .68)	1.95	.87
1. Using music streaming services does not fit well with the way I like to consume music. [R]		
2. Access-based streaming services can be no substitute for purchasing music products for me. [R]		
Attitude towards advertising (α = .83) Some media offers (e.g., TV, radio) are free of charge to consumers, but include advertisements. In how far do you agree with the following statements:	2.77	.73
1. For a lower price I am willing to accept advertisements.		
2. I find commercial breaks to be very disturbing. [R]		
3. If there is a commercial break on the radio, I switch the channel most of the time. [R]		
4. If there is a commercial break on TV, I switch the channel most of the time.[R]		
5. I like the idea of using free media offers that include advertisements.		
6. Using free media offers that include advertisements is a good idea.		
7. I prefer to use free media content offers with advertising than to pay for content.		
8. Through media offers with advertising, one can save a lot of money		
Willingness-to-pay (EUR)	6.20	5.58
Imagine an artist you like releases a new album within the next 6 months. How much money would you be willing to pay for a digital copy of the album at the most?		

Note: Variables measured on a five-point scale unless otherwise stated (1 = strongly disagree—5 = strongly agree).
[R] Scale reverted for measurement

Appendix B. Panel attrition

To test whether our results are subject to selection bias from panel attrition we apply a method which corrects for possible attrition bias (see Wooldridge 2002, pp. 585). The departing point is our main model in first differences, which controls for unobserved time-invariant consumer effects:

$$\Delta Y_{it} = \xi_t + \delta \Delta D_{it} + \Delta \varepsilon_{it}, \quad t = 2, \dots, T, \tag{B.1}$$

where Y_{it} are the expenditures for music products for individual i in period t, ξ_t are time intercepts, D_{it} denotes the adoption of a streaming service by respondent i at time t, and ε_{it} is the idiosyncratic error. Because our goal is to determine the influence of attrition on the adoption effect δ, we need to control for the attrition probability in Eq. (B.1). In our case, attrition is an absorbing state, meaning that once a respondent drops out of the survey at a given wave t s/he is out till the end of the survey.

The basic idea underlying the correction procedure is comparable to the correction for sample selection bias. This procedure involves two steps (Wooldridge 2002, pp. 585): (1) compute the "dropout-hazard" (i.e., the inverse Mill's ratio) from each individual cross-section using probit regression on the full sample (i.e., the dropouts and non-dropouts at time t); and (2) insert these correction terms as explanatory variables in Eq. (B.1) and estimate this model on the cases that remain in the survey until the end. The estimate of the adoption effect is subject to selection bias from panel attrition to the extent that the correction terms exhibits an influence on δ.

In the first step, the selection equation models the probability of remaining in the survey at time t as a function of observable variables using probit regression. Let d_{it} denote the selection indicator for each period, where $d_{it} = 1$ if (D_{it}, Y_{it}) are observed. We ignore respondents once they initially leave the survey so that $d_{it} = 1$ implies $d_{ir} = 1$ for $r < t$. Conditional on $d_{i,t-1} = 1$, the selection equation for $t \geq 2$ can be written as

$$d_{it} = 1[w_{it}\beta_t + v_{it} > 0], \qquad v_{it} \mid \{w_{it}, d_{i,t-1} = 1\} \sim Normal(0,1)\,, \tag{B.2}$$

where w_{it} contains variables observed at time *t* for all respondents with $d_{i,t-1} = 1$. Specifically, we model the probability that a respondent remains in the survey at time *t* as a function of the time-varying variables observed at time *t* – 1 with respect to the adoption of a FSS, the time that respondents had spent listening to music via physical and digital formats, the volume of pirated music-files as well as the response time. The corresponding selection equation is given by

$$\begin{aligned} \Pr(d_{it} = 1) = \quad & \beta_0 + D^{FSS}_{i,t-1}\beta_1 + \log\left(listenphysical_{i,t-1}\right)\beta_2 \\ & + \log\left(listendigital_{i,t-1}\right)\beta_3 + \log\left(piracy_{i,t-1}\right)\beta_4\,. \\ & + \log\left(responsetime_{i,t-1}\right)\beta_5 + u_{it} \end{aligned} \tag{B.3}$$

From these $T-1$ cross-section probits, we compute the inverse Mill's ratios:

$$\lambda_{it} = \frac{\phi(w_{it}\beta')}{\Phi(w_{it}\beta')}\,, \tag{B.4}$$

where ϕ denotes the standard normal density function, and Φ is the standard normal cumulative distribution function. We then add the estimates of λ_{it} for each wave as independent variables in Eq. (B.1) to correct for the attrition probability, such that:

$$\left(\Delta Y_{it} \middle| \Delta D_{it,} w_{it}, d_{it} = 1\right) = \Delta D_{it}\delta + \rho_t \lambda(w_{it}, \beta_t), \quad t = 2, \dots, T. \tag{B.5}$$

The results from the estimation of Eq. (B.5) are summarized in Table B.1. As can be seen, the correction factors do not significantly influence the dependent variable and the estimate of the main effects, *δ,* remains virtually unchanged. Thus, we conclude that our results are insensitive to panel attrition.

Table B.1

Panel attrition estimation results

Model	Coefficient	SE	T	P > | t |	95% Confidence Interval	
M B1 FSS adoption model						
FSS adoption (δ)	–.1008	.0481	–2.10	.036	–.1951	–.0065
Correction factor t_2 (λ_{i2})	–.3580	.5233	–.68	.494	–1.3837	.6677
Correction factor t_3 (λ_{i3})	.2159	.5681	.38	.704	–.8977	1.3294
Correction factor t_4 (λ_{i4})	–3.9979	5.1405	–.78	.437	–14.0739	6.0780
Correction factor t_5 (λ_{i5})	.0858	.5561	.15	.877	–1.0042	1.1758
Correction factor t_6 (λ_{i6})	–.3277	.6525	–.50	.615	–1.6066	.9512
Correction factor t_7 (λ_{i7})	.1514	2.1032	.07	.943	–3.9710	4.2738
Correction factor t_8 (λ_{i8})	–.5619	.5936	–.95	.344	–1.7254	.6016
Correction factor t_9 (λ_{i9})	4.7386	5.4999	.86	.389	–6.0419	15.5191

Note: Difference-in-Difference estimator, including time period dummies.
N = 2110, Number of observations: 16,880.

5. Predicting New Service Adoption with Conjoint Analysis: External Validity of Incentive-Aligned and Dual Response Choice Designs

Authors:

Nils Wlömert and Felix Eggers

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Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

Felix Eggers, Assistant professor, Department of Marketing, Faculty of Economics and Business, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands. E-mail: f.eggers@rug.nl, URL: www.rug.nl/feb/marketing.

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1. Introduction

Choice-based conjoint (CBC) experiments are one of the most popular techniques to measure consumer preferences, both in academic research and marketing practice. In many CBC experiments, a no-choice option is included in the choice sets to increase the proximity to real-life purchase situations, i.e., being able not to buy if none of the alternatives is acceptable (Haaijer, Kamakura, and Wedel 2001; Louviere and Woodworth 1983; Vermeulen, Goos, and Vandebroek 2008). Notably, the inclusion of a no-choice option is required if the aim is to predict consumers' adoption behavior and willingness to pay (WTP).[1] However, there are several limitations threatening the validity of the results in such applications.

First, the share of no-choice decisions may be underrepresented because the selection decisions have no consequence for respondents, e.g., in terms of a buying obligation. Because of this hypothetical bias survey participants typically act less price sensitive compared with real market settings (e.g., Miller et al. 2011). Second, apart from understating no-choices, consumers have been shown to select none of the alternatives more frequently to avoid cognitive effort, e.g., when the stimuli are similarly attractive so that the decision requires a trade-off (Dhar 1997a; Dhar 1997b). Finally, selecting the no-choice option reveals no information about the respondent's preferences for the experimentally varied stimuli (except that they are not acceptable). Consequently, the number of observations that can be used to detect utility differences between attribute levels is reduced with an increasing number of no-choice decisions (Brazell et al. 2006).

To address these issues two extensions of the standard CBC procedure have been proposed recently: Incentive-aligned (IA) mechanisms and dual response (DR) choice designs. IA mechanisms aim to attenuate hypothetical bias during data collection by rewarding partic-

[1] By the term WTP, throughout the paper, we refer to the price at which a participant is indifferent between purchasing and not purchasing a product with a certain set of features (e.g., Gensler et al. 2012). The term does not refer to the WTP for the individual product features (i.e., the amount by which the price can be raised if a feature is added), which is identified without an outside option.

ipants with a real version of the product or service under study after the experiment. Because the product that is rewarded depends on the choices made in the experiment respondents have an incentive to reveal their true preferences (Ding 2007; Ding, Grewal, and Liechty 2005). Under the DR choice format, respondents first select the most preferred concept in a forced-choice task (excluding no-choice) and indicate whether they would actually purchase the selected alternative in a second step (Brazell et al. 2006; Diener, Orme, and Yardley 2006). Thus, DR designs yield preference information about attribute levels even if none of the alternatives in a choice set would be purchased.

To date, the IA and DR conjoint extensions have only been considered independently from another so that there is no comparative evidence regarding their predictive performance. Consequently, researchers are left without guidance which method to prefer. We address this research gap and compare the traditional CBC approach with the IA and DR extensions in terms of their ability to predict new service adoption and to accurately capture consumers' WTP. In addition, we integrate both conjoint extensions in an IA-DR-CBC procedure, which inherits the conceptual benefits of both approaches.

Using music streaming services as the research context, our empirical study features a unique sample of 2679 music consumers who were randomly assigned to one of the four experimental conditions. We first conducted a conjoint choice experiment prior to the launch of a new music streaming service to predict the market demand and consumers' WTP. Five months after the market entry we contacted the same respondents again to obtain data on their actual adoption behavior, which we use to judge the methods' external validity.

The study findings provide academic and managerial researchers with evidence on state-of-the-art procedures to conduct CBC experiments.

2. Conceptual evaluation

2.1. IA-CBC

The basic idea underlying IA mechanisms is that consumers are motivated to provide truthful answers in experiments because their decisions have an impact on the reward that is provided after the experiment. In CBC studies, this may require respondents to purchase a real version of the product or service under study if the price is an attribute of interest. Different variants of IA-CBC experiments have been introduced.[2] They include mechanisms that (1) select the reward directly from the chosen alternatives in the experiment (Ding, Grewal, and Liechty 2005), (2) use the utility estimates to identify the most preferred alternative from a list of predetermined rewards (Dong, Ding, and Huber 2010), or (3) infer the respondent's WTP for one specific product version and determine if it will be rewarded according to an auction, e.g., the Becker-Degroot-Marschak (BDM) procedure (Becker, Degroot, and Marschak 1964; Ding 2007; Wertenbroch and Skiera 2002).

It has been shown that IA data collection procedures reduce hypothetical bias and can substantially increase the predictive validity of conjoint estimates (Ding 2007; Ding, Grewal, and Liechty 2005; Dong, Ding, and Huber 2010; Miller et al. 2011). One drawback of incentive alignment, however, is that its' application is limited to contexts where at least one concept of the research object can be rewarded after the experiment. This may not be feasible in many instances, e.g., when the research object is not yet available on the market, or when expensive product categories are analyzed (e.g., cars). In addition, this procedure does not tackle the problem that an increasing share of no-choice decisions limits the number of observations that can be used to estimate the part-worth utilities. This is particularly problematic

[2] We note that other IA mechanisms exist that are not choice-based, such as transaction-based approaches (e.g., Ding, Park, and Bradlow 2009).

considering that incentive-aligning CBC experiments has been shown to even increase the share of no-choice decisions (Ding, Grewal, and Liechty 2005; Miller et al. 2011).

2.2. DR-CBC

Separating the selection decision from the purchase decision in DR choice designs offers three potential conceptual benefits over traditional CBC analysis. First, it can be hypothesized that the DR procedure corrects for the underselection of the no-choice option because it increases the salience of the purchase decision (Brazell et al. 2006). Second, consumers cannot opt out of making a trade-off decision by selecting the no-choice option if choosing between the alternatives requires cognitive effort. Third, the DR process yields preference information even if none of the alternatives would be purchased, which enhances the reliability of the part-worth estimates. A drawback of this procedure, however, is that it requires twice as many decisions compared with single-stage approach and might lead to increased respondent fatigue and, consequently, higher error variance.

Brazell et al. (2006) demonstrate based on simulated data that DR outperforms CBC in terms of parameter recovery with an increasing share of no-choice decisions. However, they do not find significant improvements regarding the internal predictive validity of DR compared with traditional CBC in two empirical studies. Karty and Yu (2012) compare variants of the DR procedure with scanner data and provide evidence that DR is able to reduce the understatement of no-choices. Unfortunately, further empirical evidence regarding the (external) validity of the DR procedure remains scarce.

2.3. IA-DR-CBC

Since the IA and DR extensions are not mutually exclusive, they can be combined in an IA-DR-CBC procedure. Thus, an IA-DR-CBC experiment constitutes a DR design where both tasks, i.e., the forced choice and sequential purchase tasks, are incentive-aligned. Conceptual-ly, IA-DR combines the benefits of both approaches that it inherits. However, empirical tests of this procedure are sparse. We address this test in our empirical study.

3. Empirical study

3.1. Research context

We chose music streaming services as the research context, which provide a relatively new means of music consumption. A business model that has received increasing attention recently is the subscription model, in which customers pay a monthly flat fee to access a comprehensive online music library during the period of membership. Most competitors in this market (e.g., Deezer, Spotify) offer several versions of the service to attract different consumer segments. Typically, in addition to the paid service, one variant of the service is free of charge to consumers but relies on advertising as a revenue source instead and imposes usage restrictions, e.g., regarding mobile access. This type of business model, featuring a free version and a paid premium version, is commonly used in the Internet economy (e.g., by services such as Dropbox or Skype) and is referred to as the "Freemium" (or two-tiered) model (Anderson 2010; Oestreicher-Singer and Zalmanson 2013; Riggins 2003). For companies that rely on this business model it is vital to maintain a profitable balance between paying premium subscribers and users of the free service because the former customer segment often subsidizes the latter. Consequently, accurate predictions with respect to the market potential of the different service variants are of crucial importance to service providers. We further chose this research context to assess the validity of no-choices in CBC experiments because the existence of free alternatives decreases the adoption threshold of a service and therefore requires high discriminatory power.

3.2. Conjoint attributes and choice design

We decomposed music streaming services into their main characteristics based on insights we gained from a review of the major services that are available on international markets and interviews with industry experts. On this basis we identified six main characteristics, which are (1) price, (2) range of compatible devices and access modes, (3) monthly usage allowance, (4) sound quality, (5) advertising intensity, and (6) catalog size (see Table 1). With respect to price, we set a lower bound of 0 EUR to account for ad-funded business models that are free to consumers and consider increments of approximately 2.50 EUR up to a maximum amount of 12.49 EUR per month, above the current market price of 9.99 EUR per month (see also Papies, Eggers, and Wlömert 2011).

>>> Table 1 about here <<<

Based on these attributes and attribute levels, we constructed choice sets consisting of three alternatives (excluding the no-choice option). We used a computer generated design that accounts for minimal overlap, level balance, and orthogonality (Huber and Zwerina 1996). We assigned twelve choice sets to each respondent; ten of the sets were used for estimation and two identical hold-out sets served to assess the consistency of the respondent's choice behavior and the internal predictive validity.

3.3. Experimental procedure

We treat the IA mechanism as proposed by Ding (2007) and the DR procedure as proposed by Brazell et al. (2006) as between-subjects experimental factors (see Table 2). Respondents were randomly assigned to one of the four experimental conditions.[3]

>>> Table 2 about here <<<

[3] We only assigned respondents to the IA conditions if we had access to their real names and addresses, which is why these conditions exhibit fewer observations.

The single-stage and two-stage conditions only differed with respect to the no-choice option, which was either presented as another alternative next to the service concepts (single-stage), or after each selection decision as a separate purchase task (two-stage). The IA mechanism we applied was based on predicted WTP as introduced by Ding (2007) (see Figure 1). The instructions to the procedure that were used in the questionnaires can be found in Appendix 1.[4] To ensure that all participants had understood the auction mechanism, we included a comprehension question after the instructions. Respondents were only allowed to proceed to the conjoint part of the questionnaire if they had answered this question correctly or were referred back to the page with the instructions otherwise. After the choice experiment, we measured the methods perceived acceptability and transparency based on 5-point rating scales.

>>> Figure 1 about here <<<

3.4. Sample

The survey participants were recruited through an online access panel, which is maintained by a major worldwide media distributor to keep track of trends in media consumption. The data collection took place in Germany in March 2012. As shown in Table 3, the comparison of our sample with representative secondary market research data shows a good match, indicating that the music industry's target group is well represented. In addition, Table 3 shows that the sample composition does not significantly differ between the experimental groups.

We completed the choice experiment one week prior to the introduction of the service of the largest worldwide music streaming service provider to the German market. Overall, 2679 usable cases were obtained. Five months after the service launch we recorded information on

[4] Note that we ultimately refrained from carrying out the buying obligation after the survey because rewarding participants under incentive alignment with access to the analyzed service would have induced bias in the external validation measures. Instead, all respondents were appropriately debriefed and rewarded for their participation in the survey.

the respondent's actual music streaming service adoption, which we use for external validation. To avoid bias, we revealed no connection of this validation task to the previous study. We captured the adoption behavior of 1827 respondents.

>>> Table 3 about here <<<

3.5. Results

3.5.1. Method transparency, acceptability and response behavior. The methods perceived acceptability and transparency is presented in Table 4. As can be observed from item one, the perceived task difficulty is significantly higher under the IA experimental conditions, suggesting that the auction mechanism is more complex to understand compared with hypothetical methods. It can further be seen from item two that the DR mechanism increases the perceived difficulty of the selection decisions. This observation is consistent with previous findings that forced responses are associated with more cognitive conflict and discomfort (Dhar and Simonson 2003). Furthermore, item three shows that both conjoint extensions reduce the willingness to participate in comparable surveys in the future.

>>> Table 4 about here <<<

Inspection of the response times reveals that participants needed significantly more time under the DR choice design. This observation is not unexpected because respondents are required to make twice as many choices when the DR procedure is used. In contrast, the mean response time is significantly lower under the IA mechanism. One likely explanation for this finding is related to the substantially higher share of respondents that always selected the no-choice option, which requires less time than deciding between service concepts. As can be seen from Table 4, the share of respondents that exclusively selected the no-choice option is increased by 11%-points (9%-points) under incentive alignment in the single-stage (two-stage) model. Similarly, DR led to a substantially higher share of respondents that never selected a service concept with an increase of 10%-points (8%-points) in the non-IA (IA) experimental groups. This result confirms previous research that found higher no-choice shares under DR (Brazell et al. 2006; Dhar and Simonson 2003) and provides initial support for our expectation that the increased salience of the no-choice option leads respondents to evaluate the purchase decisions more thoroughly.

Regarding the incompletion rate, we find that more respondents exit the survey when the incentive alignment procedure is used. Despite the higher dropout rate, we find no evidence for a selection bias with respect to key demographic and socioeconomic variables (see Table 3). The higher dropout rate is more likely to be explained by the higher degree of complexity, which is also mirrored by the share of respondents that initially provided the wrong answer to the comprehension question.

Finally, the consistency measure of choices in the two identical holdout sets, i.e., the test-retest reliability, indicates that slightly more consistent responses are obtained as a consequence of incentive-aligning the experiment.

3.5.2. Predictive validity. We used a multinomial logit model for estimation in which consumer n's choice i from a choice set with J alternatives is included in the likelihood function in terms of a choice probability (Louviere, Hensher, and Swait 2000):

$$prob_n(i \mid J) = \frac{\exp(\lambda \beta_n X_i)}{\sum_j^J \exp(\lambda \beta_n X_j)}, \tag{1}$$

where individual-level part-worth utilities are denoted β_n and the characteristics of alternative i are given by X_i. λ refers to the scale of the estimates which is inversely related to the error variance $\text{Var}(\varepsilon) = \pi^2 / 6\lambda^2$ (Islam, Louviere, and Burke 2007; Ofek and Srinivasan 2002).

The no-choice option can be modeled in two different ways. In the single-response formats, the no-choice option is included as another alternative next to the product concepts in each choice set, i.e., $J_0 = \{0, \ldots, J\}$, (where 0 indicates no-choice). In the DR procedure respondents are first asked to select the most preferred product concept from a set of alternatives excluding no-choice, i.e., $J^{DR=1} = \{1, \ldots, J\}$, and indicate whether they would purchase the selected product concept *i* in a second step, i.e., $J^{DR=2} = \{0, i\}$ (Brazell et al. 2006; Diener, Orme, and Yardley 2006; Gilbride and Allenby 2004). Both decisions in the DR procedure can be included as separate factors in the likelihood function. This, however, considers twice as many observations as the single response formats. For comparability, we therefore inferred a choice set with three alternatives plus the no-choice option, i.e., J_0, in the DR conditions by replacing the selected stimulus with the no-choice option if the latter was chosen in the sequential task. With this transformation all experimental conditions are based on the same number of choices.[5]

We applied a hierarchical Bayes procedure with mixtures of normal distributions for estimating individual-level part-worth utilities (Allenby, Arora, and Ginter 1998; Allenby and Ginter 1995; Rossi, Allenby, and McCulloch 2005). In the estimation procedure we completed a total of 20,000 iterations and discarded the first half to make sure that the process converged (please refer to Appendix 2 for a summary of the estimation results). The part-worth estimates show the expected signs and indicate face validity. Moreover, the larger scale of the part-worth utilities in the DR and IA conditions suggests that the decisions are more consistent and exhibit lower error variance, which sustains the results of the test-retest reliability.

The results of the external validation are presented in Table 5. They show that about 3/4 of the respondents had not subscribed to any of the available services on the market. Most consumers of the remaining quarter had chosen the free, ad-funded alternative. 4-5% sub-

[5] The extended likelihood function with two factors per choice set in the DR conditions does not change the conclusions of our study.

scribed to the premium version that costs 9.99 €. The adoption rate of the remaining service concept at 4.99 € ranges between 1-2%.[6]

We measured the external validity with the hit rate of correct predictions and the mean absolute error (MAE) between predicted and actual choice shares (Moore, Gray-Lee, and Louviere 1998). Table 5 shows that the hypothetical single response CBC predicts the adoption decision worst. Less than half of the predictions are correct and the predicted shares differ by 19%-points. The DR procedure and IA mechanisms substantially increase the hit rate and decrease the MAE. The three tested extensions are comparable in their external validity. However, the overall maximum hit rate of 59.4% is accomplished with the new IA-DR-CBC approach and the overall lowest MAE with the standard DR procedure. DR-CBC reduces the error between actual and predicted shares to 7.5%-points, an error reduction of more than 60% compared with the standard CBC approach.

Validity measures that are based on the internal holdout sets are less distinct. The differences in hit rate between the standard CBC approach and the remaining approaches are at most 3%-points (hit rate CBC = 87.6%, hit rate IA-CBC = 90.6%). The differences in MAE are even smaller and sum to a maximum of 0.4%-points (MAE CBC = 1.1%, MAE IA-DR-CBC = 0.7%). Thus, the methods predict equally well within their experimental condition so that only the external validation is able to uncover their managerially relevant impact on the predictive accuracy.

>>> Table 5 about here <<<

3.5.3. Willingness-to-pay. The validity of the estimate for the no-choice option plays a central role in predicting consumers' WTP because it constitutes a threshold for the attractiveness of the market offerings. We calculated WTP measures for the premium music service by

[6] A comparison of the adoption rate of our sample with external representative market research data shows a good match. While in our sample between 5.1% and 6.9% of the respondents adopted a paid streaming service, the adoption rate observed in a representative sample in 2012 was 6% (BVMI 2012).

finding the price level that makes the consumer indifferent between adoption and non-adoption, i.e., balances the utility of the service and the no-choice option (e.g., Papies, Eggers, and Wlömert 2011). As another reference, an additional experimental group (n = 281) that did not participate in the conjoint experiment was queried directly regarding their WTP for the premium service in an open-ended (OE) question. A summary of these measures can be found in Table 6.

Comparing the conjoint methods, the hypothetical single response CBC exhibits the highest WTP, followed by DR-CBC, IA-CBC, and IA-DR-CBC. According to the external validation measure, only 4.1% to 5.5% of the consumers adopted the premium music service at a price of 9.99 €. In the standard CBC condition, the WTP measure would imply that 27.6% of the consumer would adopt the service at this price point (see Figure 2). The lowest adoption rate of 11.6%, which seems most plausible given the actual adoption behavior, is predicted by IA-DR-CBC. Overall, our results suggest that people act more price-sensitive under IA conditions because they appear to judge their budget constraints in a more realistic way, in support of previous findings (Miller et al. 2011; Ding et al. 2005; Ding 2007). In addition, our results provide evidence that increasing the salience of the purchase decision in DR choice designs increases the price sensitivity to a similar extent, thereby leading to more realistic WTP estimates and predictions regarding the market share of paid streaming services.

>>> Table 6 about here <<<

>>> Figure 2 about here <<<

4. Discussion and summary

Conjoint analysis is one of the most frequently used methods to elicit preference-based market demand and WTP. However, uncertainty about the external validity of recently proposed extensions of the method presents a serious drawback for researchers. We fill this void by presenting one of the first studies that compares the external validity of the standard single response CBC approach with two recent extensions: IA and DR choice designs. In addition, we integrate both conjoint extensions and test the validity of an incentive-aligned dual response (IA-DR-CBC) procedure.

Our results demonstrate that both extensions have a substantial positive effect on the predictive accuracy. The overall best results regarding the hit rate and the lowest, most realistic WTP measures are generated by the IA-DR-CBC procedure. This procedure has the benefit of motivating the respondents to answer truthfully while also increasing the salience of the purchase decision. Thus, we recommend that IA-DR-CBC should be used in applications that require accurate predictions of adoption rates, market shares, or WTP. However, IA has the drawback that the mechanism is not easily comprehensible for respondents and participants are more likely to drop out of the questionnaire accordingly – an issue that needs to be addressed in further research. Moreover, incentive alignment cannot be applied to every research context because it requires a reward from the product category that the respondents assess, which is not always feasible. In these applications our results show that the non-IA DR procedure also works remarkably well in terms of predictive validity and inferred WTP. Although DR requires a longer interview time, it should be preferred over the hypothetical single response CBC.

Importantly, the differences regarding the predictive accuracy only unfold in the external validation; the internal validity measures indicate that every method predicts equally well within their experimental condition. Our results therefore also highlight the added value of external validity measures when comparing different CBC approaches experimentally.

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Tables and figures

Table 1

Attributes and attribute levels

Attribute	*Levels*
Price per month	0.00 €, 2.49 €, 4.99 €, 7.49 €, 9.99 €, 12.49 €
Devices and access	PC & mobile (online & offline), PC & mobile (online only), PC (online only)
Usage limit	Unlimited, 20h per month, 5h per month
Sound quality	320 kbps, 192 kbps, 128 kbps
Advertising	No ads, online banner, online banner & audio ads
Catalog size	Comprehensive, large, medium, small

Table 2

Experimental design

	No-choice decision	
Selection decisions	*Single-stage*	*Two-stage*
Hypothetical	CBC	DR-CBC
Incentive-aligned	IA-CBC	IA-DR-CBC

Table 3

Comparison of group composition

	German music market	*Full sample*	*Experimental groups*			
			CBC	*DR-CBC*	*IA-CBC*	*IA-DR-CBC*
Number of respondents		2679[a]	960	837	450	432
Gender (male)	59%[b]	54%	54%	55%	57%	53%
Age (mean)	38[b]	36	36	36	37	36
Attitude towards music subscription services[c]		2.62	2.57	2.66	2.59	2.67
Number of respondents for external validation		1827	649	550	308	320

[a] For gender and age the numbers are based on 2046 consumers (76%) due to missing data.
[b] Numbers are for 2012 and refer to the German music consumer population (BVMI 2013).
[c] Mean of two-item scale: “I like the idea of using a music subscription service.” and “Using a music subscription service is a good idea.”, measured on a 5-point rating scale (1=strongly disagree—5=strongly agree) ($\alpha = 0.90$)
Note: The mean of each group is tested for significant difference against the overall mean at $p < 0.05$ or less.

Table 4

Comparison of perceived method acceptability and response behavior

	CBC	*DR-CBC*	*IA-CBC*	*IA-DR-CBC*
1. This task was easy to understand and complete.	4.24	4.19	3.81[a]	3.72[a]
2. It was easy for me to repeatedly choose among the different offers.	3.74	3.49[a]	3.70	3.44[a]
3. I will be happy to do this task again in the future.	3.83	3.75[a]	3.53[a]	3.39[a]
Time to complete the choice tasks	5:24	6:16[a]	5:00[a]	6:07[a]
Percent of respondents who always selected the no-choice option	15%	25%	26%	34%
Incompletion rate (%)	12%	14%	22%	25%
Wrong answer to initial comprehension question	N/A	N/A	35%	27%
Test-rest-reliability	78%	79%	83%	80%

[a] Significantly different from CBC at $p < 0.05$ or less.
Notes: Items 1 to 3 are measured on a 5-point rating scale (1=strongly disagree—5=strongly agree). N/A = not applicable.

Table 5

Actual adoption of music service

	CBC	*DR-CBC*	*IA-CBC*	*IA-DR-CBC*
Observed adoption rates				
No adoption	75.5%	73.0%	73.7%	78.0%
Free, ad-funded service	18.5%	20.0%	19.0%	17.0%
Standard service for 4.99 €	1.8%	1.3%	1.9%	1.0%
Premium service for 9.99 €	4.2%	5.5%	5.0%	4.1%
Predicted adoption rates				
No adoption	37.4%	58.2%	51.0%	60.0%
Free, ad-funded service	35.3%	23.5%	33.8%	26.6%
Standard service for 4.99 €	6.9%	3.5%	3.2%	3.1%
Premium service for 9.99 €	20.3%	14.9%	12.0%	10.3%
External validity measures				
Hit rate	43.8%	56.5%	57.8%	**59.4%**
MAE	19.0%	**7.5%**	11.5%	9.0%

Note: Bold values indicate highest validity.

Table 6

WTP and price sensitivity for the premium music service

	OE	*CBC*	*DR-CBC*	*IA-CBC*	*IA-DR-CBC*
Mean WTP (EUR)	4.37	5.58	4.26	3.68	2.86
SD WTP	7.79	4.55	4.32	4.30	3.87
Predicted adoption rate	18%	27.6%	18.5%	17.3%	11.6%

Figure 1

Incentive alignment mechanism

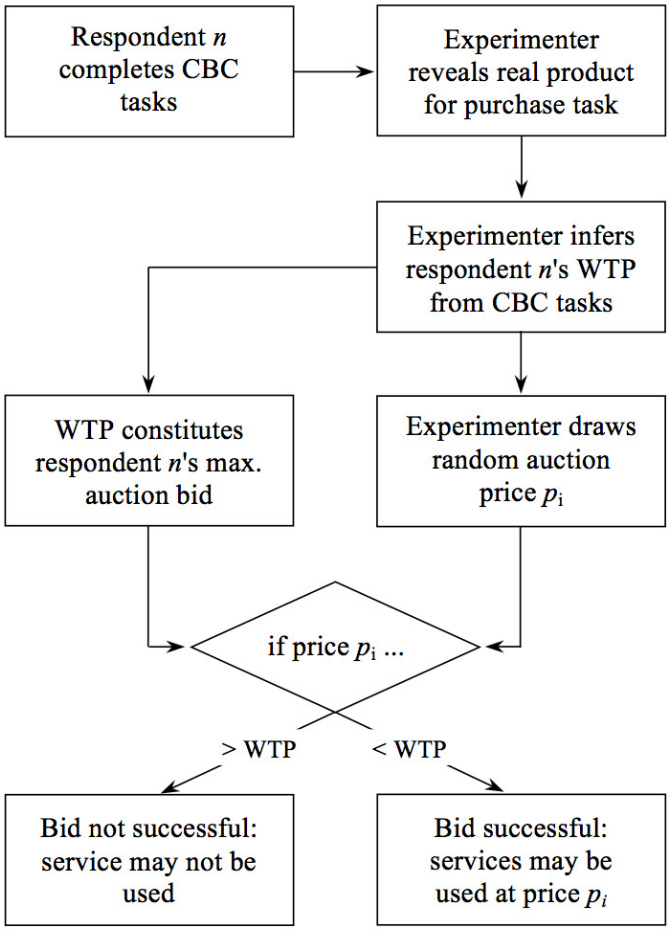
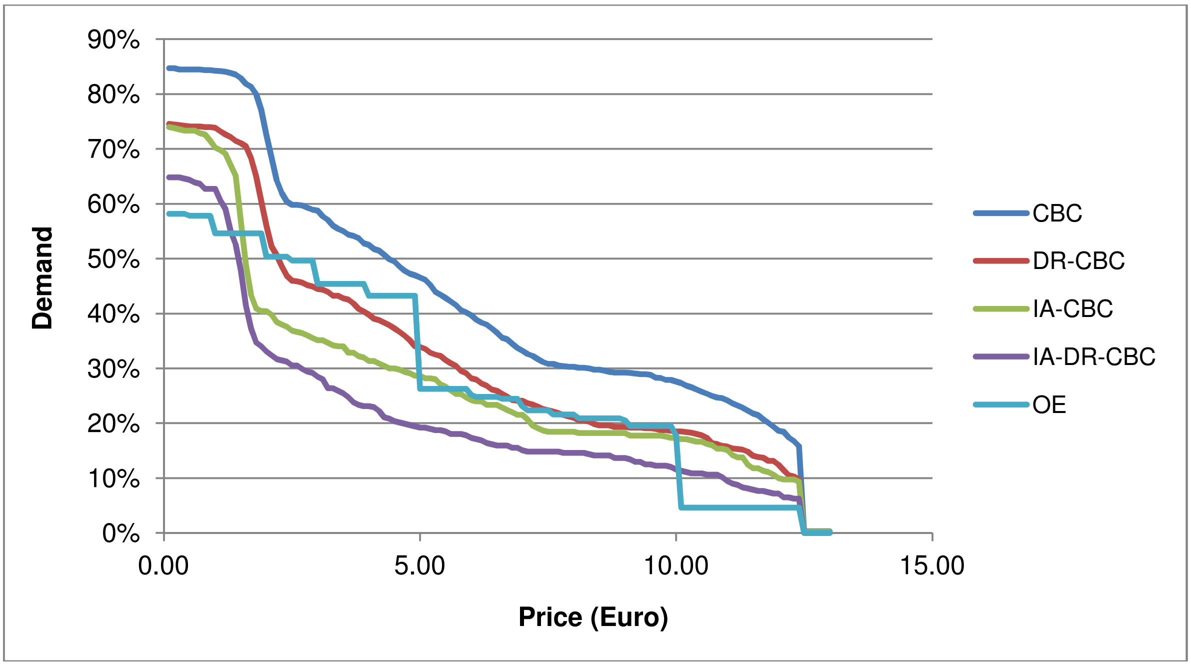


Figure 2

WTP



90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Demand
0.00
5.00
10.00
15.00
Price (Euro)
CBC
DR-CBC
IA-CBC
IA-DR-CBC
OE

Appendix

Appendix 1

Incentive alignment instructions

The following part of the questionnaire contains an auction, giving you the chance to subscribe to a real music streaming service. Your understanding of the auction process is crucially important for the remainder of the questionnaire. So please read the instructions provided on the following pages very carefully.

1. Selection decisions: Subsequent to the instructions you will be shown different service configurations in twelve consecutive selection decisions. On each page of the questionnaire, please select among the three alternatives the configuration you prefer the most. Please only select service concepts you would also subscribe to under real-world conditions. If none of the options appeal to you, please select “None of these”. You may view a short explanation regarding the services attributes by moving the mouse pointer over the texts (a screenshot was provided as visual aid).[7]
2. Calculation of your maximum auction bid: After you have completed the twelve choice tasks, we are able to calculate the maximum amount of money you would pay for a specific service configuration based on your selection decisions. This amount will be in the range between 0.00 EUR and 12.49 EUR, depending on your choices, and constitutes your maximum bid for the subsequent auction.
3. Auction process: After the survey, a random price will be drawn from an equal distribution of values in the range between 0.00 EUR and 12.49 EUR.
   - If this random price is lower than your inferred maximum bid, you may subscribe to the music service for one month (and possibly longer, if you wish). Note, however, that in this case you are obliged to pay the randomly drawn price, which gives you access to the service for one month.
   - If this random price is higher than your inferred maximum bid, you may not subscribe to the service.

[7] To ensure a high degree of comparability, we used the same wording in the non-incentive-aligned groups, stressing that service concepts should only be selected if respondents would subscribe to the respective services under real-world conditions.

Appendix 2

Posterior mean estimates

	CBC		*DR-CBC*		*IA-CBC*		*IA-DR-CBC*	
Attributes / Levels	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Price								
0.00 EUR	6.4	4.3	7.2	4.1	8.9	5.4	9.0	4.5
2.49 EUR	2.1	1.2	2.5	1.3	2.0	1.3	2.8	1.4
4.99 EUR	0.3	0.6	0.6	0.6	0.1	1.2	0.0	0.7
7.49 EUR	-2.1	1.6	-2.4	1.7	-2.8	1.9	-1.6	1.0
9.99 EUR	-2.6	1.6	-3.3	2.0	-3.1	1.8	-4.1	1.9
12.49 EUR	-4.2	1.6	-4.6	1.5	-5.1	1.3	-6.1	1.9
Usage limit								
Unlimited	1.9	1.0	1.9	0.9	1.9	1.4	1.8	0.8
20h per month	0.0	0.5	-0.2	0.5	0.0	0.6	0.3	0.5
5h per month	-1.9	1.0	-1.7	0.8	-1.9	1.2	-2.0	0.8
Devices & access								
PC & mobile (on-/offline)	1.4	1.1	1.5	1.1	1.4	1.3	1.0	1.0
PC & mobile (online)	-0.4	0.6	-0.3	0.7	-0.6	0.6	-0.1	0.6
PC (online)	-1.1	0.7	-1.1	0.7	-0.8	1.0	-0.9	0.7
Sound quality								
320 kbps	0.9	0.7	1.2	0.9	1.0	0.9	0.8	0.7
192 kbps	0.5	0.5	0.3	0.4	0.4	0.5	0.4	0.5
128 kbps	-1.4	0.8	-1.5	0.9	-1.4	1.1	-1.2	0.8
Advertising								
No ads	0.8	0.6	0.7	0.7	1.0	0.7	0.8	0.7
Online banner	-0.1	0.4	0.1	0.4	-0.1	0.6	0.0	0.6
Online banner & audio	-0.8	0.6	-0.8	0.7	-0.8	0.7	-0.8	0.7
Catalog size								
Comprehensive	1.4	0.7	1.6	0.7	1.0	0.9	1.5	0.7
Large	1.3	0.6	1.0	0.6	1.2	0.9	0.9	0.5
Medium	-0.2	0.4	-0.1	0.6	0.0	0.7	-0.2	0.6
Small	-2.5	1.1	-2.5	0.9	-2.2	1.3	-2.2	0.9
No-choice option								
	6.5	3.4	7.8	3.3	8.5	4.1	9.0	4.4
Scale								
	1.0[a]		1.08		1.18		1.18	

[a] normalized

6. Price Elasticities for Music Downloads: Experimental and Non-Experimental Findings

Authors:

Dominik Papies, Michel Clement, Martin Spann, and Nils Wlömert

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Dominik Papies, Professor of Marketing, School of Business and Economics, University of Tuebingen, Nauklerstr. 47, 72074 Tuebingen, Germany. E-mail: dominik.papies@uni-tuebingen.de, URL: www.wiwi.uni-tuebingen.de.

Michel Clement, Professor of Marketing and Media Management, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: michel.clement@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

Martin Spann, Professor of Electronic Commerce, Institute of Electronic Commerce and Digital Markets, Ludwig-Maximilians-University Munich, Geschwister-Scholl-Platz 1, 80539 Munich, Germany. E-mail: spann@spann.de, URL: www.ecm.bwl.uni-muenchen.de.

Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

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1. Introduction

Information technology has brought substantial and enduring changes to many markets, in particular to those markets in which products are exchanged digitally. Retailers selling digital products online often compete on largely homogenous products (e.g., music, movies, or e-book downloads) in a market that allows consumers to easily identify the cheapest price of a given product within seconds (Brynjolfsson and Smith 2000; Granados, Gupta, and Kauffman 2010) as well as to share price-related information with their friends (Hinz and Spann 2008). In addition, firms operating with digital products in online markets not only compete against each other but also against (illegitimate) piracy channels that offer unauthorized versions of the product at a price of zero (Danaher, Smith, and Telang 2013; IFPI 2013; Oberholzer-Gee and Strumpf 2007; Sundararajan 2004). This ready availability of a pirated copy is a unique characteristic of digital products, enabling consumers to obtain the product for free if they are unsatisfied with the price they have to pay for legal offers.

The above-mentioned changes yield substantial challenges for setting the prices of digital products in online markets. On the one hand, homogenous products, low search costs of price information, and the availability of free downloads through piracy channels are likely to increase price elasticities and will lead to a high degree of price competition (Brynjolfsson and Smith 2000). On the other hand, firms can use information technology to reduce price elasticity and competition by creating lock-in effects (Ray, Kim, and Morris 2012). For example, some firms build "walled gardens" that tie together proprietary hardware and software combinations with the download stores. Therefore, it takes a consumer several steps to transfer a file that was purchased in one download store to a device that was not intended to be used with that store.

Unfortunately, previous research does not provide insights on price elasticities for music downloads or comparable products. Therefore, it remains unclear whether the potential market transparency or the perceived switching costs associated with lock-in effects dominate the consumer decision-making process and determine the magnitude of the resulting price elasticities. A profound knowledge of how consumers react to price, however, is essential for sound pricing decisions for digital products. Therefore, our research aims to measure price elasticities for music downloads, which is one of the most frequently traded digital products (IFPI 2013).

So far, academic research has not considered price elasticities for digitally distributed products. Although the demand for *media products* has been extensively analyzed (e.g., Elberse 2010; Eliashberg, Elberse, and Leenders 2006), only a few studies empirically assess the impact of prices. Meta-analyses on price elasticities mirror this void, as they do not contain studies on media products (e.g., Bijmolt, van Heerde, and Pieters 2005). Exceptions include Clerides (2002), Chevalier and Goolsbee (2003), and Binken and Stremersch (2009). However, importantly, the prices for digital products have not been considered at all. Other publications assess the role of price on online demand for physical (non-media) products. However, the findings with regard to price elasticities are inconclusive and not generalizable, as the price elasticities range from below average (i.e., -2) to extremely high (-33) (e.g., Baye et al. 2009; Ellison and Ellison 2009). Further, previous studies show that it is difficult to conclude whether demand in the online domain is more or less price elastic than offline (e.g., Degeratu, Rangaswamy, and Wu 2000).

Given this considerable research gap, we estimate price elasticities for music downloads using three large and unique data sets from the German market, comprising two panel data sets with non-experimental price variation as well as data from a field experiment. Specifically, in Study 1 we analyze the effects of price variation based on a large set of music albums from different labels sold via one download store. In Study 2, we analyze the effects of price variation across all important download stores in Germany for a set of products from one international major label. For Study 3, we were able to run a large field experiment in one download store in which we randomly varied the prices of new album releases. This allows us to assess whether our previous findings are affected by price endogeneity. We focus on digital music products because the effects of digitization on the music industry were visible earlier and were more severe compared to other industries. Therefore, the music industry is a hotbed of developments that other industries such as the movie or e-book industries experience later (Elberse 2010; IFPI 2013).

The key finding across all three studies is that the price elasticities are surprisingly small.[1] The values are between -1.26 and -1.68. This implies that the demand is clearly less price elastic in the market for downloads than in many other markets (e.g., CPG or durables), where the mean price elasticity was found to be -2.6. This finding suggests that consumers do not utilize the price transparency and the ubiquity of free downloads offered by digital distribution to minimize the prices they must pay for a homogenous product such as music downloads. Rather, companies appear to have successfully locked their customers into company-specific usage environments by means of DRM or proprietary hardware-software combinations as well as through the provision of complementary services, such as media players and cloud services.

In addition, our results add to the methodological discussion with respect to the relevance of controlling for endogeneity in the estimation of price elasticities. Our unique data sets enable us to compare the effects of endogenous and exogenous price variation. We find that the degree of endogeneity is rather low. That is, when a researcher addresses endogeneity with easy-to-use measures, such as product-specific fixed effects and some relevant control variables, the remaining intertemporal endogeneity does not appear to be a reason for concern in our research context.

[1] Throughout this research, we will refer to price elasticities that are far away from zero (i.e., demand is highly price elastic) as large elasticities. Elasticities that are close to zero will be referred to as small elasticities.

Our paper makes two important contributions: (1) our research is one of the first to determine the price elasticities for digital products, which we do by using both experimental and non-experimental price variation. The key advantage of our multi-method approach is that we are able to identify the reaction of demand to different sources of price variation, i.e., variation across stores, across time, and random variation. Thus, we are confident that our findings are not confounded by a lack of price variation or by price endogeneity and that they are not restricted to a particular data set. Consequently, we trust that we provide sufficient empirical support to generalize price elasticities for digital music in Germany, one of the four largest music markets worldwide. (2) We compare our findings from non-experimental panel data with data from the field experiment, which allows us to determine the degree to which prices are set endogenously. This deepens our understanding of price endogeneity and suggests that endogeneity in this market can be primarily found in the cross-section dimension (across albums or artists) rather than in the time dimension.

We structure the remainder of this article as follows. Next, we review the related literature and show the current lack of studies analyzing the price elasticities of digital products. Then, we estimate the price elasticities for digital music through two panel data sets and a unique field experiment. The article concludes with a discussion of theoretical and managerial implications, limitations and implications for future research.

2. Related literature and theoretical background

To the best of our knowledge, price elasticities for digital products have not been subject to academic consideration so far. Therefore, we borrow information from previous research in two related domains. (1) We review studies that estimate the price elasticity of demand in the online domain because the purchase process is comparable to that of digital products in that the information search and purchase transaction are made online. (2) We consider studies that estimate the elasticity of demand for media products because the content that is purchased is similar to that of many digital products. Figure 1 provides an overview of the relevant studies that we could identify.

>>> Figure 1 about here <<<

Only a very limited number of studies that analyze price elasticities for online demand have been published. One group of studies looks at the online demand for durables, and these studies come to very heterogeneous conclusions about price elasticity. Whereas Baye et al. (2009) estimate price elasticities that range from -2 to -6 for handheld computers (PDA), Ellison and Ellison (2009) report instances in which the elasticity is -33 for computer memory. This result is most likely due to the homogenous product characteristics of their focal product (computer memory) and the high price transparency on the Internet.

A second group of studies assesses the demand for *media* products that are sold online but are distributed offline. These studies often analyze the book market and use ranking data from retailers, such as Amazon, as the dependent variable (e.g., Chevalier and Goolsbee 2003). Again, we encounter substantial variation in the estimated price elasticities. Whereas Ghose, Smith, and Telang (2006) report an elasticity of -1.1, Brynjolfsson, Dick, and Smith (2010) obtain an elasticity of -9.9.

A third body of research addresses the price elasticities for media products that are sold through offline channels. This group is only a small subset of all the studies that analyze the demand for media products because most studies in this domain do not include price in their analyses. Examples of studies that analyze prices include Luan and Sudhir (2010) and Hjorth-Andersen (2000), both of which estimate very moderate elasticities between -1 and -2; only Clerides (2002) arrives at an elasticity of -3.91 for a sub-sample.

Comparing the findings from this last group of studies with those from the first two groups, one can tentatively conclude that the mean and the variance in elasticity estimates appear to be smaller in the offline domain compared to the online domain. This observation is in line with the results reported by Granados, Gupta, and Kauffman (2012), who find that demand for airline travel is more price elastic in the online domain than in the offline domain. We further conclude that the elasticities vary greatly depending on the study, the source of the data, and the product.

Based on these findings, what should we expect regarding the magnitude of price elasticity for music downloads? On the one hand, economic theory suggests that the demand should be very price elastic. Not only the product assortments but also the product characteristics (e.g., quality or length of a given song) of most distributors of digital products (e.g., music download stores) are homogeneous (Brynjolfsson and Smith 2000). This should make the question of where to buy a particular song primarily a question of price, which in turn should yield high price elasticity. This effect may be amplified by the observation that the costs of online searches for the cheapest supplier are very low (Ellison and Ellison 2009), leading to high price elasticities. Further, the distributors of many digital products have to compete against free alternatives, i.e., against the illegal supply of digital products through piracy (Hennig-Thurau, Henning, and Sattler 2007; Jain 2008; Oberholzer-Gee and Strumpf 2007; Sundararajan 2004). The ready availability of a pirated copy is a unique characteristic of digital products and enables consumers to obtain the product for free if they are unsatisfied with the price they have to pay for legal offers. Hence, one can assume a high price elasticity due to the homogenous nature of the products, low search costs, and the presence of piracy.

On the other hand, several theoretical considerations suggest that we should expect the demand to be relatively inelastic. In many cases, media products are eagerly wanted products with very short product lifecycles and with the demand concentrated in the first few weeks after release (e.g., Ainslie, Drèze, and Zufryden 2005; Hirschman and Holbrook 1982). In that case, consumers have an incentive to buy a product as soon as it appears on the market to comply with the pressure exerted by advertising and the social environment (Maecker et al. 2013; Salganik, Dodds, and Watts 2006). If this “hype” and pressure are sufficiently strong, the price will be less relevant for consumers, resulting in low price elasticity.

Furthermore, the distributors of digital products, especially in the media industry, have created hardware-software combinations that create a lock-in effect for consumers and provide strong incentives to make all purchases from one download store. Indeed, previous research shows that price elasticity depends on the strength of network effects (Shankar and Bayus 2003). Consider the example of Apple’s hardware (e.g., iPod, iPhone), its software, its download store, and its cloud service. These four components are almost seamlessly tied together, making it inconvenient to transfer songs in or out of this closed system. In addition, psychological switching costs may arise because consumers are used to shopping in a particular trusted shopping environment and are reluctant to change (Zauberman 2003). Further, previous research in other product domains (e.g., consumer packaged goods; Degeratu, Rangaswamy, and Wu 2000) has shown that market transparency does not necessarily lead to higher price sensitivity. Therefore, there are theoretical arguments why price elasticity may be low.

Because previous research does not make clear predictions about which of these possible effects dominates, their net effect with respect to the price elasticity for music downloads is unclear. We therefore resolve this ambiguous situation and assess the total effect by empirically estimating the price elasticities for digital products.

3. Treatment of price endogeneity

One challenge that researchers face when analyzing price elasticities is the problem of endogeneity. All of the studies discussed in the previous section use historical transaction data to estimate the price elasticities. The observed relationship between price and demand, however, contains two components. It reflects the consumers' reaction to the prices, and it contains unobserved demand shocks (e.g., product quality, anticipated popularity), which are considered by the manager when setting the price but which are often unobserved by the researcher (e.g., Villas-Boas and Winer 1999). This situation leads to price endogeneity, which, for example, can be resolved with instrumental variables (IV) estimation if the researcher has exogenous variables available that are correlated with price but uncorrelated with the error term that contains the unobserved demand shock.

Most studies that we discussed above acknowledge the potential presence of endogeneity, but they differ widely in the way they deal with it. While some studies assume the price to be exogenous based on industry characteristics (e.g., Brynjolfsson, Dick, and Smith 2010; Ghose, Smith, and Telang 2006; Ghose and Sundararajan 2006), others explicitly correct for endogeneity by means of instrumental variable (IV) estimation (e.g., Ellison and Ellison 2009; Granados, Gupta, and Kauffman 2012; Luan and Sudhir 2010). However, the validity of the IV results hinges on the availability of adequate instruments, which proves especially difficult in the case of digital products and media products in particular. While Clerides (2002), for instance, uses the price of pulp and the weight of a book as instruments for price, or Granados, Gupta, and Kauffman (2012) use – among others – the length of a trip as an instrument for airfare price, this type of theoretically appealing instrument is not available for many media products. One of the key reasons for the lack of instrumental variables in this context is that wholesale prices that distributors have to pay to the labels are correlated with the unobserved demand shocks, such as popularity. The reason is that the content owners in the media industry (i.e., labels) will set the general price level that distributors have to pay based on those unobserved demand shocks. In many cases, the wholesale price is merely a certain share of the retail price of the download. Hence, the wholesale price, which would be a natural candidate for an instrument in many settings, cannot be used in our case. Further, there are no natural candidates for cost shifters that will affect the price for the digital product that is exchanged between the label and the distributor because the marginal costs for the digital product are effectively zero.

It is well established in previous research that relying on poor instruments can severely bias the resulting coefficients (Bound, Jaeger, and Baker 1995; Staiger and Stock 1997). Therefore, to assess the magnitude of the potential endogeneity problems in the context of digital products, we chose a different approach. In Studies 1 and 2 we estimate price elasticities under the assumption that the strongest endogeneity concerns can be addressed by using album fixed-effects and by controlling for time-varying album-level popularity, which otherwise could be an observed factor that is correlated with price. This identification strategy has been used previously (Archak, Ghose, and Ipeirotis 2011). In Study 3 we then randomly vary prices in a field experiment to assess whether our findings from Studies 1 and 2 can be generalized when endogeneity can be ruled out, as it is the case in Study 3.

4. Study 1 – Variation across labels

4.1. Data

In cooperation with a major European music download store we obtained a census of all new album releases that were brought to the market by that download store in Germany in 2008. Our observation period thus spans 52 weeks. We restricted the sample to include products that fulfilled the following criteria: (1) at least 4 weeks of sales can be observed, (2) at least 8 units are sold, and (3) the price was changed at least once during the observation period. Further, we excluded all albums (4) where the values for one of our independent variables were missing and (5) for which the artist could not be identified unanimously (e.g., soundtracks, compilations). For the remaining sample of 190 albums, we observe weekly sales and prices. Because these are non-experimental data, it is necessary to control for other relevant factors that drive demand. We therefore collected data on a set of covariates, which are displayed in Table 1.

>>> Table 1 about here <<<

First, we compute an album's *age* as the number of weeks that have passed since the album's release to account for the fact that products such as music or movies typically follow an exponentially declining demand curve. Second, we control for an artist's time-varying popularity by including the Google *search volume* per artist per week. This approach (using a proxy for otherwise unobserved popularity) has been applied before and may reduce potential time-variant endogeneity (e.g., Archak, Ghose, and Ipeirotis 2011; Baye et al. 2009). Finally, we recorded whether the download store made *advertisements* for a given album. Due to a lack of additional information, this information is recorded as a dummy variable that takes the value of 1 in a week in which a given product was advertised.

4.2. Analysis

Our dependent variable is $log(Q_{it})$, the log of the unit sales of album *i* in week *t*. Our focal independent variable is the log of price *p* of album *i* in week *t*, and we specify the following log-log demand model with the variables that we described above:

$$\log Q_{it} = \beta_0 + \beta_1 \log p_{it} + \beta_2 \log google_{it-1} + \beta_3 age_{it} + \beta_5 adv_{it} + \mu_{it} + \eta_i \quad (1)$$

We estimate the model using fixed effects (η_i) to account for time-invariant, album-specific demand shocks (e.g., popularity), which can be one source of endogeneity. μ_{it} is the idiosyncratic error. Our estimates are based on 5,363 observations, i.e., on average we have about 28 observations per album.

4.3. Results

Table 2 shows the results of Study 1. The price elasticity that we estimate from (1) is -1.673, which is remarkably inelastic. All other coefficients have the expected sign, i.e., Google searches as well as advertising have a positive association with sales, and sales decrease over the product life cycle.

>>> Table 2 about here <<<

The data that we use in this study has several important strengths because it covers a wide range of different products with different levels of popularity and from all major labels as well as independent labels. However, it only contains sales from one particular download store, and consumers in this store may differ in their price elasticity from other consumers. We therefore assess in Study 2 whether the findings hold when we use data that cover different download stores.

5. Study 2 – Variation across stores

5.1. Data

In cooperation with an international major music label, we collected a large data set that contains weekly sales and price information at the album level for the five largest download stores in the German market. Our observation period spans the years 2008 to 2012 (February 2008 until June 2012, i.e., 226 weeks). For each year from 2008 to 2011, we have information on the 25 albums that were the top-selling products of that year from that label, i.e., the sample contains in total 98 albums.[2] For each album, we observe the number of downloads per store per week, and the weekly average price per store. In addition, we collected the same covariates as in Study 1 to alleviate potential concerns regarding omitted variables. That is, we compute each album's age, measured in weeks since release to account for the development of sales across an album's life cycle, and we collected the Google search volume per artist per week to account for changes in artist-specific popularity.

In our theoretical considerations, we suggested that the magnitude of the price elasticities depends on the lock-in effect that consumers experience in the domain of music downloads. We therefore construct a competition price index, i.e., we take the mean price of a given album in a given week in all stores except the focal store. This variable captures the degree to which prices at one store affect demand at another store. If consumers compare prices across stores to find the cheapest offer, the effect of this variable will be positive and strong. If consumers are loyal to one store regardless of price, this variable will be insignificant. We summarize all variables from Study 2 in Table 3.

>>> Table 3 about here <<<

5.2. Analysis

Again, we rely on a log-log market response model with album fixed effects (η_i, as above). Because sales and prices are not only observed per album and week, but also per store, we add store fixed-effects (θ_s). These store fixed effects account for unobserved store specific factors that are related to demand. We interact the store fixed-effect with the log of the weekly album price log*p* in order to assess whether price elasticities differ across stores (due to confidentiality reasons the stores' identities were not revealed to us). In addition, we include the competition price to gain insights into the cross price elasticity.

[2] We arrive at 98 albums because we dropped two albums that were compilations with multiple artists, which makes it impossible to collect artist information (e.g., Google trends).

$$\log Q_{ist} = \beta_0 + \beta_1 \log p_{ist} + \beta_2 \log google_{it-1} + \beta_3 age_{it} + \beta_4 \log comp\_price_{ist} + \beta_5 \log p_{ist}\theta_s + \mu_{it} + \eta_i + \theta_s \quad (2)$$

5.3. Results

The results from estimating (2) are displayed in Table 4. The results reveal that the demand again is surprisingly inelastic. Based on the estimates from Table 4 we compute a mean price elasticity[3] of -1.683, which is very close to the value from Study 1 (-1.673), but again is clearly less elastic than the elasticities that have been determined in previous meta analyses (e.g., -2.6 in Bijmolt, van Heerde, and Pieters 2005).

>>> Table 4 about here <<<

The estimate of the cross-price elasticity is positive and significant, but the magnitude is small compared to findings in previous research. Sethuraman (1995) finds mean cross price elasticities of around .5, and Shankar and Bayus (2003) find cross-price elasticities between .2 and .28 for the home video game industry, where strong network effects are likely.

Further, we find that price elasticities strongly vary across stores. Four out of five interactions between store fixed-effects and $\log p_{ist}$ are significant. Only stores 1 and 2, which are, based on the store-specific intercepts, the largest stores in the data set, do not differ significantly in their price elasticities.

Consistently across Studies 1 and 2 we find that demand does not react strongly to price changes because price elasticities are relatively small (i.e., -1.7). However, as we discussed above, our analyses do not account for the fact that the price changes may be endogenous, i.e., that managers set prices based on time-varying demand shocks that we do not observe. To assess whether our results are confounded by this endogeneity in the time dimension, we

[3] The mean elasticity is computed as the weighted average across all store-specific elasticities, with the means of the respective store dummies serving as weights.

conducted a field experiment in which we vary prices exogenously. We report this field experiment (Study 3) in the next section.

6. Study 3 – Field experiment

6.1. Experimental design

In cooperation with a large European music download store we conducted a field experiment for which we selected 7 products from the product category of new album releases. This set of products was chosen because the store management expected these to be the top-selling albums during the experimental period. The experimental design was such that every visitor to the download store (>150,000 per day) was randomly assigned to one of the experimental groups (i.e., price levels). We varied prices between 7.95 Euros and 14.95 Euros in increments of 1 Euro. Consider, for example, a visitor who was assigned to the 9.95 Euro price group. S/he would see this price across all products from the sample for the remainder of the day. To avoid confounding effects, the download store did not undertake any additional promotional activities for the products that were included in the experiment. Due to this experimental design, we can attribute any difference in sales volume between the different groups to the variations in price.

To ensure the external validity of a field experiment, it is critical that the participants (i.e., customers) are not aware that they are part of an experiment. We therefore constantly monitored relevant online forums, blogs, and Twitter discussions to learn whether consumers became aware of the price experiment. Further, the customer service hotline was instructed to adequately respond to incoming calls that were related to the price experiment. However, no incoming call was related to unexpected prices in the online store. The experiment took place over a period of almost 9 weeks in 2009.

6.2. Estimation

Figure 2 displays the distribution of cumulative sales across the price levels of all the products from the sample and shows the expected negative relationship between price and demand.

>>> Figure 2 about here <<<

To obtain the price elasticities, we estimate a log-log sales response model on weekly sales data and use the log of the exogenously manipulated price as the focal predictor of sales. That is, we regress the log of sales per price group j for product i in week t on the log of price in group j and include album-specific fixed effects (η_i). In addition, we include a variable that measures the product's age in weeks (age), such that

$$\log Q_{ijt} = \beta_0 + \beta_1 \log p_{ijt} + \beta_2 age_{it} + \mu_{ijt} + \eta_i, \tag{3}$$

where Q represents sales, p is the exogenously manipulated price, and i, j, and t are the indexes for price group, album, and time, respectively. Hence, the model closely resembles the model that we use to estimate price elasticities in Studies 1 and 2, the main difference being the source of price variation, which is exogenous in this study.

We estimate the model on 303 observations, that is, we observe 303 product-price-week combinations. This is less than all potential combinations (7 products times 8 price groups times 9 weeks = 504) because some products were released during the observation period and are therefore observed for fewer weeks.

6.3. Results

The results of the field experiment are shown in Table 5. As expected, the price elasticity is significant and negative (-1.260), but again, the demand is surprisingly inelastic. The elasticity here is clearly much closer to zero than many elasticities that we described in our literature review (Figure 1) and clearly smaller than many elasticities estimated for other consumer products (Bijmolt, van Heerde, and Pieters 2005). Surprisingly, however, the elasticity that we estimate from the experimental data (-1.260) is very close to the elasticities we estimated from the non-experimental data in Studies 1 & 2 (-1.673 and -1.683). This finding suggests that the degree of price endogeneity contained in the fixed-effects estimates that we reported above is not very strong and that it is reasonable to rely on the estimates that we obtained above.

>>> Table 5 about here <<<

7. Discussion and conclusion

7.1. Discussion

7.1.1. Magnitude of price elasticity. We conducted three separate studies to obtain a conclusive estimate for the price elasticities for digital products, analyzing the domain of music downloads. In Study 1, we used a non-experimental data set from a large download provider that contains music album downloads for all relevant music labels (variation across labels, albums, and time). In Study 2, we used a data set from one major music label that contains music album downloads for all relevant download stores in the German market (variation across stores, albums, and time). As the price elasticities from Studies 1 and 2 are potentially affected by endogeneity, we conducted a field experiment in Study 3, in which we randomly varied prices in a large music download store. The results are remarkably consistent across all three studies and show that consumer demand in this domain can be generalized to be price relatively inelastic (-1.673, -1.683, and -1.260) compared to many other consumer products, e.g., clearly closer to zero than the value of -2.6 reported in Bijmolt, van Heerde, and Pieters (2005).

Theory suggests that the market for digital products could well be an efficient market because the products and product assortments are homogeneous and the search costs are low. Indeed strong price competition and extreme price elasticities have been observed in some online markets (Ellison and Ellison 2009). However, our empirical evidence suggests that the market for music downloads is clearly not efficient because the price elasticity is low despite considerable price variation in the experimental data and in the market (e.g., market prices of album downloads varied between 4.99 Euros and 14.95 Euros at the time we conducted the study). Apparently, many consumers make little attempt to look for cheaper offers even when they see high prices. Despite the fact that all preconditions for an efficient market are given in the case for music downloads (i.e., homogeneous product, distribution at zero marginal costs, low search costs), we conclude that consumers do not utilize their potential power to exert pricing pressure on the firms operating in this market by searching for the cheapest offer. Rather, consumers in many cases appear to accept the prices set by managers.

Interestingly, we do not find evidence that piracy puts strong pressure on the price elasticity because the elasticity is lower here than in many markets where piracy is not prevalent (e.g., Bijmolt, van Heerde, and Pieters 2005; Ellison and Ellison 2009). This finding suggests that higher prices do not drive the existing customers of the download stores away toward pirated products. However, it also indicates that it is difficult to attract demand from piracy channels towards legal outlets by reducing the price for music. Although this finding may appear surprising, it is supported by analytical research, which has identified piracy as a price discrimination device. That is, the availability of a pirated copy allows price-sensitive consumers to obtain the products for free by downloading a pirated copy. Firms then only compete over relatively less price-sensitive consumers, which reduces the price competition among firms (e.g., Jain 2008).

The relatively low price elasticity that we identify above suggests that consumers do not base their purchase decision primarily on the price. Hence, we conclude that firms should not attempt to use price as the key element to differentiate themselves from the competition because this is unlikely to be successful. Similarly, it does not appear to be recommendable to compete against other firms over price.

7.1.2. Lock-in effect. The relatively low price elasticity that we find in all three studies may also serve as an additional indication of a strong lock-in effect that the download platforms were able to create to prevent consumers from reverting to competing offers when they are confronted with high prices. The price elasticity that we find suggests that consumers are experiencing a strong lock-in effect due to closed hardware-software combinations with barely permeable boundaries. Apparently, the perceived opportunity costs of moving files between different store-hardware combinations are larger than the expected cost saving that can be achieved by searching for the cheapest offer. This interpretation is supported by the very moderate cross-price elasticity ($<|.2|$) identified in Study 3, which indeed suggests that little store switching is going on. Hence, firms have been successful in using information technologies to inhibit the customer mobility that was facilitated by the Internet. We observe, however, considerable variation in price elasticity across stores (Study 2), which indicates idiosyncratic store effects. One explanation is that there are significant differences in how effective stores are to create and maintain a successful lock-in strategy.

These considerations can be extended beyond the specific context of music downloads. We expect a similarly low price elasticity for markets in which firms make similar attempts to create lock-in effects. This may be true for products such as movies, e-books, or computer games (Shankar and Bayus 2003). In all of these markets, incompatibilities between different platforms have increased switching costs for consumers, making it unlikely that consumers will search for cheaper stores when confronted with high prices.

7.1.3. Price endogeneity. Our empirical approach took great care to obtain consistent parameter estimates that are not confounded by price endogeneity. Studies 1 and 2 account for potential time-invariant price endogeneity that may arise due to album-specific unobserved effects with album and album/store fixed-effects, respectively. In addition, we control for time-varying popularity by including the Internet users' interest in the artist by means of Google trends. However, because theoretically valid instrumental variables are very difficult to identify in this research context, we refrained from using IV estimation. In order to assess whether this decision invalidates the findings from Studies 1 and 2, we conducted Study 3, in which we randomly manipulate price. Hence, price endogeneity is by definition no problem in Study 3. Remarkably, the price elasticity we estimate from the experimental variation in Study 3 (-1.260) is very similar to the ones we estimated from the non-experimental data in Studies 1 & 2 (-1.673 and -1.683). One can draw several important conclusions from this finding. First, it suggests that the relatively simple measures that we took to attenuate the influence of endogeneity were sufficient in our case to mitigate the most pressing endogeneity concerns. Second, it suggests that the pricing behavior in media markets with very short product life cycles may be less endogenous than in other markets, possibly because managers barely have time to react to the demand shocks they may observe. Rather, it appears that managers are forced to anticipate the demand shocks before launching the product, a fact that will be captured by the product fixed-effects. This implies that the endogeneity that may be present is likely to be concentrated in the cross-sectional dimension (across albums and across stores), and only to a lesser extent in the time dimension. Fourth, economic theory and previous research would suggest that – if there is endogeneity in the time dimension – the estimates from Studies 1 and 2 will underestimate the elasticity, i.e., the price elasticity should be more negative than these estimates. Bijmolt, van Heerde, and Pieters (2005), e.g., find that the mean price elasticity is more negative (-3.7) when endogeneity is taken into account compared to the mean elasticity without correction (-2.47). The theoretical explanation is that managers react to positive unobserved demand shocks by increasing prices. This behavior results in a positive correlation between the price variable and the error term, which biases the estimated price coefficient towards zero, i.e., makes the uncorrected estimate less negative. This is in contrast to our findings. The price elasticity that we estimate from the non-experimental data – although it is very similar to the one obtained from the experimental data in Study 3 – is slightly more negative than the one based on exogenous price variation. We tentatively interpret this finding such that managers may react to positive demand shocks with price promotion, e.g., to obtain a larger market share by benefiting more from the demand shock.

7.2. Conclusion

To our knowledge, our study is the first analysis to assess the impact of price on the sales of digital products. Our findings, which are consistent across three studies, reveal that the demand is rather price inelastic, since the price elasticity is considerably lower than in many other product categories. Further, we find that the degree of intertemporal price endogeneity is low because the results from the field experiment with exogenous price variation are not fundamentally different from the fixed-effect estimation that uses non-experimental data.

However, we acknowledge several limitations of our study. First, although we run three studies using different data and methods, we obtain our results on the German market. Although the German market is one of the four largest in the world, we cannot rule out country specific differences with respect to the price sensitivity of users. However, previous empirical evidence suggests that we should not expect substantial differences on different markets (e.g., Bijmolt, van Heerde, and Pieters (2005) find that price elasticities do not significantly differ across regions). Second, for confidentiality reasons the identities of the respective stores in Study 2 were not disclosed to us. Therefore we cannot fully explore the reasons for the variation in store-specific price elasticities. Exploring why some stores are more effective in creating lock-in effects appears to be a fruitful avenue for future research. Third, there are no products in our data for which we observe both, experimental and non-experimental price variation for the same product. This means that we cannot exactly identify the source and strength of endogeneity but rather draw tentative conclusions by comparing the results from Studies 1 and 2 to those from Study 3. We suggest that future research could assess in more details potential sources and the strength of endogeneity.

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Tables and figures

Table 1

Descriptive statistics of non-experimental field data (study 1)

Variable	*Definition*	*Mean*	*SD*	*Min*	*Max*
Sales	Number of units sold of album i in week t	15.12	51.03	0.00	1653.00
Price	Price (Euro) of album i in week t	11.92	2.70	2.09	19.95
Age	Number of weeks since album i was released in week t	19.60	12.24	2.00	52.00
Google search volume	Index of Google search volume (Google Trends) of album i in week t	1.17	5.35	0.00	270.00
Advertising	1 if download store advertised album i in week t	0.01	0.07	0.00	1.00

Number of observations: 5,363

Table 2

Estimation results of non-experimental field data (Study 1)

	Fixed-Effects Model		
	β	t	p
logPrice	-1.673	-19.743	0.000
Age	-0.039	-45.983	0.000
logGoogle_{t-1}	0.557	22.595	0.000
Advertising	0.389	2.973	0.003
Constant	6.158	29.477	0.000
R^2 (within)	.42		
R^2 (between)	.18		
F	928.49		
n	5,363		

Table 3

Descriptive statistics of non-experimental field data (study 2)

Variable	*Definition*	*Mean*	*SD*	*Min*	*Max*
Sales	Number of units sold of album i in week t in store s	56.69	199.76	1.00	7308.00
Price	Price (Euro) of album i in week t in store s	7.86	1.97	0.03	20.97
Age	Number of weeks since album i was released in store s in week t	57.99	44.06	2.00	230.00
Google search volume	Index of Google search volume (Google Trends) of album i in week t	27.47	19.88	1.00	100.00
Competitionprice	Mean price for album i in week t across all competing stores	7.86	1.45	2.17	16.35
Store1	Dummy that is 1 of observation is from store 1, zero else	0.26	0.44	0	1
Store2	Dummy that is 1 of observation is from store 2, zero else	0.28	0.45	0	1
Store3	Dummy that is 1 of observation is from store 3, zero else	0.10	0.31	0	1
Store4	Dummy that is 1 of observation is from store 4, zero else	0.14	0.35	0	1
Store5	Dummy that is 1 of observation is from store 5, zero else	0.21	0.41	0	1

Number of observations: 40,961

Table 4

Results of non-experimental field data (study 2)

	Fixed-Effects Model		
	β	*t*	*p*
logPrice	-1.858	-54.239	0.000
Age	-0.014	-114.535	0.000
logGoogle_{t-1}	0.906	118.852	0.000
logCompetitionprice	0.178	6.402	0.000
logPrice*Store2	0.046	0.860	0.389
logPrice *Store3	-0.316	-5.710	0.000
logPrice *Store4	-0.566	-10.830	0.000
logPrice *Store5	1.295	26.220	0.000
Constant	3.559	37.880	0.000
R^2 (within)	.57		
R^2 (between)	.006		
F	6,711.26		
n	40,961		

Table 5

Results of price experiment

	Fixed-Effects Model		
	β	*t*	*p*
logPrice	-1.260	-9.242	0.000
Age	-0.219	-19.514	0.000
Constant	1.924	76.156	0.000
R^2	.33		
F	229.09		
n	303		

Figure 1

Price elasticities for media products or online demand

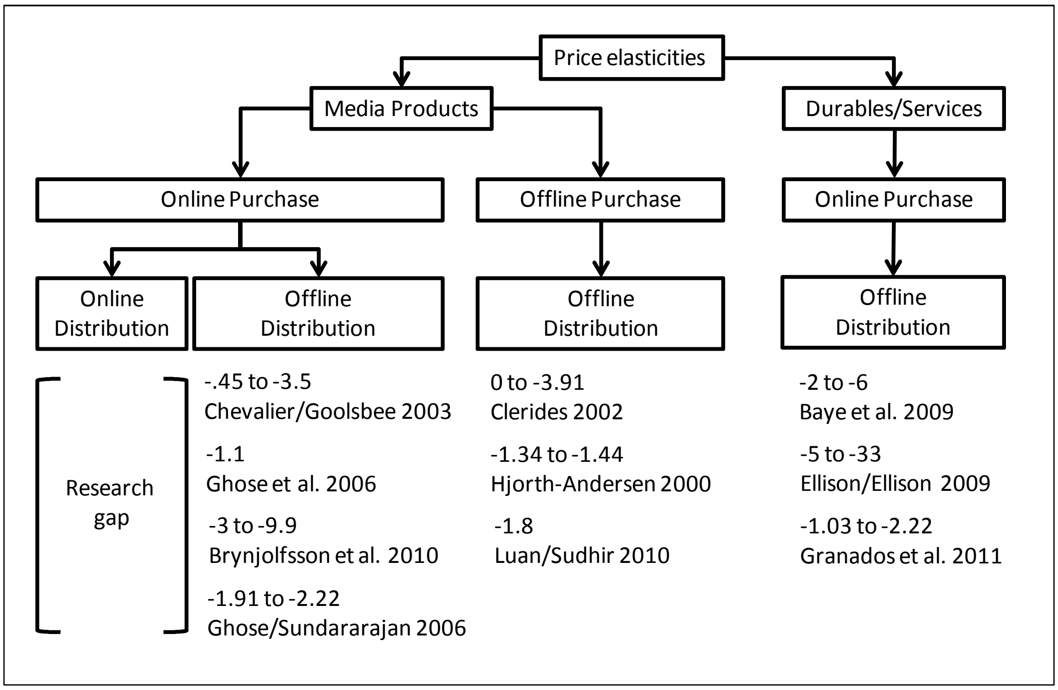
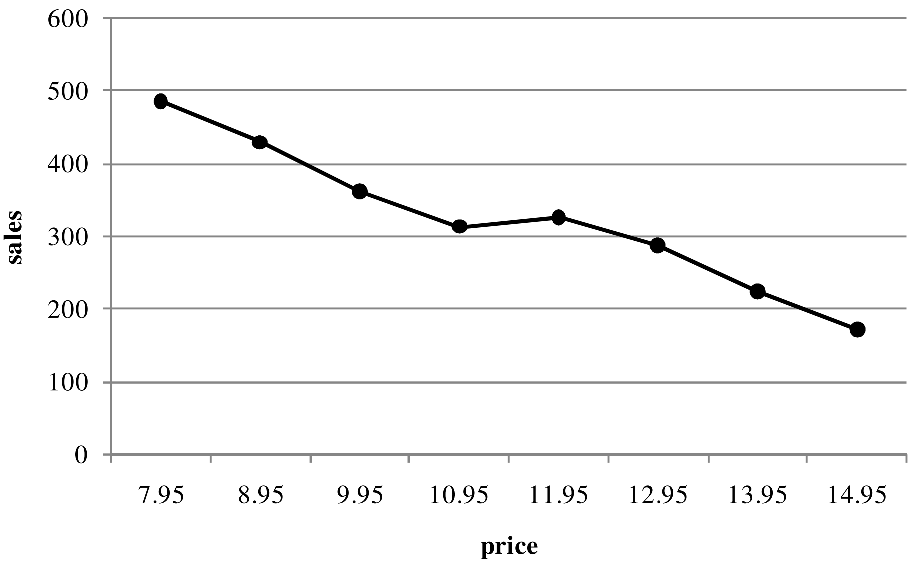


Figure 2

Distribution of sales in price experiment



Note. The sales numbers have been rescaled for confidentiality reasons

V. Appendix

1. Project summaries

Investigating the Antecedents and Consequences of Consumer Music Piracy and Purchase Intentions: A Multivariate Item Randomized Response Analysis

Summary:

Digital piracy is considered a major threat to the legitimate demand for recorded music products. This issue raises many important questions for marketers, particularly whether piracy cannibalizes the demand for legitimate music products and how to most effectively shift consumer preferences away from piracy toward commercial distribution channels. Unfortunately, research on these questions is significantly complicated by two methodological challenges: (i) socially desirable responding (SDR) might bias the results of surveys because piracy is a legally and socially sensitive topic; and (ii) endogeneity problems may lead to inaccurate estimates in determining the relationship between piracy and purchases if uncontrolled variables exist that influence both piracy and purchases. To address these issues, the authors present and validate a multivariate item randomized response model that controls for SDR and attenuates endogeneity bias through the joint modeling of the latent piracy and purchase variables. We demonstrate the performance of the proposed method in a simulation study and via three large-scale empirical studies. Building upon extant research and utility theory, a behavioral model of the determinants and consequences of piracy and purchase intentions is proposed and empirically tested on a sample of 3,246 music consumers. Our results demonstrate that SDR may not only lead researchers to underestimate the true extent of piracy but that it may also systematically affect the coefficients in structural models. We further show that endogeneity problems exert a systematic influence on the effect of piracy on purchase variables, with the effect reinforced when our proposed model is applied. The study findings suggest a cannibalistic relation between piracy and purchases and provide managers with strategic direction on how to address the problem of music piracy.

Zusammenfassung:

Digitale Piraterie stellt eine große Bedrohung für die kommerzielle Vermarktung von Musikprodukten dar. Zwei entscheidende Fragen ergeben sich hieraus für betroffene Unternehmen: (1) wird durch Piraterie die Nachfrage nach legalen Musikprodukten verdrängt, und (2) wie lässt sich die Nachfrage nach illegalen Angeboten am effektivsten in Richtung kommerzieller Vertriebskanäle verschieben? Die empirische Erforschung dieser Fragen wird jedoch durch

zwei methodischen Herausforderungen erschwert: (i) sozial erwünschtes Antwortverhalten kann die Ergebnisse von Befragungen verzerren, weil Piraterie ein rechtlich und sozial sensibles Thema ist, und (ii) bei der Ermittlung der Beziehung zwischen dem Piraterie- und Kaufverhalten kann es aufgrund von Endogenitätsproblemen zu verzerrten Ergebnissen kommen, wenn unbeobachtete Variablen existieren, die sowohl das Piraterieverhalten als auch das Kaufverhalten beeinflussen. Um diese Probleme zu adressieren, wird ein multivariates Item Randomized Response Modell entwickelt und validiert, welches für sozial erwünschtes Antwortverhalten kontrolliert und Verzerrungen aufgrund von Endogenität durch die simultane Modellierung der Piraterie- und Kauf-Variablen reduziert. Die Wirksamkeit des vorgeschlagenen Verfahrens wird in einer Simulationsstudie und in drei umfangreichen empirischen Studien demonstriert. Aufbauend auf vorhandenen Forschungsergebnissen und der Nutzentheorie wird ein Verhaltensmodell hinsichtlich der Determinanten und Konsequenzen von Piraterie -und Kaufabsichten entwickelt und empirisch auf Basis einer Stichprobe von 3.246 Musikkonsumenten getestet. Die Ergebnisse zeigen, dass sozial erwünschtes Antwortverhalten nicht nur zu einer Unterschätzung des wahren Ausmaßes der Piraterie führen kann, sondern dass hierdurch auch die Koeffizienten in Strukturmodellen systematisch beeinflusst werden. Die Ergebnisse zeigen weiterhin, dass Endogenitätsprobleme einen systematischen Einfluss auf den ermittelten Verdrängungseffekt von Piraterie auf das Kaufverhalten haben, wobei der Effekt stärker (negativ) ist, wenn das vorgeschlagene Modell angewendet wird. Auf Basis der Erkenntnisse werden direkte Handlungsempfehlungen für betroffene Unternehmen abgeleitet, wie sich die Nachfrage nach illegalen Angeboten am effektivsten in Richtung kommerzieller Vertriebskanäle verschieben lässt.

Investigating the Influence of Country Characteristics on the Relationship between Internet Piracy and Music Sales: Evidence from a Longitudinal Cross-Country Study

Summary:

Global music sales have declined by almost 50% over the past 15 years and Internet piracy has been identified as one potential cause for this decline. While a large body of research has analyzed the effect of Internet piracy on the legitimate demand for media products, not much is known about the factors that can explain the large differences that we observe between countries with respect to the sales development since Internet piracy became available. Why did some countries experience a much steeper decline in sales than others? Using a panel data set including music sales and various control variables for 38 countries over the period from 1996 to 2010, I first investigate the effect of piracy on music sales and estimate that in 2010, the sales decline due to Internet piracy amounted to 36%. Subsequently, I identify country characteristics which can explain cross-country differences in displacement rates due to piracy. Specifically, the results show that sound economic policies, the emergence of a global consumer culture, as well as infrastructural conditions and a country's openness to change moderate the extent to which music sales are cannibalized by illegal file-sharing. The results provide policymakers and marketing managers with strategic implications on how to address the problem of Internet piracy.

Zusammenfassung:

Der globale Umsatz der Musikindustrie ist in den vergangenen 15 Jahren um ca. 50% zurückgegangen und Internetpiraterie wurde als eine Ursache für diesen Rückgang identifiziert. Während eine große Anzahl von Studien den Effekt der Internetpiraterie auf die Nachfrage nach Medienprodukten analysiert hat, existiert nur wenig Forschung hinsichtlich der Faktoren, welche die großen Unterschiede zwischen den Ländern in Bezug auf die Umsatzentwicklung seitdem Internetpiraterie verfügbar wurde erklären können. Warum ist der Umsatz in einigen Ländern deutlich stärker zurückgegangen als in anderen Ländern? Auf Basis eines Paneldatensatzes, welcher den Musikabsatz und verschiedene Kontrollvariablen für 38 Länder über den Zeitraum von 1996 bis 2010 umfasst, wird zunächst die Wirkung der Internetpiraterie auf den Musikabsatz untersucht. Die Ergebnisse zeigen, dass sich der Umsatzrückrang aufgrund von Piraterie bis zum Jahr 2010 auf 36% belief. Anschließend werden mittels einer

Moderatoranalyse Ländermerkmale identifiziert, welche die Unterschiede zwischen den Ländern hinsichtlich des Ausmaßes der Verdrängung von Musikkäufen durch Piraterie erklären können. Insbesondere zeigt sich, dass eine solide Wirtschaftspolitik, die Entstehung einer globalen Konsumkultur sowie infrastrukturelle Rahmenbedingungen und die Offenheit eines Landes gegenüber Veränderungen beeinflussen, in welchem Ausmaß die Nachfrage nach legalen Musikprodukten durch Internetpiraterie reduziert wird. Auf Basis der Ergebnisse werden direkte Handlungsempfehlungen für betroffene Unternehmen und politische Entscheidungsträger hinsichtlich der Eindämmung der Internetpiraterie abgeleitet.

Music for Free?
How Free Ad-funded Downloads Affect Consumer Choice

Summary:

The market for digital content (e.g., music or movies) has been affected by large numbers of Internet users downloading content for free from illegitimate sources. The music industry has been exposed most severely to these developments and has reacted with several different online business models but with only limited success thus far. These business models include attempts to attract consumers by offering free downloads while relying on advertising as a revenue source. Using a latent-class choice-based conjoint analysis, we analyze the attractiveness of these business models from the consumer's perspective. Our findings indicate that advertising-based models have the potential to attract consumers who would otherwise refrain from commercial downloading, that they cannot (yet) threaten the dominance of download models like iTunes, and that current market prices for subscription services are unattractive to most consumers.

Zusammenfassung:

Das kostenlose Herunterladen urheberrechtlich geschützter Inhalten (z.B. Musik oder Filme) aus illegalen Quellen stellt eine ernsthafte Bedrohung für kommerzielle Verwerter digitaler Inhalte dar. Die Musikindustrie ist von dieser Entwicklung in besonderem Maße betroffen und begegnet der Nachfrage nach den Inhalten zunehmend mit legalen Online-Angeboten, um den Konsumenten attraktive Alternativen zum kostenlosen, illegalen Herunterladen bereitzustellen – bisher jedoch nur mit begrenztem Erfolg. Unter anderem versuchen Unternehmen dabei, Konsumenten mit werbefinanzierten Angeboten zu gewinnen, bei denen die Inhalte kostenlos zur Verfügung gestellt werden. Mittels eines Latent-Class Choice-based Conjoint Ansatzes wird in diesem Artikel die Attraktivität verschiedener Online-Geschäftsmodelle aus Konsumentensicht analysiert. Die Ergebnisse zeigen, dass werbebasierte Musikangebote das Potenzial haben, Konsumenten zu binden, die sonst keine kommerziellen Downloadangebote nutzen würden. Weiterhin zeigen die Ergebnisse, dass zugangsbasierte Angebote kurzfristig nicht die Dominanz des Download-Modells (z.B. iTunes) bedrohen können, und dass die aktuellen Marktpreise für Abo-Dienste für die meisten Konsumenten unattraktiv sind.

Friend or Foe?
Assessing the Impact of Free Streaming Services on Music Purchases and Piracy

Summary:

The latest phase of the music industry's ongoing struggle against plummeting revenues saw the introduction of free advertising-based streaming services (e.g., Spotify) in an attempt to address the legitimate demand for online music while tackling the problem of music piracy at the same time. However, this addition of a free streaming channel to the music industry's distribution mix entails the risk of cannibalization of other distribution channels. It is therefore unclear whether this channel addition is beneficial, and previous research on cannibalization effects of channel additions is inconclusive. Our research fills this void and assesses the impact of free streaming services on music expenditures and piracy. To this end, we constructed a research design in which we observe a panel of more than 2,000 music consumers repeatedly over more than one year. By using a difference-in-difference estimator, our research design allows us to eliminate individual-specific unobserved effects. Our results show that the adoption of a free streaming service (FSS) reduces music expenditures by approximately 10% and that this effect increases with the intensity with which the service is used. In a similar vein, the adoption of a FSS will only reduce piracy for intensive users of the FSS. Interestingly, we find that cannibalization effects do not occur for every type of streaming service. In particular, the adoption of a paid streaming service has a significant positive effect on total music expenditures, suggesting that marketing managers should focus on business models that directly generate income.

Zusammenfassung:

In der jüngsten Phase des Umbruchs in der Musikindustrie begegnen Medienunternehmen der Nachfrage nach ihren Inhalten zunehmend mit kostenlosen, werbefinanzierten Angeboten (z.B. Spotify), um den Konsumenten attraktive Alternativen zum kostenlosen, illegalen Herunterladen der Inhalte zu bieten. Die Inhalte kostenlos anzubieten birgt jedoch Risiken für Unternehmen, insbesondere das Risiko der Kannibalisierung existierender Vertriebskanäle. Es ist daher unklar, ob dieser zusätzliche Vertriebskanal vorteilhaft für Unternehmen ist und auch auf Basis existierender Forschung in diesem Bereich lässt sich diese Frage nicht eindeutig beantworten. In diesem Forschungsprojekt adressieren wir diese Forschungslücke, indem

wir den Einfluss von kostenlosen Streaming-Services auf das Kaufverhalten und Piraterie untersuchen. Zu diesem Zweck haben wir ein Forschungsdesign entwickelt, welches es uns erlaubt, das Verhalten von mehr 2.000 Musikkonsumenten über einen Zeitraum von mehr als einem Jahr zu beobachten. Mittels eines Difference-in-Difference Schätzers können wir so für unbeobachtete Individualeffekte bei der Ermittlung der Effekte kontrollieren. Die Ergebnisse zeigen, dass Konsumenten ihre Ausgaben für Musikprodukte nach der Adoption eines kostenlosen Streaming-Services um etwa 10% reduzieren, wobei die Substitutionsrate mit zunehmender Nutzung steigt. Außerdem zeigen die Ergebnisse, dass kostenlose Streaming-Services die Anzahl der illegal heruntergeladenen Titel derjenigen Nutzer reduziert, die den Service intensiv nutzen. Solche Kannibalisierungseffekte treten jedoch nicht bei jeder Art von Streaming-Service auf. Zwar geben Konsumenten auch nach der Adoption eines kostenpflichtigen Streaming-Services weniger Geld für Musikprodukte aus, jedoch wird diese Reduktion der Ausgaben durch die monatlichen Ausgaben für den Streaming-Service überkompensiert. Manager sollten daher bei der Angebotsgestaltung auf Geschäftsmodelle fokussieren, die direkte Einnahmen generieren.

Predicting New Service Adoption with Conjoint Analysis: External Validity of Incentive-Aligned and Dual Response Choice Designs

Summary:

Uncertainty about the external validity of choice-based conjoint (CBC) studies presents a serious drawback for researchers. To address this issue, this paper compares the standard hypothetical, single response CBC approach with incentive-aligned (IA-CBC) and dual response (DR-CBC) choice designs in terms of their external predictive validity and their ability to accurately capture consumers' willingness to pay. In addition, we integrate both choice designs in an incentive-aligned dual response (IA-DR-CBC) procedure. Our empirical study features a unique sample of 2,679 music consumers who were randomly assigned to the experimental conditions and participated in a conjoint choice experiment prior to the market entry of a new music streaming service. To judge the methods predictive accuracy, we contacted the same respondents again five months after the launch and compared the predictions with the actual adoption decisions. The results demonstrate that the IA-CBC and DR-CBC procedures increase the predictive accuracy to a similar extent. This result is promising since IA-CBC is not applicable to every research context, so that DR-CBC provides a viable alternative. The overall best results are generated by the IA-DR-CBC procedure, which inherits the conceptual benefits of IA-CBC and DR-CBC choice designs.

Zusammenfassung:

Wahlbasierte Conjoint-Experimente sind eines der am häufigsten eingesetzten Instrumente zur Erforschung von Konsumentenpräferenzen. Die Unsicherheit hinsichtlich der externen Validität der auf Basis dieser Methode ermittelten Ergebnisse stellt jedoch einen erheblichen Nachteil für Forscher dar. Um dieses Problem zu adressieren, vergleichen wir in dieser Studie das hypothetische, einstufige Befragungsverfahren, welches traditionell bei wahlbasierten Conjoint-Experimenten zum Einsatz kommt, mit anreizkompatiblen und zweistufigen Befragungsverfahren in Bezug auf deren externe Prognosegenauigkeit und die Fähigkeit, Zahlungsbereitschaften realistisch zu schätzen. Darüber hinaus kombinieren wir beide Befragungsmethoden in einem anreizkompatiblen, zweistufigen Befragungsverfahren. Unsere empirische Studie umfasst 2.679 Musikkonsumenten, die den Experimentalgruppen zufällig zugeteilt wurden. Die Teilnehmer wurden anschließend mittels der unterschiedlichen Befragungsmethoden hinsichtlich ihrer Präferenzen für einen neuen Musik Streaming-Service vor dessen Markteinführung befragt. Um die Prognosegenauigkeit der Methoden zu beurteilen,

kontaktierten wir die gleichen Teilnehmer fünf Monate nach der Markteinführung des Services erneut und können so die Verhaltensprognosen mit den tatsächlichen Adoptionsentscheidungen vergleichen. Die Ergebnisse zeigen, dass das anreizkompatible Verfahren und das zweistufige Verfahren die Prognosegenauigkeit im Vergleich mit dem traditionellen Befragungsverfahren in einem ähnlichen Ausmaß erhöht. Dieses Ergebnis ist vielversprechend, da anreizkompatible Verfahren nicht in jedem Forschungskontext realisierbar sind, sodass das zweistufige Befragungsverfahren eine Alternative darstellt. Die insgesamt besten Ergebnisse werden auf Basis des anreizkompatiblen, zweistufigen Verfahrens ermittelt, welches die konzeptionellen Vorteile der anreizkompatiblen und zweistufigen Verfahren vereint.

Price Elasticities for Music Downloads: Experimental and Non-Experimental Findings

Summary:

Although information technologies turned the Internet into a market place for digital products more than a decade ago, our knowledge about price elasticities for digital products is surprisingly incomplete. We therefore estimate price elasticities for digital music downloads using three large and unique data sets from the German market, comprising two panel data sets with non-experimental price variation as well as data from a field experiment. Specifically, in Study 1 we analyze the effects of price variation based on a large set of music albums from different labels sold via one download store. In Study 2, we analyze the effects of price variation across all important download stores in Germany for a set of products from one international major label. For Study 3, we were able to conduct a large field experiment in one download store in which we randomly varied the prices of new album releases. This allows us to assess whether our previous findings are affected by price endogeneity. Across all three studies, we consistently find that the demand is surprisingly price inelastic, with price elasticities between –1.26 and –1.68. This finding as well as the low cross-price elasticity across stores suggests that consumers rarely compare prices and that providers have been successful in creating strong lock-in effects. Surprisingly, elasticities are lower here than in many markets where piracy is not prevalent. The degree of intertemporal price endogeneity appears to be low because the price elasticities inferred from the field experiment are very similar to those obtained from the non-experimental data.

Zusammenfassung:

Obwohl Entwicklungen im Bereich der Informationstechnologie das Internet vor mehr als einem Jahrzehnt zu einem Marktplatz für digitale Produkte gemacht haben, ist unser Wissen hinsichtlich der Preiselastizitäten für digitale Produkte noch immer unvollständig. In diesem Artikel untersuchen wir daher Preiselastizitäten für digitale Musik-Downloads auf Basis von drei umfangreichen Datensätzen aus dem deutschen Musikmarkt. Die Datensätze umfassen zwei Panel-Datensätze, auf deren Basis wir den Einfluss von nicht-experimentellen Preisänderungen auf den Absatz untersuchen, sowie einen Panel-Datensatz aus einem Feldexperiment, bei dem der Preis experimentell manipuliert wurde. In Studie 1 analysieren wir die Auswirkungen von Preisänderungen auf die Nachfrage basierend auf einer großen Anzahl von Musik-Alben von verschiedenen Musik-Labels, die über einen Download-Store verkauft

wurden. In Studie 2 analysieren wir die Auswirkungen von Preisänderungen auf die Nachfrage in allen wichtigen Download-Stores in Deutschland für eine große Anzahl von Produkten eines internationalen Major-Labels. In Studie 3 untersuchen wir den Einfluss von Preisänderungen auf die Nachfrage auf Basis eines Feldexperiments, bei dem der Preis von Neuveröffentlichungen in einem Download-Shop experimentell variiert wurde. Durch einen Vergleich der Ergebnisse können wir so beurteilen, inwieweit die Ergebnisse aus den Studien 1 und 2 aufgrund möglicher Endogenitätsprobleme verzerrt sind. Die berechneten Preiselastizitäten sind mit Werten zwischen –1,26 und –1,68 über die Studien hinweg relativ konsistent und zeigen, dass die Nachfrage überraschend preisunelastisch ist. Diese Ergebnisse und die geringe Kreuzpreiselastizität zwischen den Download-Stores deuten darauf hin, dass die Konsumenten nur selten Preise vergleichen und die Anbieter erfolgreich Lock-in-Effekte erzeugt haben, die Konsumenten an einen Download-Store binden. Überraschenderweise sind die Elastizitäten in dem Markt für Musik-Downloads geringer als in vielen Märkten, die nicht (so stark) von Piraterie betroffenen sind. Die Ergebnisse deuten außerdem darauf hin, dass der Grad der intertemporalen Endogenität gering ist, da die auf Basis des Feldexperiment berechneten Preiselastizitäten sehr ähnlich zu denen sind, die auf Basis der nicht experimentell erhobenen Daten berechnet wurden.

2. Practice transfer

Aus analog wird digital

Michel Clement

Tim Prostka

Nils Wlömert

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Michel Clement, Professor of Marketing and Media Management, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: michel.clement@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

Tim Prostka, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: tim.prostka@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

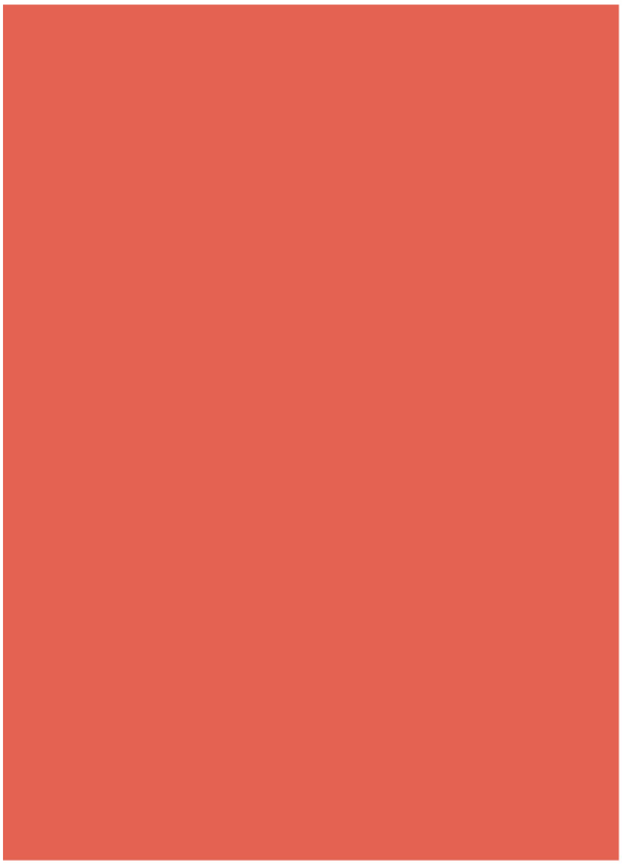
Aus analog wird digital

Die Musikindustrie hat seit der Jahrtausendwende durch die Digitalisierung einen massiven Umbruch im Wertschöpfungsprozess erlebt. Nun kommt auch die Buchindustrie unter die Räder.

MICHEL CLEMENT, TIM PROSTKA UND NILS WLÖMERT

Medienprodukte sind für die digitale Distribution über das Internet optimal geeignet. Sie bestehen aus Texten, Bildern sowie Audio- und Video-Inhalten, die sich problemlos digitalisieren lassen. Die Digitalisierung führt allerdings zu starken Umbrüchen in den betroffenen Industrien: Nach den «goldenen Jahren» von 1998 bis 2000 hat die Musikindustrie im Zuge der Digitalisierung des globalen Marktumfeldes knapp 50 Prozent an Umsatz verloren. Dieser dramatische Umsatzverlust im physischen Segment ist bis heute nicht durch Einnahmen aus kommerziellen digitalen Vertriebswegen zu kompensieren (vgl. Grafik 1 auf Seite xy).

Eine kürzlich vom Institut für Marketing und Medien & Research Center for Media and Communication der Universität Hamburg durchgeführte repräsentative Online-Befragung in



Deutschland (1015 E-Book-Leser) bestätigt die steigende Akzeptanz von digitalen Buchinhalten – bisher jedoch noch nicht merklich zulasten gedruckter Bücher. Vielmehr ist in der Frühphase des deutschen E-Book-Marktes eine generelle Mehrnutzung von Buchinhalten festzustellen – sowohl in digitaler als auch gedruckter Form.

E-Books im Vormarsch | Das wachsende Angebot attraktiver Endgeräte legt jedoch nahe, dass langfristig ein Nachfragerückgang bei gedruckten Büchern eintreten wird. Dies bestätigt auch ein Blick in die USA. Der dortige Buchmarkt ist dem deutschen und dem schweizerischen Markt um rund drei Jahre in der Entwicklung voraus und bietet daher die Möglichkeit, die Angebots- und Nachfrageentwicklung in Deutschland bzw. der Schweiz zu prognostizieren. Eine entsprechende Analyse zeigt, dass eine frühzeitige Positionierung der Anbieter im Vertrieb digitaler Inhalte eine zentrale Rolle einnimmt.

Bei den bevorzugten Bezugsquellen für E-Books liegt Amazon bei den E-Book-Käufern mit 63 Prozent mit weitem Abstand auf Platz eins. Es folgt mit 10 Prozent iTunes, erst danach werden mit etwa 8 Prozent immerhin noch die Filialisten Thalia und Weltbild/Hugendubel genannt. Dies zeigt, dass es der Buchindustrie bisher nicht gelungen ist, einen eigenen, übergreifenden und attraktiven Vertriebskanal für digitale Inhalte zu etablieren. Dies wird voraussichtlich auch in Zukunft nicht geschehen. Für die zukünftige Entwicklung der Anteile am Geschäft mit Buchinhalten spielen die Lesegeräte eine wesentliche Rolle. Während in der aktuellen Frühphase der Digitalisierung des Buchmarktes mehrheitlich noch spezielle E-Reader (wie etwa Sony Reader oder Amazon Kindle) genutzt werden, deutet derzeit in den USA vieles darauf hin, dass (e-Ink-basierte) E-Reader ihren Zenit überschritten haben. Die schnelle Verbreitung multimedialer Geräte wie Apples iPad und Amazons Kindle Fire in Übersee zeigt bereits jetzt, dass mittelfristig diejenigen Content-Anbieter weiter wachsen werden, die proprietäre, multimediale Geräte in Kombination mit einem breiten Medienangebot am Markt platzieren. Dies gilt auch für den deutschen und schweizerischen Markt, wo in den kommenden Jahren neben Amazon auch Apple wieder massiv aufholen kann.

Triebfedern der Veränderung | Die traditionelle Buchindustrie sieht sich daher einem zunehmenden Druck internationaler Content-Anbieter ausgesetzt. Hier bestehen deutliche Parallelen zur Musikindustrie, in der ebenfalls viele Unternehmen ihre bisherige Alleinstellung eingebüsst haben und sich der Konkurrenz neuer, vorher marktfremder Akteure gegenüber sehen.

Veränderungen in digitalisierten Märkten lassen sich anhand der Wertschöpfungskette von Medienindustrien beschreiben. Die zentralen Änderungen der Wertschöpfung in der Medienbranche – und die damit einhergehende Umverteilung der Umsatzanteile – sind auf zwei zentrale Treiber zurückzuführen (vgl. Grafik 2 auf Seite xy). Zum einen haben technologische Innovationen erhebliche Einflüsse auf die Elemente der Wertschöpfung («Technology Push»). Zum anderen führen die technologischen Neuerungen zu erheblichen nachfragerelevanten Veränderungen bei den Akteuren im Markt («Market Push»).

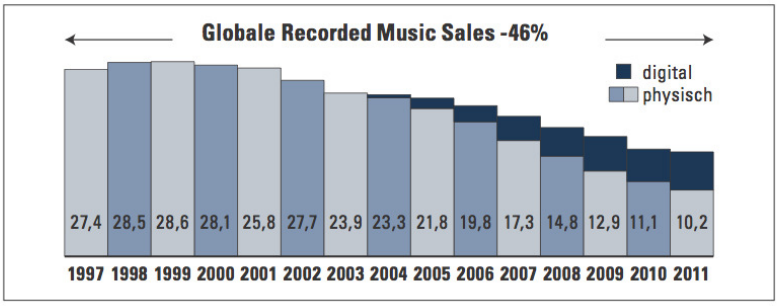
DIE AUTOREN

***Michel Clement,** Prof. Dr., ist Inhaber des Lehrstuhls für Marketing und Medienmanagement am Institut für Marketing und Medien & Research Center for Media and Communication der Universität Hamburg.*
michel.clement@uni-hamburg.de

***Tim Prostka,** ist Doktorand am Institut für Marketing und Medien und an der Graduate School for Media and Communication an der Universität Hamburg.*
tim.prostka@uni-hamburg.de

***Nils Wlömert,** ist Doktorand am Institut für Marketing und Medien und an der Graduate School for Media and Communication an der Universität Hamburg.*
nils.wloemert@uni-hamburg.de

Die Entwicklung des globalen Musikmarktes (Handelswert in Milliarden US-Dollar) *Grafik 1*



Die Musikindustrie hat seit den späten Neunzigerjahren knapp die Hälfte des Umsatzes eingebüsst. Quelle: IFPI (2012)

In der Produktion verursachen technologische Neuerungen zentrale Veränderungen. So lassen sich sämtliche Inhalte problemlos mit – teilweise kostenlos verfügbarer – Software digital erstellen. Hierbei geht es nicht nur um die Digitalisierung von Musik oder Text, sondern um das gesamte «Produkt», das auch eines Covers bedarf. Die Digitalisierung kann entweder im Nachhinein (durch Rippen oder Scannen) oder bereits während der Produktion vorgenommen werden. Das Kernproblem kommerzieller Verwerter von digitalen Inhalten ist die beliebige Kopierbarkeit und Weiterverbreitung der urheberrechtlich geschützten Inhalte, die ohne jeden Qualitätsverlust und ohne nennenswerten Aufwand zu marginalen Kosten erfolgt. Diese Entwicklung ist für die Medienindustrie grundsätzlich positiv. Der Nachteil ist jedoch, dass die Inhalte aufgrund ihrer eindeutigen Klassifizierbarkeit unrechtmässig und ohne Kompensation der Rechteinhaber weltweit dezentral über Netzwerke (etwa Peer-to-Peer oder auch Social Networks) verfügbar sind. Faktisch sind fast alle interessanten Inhalte bereits digitalisiert – ob die Inhaber der Rechte es wünschen oder nicht.

Das Wissen der Konsumenten um die problemlose Digitalisierung von Medieninhalten führte zu einem immensen Nachfragedruck. Labels und Künstler waren nicht in der Lage, die starke Nachfrage nach digitaler Musik schnell und umfassend kommerziell zu bedienen. In der Folge wurden sie durch die zahlreichen illegalen Angebote quasi überrollt. Das Nutzungsverhalten bei Büchern war durch die zu investierende Zeit beim Konsum von Büchern und den damals nicht umfassend verfügbaren Lesegeräten anders. Dennoch machte die Digitalisierung auch im Buchbereich nicht halt. Interessanterweise begingen die Verlage den gleichen Fehler wie die Musikindustrie und begaben sich in die unvorteilhafte Warteposition. Entsprechend haben Internetkonzerne wie Google bereits vor Jahren eine umfangreiche Digitalisierung von Büchern vorgenommen – allerdings unter Protest zahlreicher Autoren und Verlage. Dieser Protest ist jedoch wirkungslos, wenn Nutzer die Inhalte digitalisieren und illegal über Cloud Services vertreiben. Es ist ein Irrglaube, zu denken, dass die relevanten Inhalte nicht schon längst digitalisiert sind und illegal kursieren.

Inhalte nach Vorlieben bündeln | In der Aggregation machen es technische Neuerungen im Content-Management, aber auch neue Such-Technologien und Empfehlungsalgorithmen möglich, Medienprodukte automatisiert und vor allem personalisiert zu bündeln. Durch Messung der Präferenzen werden dem Nutzer neue Vorschläge unterbreitet. Diese lassen sich durch technische Massnahmen des Lizenzmanagements (Digital Rights Management) auch in Leihangebote überführen, in denen grosszahlige Bündel zur Verfügung gestellt werden.

Leihangebote wie Napster oder Spotify im Musikbereich oder Skoobe im Buchbereich können auf diese Weise als Geschäftsmodell funktionieren, denn die bereitgestellten Inhalte sind nur während der Abonnementlaufzeit nutzbar und lassen sich (wenn überhaupt) nur eingeschränkt weitergeben. Die Produktbündelung hat gegenüber dem separaten Verkauf der gleichen Produkte einen wesentliche Vorteil: sie homogenisiert heterogene Präferenzen für einzelne Programmbestandteile. Insbesondere wenn für die einzelnen Bündelgüter geringe variable Kosten anfallen – wie im Online-Medienvertrieb – ist eine Bündelungsstrategie aus Anbietersicht erfolgversprechend. Eine ebenfalls vom Institut für Marketing und Medien & Research Center for Media and Communication durchgeführte Studie zum digitalen Musikmarkt hat darüber hinaus gezeigt, dass sich durch derartige Komplettangebote auch Kundensegmente ansprechen lassen, die andernfalls keine kommerziellen Download-Angebote nutzen würden.

Die Digitalisierung ermöglicht prinzipiell auch das Entbündeln von Produkten. So kann etwa ein Musikalbum zum Beispiel in Einzelteile, die einzelnen Musiktracks, zerlegt werden. Für eine personalisierte Bündelung in Form von Playlists ist es nötig, die Kundenpräferenzen zu messen. Interessanterweise liegen diese Daten nicht bei den Labels oder Verlagen vor, sondern werden von den entsprechenden Aggregatoren und Serviceanbietern (etwa iTunes) kontrolliert. Diese zeichnen umfangreiche Kundenprofile auf, erfassen Kundenbewertungen und unterbreiten passende Vorschläge. Entsprechend nimmt die Kundenbindung mit digitalen Services zu. Dies zu Lasten des physischen Handels, der zum einen nicht die Sortimentsbreite eines iTunes oder Spotify anbieten kann (sogenannte «long tail»), zum anderen aber auch nicht so einfach in der Lage ist, Playlists oder spezifische Leseangebote automatisiert zu generieren und zuzuspielen.

Soziale Netzwerke nutzen | Im Marketing verändert sich die Vermarktung durch die technische Einbindung interaktiver Elemente. Vor allem die Einbindung des Kunden und seines sozialen Netzwerks in den Service (wie es etwa Spotify mit Facebook realisiert hat) ermöglicht es, innerhalb des sozialen Umfelds des Users umfangreich über dessen Nutzung zu kommunizieren. Die Interaktivität bezieht sich neben dem reinen Bewerten von Inhalten vor allem auch auf das Bereitstellen von Playlists und «Radio-Kanälen», die sehr häufig nutzergetrieben sind. Faktisch könnten Online-Anbieter wie Apple (iTunes), Spotify oder Amazon problemlos rückwärts integrieren und in das Label- oder Verlagsgeschäft einsteigen. Bei Amazon findet eine solche Rückwärtsintegration bereits statt, wie Unternehmenszukäufe und personelle Neuzugänge aus der Verlagslandschaft sowie eigene verlegerische Angebote zeigen.

Eine wesentliche technische Neuerung sind Werbeplattformen, in denen Mittler wie etwa «zanox» viele kleine Websites und deren dazugehörenden Werbeflächen bündeln und diese in den «long tail» der Websites schalten können. Durch das Sammeln von «kleinen» Websites wird vergleichsweise preiswert zielgruppenkonform Werbung betrieben. Entsprechend ist es auch kleineren Verlagen oder Labels möglich, effiziente Vermarktungsstrategien vorzunehmen. Aus Marktsicht entsteht durch die Digitalisierung ein erheblicher Druck auf die Communities, die eine eigene Dynamik aufweisen und somit eine Herausforderung für die Kommunikation darstellen.

Eine weitere Herausforderung ist die Einbindung von Musik- oder Lese-Services in Bündelangeboten. Die Bündelung von Medien-Services in Form von Beigaben hat das Ziel, den Verkauf von margenträchtiger Hardware, wie etwa iTunes bei Apple, oder Primärkomponenten, wie etwa DSL- oder Mobilfunkverträge – beispielsweise Spotify bei der Deutschen Telekom – , zu fördern. Dies kann die Referenzpreise der Nachfrager negativ beeinflussen. Denn diese kaufen im Wesentlichen den Zugang oder das Abspielgerät und empfinden

Die vier zentralen Wertschöpfungsebenen der Medienindustrie *Grafik 2*

Produktion	Aggregation	Marketing	Distibution
Content wird von Amateuren und Profis produziert.	Content wird von Amateuren und Profis aggregiert.	Content wird von den Autoren (z.B. den Künstlern), Aggregatoren (z.B. Lables) oder durch Dritte (z.B. Werbepartner) promoted.	Content wird über multiple Kanäle digital vermarktet.
– Digitalisierung – Software – Hardware – Network – Open Source	– XML – Search technology – Recommendation Systems – Digital Rights Management (DRM)	– Interactivity – Advertising Plattforms	– Cloud – Hardware – Mobile
– Angebotslücke – Communities & Collaboration – User Ripped Content	– Playlists und Sortimente – User Unbundled Content – User Rated Content – User Bunled Content – Tagging	– Communities – CRM – Bundling («Triple Play») – Content as «add-on»	– Parallel Release – Internationale Varianten – Multichannel

1. In der Produktion geht es um die Erstellung von Inhalten. Diese Inhalte werden dann
2. aggregiert
3. als Produkt vermarktet und
4. distribuiert.

Quelle: Clement, M. (2012)

die Medieninhalte als «add-on». Entsprechend kann der Wert, den die Nutzer den Inhalten beimessen, über die Zeit sinken. Diese Promotionstrategie birgt somit langfristig Risiken.

Einen bedeutenden Einfluss übt die Digitalisierung auf die Distribution aus. Vor allem Cloud-Services in Verbindung mit mobiler Hardware ermöglichen es den Nutzern, digitale Medieninhalte einmal zu kaufen und innerhalb des Services über verschiedene Endgeräte zu nutzen. Diese hardwareübergreifende Nutzung führt mit steigender Nutzungsintensität zu einer verstärkten Bindung des Konsumenten an einen Service-Anbieter, wodurch Wechselkosten (sogenannte «Lock-In») entstehen. Je mehr Musikstücke ein Nutzer beispielsweise bei Apples iCloud einstellt, desto geringer ist die Bereitschaft, den Anbieter zu wechseln. Für Verlage oder Labels auf der anderen Seite sinkt die Möglichkeit, die Kunden an sich zu binden.

Kleine Auflagen dank Digitalisierung | Durch die Digitalisierung sehen sich Medienunternehmen darüber hinaus mit stark veränderten Wettbewerbsverhältnissen konfrontiert. Die digitale Piraterie etwa führt dazu, dass es immer weniger möglich ist, Produkte zeitlich nacheinander in den Markt einzuführen, sodass «Blockbuster» nahezu zeitgleich global angeboten werden müssen. Zugleich bietet die Digitalisierung auch die Chance, kleinere Auflagen in den Markt einzuführen. Wo im physischen Geschäft die Druck- und Lagerkosten etwa bei englischsprachigen Büchern im Vergleich zum erwarteten Absatz oftmals dazu führten, dass die Produkte nicht in der englischen Fassung auf den deutschsprachigen Markt kamen, ist es im digitalen Vertrieb problemlos möglich, auch die englischen Varianten bei den E-Book-Anbietern zu listen. Entsprechend können mehr Varianten auf vielen Kanälen erscheinen.

Die traditionelle Wertschöpfung der Medienindustrie ist also erheblich von der Digitalisierung betroffen. Neben Bedrohungen durch digitale Piraterie sind es vor allem neue, bisher branchenfremde Anbieter, die auf Basis nicht standardisierter Geräte und integrierter Cloud-Services den traditionellen Akteuren der Industrien die Umsätze streitig machen. Während die Musikindustrie von dieser Entwicklung bereits stark betroffen ist, wird sie insbesondere im Buchmarkt weiterhin zu erheblichen Umsatzverschiebungen zu Lasten der Verlage und des stationären Handels führen. <

Musikstreaming und illegale Musiknutzung

Michel Clement

Dominik Papies

Nils Wlömert

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Michel Clement, Professor of Marketing and Media Management, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: michel.clement@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

Dominik Papies, Professor of Marketing, School of Business and Economics, University of Tuebingen, Nauklerstr. 47, 72074 Tuebingen, Germany. E-mail: dominik.papies@uni-tuebingen.de, URL: www.wiwi.uni-tuebingen.de.

Nils Wlömert, PhD candidate, Institute of Marketing, University of Hamburg, Welckerstr. 8, 20354 Hamburg, Germany. E-mail: nils.wloemert@uni-hamburg.de, URL: www.imm.uni-hamburg.de.

EINE FRAGE DES PERSÖNLICHEN STILS

Musik ist emotional, bindet, polarisiert und spaltet nicht selten die Gemüter. Stimmungsvoller Hintergrund oder Ausdruck der persönlichen Identität – kaum jemanden lässt Musik völlig kalt: Wie Abb. 13 zeigt, geben 84 Prozent der Deutschen an, in ihrer Freizeit gerne oder besonders gerne Musik zu hören, bei den unter Dreißigjährigen werden Zustimmungswerte von über 93 Prozent erreicht.

Neben der Frage des persönlichen Geschmacks bei der Musikrichtung (Abb. 25 B) entwickelt sich die Art des Musikhörens immer mehr zu einer Frage des individuellen Stils. Knapp die Hälfte der Zeit zum Musikhören geht weiterhin auf das Konto gezielt abgespielter Songs von Tonträgern (21 Prozent) oder per digitaler Datei vom Computer (24 Prozent). Und auch das klassische Radio spielt mit 34 Prozent weiterhin eine zentrale Rolle im täglichen Musikmix der Deutschen (siehe auch Abb. 14).

Neben diesen traditionellen Wegen der Musiknutzung gewinnen vor allem die Angebote im Internet (Abb. 14 A) zunehmend an Bedeutung. Mehr als 500 legale Musikdienste zählt das Musikportal Pro-Music weltweit, allein in Deutschland steht aktuell eine Anzahl von knapp 70 Diensten zur Verfügung.

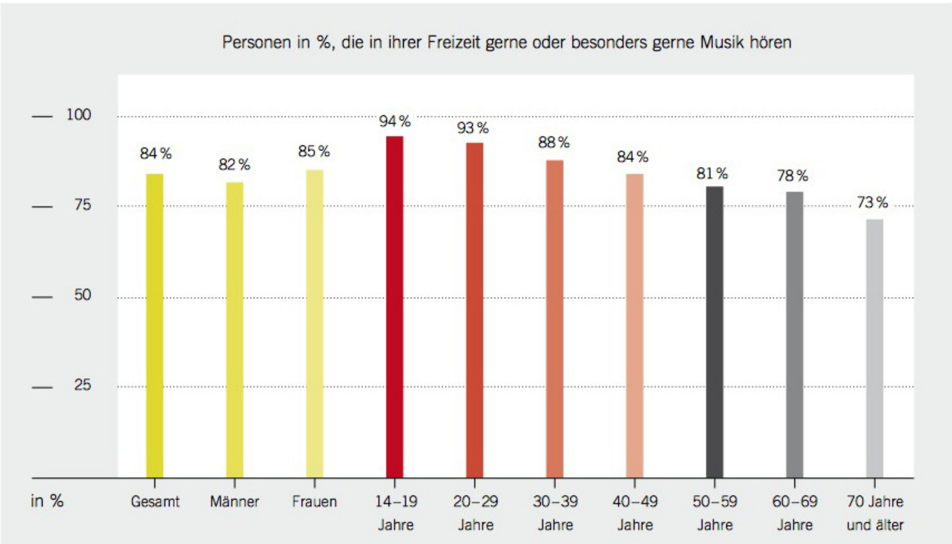


ABBILDUNG 13:
Stellenwert von Musik in Deutschland 2012

Quelle: VerbraucherAnalyse 2012 Klassik I; Axel Springer AG, Bauer Media Group

PROF. DR. MICHEL CLEMENT (UNIVERSITÄT HAMBURG)
PROF. DR. DOMINIK PAPIES (EBERHARD KARLS UNIVERSITÄT TÜBINGEN)
DIPL.-KFM. NILS WLÖMERT (UNIVERSITÄT HAMBURG)

MUSIKSTREAMING UND ILLEGALE MUSIKNUTZUNG: AKTUELLE FORSCHUNGSPROJEKTE

In einer Kooperation zwischen dem Bundesverband Musikindustrie und dem Research Center for Media and Communication der Universität Hamburg wird derzeit zu aktuellen Themen der Musikwirtschaft geforscht. Unter anderem werden Einstellungen zum Streaming, Erfolgsfaktoren neuer Dienste sowie der Einfluss werbefinanzierter Services auf traditionelle Vertriebskanäle untersucht.

In einer im März 2012 vom Institut für Marketing und Medien der Universität Hamburg unter 2.600 Musikkonsumenten durchgeführten Onlinebefragung wurde ein Marktpotenzial von kostenpflichtigen Streaming-Services in Deutschland in Höhe von etwa 16 Prozent ermittelt. Die Ergebnisse zeigen, dass zugangsbasierte Angebote den Besitz von Musikprodukten für die meisten Konsumenten noch nicht ersetzen können. Vielmehr werden solche Angebote primär als Vorhör-Möglichkeit gesehen, um Kaufentscheidungen vorzubereiten, und bieten daher Potenzial für zusätzliche Musikverkäufe, z. B. als Download oder CD. Das Marktpotenzial von kostenlosen werbefinanzierten Streaming-Angeboten liegt den Ergebnissen zufolge hingegen bei ca. 40 Prozent. Ein Vorteil solcher Angebote ist, dass sich mit ihnen auch Kundensegmente ansprechen lassen, die andernfalls keine kommerziellen Download-Angebote nutzen würden[1]. Jedoch deuten die Ergebnisse auch darauf hin, dass die Konvertierung von Nutzern des kostenlosen werbefinanzierten Modells zu zahlenden Nutzern eines Premium-Services langfristig nur schwer möglich ist. So ergab eine Marktsimulation, dass beim Ausscheiden des kostenlosen Services zahlreiche Nutzer den Streaming-Markt verlassen würden, anstatt zu zahlenden Kunden zu werden.

Ein weiterer Forschungsschwerpunkt liegt auf der Messung des Effektes der Nutzung von werbefinanzierten kostenlosen Streaming-Services auf Musikkäufe über existierende Vertriebskanäle (z. B. kommerzielle Downloads, CD-Käufe). Diese umfangreichen Untersuchungen sind derzeit noch nicht abgeschlossen.

ANALYSE DER ILLEGALEN MUSIKNUTZUNG

Zur Erforschung der Einflussfaktoren illegaler Musiknutzung auf das Kaufverhalten wurde im November 2011 eine Befragung mit über 3.200 Teilnehmern durchgeführt, wobei durch neue methodische Verfahren zwei grundlegende Probleme bei der Messung von Piraterie, (I) das Problem der sozialen Erwünschtheit – also zum Beispiel bewusstes Herunterspielen des eigenen illegalen Verhaltens – und (II) unbeobachtete Heterogenität, umgangen werden konnten. In Bezug auf Letzteres ist beim Vergleich von „Piraten“ mit „Nicht-Piraten“ beispielsweise oft festzustellen, dass Nutzer illegaler Bezugsquellen im Vergleich mehr Geld für Musikprodukte ausgeben. Lässt sich aber daraus schließen, dass Piraterie den Absatz von Musik erhöht? Mit hoher Wahrscheinlichkeit nicht, denn stattdessen muss die Analyse dahingehend korrigiert werden, dass solche Konsumenten, die Musik aus illegalen Quellen beziehen, generell ein höheres Interesse am Konsum von Musik haben. Aus methodischer Sicht handelt es sich bei dem erhöhten Interesse am Musikkonsum um einen unbeobachteten Faktor, der zur Unterschätzung des Effekts von Piraterie auf das Kaufverhalten führt, da er beide Variablen gleichermaßen beeinflusst.

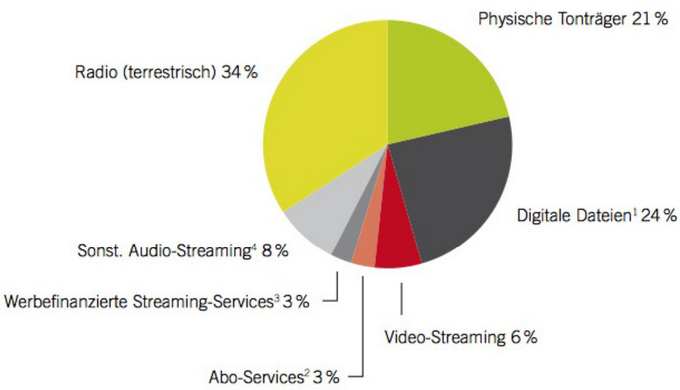
Tatsächlich deuten die auf diese Art berechneten Ergebnisse darauf hin, dass Piraterieverhalten in Befragungen tendenziell unterschätzt wird. In Übereinstimmung mit vorherigen wissenschaftlichen Studien weisen die Ergebnisse außerdem auf einen negativen Einfluss von Piraterie auf das Kaufverhalten hin[2]. Um diesem Einfluss entgegenzuwirken, ist eine Kombination aus rechtlicher Abschreckung gegen die Nutzung illegaler Angebote und wirtschaftlichen Anreizen für die Nutzung legaler Angebote empfehlenswert. Das Ineinandergreifen beider Komponenten ist dabei von zentraler Bedeutung für den Erfolg der Strategie. So erhöht beispielsweise die Verfügbarkeit attraktiver legaler Bezugswege zwar die Bereitschaft zu deren Nutzung, beeinflusst jedoch im Gegensatz zur abschreckenden Wirkung rechtlicher Maßnahmen nicht die Nutzungswahrscheinlichkeit illegaler Bezugsquellen.

Ausführliche Zusammenfassung mit Details zur Methodik und den Autoren →

[1] *Dominik Papies, Felix Eggers, Nils Wlömert (2011), „Music for free? How free ad-funded downloads affect consumer choice“, Journal of the Academy of Marketing Science, 39 (5), 777-794.*
[2] *Michael D. Smith, Rahul Telang (2012), „Assessing the Academic Literature Regarding the Impact of Media Piracy on Sales“, SSRN Working Paper.*

ABBILDUNG 14:
Hörgewohnheiten in Deutschland
Musiknutzung in den letzten 7 Tagen

Prozentuale Anteile an der Gesamtzeit des Musikhörens



[1] *Von der Festplatte des Computers oder anderer Speichermedien*
[2] *Zum Beispiel Napster, Juke, simfy Premium etc.*
[3] *Zum Beispiel Spotify Free*
[4] *Zum Beispiel Webradios, Last.fm etc.*

Quelle: Mittel der Onlinebefragungen von Januar 2012 bis Februar 2013; 2.500 Teilnehmer; Bundesverband Musikindustrie e. V./Universität Hamburg, Institut für Medien und Marketing

MUSIKSTREAMING KOMMT AN

Ein Fünftel der täglich gehörten Musik geht auf das Konto streamingbasierter Musikservices im Netz. Wie Abb. 14 zeigt, werden vorrangig Musikvideoportale (6 Prozent) und Webradios (8 Prozent) genutzt, seit 2012 erhalten darüber hinaus On Demand Audio-Streaming-Dienste starken Zulauf. Machten diese abo- und werbefinanzierten Musikservices in der Vorjahresbefragung gerade 2 Prozent der täglichen Musiknutzung aus, lag der Anteil im Jahr 2012 bereits bei 6 Prozent.

Nach dem Markteintritt zahlreicher Streaming-Anbieter in den deutschen Markt sowie der wachsenden Bekanntheit der Dienste und ihrer Funktionalitäten ist auch hierzulande in den kommenden Jahren mit einer verstärkten Nutzung zu rechnen. Dabei stellt sich dem Konsumenten die zentrale Frage, ob er seine Musik besitzen und eine eigene Musiksammlung – digital wie physisch – aufbauen möchte oder stattdessen im Rahmen eines Streaming-Abonnements auf ein unendlich erscheinendes Repertoire an Songs in der Cloud zugreifen will.

Viele Kunden befinden sich in einer Orientierungsphase, in der ausprobiert, experimentiert und dabei viel Musik entdeckt wird. Gerade für junge Menschen, die oft mit der Erwartungshaltung groß geworden sind, zu jeder Zeit und an jedem Ort auf ein riesiges Musikrepertoire zugreifen zu können, und die sich bislang eventuell nur bedingt durch das existente Musikangebot angesprochen gefühlt haben, stellt das Streaming dabei eine spannende Option dar. Denen, die sich bislang illegal mit Musik versorgt haben, baut es darüber hinaus sogar eine Brücke zum legalen Konsum.

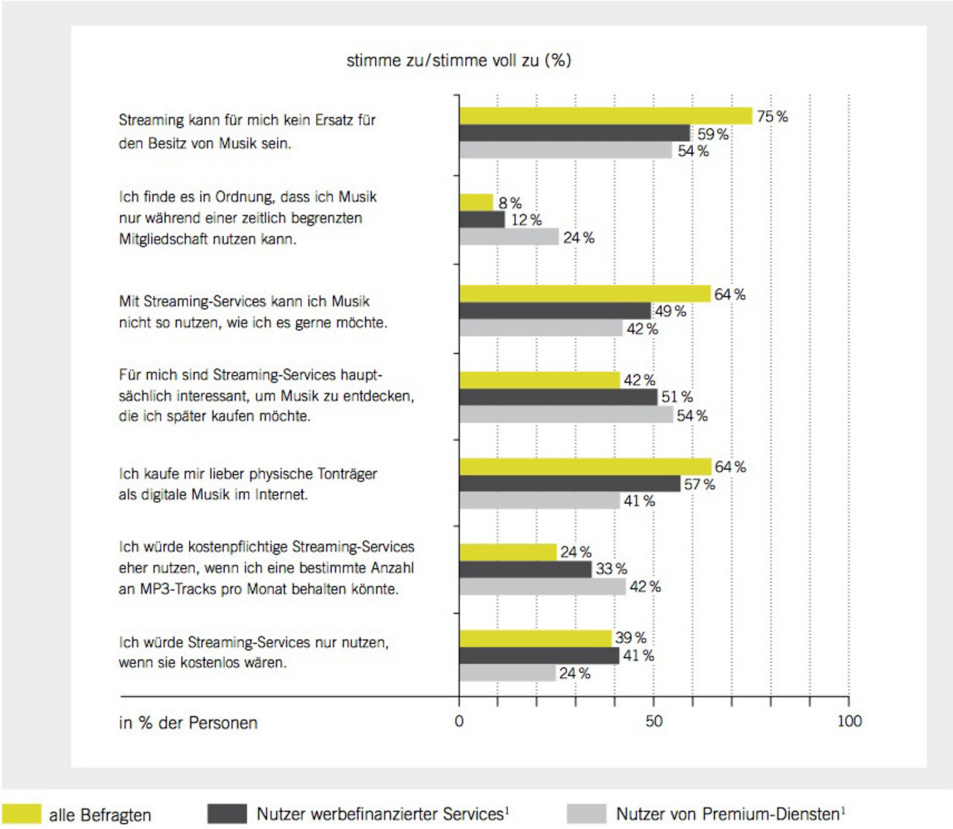


ABBILDUNG 15:
Einstellungen zum Musikstreaming in Deutschland

[1] *User, die im 9-monatigen Beobachtungszeitraum mind. 1 x einen solchen Service nutzten*

Quelle: Onlinebefragung Februar 2013; 2.066 Teilnehmer; Bundesverband Musikindustrie e. V./Universität Hamburg, Institut für Medien und Marketing

KEIN ERSATZ FÜR DEN BESITZ VON MUSIK

In Kooperation mit dem BVMI untersuchte die Universität Hamburg zentrale Fragen des Musikstreamings, darunter auch die grundlegende Frage des Besitzes von Musik. Wie Abb. 15 zeigt, stellt das Musikstreaming für drei von vier Internetnutzern keinen Ersatz für den Besitz von Musik dar, dies sogar auch noch für die Mehrheit derer, die entweder werbefinanzierte Varianten (59 Prozent) oder Premium-Modelle (54 Prozent) bereits genutzt haben.

In den Einstellungen zum Streaming kommt auch die starke Bindung der Deutschen an die CD zum Ausdruck: Zwei Drittel der Internetnutzer geben an, sich lieber physische Tonträger als digitale Musik im Internet zu kaufen – eine Ansicht, die im Übrigen auch unter den Nutzern der Streaming-Dienste stark ausgeprägt ist. Mehr als die Hälfte der Nutzer der neuen Musikservices schätzt beim Streaming die Möglichkeit des Vorhörens, um neue Songs und Alben zu entdecken und diese später zu kaufen. Dabei spielt auch der digitale Besitz von Musik weiterhin eine große Rolle. So geben 42 Prozent der Nutzer von Premium-Diensten an, kostenpflichtige Streaming-Services eher nutzen zu wollen, wenn sie eine bestimmte Anzahl an MP3-Tracks pro Monat behalten könnten.

SMARTPHONE WIRD MULTIFUNKTIONALER MEDIAPLAYER

Mit der zunehmenden Marktdurchdringung von Handys, Smartphones und Tablet-PCs hat sich auch bei der mobilen Musiknutzung viel bewegt. War noch vor wenigen Jahren der MP3-Player das zentrale mobile Abspielgerät für Musik, rangiert nach einer internationalen Studie des Marktforschungsinstituts IPSOS MediaCT heute das Smartphone an erster Stelle. Jeder zweite Deutsche (49 Prozent) hat schon einmal ein Smartphone genutzt, um unterwegs Musik zu hören. Damit rangiert das Smartphone an erster Stelle der beliebtesten Geräte zur mobilen Musiknutzung – vor dem MP3-Player (33 Prozent), dem Mobiltelefon ohne Smartphone-Funktionalität (30 Prozent) sowie dem Tablet-PC (17 Prozent).

3. List of publications

List of publications

Published articles

Papies, D., F. Eggers, and N. Wlömert (2011). Music for Free? How Free Ad-funded Downloads Affect Consumer Choice. *Journal of the Academy of Marketing Science*, 39(5), 777-794.

Unpublished working papers

Wlömert, N., J.-P. Fox, and M. Clement (2013). Investigating the Antecedents and Consequences of Consumer Music Piracy and Purchase Intentions: A Multivariate Item Randomized Response Analysis. Submitted to *Information Systems Research*, under review (first round).

Wlömert, N. (2014). Investigating the Influence of Country Characteristics on the Relationship between Internet Piracy and Music Sales: Evidence from a Longitudinal Cross-Country Study. Destined for submission to *Management Information Systems Quarterly*.

Wlömert, N. and D. Papies (2014). Friend or Foe? Assessing the Impact of Free Streaming Services on Music Purchases and Piracy. Destined for submission to the *International Journal of Research in Marketing*.

Wlömert, N. and F. Eggers (2013). Predicting New Service Adoption with Conjoint Analysis: External Validity of Incentive-Aligned and Dual Response Choice Designs. Submitted to *Marketing Letters*, revise and resubmit (first round).

Papies, D., M. Clement, M. Spann, and N. Wlömert (2013). Price Elasticities for Music Downloads: Experimental and Non-Experimental Findings. Submitted to *International Journal of Research in Marketing*, reject and resubmit (first round).

Practice transfer

Clement, M., T. Prostka, and N. Wlömert (2012). Aus analog wird digital. *IO Management* 06/2012, 16-20.

Clement, M., D. Papies, and N. Wlömert (2013). Musikstreaming und illegale Musiknutzung. *Musikindustrie in Zahlen 2012*, 25-28.

4. Affidavit

Eidesstattliche Versicherung (Affidavit)

Ich, Dipl.-Kfm. Nils Wlömert, versichere an Eides statt, dass ich die Dissertation mit dem Titel:

"Information Technology and Online Content Distribution:
Empirical Investigations and Implications for the Marketing of Entertainment Products"

selbst und bei einer Zusammenarbeit mit anderen Wissenschaftlerinnen oder Wissenschaftlern gemäß den beigefügten Darlegungen nach § 6 Abs. 3 der Promotionsordnung der Fakultät Wirtschafts- und Sozialwissenschaften vom 24. August 2010 verfasst habe (siehe Selbsterklärung). Andere als die angegebenen Hilfsmittel habe ich nicht benutzt. Insbesondere habe ich nicht die entgeltliche Hilfe von kommerziellen Vermittlungs- bzw. Beratungsdiensten in Anspruch genommen. Niemand hat von mir unmittelbar oder mittelbar geldwerte Leistungen für Arbeiten erhalten, die im Zusammenhang mit dem Inhalt der vorliegenden Dissertation stehen. Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

Ich versichere, dass ich nach bestem Wissen die reine Wahrheit gesagt und nichts verschwiegen habe.

Hamburg, den 16. April 2014

Nils Wlömert