International Heterogeneity in the Associations of New Business Models and Broadband Internet with Music Revenue and Piracy

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ABSTRACT

Broadband Internet has fundamentally changed business models in many industries. In the music industry, for instance, old business models were challenged by illegal competitors, and broadband Internet has enabled value creation through new business models. The changes that established business models experienced in the wake of broadband Internet, however, differed vastly across national markets, and these differences are not well understood. We build a conceptual framework and study the extent to which differences in economic and cultural factors are associated with different market outcomes in the wake of the proliferation of broadband Internet. Thus, we compile two unique data sets from the music industry, comprising (1) revenue data for 36 countries and 22 years and (2) piracy data for 47 countries and more than 2 years. We use a Bayesian multilevel model to explore between-country heterogeneity in the associations between these variables and broadband Internet adoption and business model innovations. Our results show that the negative association between broadband Internet penetration and music revenue is weaker in high-income countries, where income restrictions are less likely to drive demand towards illegitimate piracy services. In terms of cultural factors, we find that a market's response to the introduction of broadband Internet is less negative in countries scoring high on Hofstede's individualism and uncertainty avoidance dimensions. Furthermore, we find that overall revenues only recover after the latest generation of streaming services (e.g., Spotify) has been introduced, and the adoption of these services is associated with lower levels of online music piracy.

Keywords: business models, national culture, online piracy, multilevel modeling, Bayes, panel data

1 Introduction

The market for recorded music has seen unprecedented change and upheaval in recent years. Sales in the traditional channels and total industry revenue plummeted by 50% since sales peaked in 1998 (IFPI, 2014). At the same time, piracy surged, and new digital business models slowly started to enter the market. These developments were initiated and fueled by the broadband Internet, and this setting is one example of how there are costs and benefits to new technologies, such as innovations in the IT domain (e.g., Chandy & Tellis, 2000; Rosenbloom & Christensen, 1994). One benefit is that these innovations create opportunities because they enable business model innovations that have the potential to be disrupting (e.g., music downloads at iTunes, streaming services such as Deezer or Spotify; e.g., Markides, 2006; Christensen et al., 2015). Through e-commerce and online shopping, these innovations facilitate access to music and make it easier for content producers in these industries (e.g., artists) to stay connected to a global audience. This implies that the technological innovation of broadband Internet enables new business models that are beneficial to firms (Markides, 2006). However, the innovation of broadband Internet has also facilitated the illegal online exchange of content among consumers at a global scale (e.g., via file-sharing networks). These developments continue to be a major challenge in many industries. In the music industry, for example, the global number of visits to piracy websites amounted to 73.9 billion in 2017, up 14.7% compared to 2016 (Music Business Worldwide, 2018). Hence, the broadband Internet is an example of a technological innovation that enables new business models, some of which enhance consumer demand and revenue, while also enabling technologies that are detrimental to consumer demand.

Interestingly, however, national markets strongly differ in how they react to the proliferation of broadband Internet, i.e., they differ substantially in the extent to which revenues decline in the wake of broadband Internet. Figure 1 shows for a set of selected countries from our sample the development of recorded music revenue and broadband Internet penetration. It illustrates that some countries (e.g., the US or Colombia) experienced a much stronger decline in revenues in the wake of broadband Internet than other countries (e.g., Finland). This finding implies that not only the degree to which a new technology is embraced by a country's population differs greatly across countries (e.g., Talukdar, Sudhir, & Ainslie, 2002), but there is variance in the consequences of technology adoption for the survival of established business models and the creation of business model innovations. This leads us to our first research question:

RQ1*: To what extent do the countries' music markets show differences in the response to the proliferation of broadband Internet, and how are these differences related to country characteristics (e.g., economic, cultural, and market factors)?*

Our second research goal pertains to the opportunities that arise due to broadband Internet. Firms can utilize the new technology of broadband Internet and respond by creating new digital business models (e.g., Markides, 2006; Bart et al., 2018), and these may dampen potential declines in revenues in the wake of broadband Internet by creating new sources of sales and revenue. However, this will only hold if the new business models do not lead to a widespread displacement of revenue that exceeds the revenue they create. There is initial evidence that at least some consumer segments who use new digital business models in the music market may spend less after adoption (e.g., Elberse, 2010; Wlömert & Papies, 2016). We will therefore shed light on these aspects by addressing our second research question:

RQ2*: Is the introduction of new digital business models that are enabled by broadband Internet associated with an increase in music revenues, and how does this association differ across countries?*

Third, there is consensus in the literature that broadband Internet has enabled widespread online piracy, and one reason is the lack of attractive legal business models that would allow consumers to conveniently consume music online (e.g., Sinha & Mandel, 2008). With the advent of new business models such as iTunes or Spotify, this notion can no longer be used to explain the use of pirated content. However, there is only very limited empirical evidence regarding whether this "carrot-and-stick" approach indeed works and whether business model innovations such as streaming services in fact reduce music piracy globally. Therefore, the third research question is:

RQ3*: Is the introduction of new digital business models that are enabled by broadband Internet associated with a decrease in music piracy and how does this association differ across countries?*

Previous research has recognized the relevance of country-level factors as predictors of market outcomes, e.g., the adoption of innovations (e.g., Talukdar, Sudhir, & Ainslie, 2002; Gelper & Stremersch, 2014). Another stream of research addresses the effect of new business models on demand in the music industry (e.g., Elberse, 2010; Wlömert & Papies, 2016), and there is initial evidence that consumers in the context of music piracy may respond positively to a "carrot-and-stick" approach (e.g., Sinha & Mandel 2008; Danaher et al. 2010). Importantly, however, we see three voids in the literature. First, while there is ample research on the international heterogeneity of new technology adoption (e.g., broadband Internet), we are not aware of any research that studies international heterogeneity in the *consequences of the adoption* of an innovative technology for business models or demand in related markets. Hence, we only know little about which countries embrace a new technology such as broadband Internet in a value-destroying way (e.g., through piracy) or in which countries new business models that are enabled by broadband Internet are particularly effective in stimulating demand and revenue. Second, it is difficult to transfer knowledge from other domains, e.g., from the international product diffusion literature, to this particular question because there is substantial disagreement as to the extent that cultural factors matter beyond economic factors. Stremersch and Tellis (2004), e.g., find that heterogeneity in new product adoption speed between countries is best explained by economic condition, whereas Tellis et al. (2003) find the opposite. Third, the music industry has seen an unparalleled decline in revenue since the advent of the broadband Internet, and firms and artists have been struggling to find a proper response. Academic research has addressed several aspects of this development and potential remedies (e.g., Liebowitz, 2016, Elberse, 2010, Danaher et al., 2014, Aguiar & Waldfogel, 2018). However, most studies focus on single, well-developed markets, and we are not aware of any research that studies digital business models in the music industry and their potential to stop the music industry's downward trend beyond single markets. We therefore contribute to the literature by studying international differences in the feasibility of digital business models in the music industry and by studying to which these new digital business models indeed can act as a "carrot" to curb music piracy.

To address these voids, we build a conceptual framework that covers two main themes. First, the framework assesses the relation between (a) new technologies and (b) business model innovations that are enabled by new technologies on one side and revenue in the music market and music piracy on the other side. Second, the framework assesses how these coefficients are moderated by country (economic and cultural) and market characteristics. To empirically test our framework, we compile two data sets. In Study 1, we rely on a longitudinal data set at the macrolevel, comprising recorded music revenue (both physical and digital, including new revenue sources such as streaming) for 36 countries, covering approximately 95% of the global music market, over a period of 22 years (from 1996 to 2017). In addition, we collect broadband Internet penetration rates and a comprehensive set of control variables. We use Study 1 to analyze research questions 1 & 2.

In Study 2, we address research question 3. To this end, we utilize a data set that covers music piracy at the week-country level for a period of more than two years and relate these data to the number of music streaming users at the week-country level. We estimate the models in both studies using a Bayesian hierarchical linear model.

Our research contributes to the literature that lies at the interface between research on product diffusion and research on business model innovations, and it extends our knowledge on how countries differ in their response to innovations, including technological innovations such as broadband Internet or business model innovations such as music streaming services (e.g., Markides 2006). The results from Study 1 demonstrate that the average association between broadband Internet adoption and music industry revenue is negative, and the association is stronger for physical revenue than for total revenue. This finding is in line with the notion that digital business model innovations enable companies to exploit new income streams. In addition, there is strong variation in these coefficients across countries. The negative association between broadband Internet and revenues is particularly pronounced in less wealthy countries and in countries that score low on Hofstede's uncertainty avoidance and individualism scales, in which we hypothesize consumers to be more prone to digital piracy. Second, the coefficients that we estimate are consistent with the idea that new business models heavily cannibalize revenue from "old" business models. Only when new streaming-based business models such as Spotify are introduced do we see that revenue does not continue to decline. Third, in Study 2, we find a negative association between the adoption of streaming services and music piracy. One likely explanation for this observation is that these new business models make piracy less attractive and lead to its reduction.

>>>Figure 1 about here<<<

2 Related Literature

Our research contributes to three main streams in the literature, which we will briefly discuss. First, a rich body of literature has studied the international heterogeneity in the diffusion of innovations. Many of these studies estimate parameters of models that characterize the diffusion of innovations (e.g., sales growth, time-to-takeoff, parameters from the Bass diffusion model) and relate the country-specific estimates to country characteristics. In a meta-analytic approach, Van den Bulte and Stremersch (2004) combine estimates from more than 50 publications published until 2000 that have estimated the Bass diffusion model and regress the ratio of q/p on a rich set of characteristics for 28 countries. They find that a country's culture (measured by the Hofstede characteristics) and income heterogeneity are relevant predictors of this ratio. Talukdar, Sudhir, and Ainslie (2002) study 6 product categories and 31 countries and conclude that economic wealth is a strong driver of the diffusion process. These findings are in line with Stremersch and Tellis (2004) and Gelper and Stremersch (2014), the latter identifying economic wealth as the single most important predictor.

These publications share important characteristics with our research because they relate characteristics of an international diffusion process to country characteristics, and hence, we built on these publications. However, these publications differ in a key aspect to our study because they utilize the diffusion (or shape of the diffusion curve) as the dependent variable. In contrast, the diffusion of an innovation (i.e., broadband Internet) is the focal *independent* variable in the present study because we seek to understand how a technological innovation is associated with outcomes in related markets and to what extent the new business models that are enabled by this innovation affect these market outcomes. We are not aware of any prior research that has studied this, and this is our first such contribution to the literature.

Second, this research contributes to the literature on the development of business models that are enabled by digital technologies. Firms can utilize the new technology of broadband Internet and respond by creating new digital business models (e.g., Markides, 2006), and these business model innovations may be "disruptions" because they challenge the incumbents' positions (e.g., Christensen et al., 2015). In the present context, the driving force behind these business models innovations is broadband Internet and associated digital technologies. In an overview article on digital business model innovations, Bart et al. (2018) identify digital transformation as the most advanced response of firms to the opportunities offered by digital technologies because digital transformation changes how value is created and captured (as opposed to individual components of the value generating process). However, they note that the high failure rate of business model innovations in the context of digital transformation is a clear indication of the necessity of additional research in this domain. Most of the research in this domain that we are aware of is conceptual in nature (e.g., Osterwalder & Pigneur, 2010), which is in line with other publications that note the scarcity of empirical research on the viability of digital business models (e.g., Zott et al., 2011). Our research addresses this void by providing an empirical assessment of the viability of different digital business models.

Third, our research contributes to the literature on digital business models in the music industry. As we outline in the introduction, the music industry has seen an unparalleled decline in revenue since the advent of broadband Internet (see also Figure 1), and firms, artists, and industry representatives have been struggling to find a proper response. Academic research has addressed several aspects of this development and potential remedies. Several publications assess the extent to which the decline in sales can be attributed to digital piracy (see Liebowitz, 2016 for an overview). Other research has assessed ways to address music piracy (e.g., Sinha & Mandel, 2008; Danaher et al., 2010), the role of unbundling (e.g., Elberse, 2010), pricing (e.g., Danaher et al., 2014), or the effect of new business models such as video streaming (Hiller, 2016) or subscription-based audio streaming (e.g., Aguiar & Waldfogel, 2018; Wlömert & Papies, 2016). However, most studies focus on single, well-developed markets, and we are not aware of any research that studies international heterogeneity in the response to digital business models in the music industry. Therefore, we add to the literature by studying the feasibility of digital business models in the music industry with a focus on across-country heterogeneity.

3 Conceptual Framework

We will now develop our conceptual rationale for the proposed relationships based on the literature. Figure 2 and Table 1 summarize the conceptual framework. We assess all relations with revenue from recorded music as the dependent variable in Study 1, and these relations are represented by solid lines in Figure 2. In Study 2, we analyze piracy as the dependent variable, and these relations are shown with dashed lines in the conceptual framework.

>>>Figure 2 & Table 1 about here<<<

The first main theme of this framework is that broadband Internet is a technological innovation that affects markets in two main ways.[1] (1) Broadband Internet affects the established business models of the incumbents. In the case of the music industry, this implies that the broadband Internet destroys the revenue of firms selling CDs because it enables and fosters piracy and paves the way for entertainment alternatives for users. (2) Broadband Internet enables new business models or business model innovations such as music download services (e.g., iTunes, Amazon) or music streaming services (e.g., Spotify, Deezer). We will assess how these business model innovations will affect the incumbents' business models and the total revenue generated in the industry (Study 1), as well as piracy (Study 2). The second main theme is that we expect that these relationships will be heterogeneous across countries, and we will seek to explain the international heterogeneity.

[1] In the conceptual framework we will refer to the relation between constructs as "effects". In the empirical section below, we will refer to "associations" to highlight the caveat that our empirical setup may not be able to firmly establish causality.

3.1 Main Effects

Effect of Broadband Internet. We expect that the main effect of broadband Internet on music sales and revenue is negative. Broadband Internet facilitates the illegal exchange of music files (e.g., via file-sharing networks) and provides consumers with access to alternative entertainment options (e.g., video streaming, social networking), which compete for the consumer's time and entertainment budget (e.g., Liebowitz, 2008). Hence, broadband Internet threatens established business models and reduces incumbents' revenue in the music industry. At the same time, the industry's business model heavily relies on the international exploitation of copyrights, and music companies can use the Internet as a new sales and promotion channel to stimulate demand more efficiently (Papies, Eggers, & Wlömert, 2011). However, there appears to be a consensus in the literature that the net effect of Internet adoption on music sales is negative (e.g., Liebowitz, 2016), and we thus expect a negative effect of Internet adoption on music sales, which we will assess in Study 1. However, we expect this effect to vary predictably across countries according to country characteristics and market characteristics, as we will detail subsequently.

Effect of Business Model Innovations. We define a business model innovation as an innovation that redefines an existing product and how this product is delivered to the customer (Markides, 2006). Business model innovations in the present context are, e.g., services such as iTunes for music downloads or Spotify and Deezer as music streaming services. These business model innovations are enabled by the technological innovation of broadband Internet, and they may constitute the "carrot" in a "carrot-and-stick" approach (Sinha & Mandel, 2008). In the absence of attractive legal offers, it is likely that consumers will revert to practices such as piracy (Danaher et al., 2010). However, we expect that these new digital business models will cannibalize revenue from the incumbents, and hence, we expect a negative coefficient of the introduction of these new business models on revenue from the established physical music market. However, these new business models themselves also create some revenue. Hence, while we expect that the net effect on total revenue will be less negative when this revenue is taken into account, we do not have clear expectations if it will still be negative. Elberse (2010) argues that unbundling reduces total revenue in the wake of the introduction of music downloads because consumers can cherry-pick their preferred title, whereas previously, they had to buy entire albums. Hence, the main effect on total revenue would remain negative. For music streaming (e.g., Spotify), there is some indication that its cannibalization may be offset by the revenue it generates (e.g., Wlömert and Papies 2016).

The “carrot-and-stick” analogy suggests that these business model innovations may reduce piracy because they attract consumers back into the market. Based on the evidence that we cited above, which suggests that piracy is still a major problem, we do not expect that these business model innovations such as iTunes or Spotify eliminate the problem of piracy, but we expect that they reduce it. We will assess this relationship in Study 2.

Importantly, however, we expect that these effects (i.e., the effect of broadband and new digital business models on revenue and piracy) will vary predictably across countries.

3.2 Explaining International Heterogeneity

3.2.1 Economic Factors

Previous research has highlighted the role of economic conditions (e.g., income) on the adoption of innovations (Gelper & Stremersch, 2014). Stremersch and Tellis (2004), e.g., find that differences in the growth of innovations across countries can mostly be explained by economic conditions. The underlying mechanism is that consumers in wealthy countries have more discretionary income available to purchase new and potentially expensive products.

This also applies to the case of entertainment products because expenditures for these products are discretionary expenditures. This implies that for consumers in countries with less disposable income, the option to use piracy channels becomes relatively more attractive, and thus, we expect the coefficient of broadband Internet will be less negative in richer countries.

We propose that economic wealth also moderates the impact of the introduction of new business models on revenue and piracy. The reasoning is that in countries in which consumers have more income at their disposal, it is more likely that consumers can actually act on the introduction of new business models. This implies that the effect of new business models on revenue will be less negative, and the effect of new business models on piracy will be more negative in high-income countries.

3.2.2 Cultural Factors & Market Factors

We will assess the role of two key cultural factors to shed light on their relevance beyond the impact of economic factors.[2]

Individualism. Individualism refers "the degree to which people in a country prefer to act as individuals rather than as members of groups" (Hofstede, 1994). Previous research suggests a connection between the individualism dimension and the prevalence of intellectual property rights violation in a society such that in collectivistic societies, the sharing of resources with others is regarded as a social norm with which individuals comply to increase the overall welfare of the group (e.g., Shin, Gopal, Sanders, & Whinston, 2004). In addition, individualism encourages social institutions that protect individual rights, whereas collectivism encourages institutions that emphasize resource sharing (Marron & Steel, 2000). Hence, it is likely that broadband Internet in collectivistic countries will be embraced by consumers to engage in piracy, and hence, the effect of broadband Internet will be more negative here.

[2] We will develop our theoretical argument based on the Hofstede cultural dimensions because they are typically viewed as the foundation for other definitions of cultural dimension. In a robustness check we have assessed alternative conceptualizations, and the results are available upon request.

The effect of the introduction of business model innovations on revenue should be more positive in individualistic societies because consumers in these countries are more likely to try these innovations and to positively respond to these innovations (e.g., Steenkamp et al., 1999). In a similar vein, the effects of new business models on piracy should be more negative in individualistic societies.

Uncertainty Avoidance. Uncertainty avoidance refers to the "degree to which people in a country prefer structured over unstructured situations" (Hofstede, 1994). Consumers in countries that score high on this dimension (e.g., Japan) prefer strict laws and regulations. Engaging in piracy is associated with strong uncertainty because it entails considerable legal risks (Bhattacharjee et al., 2007). This dynamic implies that countries with strong uncertainty avoidance will exhibit an effect of broadband on the music market that is less negative. In contrast, uncertainty avoidance should foster the effect that new business model introductions have on revenue. Consumers in countries that score high on uncertainty avoidance will be more eager to embrace these new business models instead of relying on sources such as piracy. Hence, we expect that the effect of new business models on revenue (on piracy) will be more positive (more negative) in societies that score high on uncertainty avoidance.

Local repertoire. Brands and firms that are active in the international marketplace face the decision of whether to address consumer needs with global or local brands (e.g., Song et al., 2017), which is related to the question to which degree an adaption of international strategies is warranted. We add to this discussion and propose that the effect of broadband Internet will depend on the presence and strength of local brands. We base our argument on social identity theory (e.g., Ashforth & Mael, 1989) and suggest that if consumers are exposed to more local repertoire, they will more easily identify with the artists, i.e., these consumers' artist brand-self-connections will be stronger (Eisingerich & Rubera, 2010). This identification with local artists will make consumers more reluctant to obtain the music from illegal sources, which will make the broadband effect less negative and the effect of new business models more positive. In addition, this implies that the effect of new business models on piracy will be more negative in countries where the local repertoire share is high.

4 Visualization of Key Developments

We present some model-free insights for selected countries (Figure A.1 shows all countries). All four countries in Figure 1 show a strong decline in recorded music revenue (solid black line) over time (x-axis), although the decline is not equally strong. Colombia and the Philippines, e.g., show a particularly strong decline, while other countries lose less (e.g., Finland). At the same time, broadband Internet strongly grows, and it reaches a saturation level towards the end of the observation period. In some countries, the introduction of iTunes is accompanied by a continuous decline in revenue (USA), while in others (e.g., Philippines), iTunes is introduced near the low of revenue development. Furthermore, in most markets, the introduction of new business models does not go hand in hand with a strong growth in revenue. Hence, it would be unreasonable to expect a strong positive association between business model innovations and revenue. There is a slight growth in revenue towards the end of the observation period, but this growth is much smaller than the initial decline.

5 Study 1

5.1 Sample

Our observation period (1996-2017; 22 years) starts before the introduction of broadband Internet and hence covers the entire range, from the peak of revenues around the year 2000 to the sharp decline until recently. Our primary data source (IFPI's recording industry in numbers) contains data for 49 countries. However, the time series of 13 countries exhibited gaps of 5 years or more. We restrict our analyses to 36 countries[3], for which we could obtain data without large gaps for the observation period. The 36 countries in our sample include the 20 largest music markets worldwide that together account for more than 95% of the global music industry's revenue (IFPI, 2017). The number of observations is 782 (36 x 22 = 792, minus observations with missing values on the dependent variable for Argentina, Brazil, Chile, Colombia, and Mexico for 1996, Indonesia for 2016 and 2017, Portugal for 2011 and 2012, and Greece for 2012).

5.2 Measures

Table 2 shows all measures and the descriptive statistics. Table A.1 in the appendix displays the correlations for our model variables. We will now describe the measures.

>>>Tables 2 about here<<<

Music revenue. Our focal dependent variables measure music revenue. We obtain data on physical and digital recorded music sales and revenues from various issues of the IFPI's recording industry in numbers report for all 36 countries in our sample. The reports provide information on revenues, subdivided into the various available formats (e.g., albums, singles) and comprise revenues from old business models (e.g., CD sales) and new digital business models (i.e., download and streaming revenues).[4] The revenue from new business models also covers streaming revenue both from subscriptions fees and advertising. We create two different variables. One is the per capita revenue from old business models that does not include revenue from download and streaming services. The second is total revenue per capita, which does include revenue from old business models plus revenue from new digital business

[3] The excluded countries are Bulgaria, Croatia, China, Ecuador, Hong Kong, Peru, Russia, Singapore, Slovakia, Taiwan, Turkey, Uruguay, and Venezuela.
[4] All revenues refer to trade value in US$ computed from the local currencies, which were converted using the PPP (purchasing power parity) conversion rate and deflated using 2010 as the base year. The reports always contain information on the five most recent years, and IFPI occasionally updates numbers in subsequent reports. In these cases, we always rely on the most recent report.

models. The means of these variables are US$ 11.87 (old and new business models) and US$ 9.99 (old business models), and these mean revenues decayed by approximately 60% (old and new business models) and 90% (old business models).

Broadband Internet adoption. We collected the broadband Internet penetration (the number of fixed broadband Internet subscribers per 100 people) from the World Bank's world development indicators databank. The mean was 13.9%, and broadband Internet penetration increased substantially over the observation period (Figure 1).

New business models. We measure the introduction of new business models in two ways. The first major player that successfully entered the online market for music was the iTunes music store in 2003, which marked the beginning of the era in which paid downloads played a major role in online music. This era lasted until 2008, when streaming services such as Spotify started to become more and more prevalent. To capture this development and the introduction of these business models, we create two step dummy variables that take the value of one in the years after iTunes and Spotify, respectively, are introduced in a given market. Figure 1 indicates that these different "eras" overlap because the new digital business models were introduced in different countries at different points in time, which makes the interpretation of the estimated coefficients as causal effects more plausible.

Income. We measure the economic situation through the per capita gross domestic product (GDP) from the World Bank's world development indicator databank, measured in '000 constant purchasing power parity (PPP) adjusted 2010 US dollars.

Cultural value dimensions. We obtained measures of the cultural value dimensions based on the scores developed by Hofstede (1980) and updated in his later research (http://www.geerthofstede.nl/dimension-data-matrix).

Local repertoire share. We collect data regarding the share of local versus international repertoire as a percentage of the overall physical sales volume from the IFPI reports.

Because this information is not available for all years, we compute the mean of this variable per country based on the available years (1996-2005, 2008-2011).

Price. We include the mean price of products in physical sell-through channels (i.e., i.e., channels in which recorded music is sold on physical units like CDs) as a control variable. Because we observe both unit sales and revenue, we can compute the average price per unit of music purchases. We provide details on the price measurement in Appendix B.

IPR protection. We control for the level of intellectual property rights (IPR) protection because regulatory efforts that strengthen IPR protection laws and enforcement should make piracy less prevalent. We use the property rights index provided by The Heritage Foundation because this is the only measure that we are aware of that covers the entire observation period. This index measures "the degree to which a country's laws protect private property rights and the degree to which its government enforces those laws" (*www.heritage.org*).

5.3 Model and Estimation

We assess the conceptual framework with a hierarchical linear model, which accounts for the lack of independence across observations that arises because the observations are nested within countries (Gelman & Hill, 2006). This is a common approach in studies that consider the contingency of effects across countries (Griffith, Yalcinkaya, & Rubera, 2014). We include (1) time-varying variables that are nested within countries (e.g., broadband Internet) and (2) time-invariant variables at the country level (e.g., cultural and economic factors). We include cross-level interactions between the broadband Internet and the introduction of new business models on the one hand and the country-level variables on the other hand to assess whether the relation between the focal variables and revenue differs predictably along country characteristics. The full model considers observations for year t (Level 1) nested within countries i (Level 2):

Level 1: $\log(Revenue_{ti}) = \beta_{0i} + \beta_{1i}Broadband_{ti} + \beta_{2i}(iTunes_{ti}) + \beta_{3i}(Spotify_{ti}) + \beta_{4i}(Trend_t) + \beta_5 log(Price_{ti}) + \beta_6 log(IPR_{t-1i}) + \beta_7 log(INC_{ti}) + \varepsilon_{ti},$ (1)

Level 2: $\beta_{0i} = \gamma_{00} + \gamma_{01}\log(INC_i) + \gamma_{02}\log(IND_i) + \gamma_{03}\log(UA_i) + \gamma_{04}\log(LRS_i) + \delta_{0i},$ (2)

$$\beta_{1i} = \gamma_{10} + \gamma_{11}\log(INC_i) + \gamma_{12}\log(IND_i) + \gamma_{13}\log(UA_i) + \gamma_{14}\log(LRS_i) + \delta_{1i}, \quad (3)$$

$$\beta_{2i} = \gamma_{20} + \gamma_{21}\log(INC_i) + \gamma_{22}\log(IND_i) + \gamma_{23}\log(UA_i) + \gamma_{24}\log(LRS_i) + \delta_{2i}, \quad (4)$$

$$\beta_{3i} = \gamma_{30} + \gamma_{31}\log(INC_i) + \gamma_{32}\log(IND_i) + \gamma_{33}\log(UA_i) + \gamma_{34}\log(LRS_i) + \delta_{3i}, \quad (5)$$

$$\beta_{4i} = \gamma_{40} + \delta_{4i}, \quad (6)$$

where $\varepsilon_{ti} \sim N(0, \sigma^2)$, and

$$\begin{bmatrix} \delta_{0i} \\ \delta_{1i} \\ \delta_{2i} \\ \delta_{3i} \\ \delta_{4i} \end{bmatrix} \sim MVN \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00} & \tau_{01} & \tau_{02} & \tau_{03} & \tau_{04} \\ \tau_{10} & \tau_{11} & \tau_{12} & \tau_{13} & \tau_{14} \\ \tau_{20} & \tau_{21} & \tau_{22} & \tau_{23} & \tau_{24} \\ \tau_{30} & \tau_{31} & \tau_{32} & \tau_{33} & \tau_{34} \\ \tau_{40} & \tau_{41} & \tau_{42} & \tau_{43} & \tau_{44} \end{bmatrix} \right). \quad (7)$$

As outlined above, the dependent variable is either the log of the recorded music revenue of "old" business models (physical formats) or the log of the total revenue (incl. physical formats, downloads, and streaming) for country *i* in year *t*. We specify random intercepts (β_{0i}) that account for differences in revenue levels between countries. Our main focus is on the heterogeneity in the coefficient of broadband Internet adoption and in new business models. Therefore, we allow the broadband adoption coefficient (β_{1i}) and the coefficients for the new business model introductions (iTunes (β_{2i}) and Spotify (β_{3i})) to vary between countries. In addition, we include a country-specific trend (β_{4i}) and a set of time-varying control variables as fixed effects (β_k) in Eq. (1). The level-1 error term (ε_{ti}) captures how a country's sales level deviates from the country's mean sales level over time after accounting for the remaining predictor variables, with σ^2 denoting the within-country variance in sales across years.

The level-2 equations explain the variation in the random intercept (β_{0i}, Eq. (2)) and in the random slopes associated with the broadband Internet variable and the new business model introductions. We decompose the random intercept into the grand mean (i.e., the mean across all years and countries, γ_{00}), the coefficients of the country-level variables (γ_{01}–γ_{04}), and an error term (δ_{0i}). Thus, we use the country characteristics to explain the variation in revenue levels between countries, and the abbreviations INC, IND, UA, and LRS refer to income, individualism, uncertainty avoidance, and local repertoire share, respectively. The level-2 error term captures the unexplained deviation of the mean revenue level in a particular country from the grand mean after accounting for country characteristics, with τ_{00} as the conditional country-level variance. In Eq. (3), γ_{10} is the mean slope across countries, $\gamma_{11} - \gamma_{14}$ refer to the variation in slopes that is due to differences in county characteristics. Eq. (4) and (5) are the equivalent specifications to explain variations in the countries' response to the introduction of new business models. γ_{40} in Eq. (6) captures the mean trend, and δ_{4i} is the variation in trends across countries. We take the log of the dependent and independent variables and group mean-center all time-varying variables and grand mean-center all time-invariant variables.

We obtain estimates for the parameters in (1)-(7) using Hamiltonian Monte Carlo, which is a Bayesian Markov Chain Monte Carlo (MCMC) method (Gelman et al., 2014). We use weakly informative priors for the parameters (i.e., normal (0,1) priors on all response parameters, normal (0,1) priors on the location parameters of the intercepts, a half-normal (0,1) prior on σ, and a LKJ-prior on the covariance parameters). We estimate the model with R and Stan (Stan Development Team, 2017). We estimate four chains, for each of which we compute 20,000 draws and use 10,000 draws for warm-up and only retain the final 10,000 draws for inference to ensure that the estimation converges. All chains are well converged and mixed, as evidenced by a potential scale reduction factor of 1 (Gelman & Rubin, 1992). Furthermore, we fail to detect severe autocorrelation of the MCMC samples. The average effective sample size across all coefficients is well above 10,000. We therefore conclude that the resulting MCMC sample is representative of the underlying posterior distribution.

5.4 Identification and Causality

Before we proceed with the interpretation of the results, we will discuss whether the coefficients that we estimate can be treated as causal effects. (1) Clearly, a causal interpretation is impossible if the focal estimate is confounded with differences between countries. Danaher, Smith and Telang (2014, p. 31) describe the idea of using city- or country-level data of sales and broadband penetration and highlight the requirement to properly control for differences in the demographic characteristics of each region. They argue that – if that is achieved – changes in broadband penetration "can be treated as an experiment," and these changes can be related to changes in sales or revenue. We control for these country-level differences by including country-specific intercepts. Hence, in the level-1 equation, we are primarily exploiting the variation *within* countries over time. As the multilevel model that we propose uses partial pooling due to the inclusion of random intercepts (Gelman & Hill, 2006), we are making the assumption that the random intercepts are uncorrelated with the independent variables. In the robustness check section, we will demonstrate that the results are very similar if we estimate the model with country fixed effects that do not make this assumption. Hence, in this research, a potential threat to causality is unlikely to arise from between-country differences only. (2) A second potential problem may arise if there is a comovement between the focal independent variables (e.g., broadband Internet) and music industry revenue, driven by some underlying unobserved factor. This could be, e.g., a global societal change that makes consumers less likely to purchase music but more likely to adopt broadband Internet. One potential remedy would be to use time fixed effects at the annual level. However, these time fixed effects are highly correlated with the broadband variable, and both vary at the annual level. Regressing broadband Internet on time and country fixed effects yields an R^2 of .91, and the variance inflation factors that result from this correlation indicate that one can include either time fixed effects or the broadband Internet variable, but not both. Facing this choice, we believe that in using time fixed effects, we focus on substantially less informative dummy coefficients at the expense of a theoretically relevant variable. We therefore suggest addressing the concern of unobserved longitudinal variation with a variable that captures the time trend, which is the recommended course of action, e.g., in Wang and Maxwell (2015). In addition, we will allow the coefficients of this time trend to vary by country, which also addresses potential differences between countries in the unobserved developments. This is an advantage over time fixed effects, as they assume homogenous coefficients across countries. (3) Other variables, e.g., price, are potentially endogenous because managers in a given country may react to unobserved demand shocks by changing price, which typically leads to an underestimation of the magnitude of the price elasticity (Bijmolt, van Heerde and Pieters 2005). Price is not a focal variable in this research, and hence, price endogeneity is not a problem of first order in this research, and we refrain from correcting for endogeneity (Rossi 2014). At the same time, we will not draw causal conclusions from the price coefficient.

In sum, these considerations imply that we can only interpret the coefficients in the level-1 equation as causal if we accept these assumptions to be justified. To emphasize the caveat that we have to rely on these untestable assumptions, we will avoid causal language in the interpretation of the results, and we will revisit the issue of causal identification in the discussion. In the level-2 equations, we explain between-country heterogeneity with four variables that we derived from theory and that are constant over time. This naturally limits our ability to clearly treat these as causal effects because it is difficult to rule out an omitted variable bias. Hence, we will also refer to associations rather than (causal) effects in the level-2 results.

5.5 Results

5.5.1 Preliminaries

We estimate five main models. Models 1 & 2 have revenue from the sales of music in physical formats (e.g., CDs) as a dependent variable, while Models 3 & 4 also contain all digital revenue in the dependent variable, i.e., the revenue generated by new digital business models such as iTunes or Spotify. Model 5 has physical units (as opposed to revenue) as the dependent variable. Models 2 & 4 are the focal models, and Models 1 & 3 are baseline models that only include the focal random coefficients. Predicted and observed values for the dependent variables are close to the diagonal, indicating good model fit (Fig. A.5 & A.6, Appendix). We provide density overlay plots in Figures A.8 & A.9 that show the observed distribution of the dependent variable and the predictions for 100 simulated draws from the posterior distribution, which supports our assessment of model fit. The median posterior estimates for the random intercept and the random slopes of the broadband effect, the iTunes coefficient, the Spotify coefficient, and the trend show considerable heterogeneity (Fig. A.2 & A.3). We will explain this heterogeneity using our set of country-level variables below.

In Table 3, we report the posterior median estimates from the estimation of Models 1-5. The coefficients printed in bold are those for which the 95% posterior CI excludes zero, which we treat as equivalent to "significant" (Talukdar, Sudhir, & Ainslie, 2002).

>>>Table 3 about here<<<

We will briefly discuss the results of the control variables. In M5 (unit sales model), we find a price coefficient of –0.379, which suggests price inelastic demand. However, we must keep in mind that aggregate demand (i.e., market level) elasticities estimated on annual data are usually closer to zero than, e.g., brand level elasticities (e.g., Hjorth-Andersen, 2000; Seaman, 2006), and other studies in the music market have also reporter inelastic demand (e.g., Danaher et al., 2010; Liebowitz, 2006). However, as we include this variable as a control variable, we do not account for potential price endogeneity[5], and we caution against interpreting this coefficient as representing a causal effect. By construction, the coefficient in the model with revenue as dependent variable is less negative by 1, which results in a coeffi-

[5] We assessed a correction of potential price endogeneity by means of Gaussian Copulas (Gupta and Park 2011), however, the correction factor was insignificant.

cient of 0.627 in M2. We control for time-varying income at the country level, and the coefficient is only significant in M4. The coefficients for intellectual property protection are inconclusive (β_6= –0.081 in M2 with zero in the CI and β_6= 0.243 in M4).

Furthermore, inspecting the random effects of the baseline models M1 and M3 reveals that a large share of the total variance is between countries. Specifically, in M1, 62% (i.e., $\tau_{01}/(\sum_{j=1}^{5}\tau_{0j}+\sigma^2)$ = 1.043/1.689) and in M2, 57% (i.e., 0.957/1.359) of the variance is between intercepts. However, turning to the corresponding full model specifications, we can see that in M2 85% (i.e., $1-\tau_{01}^{M2}/\tau_{01}^{M1}$ =1 – 0.157/1.043) and in M4 87% (i.e., 1 – 0.126/0.957) of this variance can be explained by the coefficient that captures the association between country characteristics and music industry revenue in the respective countries (γ_{01} - γ_{04}, Eq. (2)). They indicate that a country's wealth matters such that wealthier countries with more disposable income have higher per capita revenue for music products, while cultural dimensions seem to matter less. The coefficient for the local repertoire share is insignificant.

The differences in the Leave-one-out information criterion (LOOIC) and the Widely Applicable Information Criterion (WAIC) between the baseline specifications (i.e., M1 & M3) and their respective full specification counterparts (i.e., M2 & M4) show that the extended set of predictors substantially increases the out-of-sample prediction accuracy (M2 vs. M1, LOOIC: expected log predictive density (ELPD) difference (SE): –28.2 (12.8); WAIC: ELPD difference (SE): –28.6 (12.4); M4 vs. M3, LOOIC: ELPD difference (SE): –116.3 (18.1); WAIC: ELPD difference (SE): –116.2 (17.5)) (Vehtari, Gelman, & Gabry, 2017).

5.6 Main model results

We now discuss the findings for the coefficients for which we developed theoretical expectations in the theoretical framework. The mean coefficient[6] of broadband Internet on

[6] The mean coefficients for the random intercepts and random slopes (β_{0i}-β_{4i}) are represented by their respective level-2 intercepts in Table 3 (γ_{00}-γ_{40}).

revenue is negative (γ_{10}= –0.284 in M2; γ_{10}= –0.259 in M4) and significant, as the posterior density excludes zero. These findings are consistent with the conclusions that one can draw from an inspection of Figure 1, i.e., broadband Internet is associated with a decline in music revenue. Furthermore, there is considerable variation in this coefficient across countries in the baseline model (τ_{11}= 0.101 in M1; τ_{11}= 0.036 in M3). Figures A.2 & A.3 visually support this assessment, i.e., for most countries, the coefficient of broadband Internet is negative, while it also highlights the substantial variation across countries. A key element of the conceptual framework pertains to understanding this heterogeneity. We rely on the interactions between country characteristics and broadband ($\gamma_{11} - \gamma_{14}$) to shed light on this issue. We find the strongest association between income and the broadband coefficient. The coefficient for income is strong, positive, and the posterior interval excludes zero in all models. This finding implies that the relation between broadband and revenue is less negative in high-income countries and more negative in low-income countries, which is consistent with the theoretical expectations. We interpret this finding to indicate that consumers with less disposable income are more likely to utilize the new technology for obtaining music through illegitimate channels that do not create revenue for artists and labels.

While these results suggest that economic conditions matter for how consumers utilize the new technology of broadband Internet, cultural characteristics seem to matter as well. The coefficient of individualism (γ_{12}) is positive and substantial, which implies that the coefficient of broadband is less negative in individualistic countries and more negative in collectivistic societies. For uncertainty avoidance (γ_{13}), we also find the expected positive coefficients, and we can conclude that in countries with higher uncertainty avoidance, consumers may be more reluctant to rely on, e.g., piracy for obtaining music, potentially because of the risks associated with piracy. Inspecting the remaining variance in the full model specifications reveals that a large portion of the variation across countries in the response to broadband Internet adoption can be explained by our country-level predictors (i.e., 89% in M2 ($1 - \tau_{11}^{M2}/\tau_{11}^{M1}$=1–0.011/0.101) and 25% in M4 (1–0.027/0.036)).

With regard to market factors, we argued that the coefficient of broadband Internet will be less negative in countries with a high share of local repertoire. We do not find empirical evidence for this expectation. The estimate (γ_{14}) is weak, and the posterior density includes zero. Hence, it does not appear that a localized branding strategy can dampen the negative association between broadband Internet and music revenue.

The second key component of the conceptual framework refers to the extent to which the development of revenue changes when new digital business models that are enabled by broadband Internet are introduced. Insights on this aspect can inform the question of whether these new business models cannibalize or create revenue or, in other words, whether they can mitigate the negative impact of broadband Internet. To this end, we assess the mean coefficient for the introduction of iTunes, which is negative in M2 (γ_{20} = –0.380). In M4, the coefficient of the iTunes introduction is much closer to zero (γ_{20} = –0.121), but it remains negative even though the dependent variable in M4 takes the revenue generated by iTunes into account. When we assess these two coefficients jointly, they are consistent with the theory that new business models in the music industry cannibalize revenue from "old" sources and that the revenue generated by the new business model is insufficient to offset the revenue that is cannibalized. This may also be due to unbundling, i.e., consumers buying their preferred music as single downloads as opposed to entire albums (Elberse, 2010).

For the introduction of Spotify, we again find a negative mean coefficient in M2, and the coefficient is substantial (γ_{30} = –0.744). In M4, the coefficient is essentially zero (γ_{20}= 0.014), and the posterior interval is almost centered on zero. When we assess these two coefficients jointly, they are consistent with the theory that new business models such as Spotify cannibalize demand from old business models and that – on average – the revenue generated by Spotify is sufficient to just offset the cannibalization that it causes in old business models, which would be in line with prior research (e.g., Wlömert & Papies, 2016).

Again, the coefficients that capture the introduction of iTunes and Spotify in the market show considerable heterogeneity (Figures A.2 & A.3). Accordingly, the last part of the framework refers to the question of whether this international heterogeneity can be explained by the country characteristics we introduced above. The takeaway here is that the factors that we derived in the conceptual framework do not explain the international heterogeneity. Most coefficients exhibit posterior distributions that clearly contain zero, and we therefore refrain from interpreting these coefficients. One exception is uncertainty avoidance. Both interactions involving uncertainty avoidance and iTunes introduction are positive and significant, which suggests that the coefficient of the introduction of iTunes is less negative in countries that exhibit a high degree of uncertainty avoidance. One explanation may be that the consumers in these countries consider iTunes and similar music services a safe option that is less risky than, e.g., piracy. Hence, it is more likely that consumers embrace this opportunity.

Figure 3 provides a visualization of the interactions and shows the predicted broadband coefficients at one standard deviation below and above the overall mean of the moderator variable in each interaction. We graph all coefficients for which the posterior interval excludes zero. The left (right) column shows the interactions from Model 2 (4). In the first row, panels (a) & (f), the horizontal axis shows income from one standard deviation below to one standard deviation above the mean. The grey area indicates the area between the 2.5th and the 97.5th percentile of all MCMC draws that we used for inference. The effect sizes show that – as income becomes larger – the coefficient of broadband Internet becomes less negative, but it remains essentially negative. Panels (b) and (g) show that the coefficient of broadband Internet becomes less negative for countries high on individualism, but the coefficient again remains negative. Panels (c), (d), (h), and (i) show the moderation of uncertainty avoidance, highlighting the finding that the coefficient of new business model introductions is less negative in countries that score high on uncertainty avoidance. Panels (e) and (j) show that the coefficient capturing the association with the Spotify introduction variable is less negative for countries high on uncertainty avoidance in M2 and more negative for countries high on individualism in M3.

>>>Figure 3 about here<<<

6 Study 2

One shortcoming of Study 1 is that we cannot measure the relation between the introduction of new business models (e.g., music downloads or music streaming services) and the extent to which consumers engage in piracy. This question is relevant because if indeed a "carrot-and-stick" approach to combat piracy is effective, we should see that new business model introductions reduce piracy. The reason why we do not cover this in Study 1 is that we are not aware of any data source that has tracked music piracy over an extended period of time. Most published research relies on piracy data that cover one country or a relatively short period of time compared to the 22 years that Study 1 covers. The best international coverage of music piracy that we could obtain was through the now defunct website musicmetric.com. These data, which we describe in more detail below, allow us to assess the extent to which new business models are associated with a decline in piracy.

6.1 Sample

We collected data on piracy downloads for a sample of 1,628 artists randomly sampled from a full set of 3,123 artists who were associated with an album that appeared in the Billboard Top 200 album charts between 2008 and 2014. The piracy data are available for a period of 135 weeks between 2012 and 2014. We observe weekly downloads through BitTorrent networks for the set of artists at the country level. Because our main focus is on the question of whether new business models such as streaming services are associated with a reduction in piracy, we restrict the analysis to 47 countries in which a global streaming service for which we could obtain data on user numbers was available during the observation period, which allows us to relate the user numbers to the extent of piracy in a country. Hence, this data set consists of 6,345 observations (i.e., 47 countries x 135 weeks).

6.2 Measures

Piracy. The dependent variable in Study 2 is the weekly country-specific sum of downloads through BitTorrent networks over all 1,628 artists. We divide the number of downloads by the mean population size over the observation period to allow for better comparison between countries.

Streaming users. To capture variation in the adoption and use of music streaming services, we introduce a variable that measures the weekly per country number of unique active users of a global streaming service provider.[7]

Control variables. Similar to the first study, we include control variables that capture the effects of Broadband penetration, population, and intellectual property protection, which we obtain from the same sources (Table 2). Further, we control for the number of different artists for which music is downloaded as pirated content as a control variable.

6.3 Model

We specify a hierarchical linear model that is very similar to the model we used in the previous section. In contrast to Study 1, we now use the weekly piracy level per country as the dependent variable. The focal regressor is the number of weekly unique users of a global

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[7] We are not able to disclose the name of the streaming service provider.

streaming service per country. The relation between this variable and the weekly music piracy level is captured by β_{1i}, which is the main coefficient of interest in this model. In addition, we capture the extent to which the availability of broadband Internet is associated with piracy by including country-specific broadband Internet penetration, as defined above in Study 1. Because we have weekly variation in this data set but only observe slightly more than two years, we interpolate the variables observed on an annual level (i.e., Broadband, IPR, and Income) to avoid the discrete jumps that would otherwise occur at the beginning of each year. To account for the substantial variation in piracy levels over time, we include a random week intercept:

$$\text{Level 1:}\quad \log(Piracy_{ti}) = \beta_{0i} + \beta_{1i}\log(StreamingUsers_{ti}) + \beta_2\log(Broadband_{ti}) + \beta_3\log(IPR_{t-1i}) + \beta_4\log(Income_{ti}) + \beta_5\log(NumberOfArtists_{ti}) + \beta_{6t}(Week_t) + \varepsilon_{ti}, \tag{8}$$

$$\text{Level 2:}\quad \beta_{0i} = \gamma_{00} + \gamma_{01}\log(INC_i) + \gamma_{02}\log(IND_i) + \gamma_{03}\log(UA_i) + \delta_{0i}, \tag{9}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11}\log(INC_i) + \gamma_{12}\log(IND_i) + \gamma_{13}\log(UA_i) + \delta_{1i}, \tag{10}$$

where $\varepsilon_{ti} \sim N(0, \sigma^2)$, and

$$\begin{bmatrix}\delta_{0i}\\ \delta_{1i}\end{bmatrix} \sim N\left(\begin{bmatrix}0\\ 0\end{bmatrix}, \begin{bmatrix}\tau_{00} & \tau_{01}\\ \tau_{10} & \tau_{11}\end{bmatrix}\right). \tag{11}$$

We report these results as Model 3 in Table 4.

>>>Table 4 about here<<<

6.4 Results

Study 2 yields two main results with regard to focal relationships. First, the coefficient that captures the relation between broadband Internet and piracy is positive. This positive coefficient is to be expected, and it is in line with the arguments brought forward in previous research (e.g., Liebowitz, 2006 & 2008) that broadband Internet is the key facilitator of piracy activities. The second result, which is more central to the theme of the paper, is that an increase in the number of streaming users is, on average, associated with a decline in music piracy. The coefficient (γ_{10}) is negative, and the posterior interval excludes zero. The effect size suggests that a 1% increase in the number of users is associated with a 0.112% decline in piracy. Again, we see substantial heterogeneity in this coefficient, which means that consumers do not respond uniformly across countries to the introduction of new business models. However, neither income nor cultural variables appear to explain much of the variation in this effect. We provide the estimates for the random coefficient, posterior predictive checks, and the density overlay plot for Model 3 in Figures A.4, A.7, and A.10 in the Appendix.

7 Robustness checks

We conduct a series of 12 robustness checks for Study 1 to verify that the results we report are not idiosyncratic to this one particular model specification. We report the results of the main set of robustness checks for Study 1 in Table 5. Table A.3 in the Appendix has an additional set of 6 robustness checks. In Table 5, M8 and M9 are variants of the focal models that we discussed above, estimated without the price variable. The results of M8/M9 are very similar to the results of M2/M4, indicating that the role of the price variable in the present context appears to be of secondary importance. To rule out the possibility that broadband Internet and music revenue are jointly determined by some unobserved variable, we lag broadband by one year in models M10 and M11. Again, the results remain very similar compared to M2/M4, which makes it less likely that the association between broadband Internet and music revenue is merely a correlation caused by some unobserved underlying factor. Models M12 & M13 do not rely on random intercepts and random slopes but rather on country fixed effects, which are interacted with the trend variable to obtain country-specific trends. This specification does not make the assumption that the intercepts are correlated with the independent variables. Again, the results are quite similar to our focal models M2 & M4. For additional robustness checks, please see Table A.3 & A.4 in the Appendix, where we also establish that the results hold if we use a model in which broadband is not log transformed.

For Study 2, one obvious alternative model would be a difference-in-difference specification that also includes countries in which popular streaming services had not yet been introduced as control group. The focal regressor is then either the number of adopters or a dummy variable, which takes the value of 1 once the streaming service enters the market. This robustness check supports the results we showed above.

>>>Table 5 about here<<<

8 General Discussion

Innovations in one domain often have ramifications for markets and business models in other domains. One example is the music industry, where the incumbents' business models came under strong pressure by the proliferation of broadband Internet. The extent, however, to which "old" business models appear to be affected, differed strongly across countries (Figure 1). We therefore investigated how country characteristics (i.e., cultural, economic, and market-level factors) are associated with differences in the relationship between Internet adoption and music revenue. The second research question assesses the extent to which new digital business models, which are enabled by broadband Internet, are associated with changes in music industry revenue and how this association varies over countries. The third research question assesses whether music piracy declines once these new business models are introduced in a market. In this section, we discuss the main findings from our research.

Broadband Internet is associated with a decrease in revenue from recorded music. We find that the proliferation of broadband Internet adoption is accompanied by a strong decline in music revenue. While the data that we were able to collect and the model that we propose do not allow us to exactly pin down the causal effect in this association, we view broadband Internet as the most likely explanation of this observed pattern in music revenue, and this argument is in line with the consensus in the literature (e.g., Liebowitz, 2006 & 2008).

The most likely mechanism by which this occurs is that broadband Internet drastically reduced the costs for reproducing digital goods and for consumers to exchange large data volumes, which paved the road for widespread digital piracy (e.g., Liebowitz, 2016). On top of that, broadband Internet enabled alternative entertainment options (e.g., online games and video, social networks) that artists now have to compete against. Are there important alternative explanations to a causal effect of broadband Internet? The model that we propose controls for income and country-specific trends over time, i.e., the broadband coefficients that we estimate, are the coefficients that capture the association between broadband Internet and music revenue above and beyond what is contained in the country-specific trend and changes in income. The pertinent literature that we are aware of discusses broadband Internet as the major development in this period, and neither the analysis of the literature nor our work gave us any theoretical or empirical indication of strong alternative explanations[8]. We therefore believe that a causal effect of broadband Internet on music revenue is the most likely explanation of the observed pattern, and most likely, most of this effect is due to piracy.

The broadband coefficient varies across countries. This association between broadband Internet and music industry revenue varies substantially across countries. It is less pronounced in wealthy countries, although the diffusion of broadband Internet was faster in high-income countries (Talukdar, Sudhir, & Ainslie, 2002). Furthermore, the coefficient is less pronounced in individualistic societies. Taken together, these results are consistent with the idea that consumers in countries with more disposable income and in more individualistic societies are less likely to embrace piracy, and these findings converge in a way that one

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[8] Liebowitz (2006) assesses different alternative explanations and does not find support for them.

would expect from a variable that measures piracy. For artists and labels, these findings imply that – in the face of technological innovations – they should focus their attention on countries that match the profile of high income and high individualism.

The introduction of new digital business models is associated with declines in existing channels. Broadband Internet enables business model innovations, and these business model innovations can contribute to revenue generation that in turn may dampen the negative consequences broadband Internet. However, the road to successful implementation of this strategy is by no means direct, and this research presents findings that are consistent with the notion that new digital business models (e.g., iTunes and Spotify) cannibalize existing distribution channels and business models. These findings are also in line with other publications (Aguiar & Waldfogel, 2018; Wlömert & Papies, 2016). If we accept the identifying assumptions that we outlined above and treat this coefficient as a causal effect, this finding poses a strategic dilemma because the unwillingness to cannibalize the own established revenue sources, in this case, e.g., CD's, may have contributed to the firms' inertia to offer attractive digital business models once broadband Internet was on the horizon. These inertias likely contributed to a situation in which firms did not meet consumer demand in the online domain with attractive business models, which may have contributed to the proliferation of piracy. Clearly, this is conjecture, but we view it as possible that the detrimental effect of broadband Internet in its early days may have occurred not because it was inevitable, but primarily because firms did not meet consumer demand with attractive business models. However, the findings from this research are in line with the notion that it may be beneficial to create new digital business models because – while they cannibalize revenue – they can reduce piracy and create revenue that at least mitigates its cannibalizing effects. This conclusion holds at least for the case of music streaming services. Hence, music streaming services appear to be an example of a case where it is beneficial to "eat your lunch before someone else does" (Nault & Vandenbosch, 1996). In other words, it appears to be better to cannibalize established business models with your own new digital business models before competitors (e.g., file-sharing networks) do. However, we note that this approach has not been effective for the case of iTunes.

The introduction of streaming services is associated with a decline in music piracy. Previous research suggests that it may be possible to curb music piracy with a “carrot-and-stick” approach, in which attractive legal business models constitute the carrot (Sinha & Mandel, 2008). Empirical evidence, however, on the feasibility of this approach is scarce (e.g., Danaher et al., 2010). To this end, we collect a unique data set that covers music piracy in close to 50 countries over more than two years and the number of users per country of one global streaming service. The results show that – on average – music streaming services are associated with a reduction in piracy. The model results as well as the descriptive statistics clearly indicate, however, that there is only a decrease, and streaming services do not eliminate piracy. In addition, there is substantial heterogeneity across countries, and for many countries, the effect is essentially zero. Streaming services are associated with a decline in piracy primarily in high-income countries. This highlights that streaming services are by no means a panacea to attract consumers into the legal market and to combat piracy.

National culture is relevant above and beyond economic wealth. The role of culture has received a great deal of attention in previous research that seeks to understand international heterogeneity (e.g., Van den Bulte & Stremersch, 2004), and the general notion is that cultural characteristics of countries (e.g., captured by the Hofstede criteria) are important to understanding a society’s behavior. The findings of the present research do not unambiguously support this notion. The models that we estimate control for a country’s income and the effects of the cultural characteristics, as measured by the Hofstede criteria, are less strong than the coefficients for income. Interestingly, the income is rather strong in explaining the intercepts, while the variation in the coefficients is explained both by income and the cultural factors. These findings suggest that culture, above and beyond economic factors, has some explanatory power when we try to understand the relationship between new technologies and demand on a cultural market and the role of new business models in this context. We conclude that the finding that both economic and cultural factors matter is noteworthy and a valuable addition to the literature.

Localization of content does not mitigate the negative associations. Music artists – similar to other providers of cultural content (e.g., Song et al., 2017) – can either offer more localized or more internationally standardized content, which is related to the debate on the adaptation vs. standardization of international business activities (e.g., Katsikeas, Samiee, & Theodosiou, 2006). However, in our research setting, this decision does not appear to matter because the findings with regard to this aspect are weak and inconclusive. Hence, we conclude that neither localization nor standardization is certain to provide a competitive edge.

Revenue generation from recorded music remains difficult. The results suggest that it appears to remain difficult for artists to generate revenue in the wake of the proliferation of broadband Internet. Not only did revenue from recorded music sharply decline in all markets as broadband Internet surged. In addition, the new business models enabled by the broadband Internet appear to heavily cannibalize “old” business models, and only the latest generation (i.e., streaming) appears to generate sufficient revenue to offset its own cannibalizing effect. We do not have evidence that these new business models can induce substantial new growth in the music industry. One potential avenue for artists may be the option to give concerts because this experience seems largely immune to piracy and displacement by digital alternatives. Indeed, concerts have been on the rise in recent years and have become an important source of income for artists (e.g., Krueger, 2005; Papies & van Heerde, 2017).

We argue that the insights from our studies are relevant for businesses (e.g., music labels) that operate internationally. As they deliberately choose which markets to enter with new business models, how to respond to technological innovations, how to allocate their investments across countries, and how to adapt their content to local markets, knowledge on how certain markets react to innovations is crucial. Hence, this research identifies factors that indicate which countries are more or less suited for using innovations to create new value.

The music industry is an economically and culturally highly relevant market, and developments in this market affect billions of consumers worldwide. In line with this relevance, academic research in marketing and other disciplines (e.g., economics) has devoted considerable attention to this market (e.g., Elberse, 2010; Danaher et al., 2014; Krueger, 2005). Nonetheless, it is important to consider whether the findings from this study may also hold implications for other domains outside the music industry. The phenomenon that the technological innovation of broadband Internet has affected other markets, in part by fueling business model innovations, is not unique to the music industry. The book industry is a related example in which "old" business models (e.g., independent book stores) were strongly affected, and ecommerce and e-books entered the market as business model innovations. A similar case is the video market. Video rental stores all but disappeared, linear TV consumption is under pressure, and video-on-demand in different forms is starting to replace incumbents' business models (Hiller, 2017). These markets also share the common threat of online piracy with the music market. Hence, it is reasonable that the implications that we derived above may also be relevant for these markets. Internationally active firms in these markets should therefore be aware of the potential heterogeneity in consumer responses that we identified above. Furthermore, while low-income countries may appear less attractive because they are more likely to embrace pirated versions of content, these markets may be attractive on second sight due to their substantial upward potential when new business models are introduced. A related example is the newspaper industry, where the established business model of selling printed newspapers came under severe pressure through (free) online news (e.g., Deleersnyder et al., 2002). We speculate that these findings may also extend to other industry sectors that are heavily affected by digital transformation and digital business models. Examples include navigation services (selling maps and devices has been replaced by online services that require broadband Internet), the transportation and tourism sector (e.g., taxis face competition from services such as Uber, travel agencies face constant pressure from online services). The international heterogeneity in the response and the opportunities that arise when firms are willing to cannibalize their own business to preempt competition may be valuable lessons.

This research is subject to limitations. First, as we have repeatedly mentioned, the most direct limitation is that we cannot make strong causal statements based on the available data. Second, broadband Internet enables different reactions of market participants. On the one hand, it enables new business models, and on the other hand, it gives rise to digital piracy. In an ideal world, we would be able to measure piracy directly in Study 1 to disentangle these effects more directly. However, to the best of our knowledge, there is no measure available that measures piracy across many countries and across many years. Third, research that focuses on between-country differences always faces the challenge that the number of countries that can be analyzed is limited, which puts severe restrictions on the number of country-level variables. Despite these limitations, we believe that this research makes a useful contribution to our understanding of the internationally heterogeneous impact of innovations.

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Tables and figures

Table 1

Summary of theoretical expectations

Theoretical expectation	***Rationale***	***Study***
The relation between **broadband Internet** and **revenue**		
… is negative	Piracy and entertainment alternatives, enabled by broadband Internet, reduce revenue	Study 1
… is less negative in wealthy countries	More disposable income makes piracy relatively less attractive	
… is less negative in individualistic countries	Collectivism encourages information sharing	
… is less negative in uncertainty avoiding countries	Uncertainty avoidance lets consumers avoid legal risk of piracy	
… is less negative in countries with high local repertoire share	Stronger social connections with local artists	
The relation between **new digital business models** and **revenue**		
… is negative (for revenue from "old" business models)	Cannibalization of incumbents through business model innovations	Study 1
… is negative / positive (for total revenue)	New business models generate revenue that offsets (part of) the cannibalized revenue	
… is less negative in wealthy countries	More disposable income allows consumers to act on the availability of new business models	
… is less negative in individualistic countries	Consumers in individualistic societies are more innovative	
… is less negative in uncertainty avoiding countries	New business models allow uncertainty avoiding consumers to avoid legal risk of piracy	
… is less negative in countries with high local repertoire share	Stronger social connections with local artists	
The relation between **new digital business models** and **piracy**		
… is negative	Business models as "carrot" to curb piracy	Study 2
… is more negative in wealthy countries	More disposable income allows consumers to act on the availability of new business models and abandon piracy	
… is more negative in individualistic countries	Consumers in individualistic societies are more innovative and embrace new business models	
… is more negative in uncertainty avoiding countries	New business models allow uncertainty avoiding consumers to avoid legal risk of piracy	
… is more negative in countries with high local repertoire share	Stronger social connections with local artists	

Table 2

Measures and descriptive statistics

Variable	*Definition*	*Source*	*Mean*	*SD*	*Min.*	*Max.*
Study 1						
Revenue from old business models	Recorded music revenue per capita from physical music products (i.e., CDs, MCs, LPs) in market *i* in year *t* (in 2010 constant US$; trade value)	IFPI	9.99	10.00	0.02	39.10
Revenue from old and new business models	Recorded music revenue per capita from physical music products, paid downloads, and advertising and subscription revenues from streaming services in market *i* in year *t* (in 2010 constant US$; trade value)	IFPI	11.87	9.63	0.22	39.11
Physical unit sales	Album sales per capita from physical music products (i.e., CDs, MCs, LPs, physical singles; singles are weighted with a factor of .30) in market *i* in year *t*	IFPI	1.03	0.97	0.01	4.09
Broadband	Fixed broadband subscriptions (downstream speeds ≥ 256 kbit/s) per 100 people in market *i* in year *t*	World Bank/ITU	13.19	13.61	0.00	45.42
iTunes	Indicator variable that is 1 if iTunes was available in market *i* in year *t* and 0 else	own calc.	0.44	0.50	0	1
Spotify	Indicator variable that is 1 if Spotify was available in market *i* in year *t* and 0 else	own calc.	0.21	0.41	0	1
Price	PPP adjusted average wholesale price per sold album unit in market *i* in year *t* (in 2010 constant US$)	IFPI; own calc.	9.13	2.71	3.03	17.64
IPR protection	Property rights score in market *i* in year *t*-1 (0 = min – 100 = max)	Heritage Found.	72.57	19.49	15.00	97.10
Income	PPP adjusted GDP per capita in market *i* in year *t* (in ‘000 2010 constant US$)	World Bank	30.60	15.79	2.15	85.53
Individualism	Individualism index of market *i*	Hofstede	55.92	23.10	13.00	91.00
Uncertainty avoidance	Uncertainty avoidance index of market *i*	Hofstede	62.30	23.28	8.00	100.00
Local repertoire share	Mean local repertoire market share of physical sales in market *i* in years 1996-2005 & 2008-2011	IFPI	39.18	20.77	9.46	92.70
Study 2						
Piracy	Sum of BitTorrent downloads in country *i* in week *t* (per ‘000 inhabitants)	Musicmetric	4.03	4.43	0.06	29.52
Streaming Users	Number of unique active streaming service users in market *i* in week *t* (the actual number was divided by an arbitrary constant to preserve confidentiality)	Industry partner	11,591	26,133	0	152,645
Broadband	See above	World Bank	23.25	11.23	1.84	42.97
IPR protection	See above	Heritage Found.	66.90	22.52	15.00	95.00
Individualism	See above	Hofstede	51.19	24.76	6.00	91.00
Uncertainty avoidance	See above	Hofstede	68.06	22.86	8.00	100.00
Income	See above	World Bank	31.54	17.81	6.25	90.95
Number of artists	Number of artists of which piracy downloads were observed in country *i* in week *t*	Musicmetric	1,156	168	508	1,573

The observation period spans 22 years from 1996 to 2017 for 36 countries in study 1 (N = 782), and 135 weeks between 2012 and 2014 for study 2 (N = 6,345). IFPI = International Federation of the Phonographic Industry, ITU = International Telecommunication Union, PPP = Purchasing Power Parity, GDP = Gross Domestic Product.

Table 3
Posterior median estimates and 95% CIs (Study 1)

Independent variables	Exp.	*M1: Log(Phys. revenue)* Coeff. [CI]	*M2: Log(Phys. revenue)* Coeff. [CI]	*M3: Log(Total revenue)* Coeff. [CI]	*M4: Log(Total revenue)* Coeff. [CI]	*M5: Log(Phys. units)* Coeff. [CI]
Intercept (γ_{00})		**1.519** [1.19; 1.84]	**1.555** [1.42; 1.68]	**1.815** [1.49; 2.14]	**1.970** [1.85; 2.08]	**–0.561** [–0.71; –0.41]
Log(Broadband) (γ_{10})	–	**–0.317** [–0.44; –0.20]	**–0.284** [–0.36; –0.21]	**–0.267** [–0.34; –0.19]	**–0.259** [–0.33; –0.19]	**–0.290** [–0.37; –0.22]
iTunes (γ_{20})	–	**–0.439** [–0.57; –0.31]	**–0.380** [–0.49; –0.27]	**–0.236** [–0.33; –0.14]	**–0.121** [–0.21; –0.04]	**–0.358** [–0.46; –0.26]
Spotify (γ_{30})	–/+	**–0.834** [–0.99; –0.68]	**–0.744** [–0.85; –0.63]	–0.117 [–0.23; 0.01]	0.014 [–0.06; 0.09]	**–0.715** [–0.82; –0.59]
Trend (γ_{40})	–	**–0.239** [–0.33; –0.15]	**–0.256** [–0.34; –0.17]	**–0.161** [–0.24; –0.08]	**–0.195** [–0.27; –0.12]	**–0.247** [–0.33; –0.16]
Log(INC) (γ_{01})			**1.276** [1.02; 1.53]		**1.276** [1.04; 1.51]	**1.122** [0.89; 1.40]
Log(IND) (γ_{02})			**0.476** [0.17; 0.77]		**0.392** [0.12; 0.67]	**0.555** [0.22; 0.88]
Log(UA) (γ_{03})			0.233 [–0.05; 0.51]		0.141 [–0.10; 0.38]	0.160 [–0.16; 0.40]
Log(LRS) (γ_{04})			0.008 [–0.24; 0.26]		0.027 [–0.19; 0.24]	0.124 [–0.15; 0.40]
Cross-level interaction						
Log(Broadband) x Log(INC) (γ_{11})	+		**0.400** [0.26; 0.56]		**0.308** [0.19; 0.43]	**0.402** [0.26; 0.56]
Log(Broadband) x Log(IND) (γ_{12})	+		**0.238** [0.11; 0.36]		**0.151** [0.03; 0.27]	**0.224** [0.09; 0.34]
Log(Broadband) x Log(UA) (γ_{13})	+		**0.127** [0.01; 0.26]		**0.130** [0.03; 0.24]	**0.128** [0.02; 0.25]
Log(Broadband) x Log(LRS) (γ_{14})	+		–0.024 [–0.12; 0.07]		–0.008 [–0.10; 0.08]	–0.016 [–0.12; 0.08]
iTunes x Log(INC) (γ_{21})	+		0.042 [–0.16; 0.24]		–0.019 [–0.18; 0.14]	–0.039 [–0.22; 0.14]
iTunes x Log(IND) (γ_{22})	+		–0.083 [–0.31; 0.16]		0.023 [–0.17; 0.21]	–0.036 [–0.26; 0.19]
iTunes x Log(UA) (γ_{23})	+		**0.370** [0.15; 0.59]		**0.278** [0.11; 0.44]	**0.329** [0.09; 0.54]
iTunes x Log(LRS) (γ_{24})	+		0.012 [–0.19; 0.21]		0.056 [–0.10; 0.21]	0.025 [–0.16; 0.21]
Spotify x Log(INC) (γ_{31})	+		–0.122 [–0.35; 0.11]		–0.066 [–0.22; 0.08]	–0.198 [–0.48; 0.09]
Spotify x Log(IND) (γ_{32})	+		–0.038 [–0.29; 0.21]		**–0.178** [–0.35; –0.01]	0.006 [–0.26; 0.27]
Spotify x Log(UA) (γ_{33})	+		**0.402** [0.18; 0.63]		–0.000 [–0.14; 0.14]	**0.327** [0.09; 0.56]
Spotify x Log(LRS) (γ_{34})	+		0.024 [–0.15; 0.20]		0.053 [–0.07; 0.17]	0.041 [–0.13; 0.22]
Control variables						
Log(Price) (β_5)			**0.627** [0.48; 0.78]		**0.257** [0.17; 0.34]	**–0.379** [–0.52; –0.23]
Log(LagIPRProtection) (β_6)			–0.081 [–0.31; 0.15]		**0.243** [0.11; 0.38]	–0.013 [–0.24; 0.21]
Log(Income) (β_7)			0.289 [–0.18; 0.77]		**0.747** [0.45; 1.05]	0.357 [–0.11; 0.84]
Random effects						
Intercept (τ_{00}), Log(Broadband) (τ_{11}), iTunes (τ_{22}), Spotify (τ_{33}), Trend (τ_{44}), Residual (σ^2)		1.043, 0.101, 0.080, 0.136, 0.030, 0.299	0.157, 0.011, 0.035, 0.038, 0.020, 0.289	0.957, 0.036, 0.050, 0.092, 0.045, 0.179	0.126, 0.027, 0.042, 0.025, 0.035, 0.154	0.201, 0.011, 0.025, 0.038, 0.021, 0.278
LOOIC (WAIC)		474.9 (462.7)	417.3 (405.6)	–309.9 (–330.8)	–542.5 (–563.2)	354.9 (342.0)

Notes: N = 782 (number of countries = 36, number of years = 22), N = 766 in M5 due to missing values on the DV, CI = Credible Interval, 95% CI's in parentheses.

Table 4

Posterior median estimates and 95% CIs (Piracy)

Independent variables	*Exp.*	*M6: Log(Piracy)* Coeff. [CI]	*M7: Log(Piracy)* Coeff. [CI]
Intercept (γ_{00})		0.803 [0.49; 1.11]	0.816 [0.59; 1.09]
Log(StreamingUsers) (γ_{10})	–	**–0.139** [–0.27; –0.01]	**–0.112** [–0.22; –0.01]
Log(INC) (γ_{01})			0.479 [–0.12; 1.07]
Log(IND) (γ_{02})			**0.572** [0.09; 1.05]
Log(UA) (γ_{03})			–0.067 [–0.65; 0.51]
Cross-level interaction			
Log(StreamingUsers) x Log(INC) (γ_{11})	–		–0.166 [–0.44; 0.11]
Log(StreamingUsers) x Log(IND) (γ_{12})	–		–0.052 [–0.27; 0.17]
Log(StreamingUsers) x Log(UA) (γ_{13})	–		0.074 [–0.18; 0.33]
Control variables			
Log(Broadband) (β_2)			**0.871** [0.70; 1.04]
Log(LagIPRProtection) (β_3)			**–1.584** [–1.74; –1.42]
Log(Income) (β_4)			**–0.657** [–1.04; –0.27]
Log(NumberOfArtists) (β_5)			**0.772** [0.60; 0.94]
Random effects			
Countries (τ_{00})		**1.099** [0.75; 1.70]	**0.734** [0.48; 1.12]
Log(StreamingUsers) (τ_{11})		**0.190** [0.13; 0.30]	**0.133** [0.08; 0.21]
Weeks (τ_{22})		**0.386** [0.34; 0.44]	**0.451** [0.40; 0.52]
Residual (σ^2)		**0.147** [0.14; 0.15]	**0.139** [0.14; 0.14]
LOOIC (WAIC)		–6127.5 (–6128.1)	–6807.5 (–6808.1)

Notes: N = 6,345 (number of countries = 47, number of weeks = 135), CI = Credible Interval, 95% CI's in parentheses. Both models include random week intercepts that are not shown in this table in the interest of brevity. The difference in out-of-sample prediction accuracy between M6 and M7 is significant based on the LOOIC (ELPD difference (SE): –340.0 (34.1)) and WAIC (ELPD difference (SE): –340.0 (34.1)), ELPD = expected log predictive density, WAIC = Widely Applicable Information Criterion, LOOIC = Leave-one-out Information Criterion.

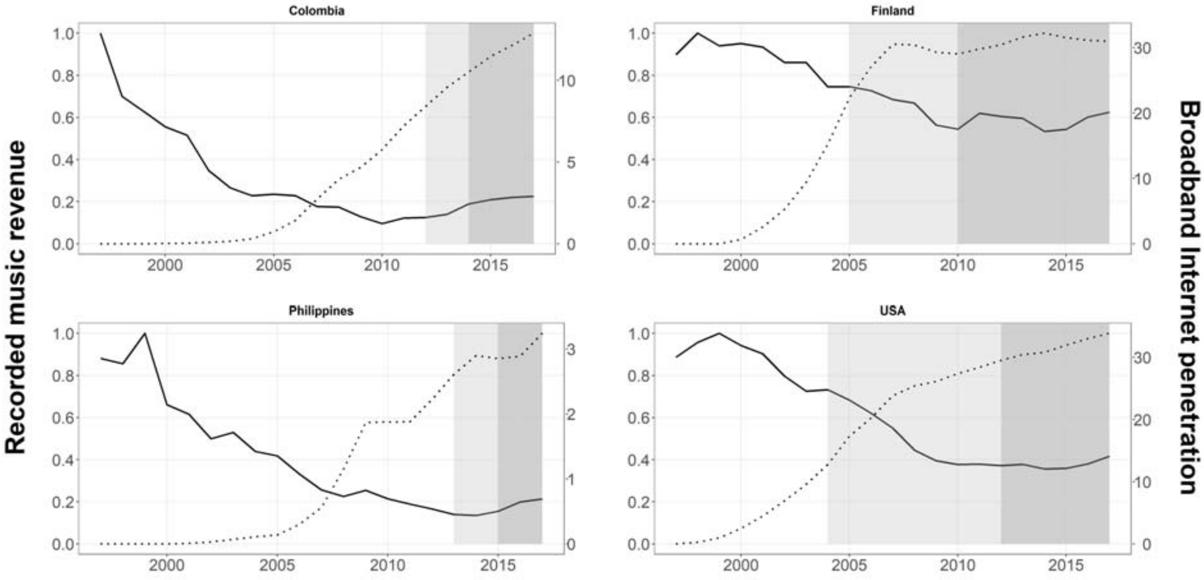
Table 5
Robustness tests (Study 1)

	M8: Log(Phys. revenue)	*M9: Log(Total revenue)*	*M10: Log(Phys. revenue)*	*M11: Log(Total revenue)*	*M12: Log(Phys. revenue)*	*M13: Log(Total revenue)*
Independent variables	Coeff. [CI]	Coeff. [CI]	Coeff. [CI]	Coeff. [CI]	Coeff. (Cluster SE)	Coeff. (Cluster SE)
Intercept (γ_{00})	**1.556** [1.42; 1.68]	**1.969** [1.85; 2.09]	**1.555** [1.42; 1.69]	**1.969** [1.85; 2.09]	included	included
Log(Broadband) (γ_{10})	**–0.344** [–0.42; –0.27]	**–0.282** [–0.35; –0.21]	**–0.323** [–0.41; –0.24]	**–0.268** [–0.34; –0.19]	**–0.288** (0.060)	**–0.250** (0.040)
iTunes (γ_{20})	**–0.447** [–0.54; –0.34]	**–0.150** [–0.23; –0.07]	**–0.283** [–0.39; –0.17]	–0.040 [–0.12; 0.04]	**–0.394** (0.051)	**–0.131** (0.040)
Spotify (γ_{30})	**–0.799** [–0.91; –0.67]	–0.010 [–0.09; 0.07]	**–0.723** [–0.83; –0.62]	0.042 [–0.03; 0.11]	**–0.733** (0.049)	0.069 (0.036)
Trend (γ_{40})	**–0.272** [–0.36; –0.18]	**–0.204** [–0.28; –0.13]	**–0.227** [–0.32; –0.13]	**–0.192** [–0.27; –0.11]	included	included
Log(INC) (γ_{01})	**1.278** [1.02; 1.53]	**1.276** [1.04; 1.51]	**1.255** [0.99; 1.51]	**1.271** [1.03; 1.50]		
Log(IND) (γ_{02})	**0.470** [0.17; 0.77]	**0.389** [0.12; 0.66]	**0.467** [0.16; 0.77]	**0.390** [0.11; 0.67]		
Log(UA) (γ_{03})	0.231 [–0.05; 0.51]	0.143 [–0.10; 0.38]	0.238 [–0.04; 0.51]	0.153 [–0.09; 0.39]		
Log(LRS) (γ_{04})	0.003 [–0.24; 0.25]	0.025 [–0.19; 0.24]	0.006 [–0.24; 0.25]	0.025 [–0.19; 0.24]		
Cross-level interaction						
Log(Broadband) x Log(INC) (γ_{11})	**0.449** [0.30; 0.61]	**0.319** [0.19; 0.44]	**0.368** [0.21; 0.54]	**0.277** [0.15; 0.41]	**0.376** (0.101)	**0.172** (0.075)
Log(Broadband) x Log(IND) (γ_{12})	**0.226** [0.09; 0.35]	**0.136** [0.01; 0.26]	**0.247** [0.10; 0.38]	**0.167** [0.04; 0.30]	**0.205** (0.082)	0.092 (0.071)
Log(Broadband) x Log(UA) (γ_{13})	**0.126** [0.01; 0.26]	**0.131** [0.02; 0.24]	0.112 [–0.01; 0.25]	0.105 [–0.00; 0.22]	0.009 (0.075)	0.065 (0.062)
Log(Broadband) x Log(LRS) (γ_{14})	–0.038 [–0.14; 0.06]	–0.014 [–0.11; 0.08]	–0.038 [–0.15; 0.07]	–0.012 [–0.11; 0.09]	–0.011 (0.054)	–0.036 (0.036)
iTunes x Log(INC) (γ_{21})	0.114 [–0.08; 0.29]	0.000 [–0.16; 0.16]	0.083 [–0.11; 0.27]	0.011 [–0.14; 0.17]	0.077 (0.092)	0.021 (0.061)
iTunes x Log(IND) (γ_{22})	–0.079 [–0.30; 0.14]	0.024 [–0.16; 0.21]	–0.100 [–0.32; 0.12]	0.025 [–0.15; 0.21]	–0.104 (0.107)	–0.043 (0.084)
iTunes x Log(UA) (γ_{23})	**0.433** [0.22; 0.65]	**0.301** [0.13; 0.47]	**0.398** [0.18; 0.61]	**0.269** [0.10; 0.43]	**0.391** (0.131)	**0.304** (0.107)
iTunes x Log(LRS) (γ_{24})	0.058 [–0.13; 0.24]	0.070 [–0.08; 0.22]	0.028 [–0.16; 0.23]	0.065 [–0.08; 0.22]	–0.020 (0.073)	0.021 (0.051)
Spotify x Log(INC) (γ_{31})	–0.186 [–0.43; 0.07]	–0.077 [–0.23; 0.08]	–0.135 [–0.35; 0.09]	–0.080 [–0.22; 0.07]	**–0.198** (0.099)	**–0.202** (0.092)
Spotify x Log(IND) (γ_{32})	–0.008 [–0.29; 0.27]	–0.158 [–0.34; 0.02]	–0.051 [–0.30; 0.20]	**–0.183** [–0.35; –0.02]	–0.028 (0.122)	**–0.201** (0.092)
Spotify x Log(UA) (γ_{33})	**0.438** [0.19; 0.69]	0.014 [–0.13; 0.16]	**0.418** [0.20; 0.64]	–0.004 [–0.14; 0.13]	**0.369** (0.127)	–0.036 (0.085)
Spotify x Log(LRS) (γ_{34})	0.034 [–0.17; 0.24]	0.065 [–0.06; 0.19]	0.035 [–0.14; 0.21]	0.062 [–0.05; 0.18]	0.022 (0.086)	0.042 (0.044)
Control variables						
Log(Price) (β_5)			**0.551** [0.40; 0.70]	**0.206** [0.12; 0.29]	**0.620** (0.159)	**0.241** (0.085)
Log(LagIPRProtection) (β_6)	–0.061 [–0.30; 0.17]	**0.260** [0.12; 0.40]	0.007 [–0.22; 0.24]	**0.290** [0.16; 0.42]	–0.087 (0.246)	0.180 (0.204)
Log(Income) (β_7)	0.405 [–0.09; 0.89]	**0.809** [0.50; 1.12]	0.076 [–0.40; 0.55]	**0.507** [0.23; 0.79]	0.502 (0.819)	0.884 (0.482)
Random effects						
Intercept (τ_{00}), Log(Broadband) (τ_{11}), iTunes (τ_{22}), Spotify (τ_{33}), Trend (τ_{44}), Residual (σ^2)	0.155, 0.015, 0.020, 0.058, 0.020, 0.301	0.124, 0.026, 0.041, 0.028, 0.035, 0.157	0.161, 0.023, 0.024, 0.038, 0.029, 0.283	0.127, 0.037, 0.037, 0.023, 0.043, 0.147	R^2 (within) = 0.909	R^2 (within) = 0.857
LOOIC (WAIC)	480.9 (468.1)	–503.3 (–527.5)	388.5 (374.2)	–596.2 (–621.4)		

Notes: N = 782, CI = Credible Interval, 95% CI's in parentheses, WAIC = Widely Applicable Information Criterion, LOOIC = Leave-one-out Information Criterion. In M10 & M11 the broadband variable is lagged by one period. M12 & M13 include country fixed-effects and country-specific trends, which are not reported in this table in the interest of brevity.

Figure 1

Recorded music revenue and broadband Internet penetration by country

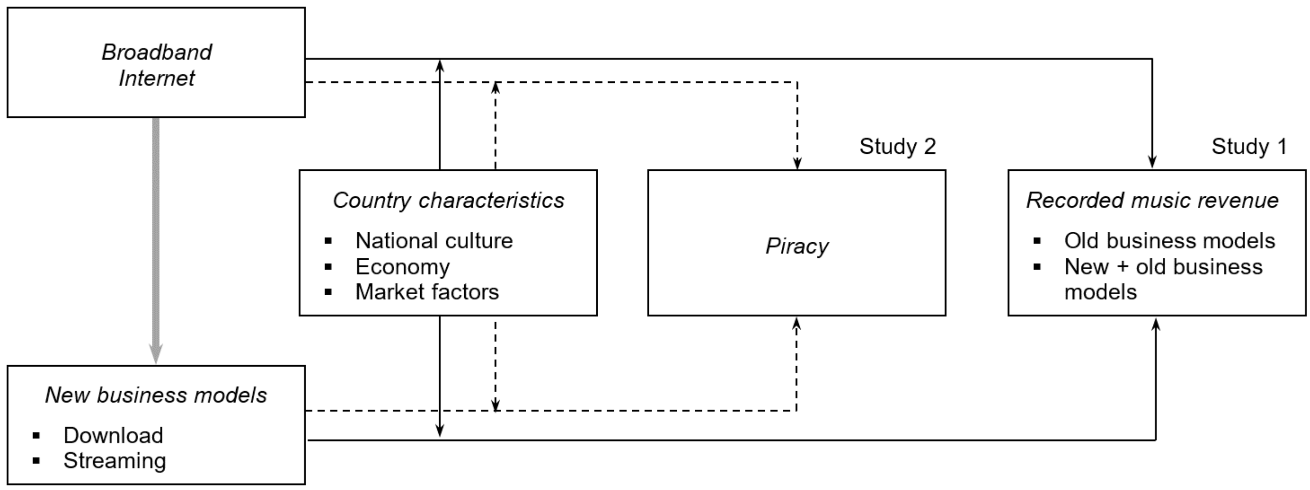


Per capita recorded music revenue (standardized) ——— Broadband Internet penetration ········

Note: grey (dark grey) areas indicate the introduction of new digital business models iTunes (Spotify)

Figure 2

Conceptual framework



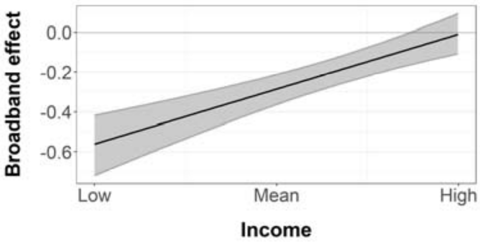
Note: solid (dashed) lines represent relations assessed in Study 1 (Study 2). Grey arrow indicates a relationship that is assumed but not empirically tested.

Figure 3

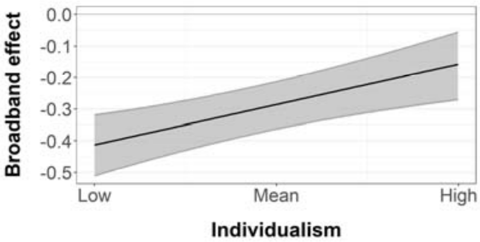
Interaction effects models 2 & 4

<u>Model 2</u>

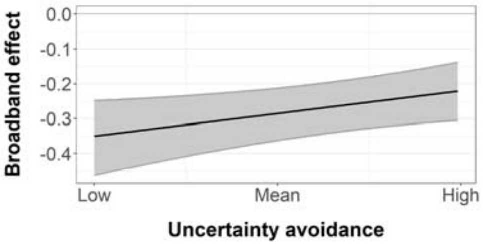
(a) The broadband coefficient is less negative in **high-income** countries



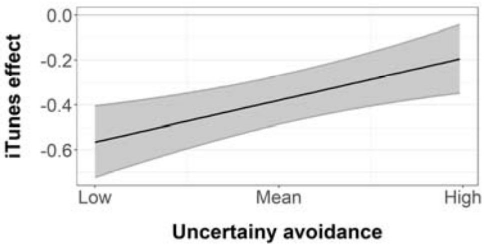
(b) The broadband coefficient is less negative in **individualistic** countries



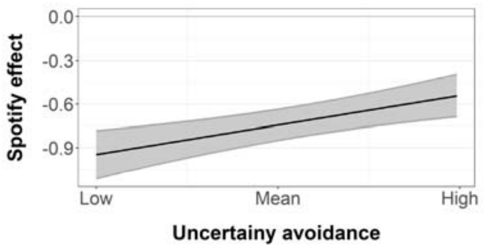
(c) The broadband coefficient is less negative in countries high on **uncertainty avoidance**



(d) The iTunes coefficient is less negative in countries high on **uncertainty avoidance**

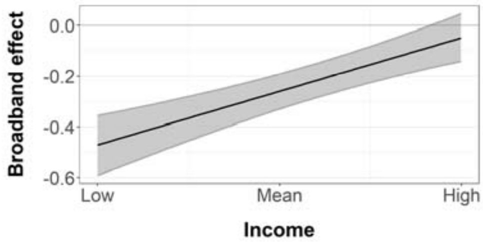


(e) The Spotify coefficient is less negative in countries high on **uncertainty avoidance**

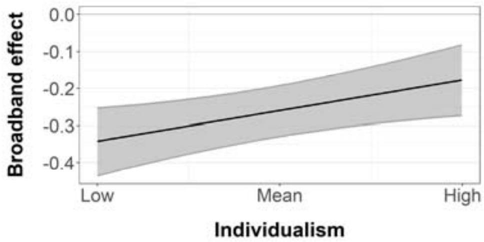


<u>Model 4</u>

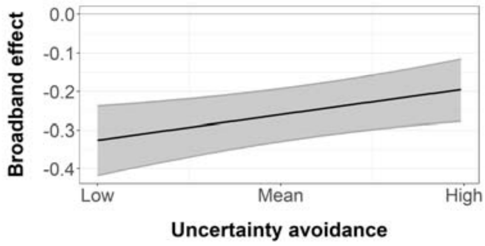
(f) The broadband coefficient is less negative in **high-income** countries



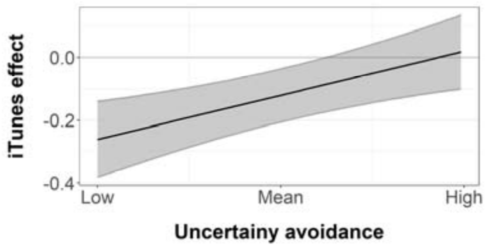
(g) The broadband coefficient is less negative in **individualistic** countries



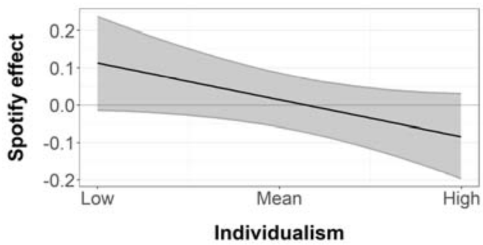
(h) The broadband coefficient is less negative in countries high on **uncertainty avoidance**



(i) The iTunes coefficient is less negative in countries high on **uncertainty avoidance**



(j) The Spotify coefficient is more positive in countries low on **individualism**



Appendix

Table A.1

Correlations among Study 1 variables

	1	2	3	4	5	6	7	8	9	10	11	12
1 Revenue old & new BM	1											
2 Revenue old BM	**0.95**	1										
3 Physical unit sales	**0.94**	**0.97**	1									
4 Broadband	–0.03	**–0.27**	**–0.17**	1								
5 iTunes	**–0.16**	**–0.35**	**–0.26**	**0.79**	1							
6 Spotify	**–0.15**	**–0.35**	**–0.31**	**0.63**	**0.58**	1						
7 Price	**0.27**	**0.38**	**0.22**	**–0.41**	**–0.45**	**–0.36**	1					
8 IPR protection	**0.66**	**0.53**	**0.58**	**0.39**	**0.16**	**0.13**	0.07	1				
9 Income	**0.56**	**0.40**	**0.46**	**0.60**	**0.36**	**0.27**	–0.01	**0.75**	1			
10 Individualism	**0.57**	**0.45**	**0.51**	**0.36**	**0.21**	**0.13**	–0.06	**0.56**	**0.51**	1		
11 Uncertainty avoidance	**–0.20**	**–0.14**	**–0.19**	–0.07	0.02	–0.02	0.06	**–0.28**	**–0.31**	**–0.19**	1	
12 Local repertoire share	**–0.10**	**0.10**	**–0.09**	**–0.13**	–0.03	**–0.08**	**–0.21**	**–0.33**	**–0.29**	**–0.11**	**0.11**	1

Note: Correlation coefficients in bold are significant at $p < 0.05$ or less (two-tailed). N = 782. BM = Business Model, IPR = Intellectual property rights

Table A.2

Correlations among Study 2 variables

	1	2	3	4	5	6	7	8
1 Piracy	1							
2 Streaming users	0.02	1						
3 Broadband	**0.39**	**0.42**	1					
4 IPR protection	**0.41**	**0.40**	**0.81**	1				
5 Income	**0.34**	**0.36**	**0.75**	**0.76**	1			
6 Individualism	**0.41**	**0.36**	**0.80**	**0.67**	**0.55**	1		
7 Uncertainty avoidance	**–0.15**	**–0.42**	**–0.39**	**–0.48**	**–0.40**	**–0.53**	1	
8 Number of artists	**–0.10**	**0.24**	**0.29**	**0.23**	**0.34**	**–0.22**	**0.19**	1

Note: Correlation coefficients in bold are significant at $p < 0.05$ or less (two-tailed). IPR = Intellectual property rights, N = 6,345.

Table A.3
Robustness tests (Study 1)

Independent variables	*MA1: Log(Phys. revenue)* Coeff. [CI]	*MA2: Log(Total revenue)* Coeff. [CI]	*MA3: Log(Phys. revenue)* Coeff. [CI]	*MA4: Log(Total revenue)* Coeff. [CI]
Intercept (γ_{00})	**1.555** [1.41; 1.69]	**1.969** [1.85; 2.09]	**1.555** [1.43; 1.68]	**1.971** [1.86; 2.08]
[Log](Broadband) (γ_{10})	**–0.086** [–0.11; –0.07]	**–0.054** [–0.08; –0.03]	**–0.363** [–0.44; –0.29]	**–0.320** [–0.38; –0.26]
iTunes (γ_{20})	–0.010 [–0.15; 0.13]	0.026 [–0.06; 0.12]	**–0.343** [–0.45; –0.23]	**–0.096** [–0.18; –0.01]
Spotify (γ_{30})	**–0.521** [–0.63; –0.39]	**0.153** [0.08; 0.23]	**–0.769** [–0.88; –0.66]	0.005 [–0.07; 0.08]
Trend (γ_{40})	**–0.130** [–0.23; –0.02]	**–0.197** [–0.29; –0.11]		
Log(INC) (γ_{01})	**1.239** [0.95; 1.51]	**1.271** [1.03; 1.51]	**1.257** [1.03; 1.48]	**1.265** [1.06; 1.46]
Log(IND) (γ_{02})	**0.468** [0.15; 0.78]	**0.394** [0.11; 0.67]	**0.505** [0.22; 0.79]	**0.429** [0.18; 0.67]
Log(UA) (γ_{03})	0.265 [–0.01; 0.54]	0.164 [–0.08; 0.41]	0.187 [–0.09; 0.46]	0.063 [–0.19; 0.31]
Log(LRS) (γ_{04})	0.008 [–0.25; 0.26]	0.031 [–0.19; 0.24]	0.120 [–0.05; 0.29]	0.115 [–0.03; 0.26]
Cross-level interaction				
[Log](Broadband) x Log(INC) (γ_{11})	**0.114** [0.06; 0.20]	**0.110** [0.06; 0.17]	**0.376** [0.23; 0.54]	**0.278** [0.16; 0.40]
[Log](Broadband) x Log(IND) (γ_{12})	0.037 [–0.01; 0.07]	0.009 [–0.03; 0.04]	**0.263** [0.12; 0.39]	**0.171** [0.05; 0.29]
[Log](Broadband) x Log(UA) (γ_{13})	**0.037** [0.01; 0.08]	**0.039** [0.01; 0.08]	**0.147** [0.03; 0.29]	**0.134** [0.02; 0.26]
[Log](Broadband) x Log(LRS) (γ_{14})	–0.006 [–0.04; 0.02]	0.000 [–0.03; 0.03]	–0.017 [–0.09; 0.06]	–0.013 [–0.86; 0.06]
iTunes x Log(INC) (γ_{21})	**0.302** [0.04; 0.56]	0.096 [–0.07; 0.27]	0.019 [–0.17; 0.20]	–0.072 [–0.23; 0.08]
iTunes x Log(IND) (γ_{22})	–0.024 [–0.32; 0.28]	0.071 [–0.13; 0.28]	–0.083 [–0.32; 0.15]	–0.041 [–0.24; 0.16]
iTunes x Log(UA) (γ_{23})	**0.424** [0.15; 0.69]	**0.185** [0.00; 0.36]	**0.323** [0.09; 0.56]	**0.269** [0.07; 0.47]
iTunes x Log(LRS) (γ_{24})	–0.011 [–0.26; 0.25]	0.013 [–0.15; 0.18]	0.056 [–0.08; 0.19]	0.011 [–0.10; 0.13]
Spotify x Log(INC) (γ_{31})	–0.020 [–0.28; 0.24]	–0.039 [–0.19; 0.12]	–0.172 [–0.40; 0.05]	–0.126 [–0.27; 0.02]
Spotify x Log(IND) (γ_{32})	–0.233 [–0.52; 0.06]	**–0.250** [–0.44; –0.06]	–0.030 [–0.30; 0.23]	**–0.184** [–0.36; –0.01]
Spotify x Log(UA) (γ_{33})	**0.632** [0.39; 0.87]	0.107 [–0.04; 0.26]	**0.364** [0.13; 0.60]	–0.033 [–0.19; 0.13]
Spotify x Log(LRS) (γ_{34})	0.080 [–0.13; 0.29]	0.056 [–0.08; 0.18]	0.002 [–0.14; 0.16]	0.025 [–0.07; 0.12]
Control variables				
Log(Price) (β_5)	**0.317** [0.17; 0.46]	**0.115** [0.03; 0.20]	**0.650** [0.49; 0.81]	**0.277** [0.18; 0.37]
Log(LagIPRProtection) (β_6)	0.027 [–0.19; 0.24]	**0.281** [0.15; 0.41]	0.176 [–0.04; 0.40]	**0.494** [0.35; 0.64]
Log(Income) (β_7)	**–0.450** [–0.88; –0.00]	**0.153** [–0.13; 0.45]	–0.419 [–0.84; 0.02]	0.203 [–0.06; 0.46]
Random effects				
Intercept (τ_{00}), [Log](Broadband) (τ_{11}), iTunes (τ_{22}), Spotify (τ_{33}), [Trend (τ_{44})], Residual (σ^2)	0.168, 0.002, 0.085, 0.067, 0.066, 0.249	0.131, 0.002, 0.046, 0.028, 0.061, 0.141	0.142, 0.016, 0.029, 0.038, 0.304	0.108, 0.020, 0.045, 0.020, 0.179
LOOIC (WAIC)	228.5 (203.9)	–645.7 (–677.3)	475.3 (466.1)	–345.4 (–353.5)

Notes: N = 782, CI = Credible Interval, 95% CI's in parentheses. MA1 & MA2 resemble the specifications of the main models M2 & M4 but the broadband variable is included in levels (instead of log-transformed); MA3 & MA4 resemble the specifications of M2 & M4 without the country-specific trend.

Table A.4

Robustness tests (Study 1)

Independent variables	*MA5: Log(Phys. revenue)* Coeff. (Cluster SE)	*MA6: Log(Total revenue)* Coeff. (Cluster SE)
I(0 < BB <= 8.5%)	**–0.220** (0.118) †	**–0.363** (0.086)***
I(8.5% < BB <= 25.6%)	**–0.566** (0.187)**	**–0.606** (0.144)***
I(BB > 25.6%)	**–0.991** (0.276)***	**–0.903** (0.182)***
iTunes	**–0.346** (0.067)***	**–0.149** (0.237)**
Spotify	**–0.673** (0.076)***	0.069 (0.050)
Log(Price)	**0.836** (0.128)***	**0.456** (0.097)***
Log(IPRProtection)	0.249 (0.246)	0.151 (0.237)
Interaction		
I(0 < BB <= 8.4%) x Log(INC)	0.148 (0.161)	0.185 (0.123)
I(0 < BB <= 8.4%) x Log(IND)	**0.668** (0.175)***	**0.484** (0.137)***
I(0 < BB <= 8.4%) x Log(UA)	0.016 (0.179)	–0039 (0.141)
I(0 < BB <= 8.4%) x Log(LRS)	0.039 (0.076)	0.030 (0.071)
I(8.4% < BB <= 25.6%) x Log(INC)	0.059 (0.289)	–0.346 (0.273)
I(8.4% < BB <= 25.6%) x Log(IND)	**1.198** (0.229)***	**0.775** (0.223)***
I(8.4% < BB <= 25.6%) x Log(UA)	–0094 (0.225)	–0.309 (0.205)
I(8.4% < BB <= 25.6%) x Log(LRS)	–0.104 (0.139)	0.024 (0.108)
I(BB > 25.6%) x Log(INC)	–0.151 (0.398)	–0.408 (0.323)
I(BB > 25.6%) x Log(IND)	**1.411** (0.364)***	**1.021** (0.253)***
I(BB > 25.6%) x Log(UA)	–0.431 (0.274)	**–0.445** (0.243) †
I(BB > 25.6%) x Log(LRS)	0.294 (0.204)	0.384 (0.133)
iTunes x Log(INC)	**0.282** (0.114)*	**0.167** (0.076)*
iTunes x Log(IND)	–0.019 (0.124)	0.024 (0.093)
iTunes x Log(UA)	**0.367** (0.154)*	**0.291** (0.120)*
iTunes x Log(LRS)	**–0.096** (0.057) †	**–0.149** (0.049) **
Spotify x Log(INC)	–0.165 (0.159)	–0.158 (0.098)
Spotify x Log(IND)	0.104 (0.192)	–0.124 (0.119)
Spotify x Log(UA)	**0.434** (0.126)***	–0.053 (0.083)
Spotify x Log(LRS)	–0.133 (0.100)	–0.059 (0.050)
R^2 (within)	0.868	0.762

Notes: † p < 0.1,* p < 0.05, **p < 0.01, ***p < 0.001; BB = Broadband

In this robustness test, we replace the broadband variable by a set of dummy variables and assess the extent to which there are non-linearities. In these models, the broadband variable is represented by a set of indicator variables (step dummies) that turns one if the condition in the parentheses is met. The categories are 1) BB = 0% (reference category), 2) 0 < BB <= 8.5% (the median), 3) 8.5% < BB <= 25.6% (the 3rd quartile), and 4) BB > 25.6%. Please note that we had to remove the trend variable from this model due to collinearity problems with the indicator variables. Our overall assessment is that the general conclusions also hold under this model specification.

Table A.5

Robustness tests (Study 2)

	MA7: Log(Piracy)	*MA8: Log(Piracy)*	*MA9: Log(Piracy)*
Independent variables	Coeff. (Cluster SE)	Coeff. (Cluster SE)	Coeff. (Cluster SE)
I(StreamingIntro = 1) (β_1)	**–0.110** (0.062)†		
Log(StreamingUsers) (β_1)			**–0.019** (0.008)*
I(0 < WeekSinceIntro <= 37) (β_{1a})		–0.054 (0.052)	
I(37 < WeekSinceIntro <= 70) (β_{1b})		**–0.372** (0.113)***	
I(WeekSinceIntro > 70) (β_{1c})		**–0.699** (0.157)***	
Log(Broadband) (β_2)	0.180 (0.159)	0.082 (0.157)	0.167 (0.160)
Log(Income) (β_3)	–0.537 (0.769)	–0.577 (0.731)	–0.530 (0.764)
Log(IPRProtection) (β_4)	–0.112 (0.066)	–0.048 (0.218)	–0.112 (0.764)
Log(NumberOfArtists) (β_5)	**1.213** (0.367)***	**1.329** (0.353)***	**1.227** (0.364)***
R^2 total (within)	0.976 (0.078)	0.977 (0.110)	0.977 (0.082)

Notes: N = 18,900 (number of countries = 140, number of weeks = 135), † p < 0.1,* p < 0.05, **p < 0.01, ***p < 0.001

In this model specification, we estimate the effect of the introduction of the streaming service on the log-transformed piracy units in week t in country i, using a difference-in-difference approach that also includes countries in which the streaming services had not yet been introduced as control group. In this specification, we exclude the countries in which the streaming service had been introduced before the observation period because for these countries no information is available from before the introduction. The focal independent variable in this model is a step dummy that turns one after the streaming service had been introduced in a given market. In addition, we include all control variable from our main model (M7) and add country and week fixed effects to control for unobserved time- and country-specific effects. Thus, the formal representation of the model MA7 is given by:

$$\begin{aligned} \log(Piracy_{ti}) = \beta_1 StreamingIntro_{ti} + \beta_2 \log(Broadband_{ti}) + \\ \beta_3 \log(Income_{ti}) + \beta_4 \log(IPR_{t-1i}) + \\ \beta_5 \log(NumberOfArtists_{ti}) + \eta_t + \mu_i + \varepsilon_{ti}, \end{aligned} \quad \text{(A.1)}$$

The magnitude of the coefficient associated with the introduction dummy ($\boldsymbol{\beta_1}$= –0.110) suggests that piracy levels decreased by approximately 10.4% (i.e., 100*($\boldsymbol{e^{\beta_1} - 1}$)) after the introduction of the streaming service, supporting the results of our main model.

In another model specification (MA8), we create separate dummy variables that turn one for different periods after the introduction of Spotify (see Datta et al. 2018 for a similar approach). The aim was to investigate if the introduction effect changes over time. The time periods that we consider are: 1) 0 weeks (reference category), 2) 1-37 weeks (the median), 3) 37-70 weeks (the 3rd quartile), and 4) >70 weeks. Thus, the formal representation of this model is given by:

$$\log(Piracy_{ti}) = \beta_{1a}I(0 < WeeksSinceIntro_{ti} \leq 37) + \beta_{1b}I(37 < WeeksSinceIntro_{ti} \leq 70) + \beta_{1c}I(WeeksSinceIntro_{ti} > 70) + \beta_2\log(Broadband_{ti}) + \beta_3\log(Income_{ti}) + \beta_4\log(IPR_{t-1i}) + \beta_5\log(NumberOfArtists_{ti}) + \eta_t + \mu_i + \varepsilon_{ti}, \tag{A.2}$$

The results suggest that the negative effect of streaming services on piracy increases over time. Specifically, our estimates suggest that the piracy levels decreases by 5.3% in the short-term (i.e., 1-37 weeks after the introduction), by 31.1% in the mid-term (i.e., 38-70 weeks after the introduction), and by 50.3% in the long-term (i.e., more than70 weeks after the introduction).

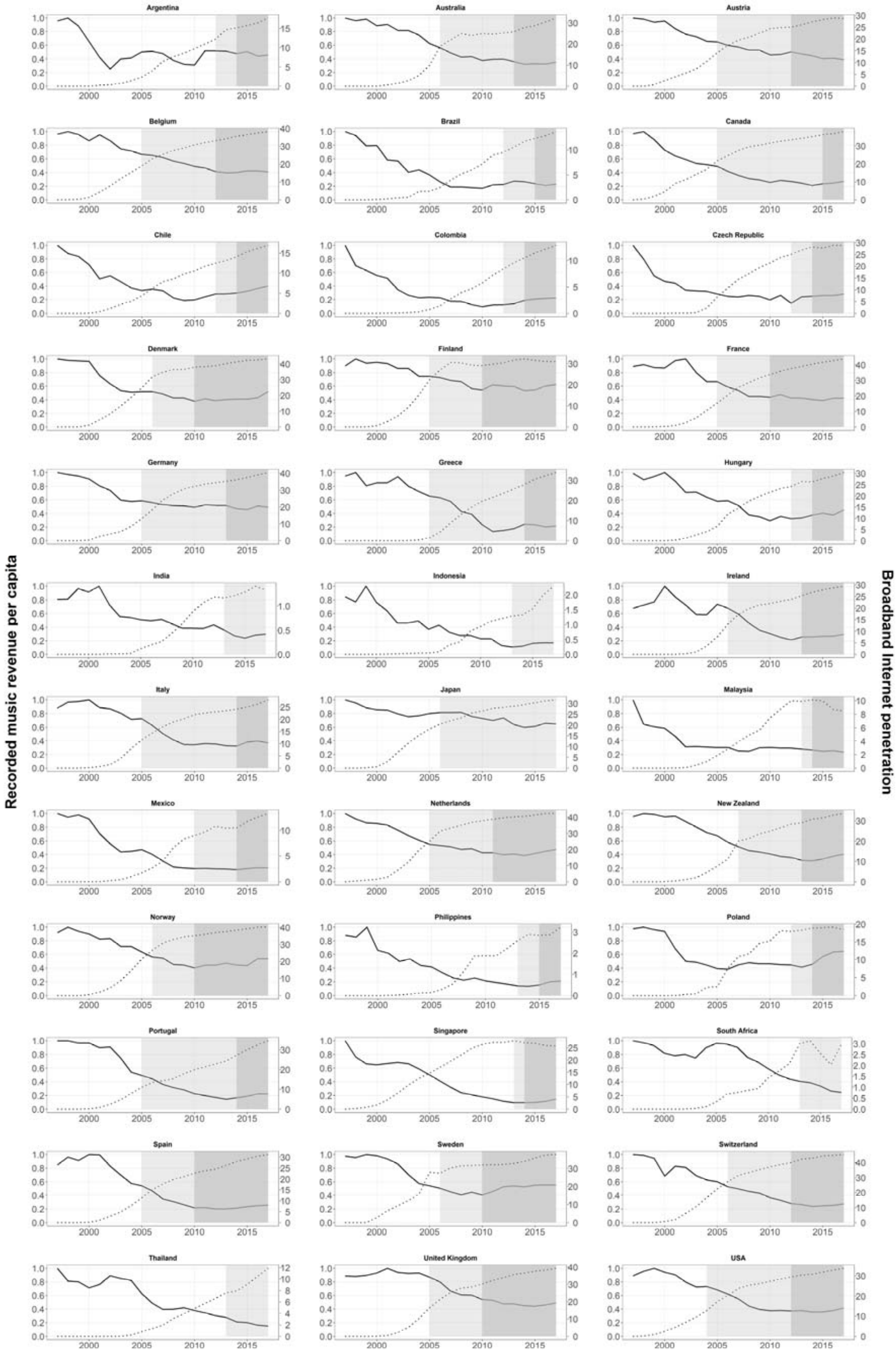
The specification reported under MA9 contains the same focal independent variables that we used in our main model (i.e., the number of streaming adopters; M7) and shows a negative effect.

Reference:

Datta, H. Knox, George, & Bronnenberg, B.J. (2018). Changing Their Tune: How Consumers' Adoption of Online Streaming Affects Music Consumption and Discovery. *Marketing Science*, 37(1), 1-175.

Figure A.1

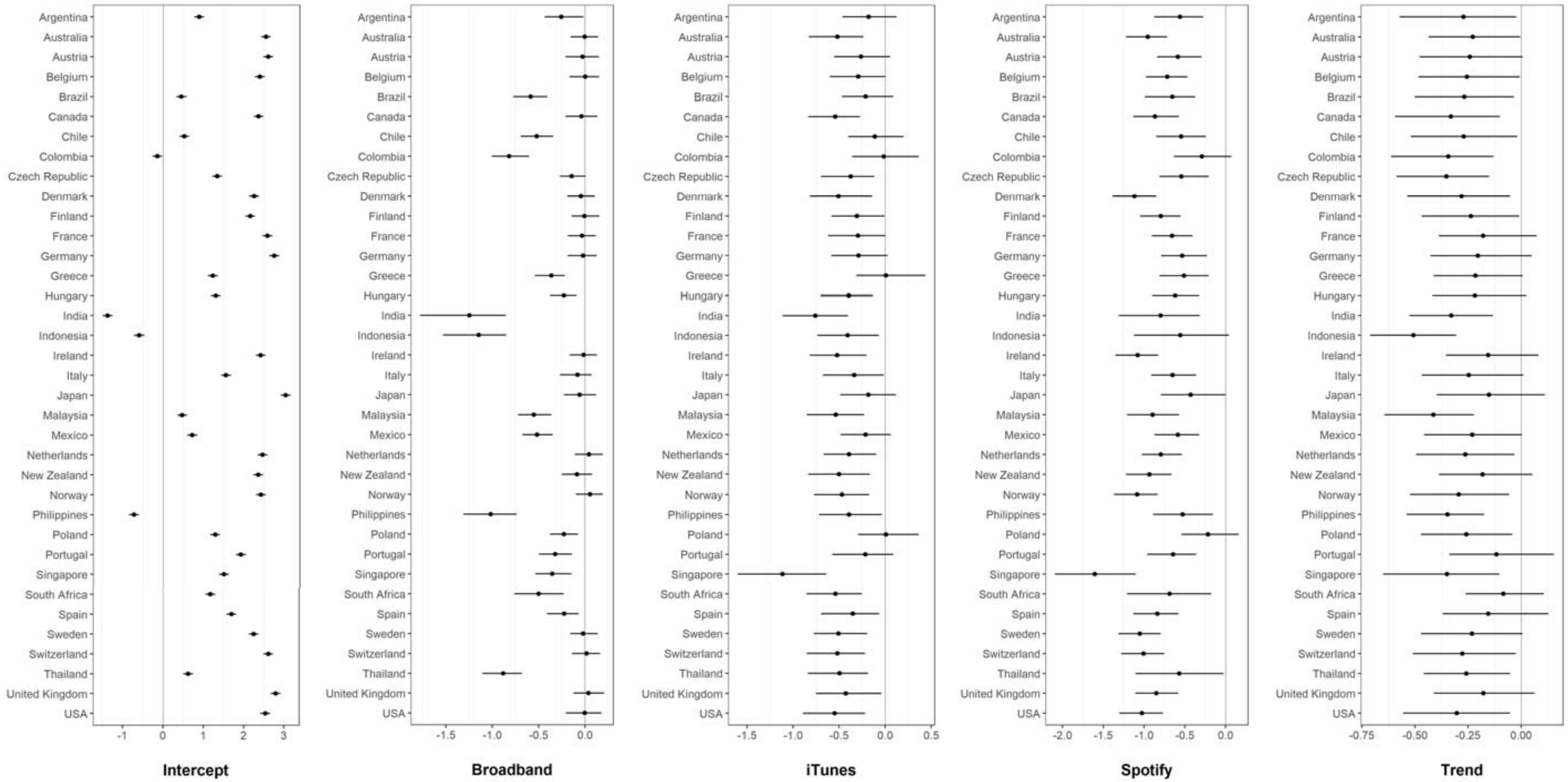
Revenue and broadband Internet penetration by country



Note: grey (dark grey) areas indicate the introduction of new digital business models iTunes (Spotify)

Figure A.2

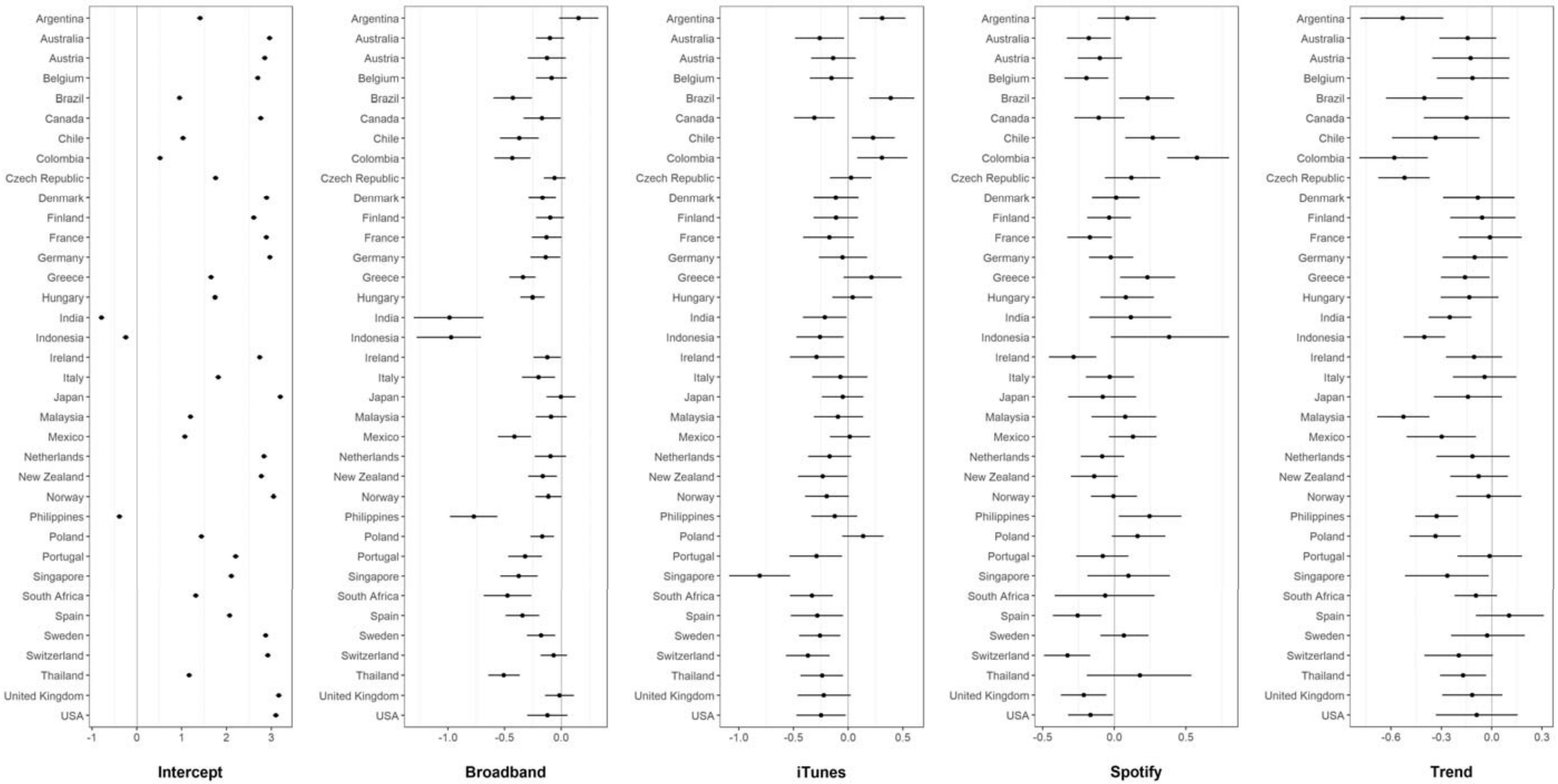
Posterior median estimates and 95% CIs for random intercepts and slopes in model 2



Note: The figure was created based on model 2 estimates. It shows the country-specific intercepts and slopes for the indicated variables.

Figure A.3

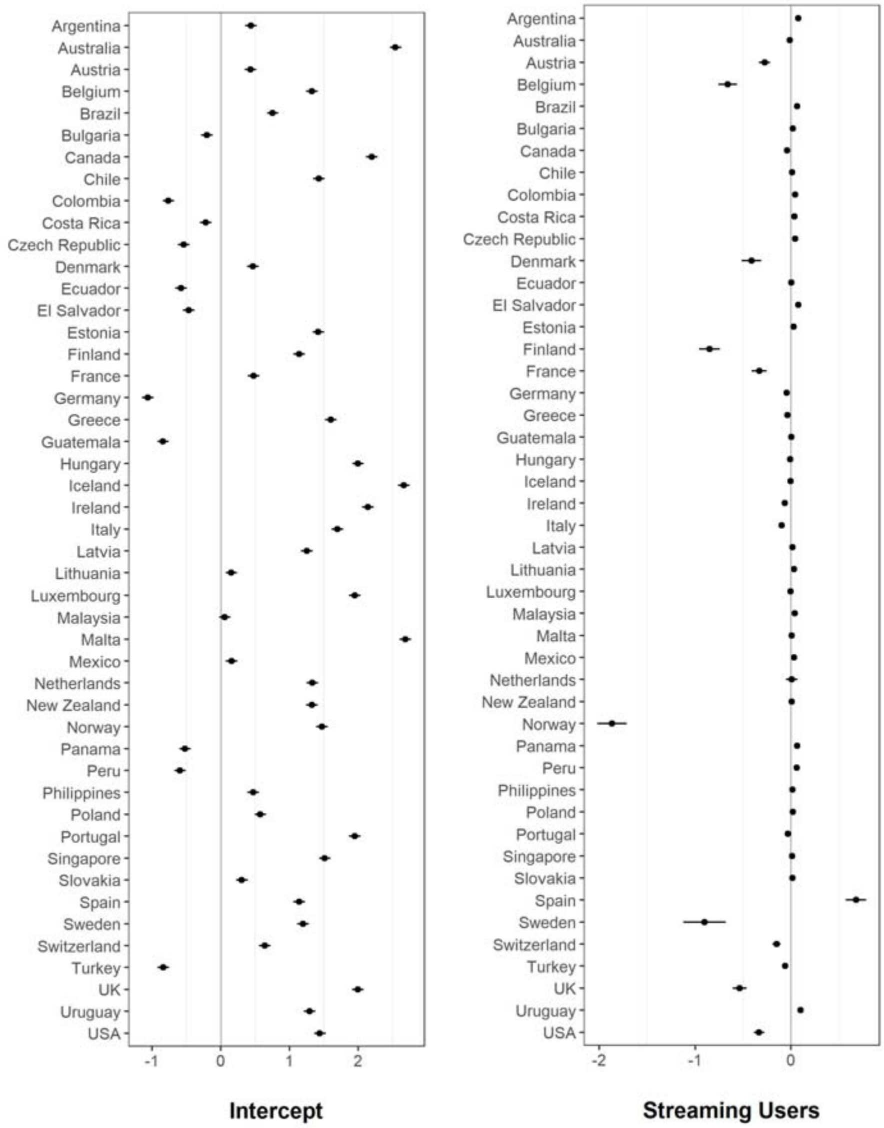
Posterior median estimates and 95% CIs for random intercepts and slopes in model 4



Note: The figure was created based on model 4 estimates. It shows the country-specific intercepts and slopes for the indicated variables.

Figure A.4

Posterior median estimates and 95% CIs for random intercepts and slopes for model 7



Note: The figure was created based on model 7 estimates. It shows the country-specific intercepts and slopes for the indicated variables.

Figure A.5

Posterior predictive check model 2

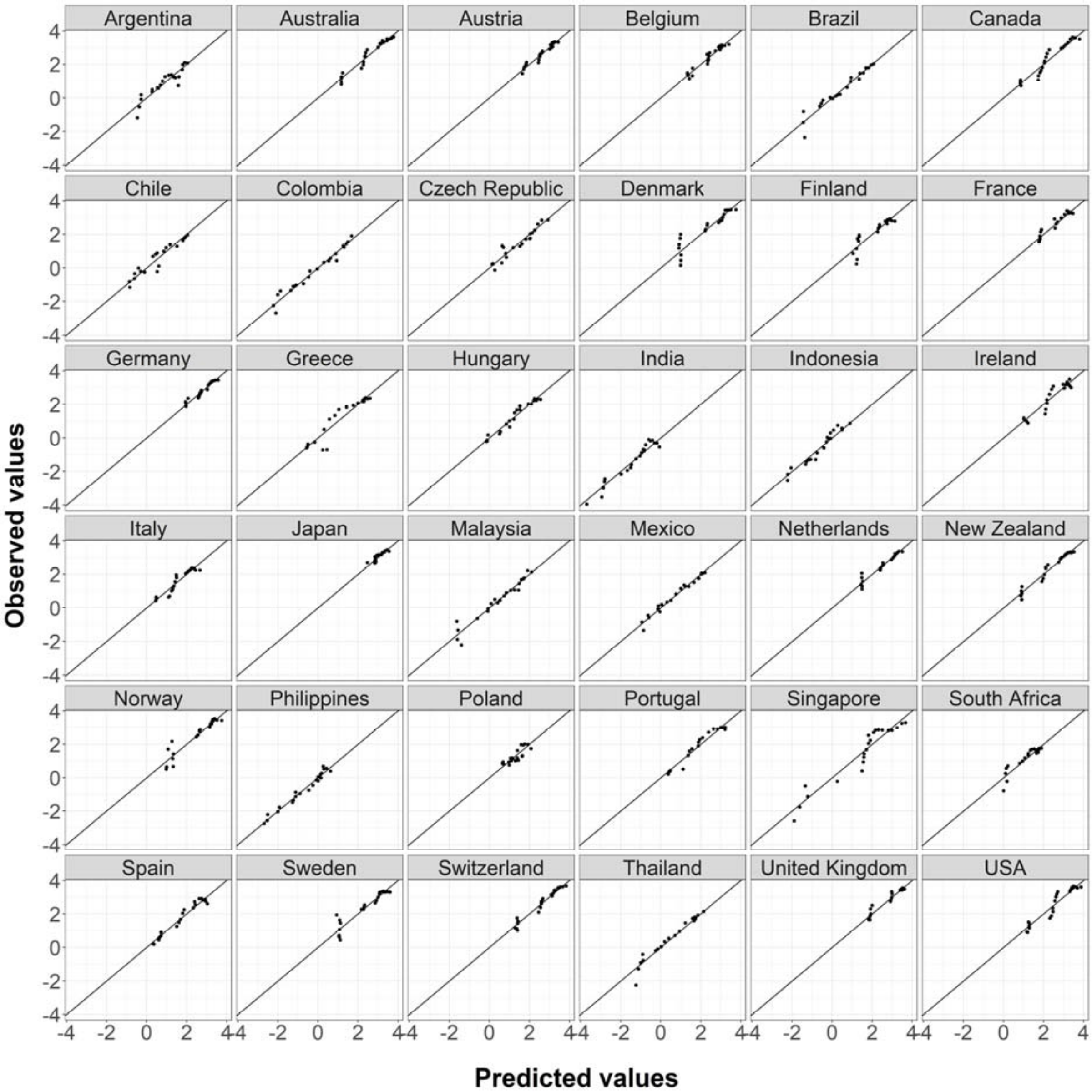


Figure A.6

Posterior predictive check model 4

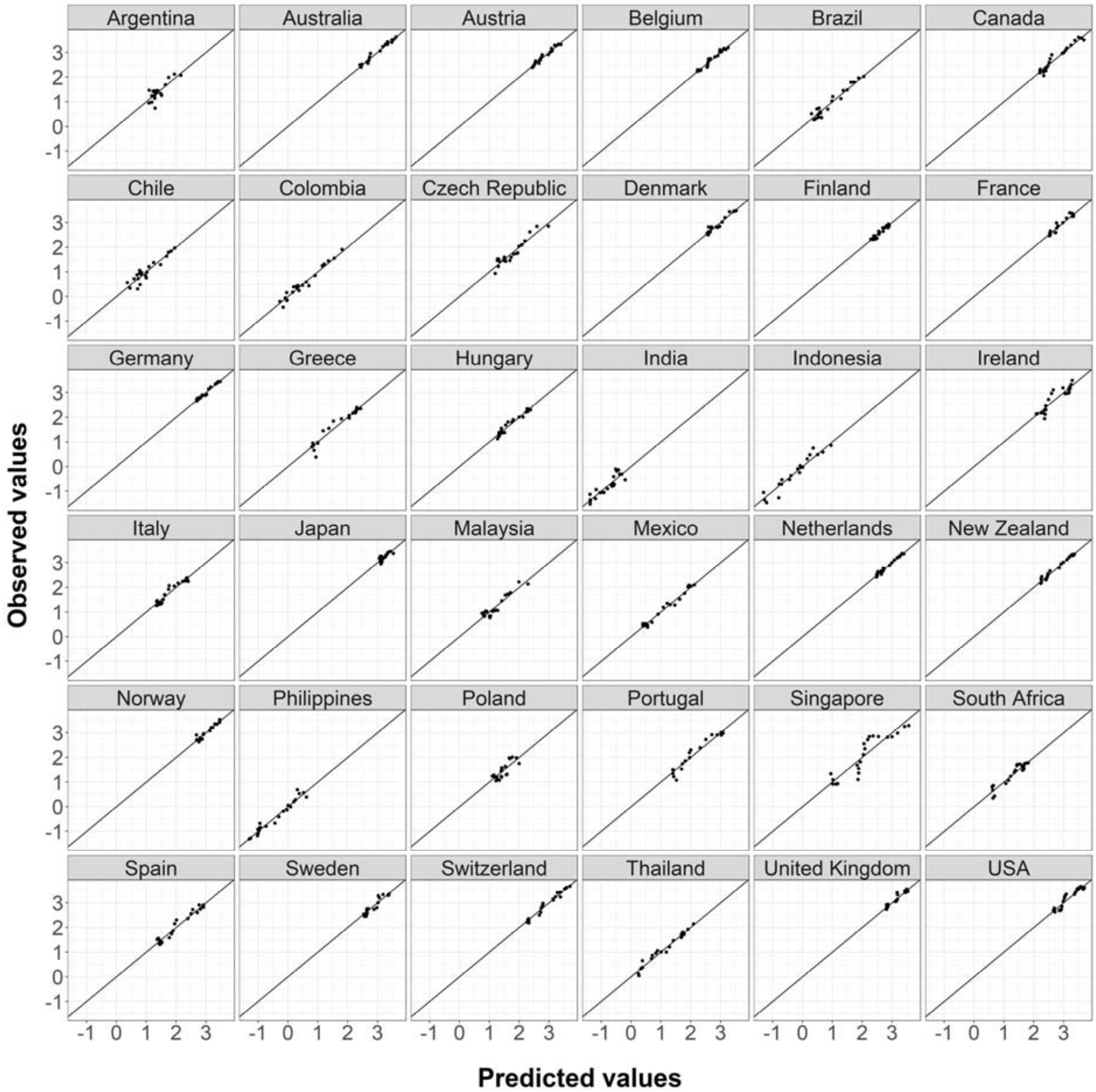


Figure A.7

Posterior predictive check model 7

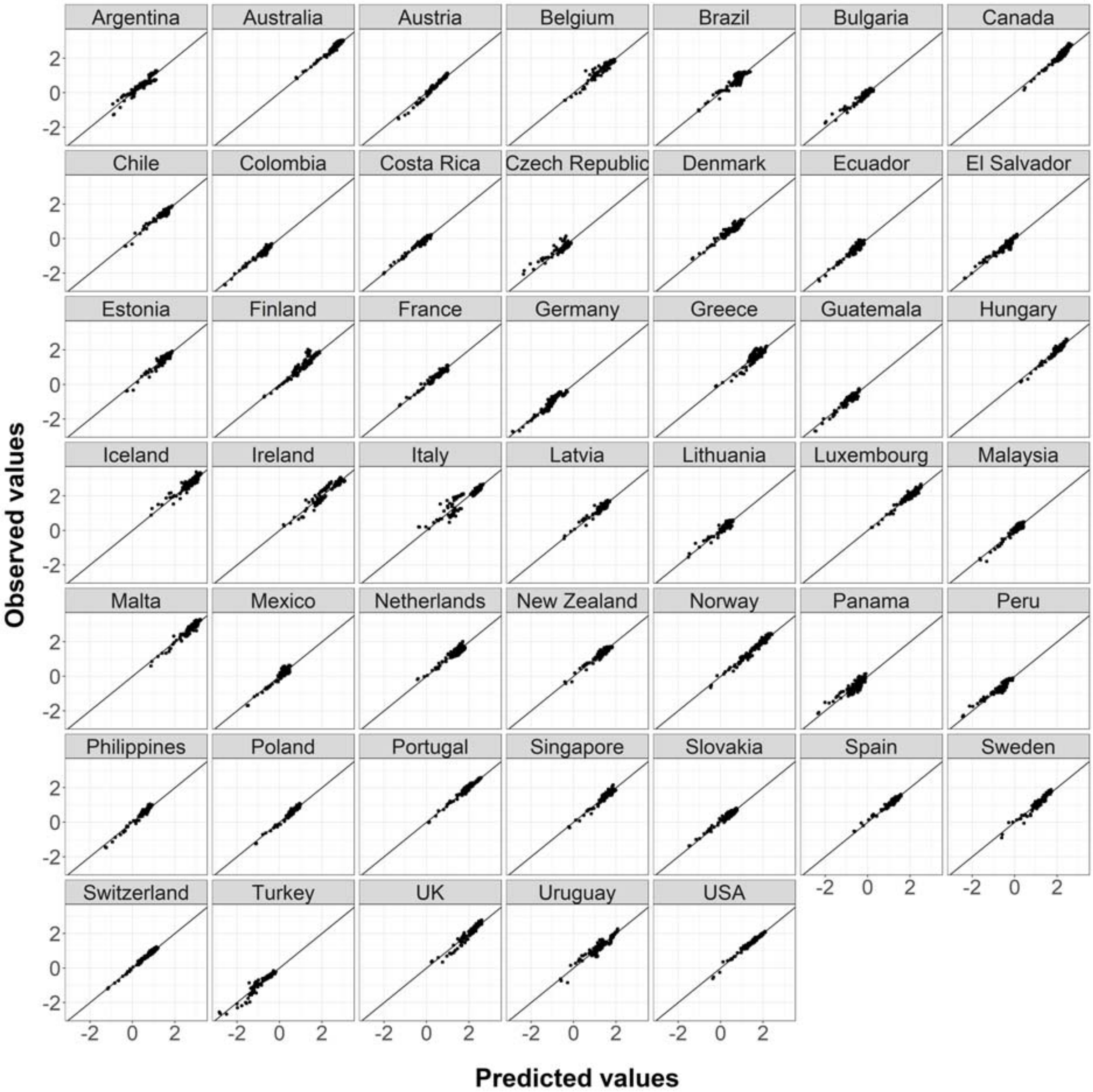


Figure A.8

Density overlay model 2

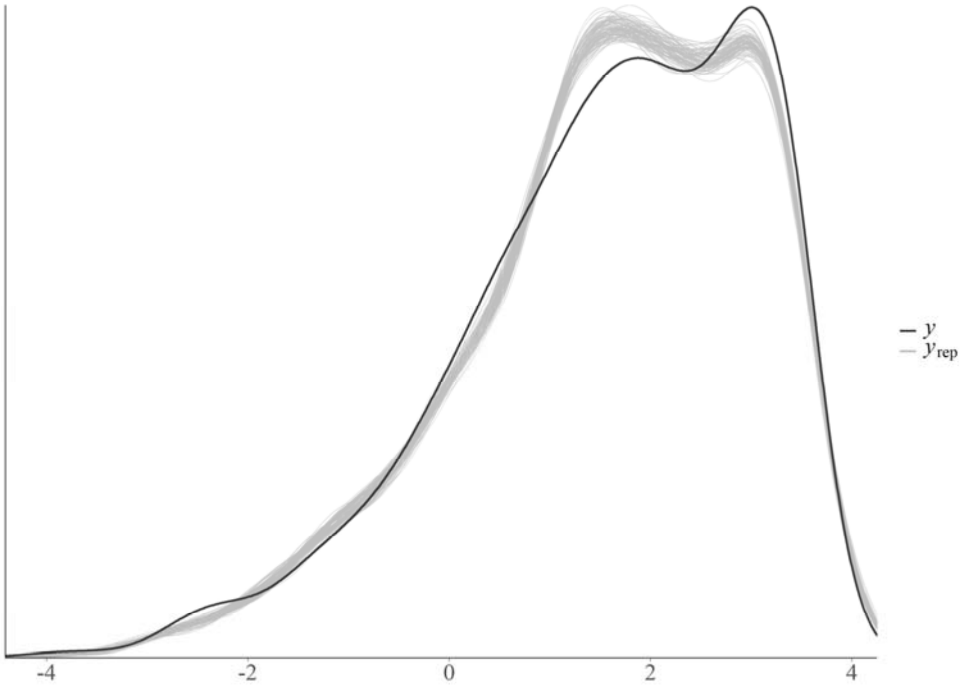


Figure A.9

Density overlay model 4

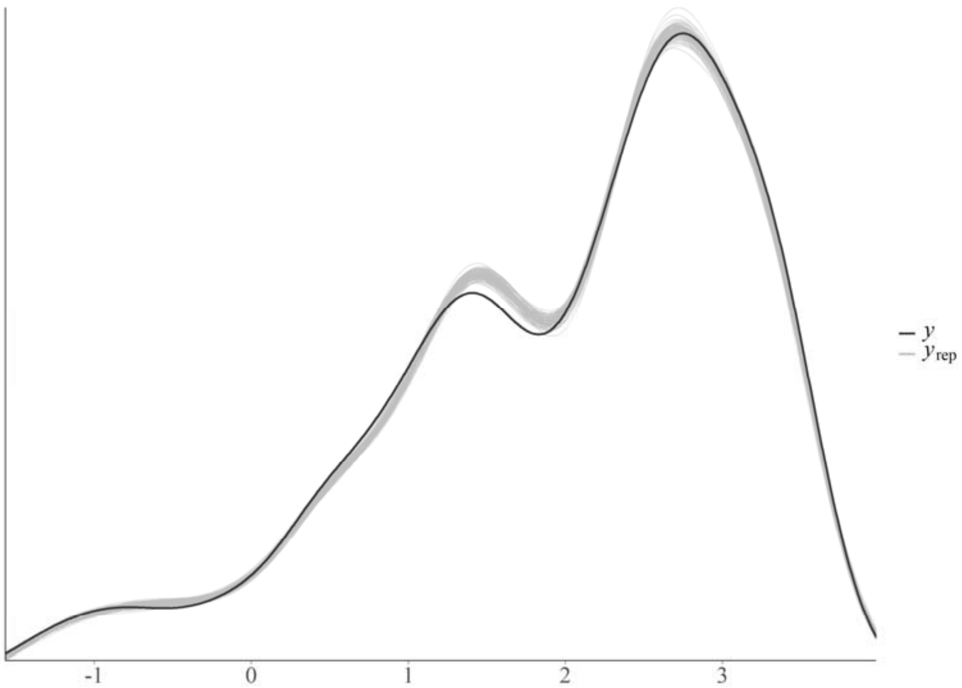
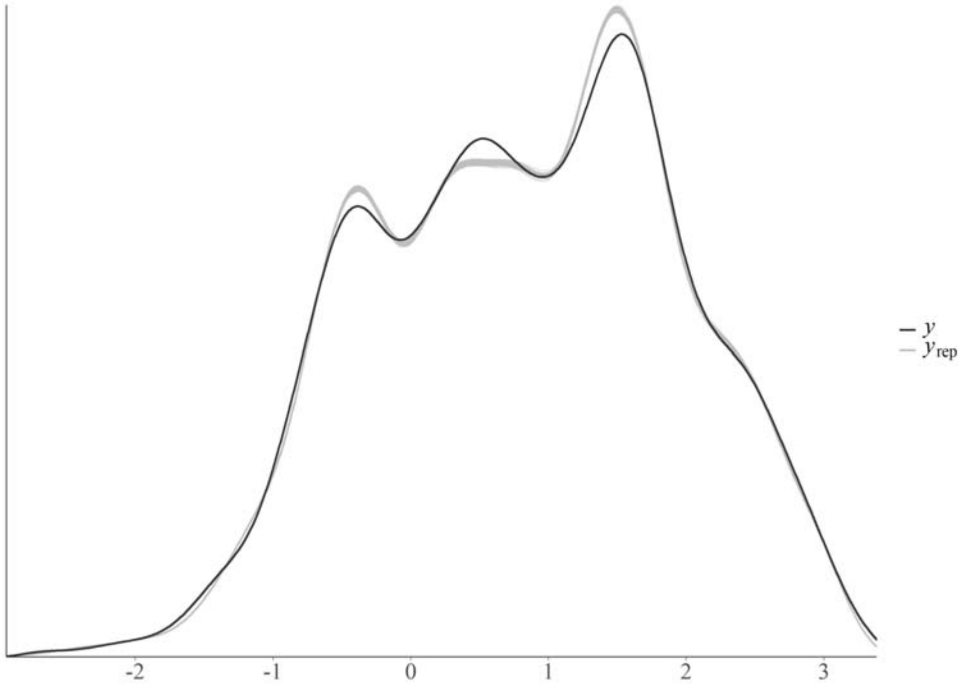


Figure A.10

Density overlay model 7



Appendix B

Price Measurement

Because we observe both units sales and revenue in the IFPI reports, we can compute the average price per unit of music purchases per country per year. IFPI reports revenues in retail value before 2001, in retail and trade value from 2001 to 2005 and in trade value since 2006. To allow for a comparison across years, we convert the historical retail values for the years before 2005 to trade 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 only 0.043.

We follow Talukdar, Sudhir, and Ainslie (2002) and rely on purchasing power parity (PPP) adjusted measures when converting from local currencies to US dollars to account for differences in prices across countries. We assign a weight of 1 to album sales (i.e., CD-, MC-, LP-, and digital albums) and convert physical singles to album units by assigning a weight of 1/3 to physical single sales (i.e., 3 singles = 1 album). To obtain the average album price, we divide the revenue from these physical formats by the number of units sold. Because revenues are reported in trade value, the price represents the wholesale price. The mean wholesale price for a unit (= music album) over the observation period was US$ 9.13. Due to the absence of reliable data on unit sales for the years 2016 & 2017 for countries Czech Republic, Denmark, Greece, Indonesia, Norway, Portugal, Thailand, and South Africa, we replace the respective values with the price from 2015. This does not influence the conclusions of our study.

Reference:

Talukdar, D., Sudhir, K., & Ainslie, A. (2002). Investigating new product diffusion across products and countries. *Marketing Science*, 21(1), 97–114.