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Video Killed the Radio Star? Online Music Videos and Digital Music Sales

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Abstract
Sampling poses an interesting problem in markets with experience goods. Free samples reveal product quality and help consumers to make informed purchase decisions (promotional effect). However, sampling may also induce consumers to substitute purchases with free consumption (displacement effect). We study this trade-off in the market for digital music where consumers can sample the quality of songs by watching free music videos online. Identification comes from a natural experiment in Germany, where virtually all videos that contain music are blocked on a popular video platform due to a legal dispute with representatives of the rights-holders. We show that promotional and displacement effects cancel out in the sales performance of individual songs, whereas online music videos trigger sales of albums.

Key words: Sampling, displacement, promotion, natural experiment
JEL: L82, M37, D83

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1 Introduction

Information is of special importance in markets with experience goods, where product quality cannot be completely assessed prior to consumption. Consumers collect external information from popularity rankings (Tucker and Zhang, 2011; Hendricks et al., 2012), recommendations (Oestreicher-Singer and Sundararajan, 2012; Dewan and Ramaprasad, 2012) and from related products whose quality attributes are already known (Hendricks and Sorensen, 2009). Firms advertise to inform consumers about product quality. A specific form of advertising is to disclose product quality by letting consumers try (parts or versions of) the product for free.[1] Examples of such advertisements are coupons and tastings at retail stores, shareware, radio airplay, and music videos. Trying before buying helps consumers to find out whether product characteristics match their preferences. This process is usually referred to as sampling.

Disclosing quality with free samples is of course costly. For example, physical experience goods such as wine or food clearly have non-zero marginal cost. In other cases, such as digital music, marginal costs are negligible, but consumers may perceive the sampling of an online music video as a close substitute to actually buying a song, especially if the song is not consumed repeatedly and via on- and offline channels. Trading-off these costs and benefits, firms can set the optimal level of sampling, i.e. how much information to disclose (Jain et al., 1995; Bawa and Shoemaker, 2004; Chellappa and Shivendu, 2005; Halbheer et al., forthcoming).

However, finding the optimal level of sampling is often not a relevant problem in digital markets. For example, music and movies files are regularly uploaded to Internet platforms (which may or may not have licenses for the distribution of such content), leaving the firm little control about whether and how much product information to disclose (Peitz and Waelbroeck, 2006; Gopal et al., 2006; Bhattacharjee et al., 2006, 2007). The interesting question then is if sampling can still be an effective trigger of demand even if the firm

[1] When quality is costly, advertising may not be credible. Theory suggests two mechanisms to solve this problem. The firm can either build a reputation for quality in a repeated interaction with the consumer (Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984), or directly disclose its true level of quality. The latter is credible either because it is costly to reveal quality or because firms have an incentive to be associated with their true quality in a sequential process of quality unraveling in the market (Grossman, 1981; Milgrom, 1981; Dranove and Jin, 2010).

cannot keep some consumers from consuming the sample instead of buying the product (Wang and Zhang, 2009).

We study this question in the empirical context of digital music. The easiest way to find out whether a song matches individual preferences is to search for the song on the Internet. In most cases, this will lead consumers more or less directly to watching a music video clip on *YouTube*.[2] Not so in Germany. Because of an ongoing royalties dispute between *YouTube* and representatives of the rights-holders, a very large fraction of videos that contain music cannot be accessed in Germany.[3] Much of the same content is easily accessible in a vast majority of other countries.[4]

We make use of this unique experiment-like setting to study the link between sampling on *YouTube* and purchases at the *iTunes* store. Identification comes from cross-country and temporal variation in a difference-in-differences setting, where we look at sales dynamics in response to changes in the supply of online videos, comparing Germany to nine other countries. Our sample consists of the daily top 300 songs and albums sold on *iTunes* between February 15th and August 26th 2013 in Australia, Austria, Canada, France, Germany, Italy, Spain, Switzerland, United Kingdom and the United States. We also observe the top 25 country-specific search results on *YouTube* for each song and day. For every video we know in which countries it is not available. From this information we construct a song-level measure of country-specific availability of music videos on *Youtube*.

We show that the promotional effect of online music videos is big enough to offset sales displacement of songs even when firms cannot control how intensely consumers sample. We further show that the displacement effect dominates when products become relatively more expensive, while the promotional effect dominates when sampling is only informative about a fraction of product characteristics. Our estimates for the latter suggest that a

[2] According to an online survey of 3,000 consumers in the US (Nielsen ePanel 2012, `http://tinyurl.com/pssqb8m`), the top three ways consumers mostly discover music is through the radio (48%), friends and relatives (10%), and *YouTube* (7%). Consumers under the age of 20 listen to music more often on *YouTube* (64%) than on the radio (56%), through iTunes (53%) or on CD (50%). Digital stores such as *Amazon*, *iTunes* and *Beatport* also offer 30–90 seconds samples for free. However search results for songs usually list music video pages much higher than digital stores. In the case of *Google* as the search engine, this is not surprising because *YouTube* is a *Google* product.

[3] See New York Times, 'Royalty Dispute Stops Music Videos in Germany', April 2, 2009, `http://tinyurl.com/lck339s`.

[4] More than 60% of the 1000 worldwide most viewed videos (which do not all contain music) are blocked in Germany, while only 0.9% are not accessible in the US, see `http://apps.opendatacity.de/gema-vs-youtube/en`.

ten percent increase in available videos leads to a two percent increase in sales of the corresponding album.

Our findings have important implications for policy interventions in the context of digital piracy. If promotional effects can offset losses even without indirect compensation via royalties or shared advertising revenues, this may mean that restricting unpaid consumption can have negative effects on overall welfare.

2 A Natural Experiment in the Market for Online Videos

The video platform *YouTube* provides a unique setting to study the effect of online music videos on digital music sales. With some 34 million monthly visits from Germany alone in 2012, *YouTube* is by far the most popular video portal. The second most popular video portal in Germany (*myvideo.de*) only receives 16% of *YouTube*'s traffic (see table A.2). A large portion of the most popular videos on *YouTube* are music video clips. While *YouTube* has contracts with rights-holders in most countries, the question of corresponding compensation is subject to a legal dispute between *YouTube* and *GEMA* in Germany.

GEMA (Gesellschaft für musikalische Aufführungs- und mechanische Vervielfältigungsrechte, society for musical performing and mechanical reproduction rights) is the state-authorized (de-facto monopolist) collecting society and performance rights organization in Germany.[5] Collecting societies exist to ensure that royalties from any kind of reproduction (e.g. physical reproduction, public performance, radio airplay, etc.) arrive at artists and publishers, making them important institutions for artists, because royalties are a major part of income, independent of any private contracts with record labels (Kretschmer, 2005). A large international network of sister collection societies represents the rights of German artists/publishers in international markets, and *GEMA* fulfills the role for international artists/publishers in the German market. That is, virtually every professional musician is either directly or indirectly a member of *GEMA*, which is also reflected in the so-called '*GEMA* presumption', a case law presumption that rights of all musical works are managed by *GEMA*.[6]

[5] Examples for international counterparts are BMI, ASCAP and SESAC in the United States of America, PRS in the United Kingdom, SACEM in France and SGAE in Spain.

[6] See `http://tinyurl.com/9d38k88`. According to the annual report, *GEMA* had 67,266 members and

Since a first agreement between *YouTube* and *GEMA* had expired in 2009, there are ongoing negotiations about the appropriate level of compensation. In fear of high subsequent payments, *YouTube* began blocking music videos in April 2009.[7] Because of the *GEMA* presumption, *YouTube* has large incentives to block every video that contains music.[8] Not surprisingly therefore, 60% of the 1000 most viewed videos worldwide are blocked in Germany, while only 0.9% are not accessible in the US.[9]

Specific legal issues seem to make it complicated to reach an agreement. According to a statement by Rolf Budde, member of the *GEMA* advisory board, *Youtube* insists on a non-disclosure agreement.[10] Because *GEMA* is required by law to publish the exact royalty paying schemes in the Bundesanzeiger, an official publication of the Federal Republic of Germany (similar to the Federal Register in the United States), this is not feasible.[11] Reportedly, because of this deadlocked situation, negotiations have been broken off, and the involved parties started to consult the arbitration board of the German Patent and Trademark Office for mediation in January 2013.[12]

2.1 Supply-Side Reactions

Anecdotal evidence suggests that the *GEMA*-*YouTube* dispute is controversial among German artists, which may explain why the negotiation strategy of *GEMA* (democratically representing its members) appears to be unchanged since 2009.

Some artists seem to believe in the promotional effect of online music videos. For example, the electro/hip-hop band *Deichkind* posted a raging comment on their *Facebook* page after

distributed 692,3 million Euro in royalties in 2012.

[7] See New York Times, 'Royalty Dispute Stops Music Videos in Germany', April 2, 2009, `http://tinyurl.com/lck339s`.

[8] We therefore have no reason to believe that there is an underlying non-random process that leaves some videos online. See footnote 19 for a detailed discussion.

[9] See `http://apps.opendatacity.de/gema-vs-youtube/en`.

[10] Budde made that statement being a panelist at an industry conference in January 2013. Perhaps ironically the corresponding video can be found on *YouTube*: `http://tinyurl.com/ndyrprc`.

[11] §13(2), Gesetz über die Wahrnehmung von Urheberrechten und verwandten Schutzrechten (UrhWahrnG; Law on the Administration of Copyright initiated in 1965).

[12] See `http://tinyurl.com/oz2gk4c`. This is an official procedure provided in §14 UrhWahrnG. It is worth noting that *YouTube* has been claiming that videos are not available "because GEMA has not granted the respective music publishing rights." According to a court ruling in February 2014 this is unlawful, because *GEMA* is obliged by law to grant rights of use to anybody under reasonable conditions on request (§11 (1) UrhWahrnG, see `http://tinyurl.com/qe23yvv`). Still, this has introduced *GEMA*, as a very specific institution that normally does not operate much in the public focus, to a large audience and turned public opinion (at least among German Internet users) largely against it.

finding out that their newly uploaded music video was being blocked.[13] Much in contrast, rap musician *Jan Delay* and the rockband *Element of Crime* say in interviews that they don't think that a potential promotional effect of *YouTube* can outweigh losses due to substitution.[14] Accordingly, both argue for an adequate compensation from streaming services to counteract sales displacement.

Although it is in principle possible for publishers and artists to negotiate independent contracts with any online and offline licensee, it seems unlikely that individual publishers and artists drop out of *GEMA* or their national collecting society to reach agreements with *YouTube* in Germany.[15] First, royalty income from digital distribution may represent too small an amount to forgo all other royalty income. Second, by joining a collecting society, individuals benefit from reduced contracting cost and increased bargaining power. This is even more beneficial for members of international collecting societies where it can be especially costly to negotiate with various potential licensees abroad.

Record labels are per definition not members of *GEMA* and therefore do not receive any royalty income. On top of a potential positive effect on record sales, they can directly benefit from advertising revenues generated by *YouTube*. Not very surprisingly therefore, representatives of *Sony Music* and *Universal Music* have publicly criticized *GEMA* for not working more towards an agreement.[16]

2.2 Demand-Side Reactions

A first natural reaction of consumers would be to search the Internet for alternatives. Surprisingly, this doesn't seem to play a big role. Figure 1 shows Google search trends for the six major platforms for music videos in Germany. While the search term 'youtube'

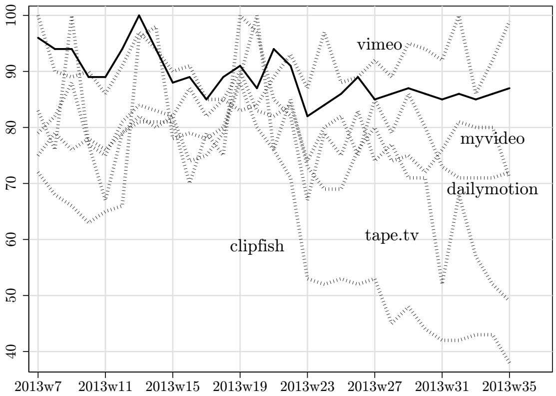
[13] The posting from March 9th, 2012 reads "Whether it's the record label, YouTube or GEMA, whoever's responsible. We want our videos to be seen. Finally get your shit sorted out and do your homework! You are a barrier to evolution and you are irritating the crap out of us.", `http://tinyurl.com/omeudbe`.

[14] The interview with *Jan Delay* was published in Der Spiegel 16/2012, `http://tinyurl.com/nfzc3fa`. In a interview with Radio Bayern 2, Sven Regener, singer of *Element of Crime*, says (referring to *YouTube*): "A business model based on people who produce the content not getting any money is not a business model, it's crap. Otherwise people are welcome to have Kim Schmitz *(founder of the filesharing website Megaupload)* sing the songs to them", see `http://tinyurl.com/7j4hk25`.

[15] After careful research, we could only find anecdotal evidence of one case where a band seemingly has opted out of *GEMA*. Videos in the official *YouTube* channel of the successful German punk-rock band 'Die Ärzte' are accessible in Germany. See `http://tinyurl.com/ov6ou67` (only in German). It is not clear whether the band opted out of *GEMA*. When we asked the management of the band, they did not want to comment on the issue.

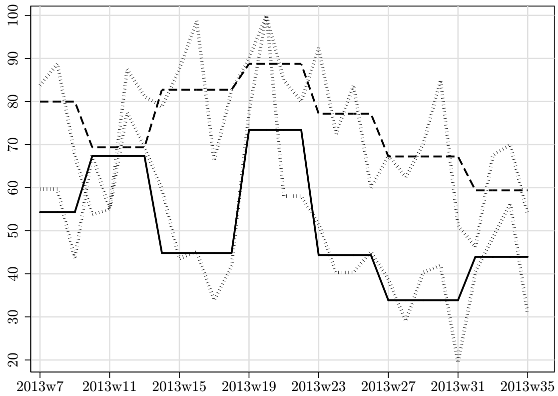
[16] See billboard.com, 2011, `http://tinyurl.com/oz8ms9j`.

Figure 1: Video Portals in Germany



***Relative Search Volume on Google**, Germany*
— *Search Volume for* 'youtube'
··· *Search Volume for* 'clipfish', 'dailymotion', myvideo', 'tape.tv', 'vimeo'

Figure 2: Unblocking YouTube



***Relative Google Search Volume**, Germany*
— 'youtube entsperren', *monthly average*
- - - 'unblock youtube', *monthly average*
··· *Respective weekly data*

remains fairly stable in our sample period (solid line), search terms related to other video sites show more variation, but there are no clear positive trends. An explanation could be that those keywords with less absolute search volume experience more noise. Importantly however, this suggests that no website has captured significant market share from *YouTube*. Some portals like *clipfish* and *tape.tv* even show decreasing trends. A second way consumers could circumvent the restrictions in Germany is the use of browser plug-ins or proxy servers that make a computer appear to be based outside of Germany. Google search data in figure 2 shows that there is some variation in the popularity of such keywords as 'unblock youtube' (and the same phrase in German), but there is no clear upward or downward trend visible.[17] It seems unlikely therefore that our estimates of the effect of video restrictions on *YouTube* are largely biased because of endogenous consumer behavior, at least in the observed period.

Given all these arguments, we conclude that the dispute between *GEMA* and *YouTube* is exogenous to sales in the recording industry. Because of legal issues the reason for not reaching an agreement is exogenous even to *GEMA* as a directly involved party. Almost needless to say, the shock is not only exogenous but relevant. *YouTube* has repeatedly produced super stars for the recording industry, e.g. PSY and Justin Bieber. This is

[17] The regression coefficient of a time trend is -0.58% (s.e. 0.16%) for the English phrase, -0.51% (s.e. 0.25%) for the German phrase.

reflected in Billboard's decision to include *YouTube* in their formula for the Top 100 starting in February 2013.[18]

3 Methods and Data

3.1 Identification Strategy

We make use of the natural experiment on *YouTube* to identify the effect of free sampling on digital sales. Our setting lets us observe counterfactual sales of songs and albums almost in the absence of *YouTube*. For the same song, on the same day, sold in the same (virtual) store, we observe exogenous differences in the availability of *YouTube* across countries.

The common terminology in experimental settings refers to treatment and control groups, and it is distinguished between before and after a treatment. Because all songs/music videos are affected by the *GEMA* shock throughout the sample period, we don't observe the songs in the treatment group (Germany) in two distinct, discrete states of the world (before and after the treatment). Instead, we exploit temporal variation in the intensity of restriction. 'Before' and 'after' then correspond to 'less treated' and 'more treated', respectively. Songs are distributed on a continuum between zero treatment and full treatment. The same song is sometimes treated more, sometimes less because of temporal differences in the intensity of restriction (new videos being uploaded but not immediately blocked). For this to work, we need to assume that the assignment to the continuum is random. We can think of the number of videos being blocked per day as a random process after controlling for song fixed effects, which for example rules out that videos containing more or less popular songs are more or less restricted.[19]

[18] New York Times, 'What's Billboard's No. 1? Now YouTube Has a Say', February 20th, 2013, `http://tinyurl.com/ba5d4ks`.

[19] A close look at the data confirms this. We observe 17,781 videos that are uploaded to *YouTube* after the corresponding song has appeared on the *iTunes* charts for the first time (this is our definition of a new video) and get restricted in Germany at some point. It takes four days on average until a newly uploaded video (that eventually gets restricted in Germany either immediately or at some later point) makes it to the top 25 *YouTube* search results for a song in some country (mean of new videos per song and day is .23, median 0). The average new video gets blocked after less than 1.5 days, although note that the majority of new videos is blocked immediately. Some 9% get restricted at some later point (mean 16.57 days, median 8 days, min 1 day, max 174 days). To test whether the timing of the video being blocked is systematic, we regress the (log) number of views on *YouTube* on an indicator of whether a new video is restricted immediately. It is conceivable that *YouTube* strategically leaves videos with more clicks longer online to leverage advertising revenues. However, without an agreement with *GEMA* this is risky, since *YouTube* may face high license fees later. Although the coefficient in a linear probability model with

To identify the sampling effect, we have to separate it from four other sources of country-specific variation: (1) different stages of the product lifecycle, (2) differences in prices (price elasticities), (3) general taste differences, and (4) differences in *YouTube* usage. We control for (1) and (2) using observable measures, assuming that (3) and (4) are time-invariant (at least in the short time-span of our sample) we can use song, genre and country fixed effects. On top of that, we include fixed effects for month, calendar week and weekday (all fixed effects are in the vector $X_{i,j,t}$) to capture as much variation as possible.

Assuming a log-linear demand function[20], we can identify the sampling effect in a standard difference-in-differences setting, i.e.

$$\begin{aligned} log(\text{Sales}_{i,j,k,t}) =& \alpha + \beta_1 log(\text{Sampling}_{i,j,t}) + \beta_2 \text{Germany}_{i,t} \\ & + \beta_3 log(\text{Sampling}_{i,j,t})\text{Germany}_{i,t} + X'_{i,j,t}\gamma + \varepsilon_{k,t}, \end{aligned} \tag{1}$$

where $\text{Sales}_{i,j,k,t}$ are unit sales of song i on album k in country j at day t. $\text{Sampling}_{i,j,t}$ is a song-level measure of availability on *YouTube*, and $\text{Germany}_{i,t}$ is a dummy indicating observations from Germany.

3.2 Unit Sales versus Sales Ranks

We do not observe unit sales, but sales ranks. We follow the literature and assume that the relationship between sales rank and unit sales follows a Pareto distribution (Chevalier and Goolsbee, 2003):

$$\text{Sales} = a\text{Rank}^b \tag{2}$$

If data on unit sales and sales ranks were observed, it would be straightforward to estimate the parameters of (2) by OLS, using

$$log(\text{Rank}) = \tilde{a} + \frac{1}{b} log(\text{Sales}), \tag{3}$$

song fixed effects is statistically significant (coefficient -.015, standard error clustered on the song level .001, $\bar{R}^2$ = .086, n=17,781), the effect magnitude is small. Doubling the views decreases the probability of immediate restriction by only 1.5%. This suggests that there is no major strategic timing of video restrictions in Germany.

[20] A log-linear demand function can for example be justified by assuming a Cobb-Douglas utility function.

where $\tilde{a} = -(1/b)log(a)$. In practice, however, unit sales are often not observed, which is why scholars have used purchase experiments (Chevalier and Goolsbee, 2003; Ghose and Sundararajan, 2006), insider information (Ghose et al., 2006; Brynjolfsson et al., 2011), or structural estimation methods (Bajari et al., 2008) to estimate the parameters of the distribution. Those studies on books and software suggest that b is in the range of -0.8 to -0.9 with standard errors of around 0.04.

Because we are mainly interested in qualitative estimates, it is sufficient to work with observed ranks. To see this, substitute (1) in (3), such that we can estimate

$$\begin{aligned} log(\text{Rank}) = \tilde{a} + \frac{1}{b}(\alpha + \beta_1 log(\text{Sampling}_{i,j,t}) + \beta_2 \text{Germany}_{i,t} \\ + \beta_3 log(\text{Sampling}_{i,j,t})\text{Germany}_{i,t} + X'_{i,j,t}\gamma + \varepsilon_{k,t}). \end{aligned} \quad (4)$$

Although we cannot directly identify β_1, β_2 and β_3, we can still interpret the signs of the estimated coefficients of (4) because $1/b$ is assumed to be negative.[21]

3.3 Data

3.3.1 Data Collection Process

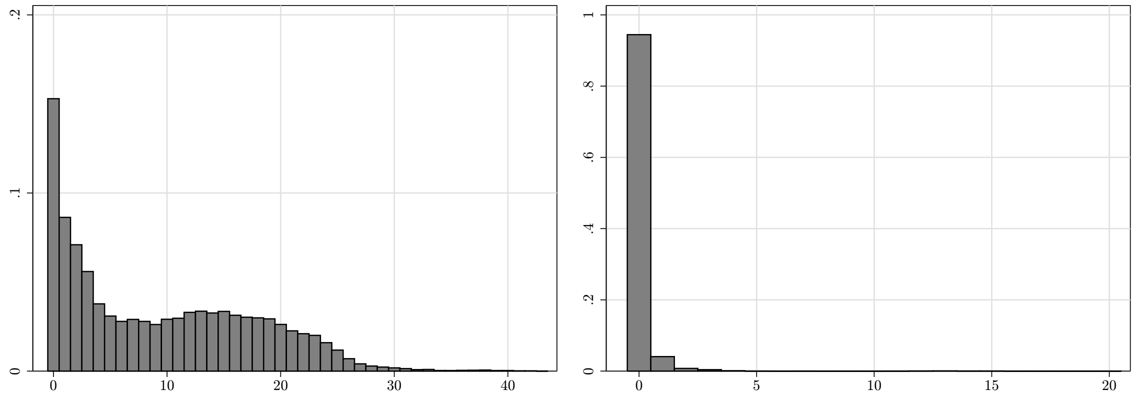
We analyze data collected during February 15th and August 26th 2013 from two public Internet sources, Apple's *iTunes* Store RSS Feed and the *YouTube* API.

Apple reports sales ranks of the 300 best selling products in all countries in which it operates an *iTunes* store. From this, we drew the bestselling songs and albums in ten countries (Australia, Austria, Canada, France, Germany, Italy, Spain, Switzerland, United Kingdom and the United States) on a daily basis, leaving us with 3,000 observations per day and category (songs/albums). Along with sales ranks, we observe prices, release dates, publishers/record labels, and the album a song belongs to. On the same day, we collected a list of country-specific search results from a query on artist name and song title for each unique song on *YouTube*. We restrict the number of search results on *YouTube* to 25, leading to 250 country-specific daily search results per song.[22] For each video we observe

[21] In section 4.3, we give a quantitative interpretation of our coefficient estimates.

[22] We chose 25 because this is the number of results displayed on the first results page after manually searching on *YouTube*. *YouTube* displays the most popular videos related to the search term, in terms of matching title, number of views and quality rating.

Figure 3: Number of Unique Blocked Videos: Germany vs. United States



Number of blocked videos in Germany **Number of blocked videos in the US**

Mean: 9.36, median: 8, min: 0, max: 43 Mean: 0.10, median: 0, min: 0, max: 20

Number of unique videos that show up in the top 25 search results across all countries, except Germany (the US) but are blocked in Germany (the US) – referring to search query "Artist – Song" on international YouTube sites. Note that the scale of the right hand side graph is five times the scale of left hand side graph.

meta information, such as title and number of views, and a list of countries in which it cannot be viewed.

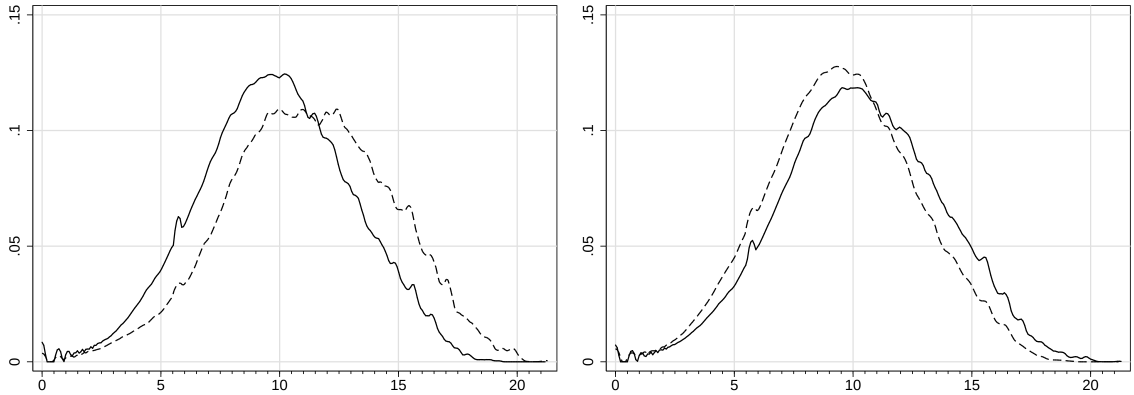
We exclude ten days for which we have incomplete chart rankings and missing video information, leaving us with 185 days and 503,028 observations.[23]

3.3.2 Descriptive Statistics

To derive a measure of video availability, for every song, we count how many videos that appear in the search results of all countries are blocked within a specific country, say Germany. This count ranges from 0 to 225. If every video that appears in at least one country is also available in Germany, the count would be zero. If the list of search results is unique across all countries, and all videos are blocked in Germany, then the count would be $25 * 9 = 225$. Figure 3 shows histograms of the number of blocked videos in Germany and the corresponding measure for the United States. On average, 9.36 videos that show up in the search results in other countries are not available in Germany. The maximum is 43, i.e. for one song on one day, there are 43 videos showing up as popular search results in the other nine countries that cannot be viewed in Germany. The difference to the US

[23] Excluded days are 2/27/2013, 3/4/2013, 3/8/2013, 3/13/2013, 5/9/2013, 5/10/2013, 5/14/2013, 7/14/2013, 7/15/2013 and 8/16/2013. The resulting theoretical number of observations is 555,000 but we lose another 51,972 observations (9,4 %) due to missing meta and video information.

Figure 4: Popularity Distribution of Videos



Log Views of Restricted Videos
---Restricted in Germany
—Restricted in at least one other country

Log Views of Top 25 Videos
---Top 25 in Germany
—Top 25 in all other countries

Observations refer to daily search queries of "Artist – Song" on 10 international YouTube *sites from February 15th until August 26th. Countries include Australia, Austria, Canada, France, Germany, Italy, Spain, Switzerland, United Kingdom, United States. Based on 85,636,197 observations from 67,309 songs and corresponding 726,434 videos.*

is striking. The mean number of blocked videos here is 0.10, with a maximum of 20.

Figure 4 shows differences in the popularity of music videos in Germany and other countries, as measured by the number of views on *YouTube*. The left-hand panel indicates that restricted videos in Germany are substantially different from videos that are restricted in other countries. The German distribution is shifted to the right, i.e. more often viewed and less niche videos are not available in Germany. It is evident from the right-hand panel that less extremely popular videos show up in German search results. Accessible videos in Germany are usually live versions, cover versions, remixes, and so on that receive relatively less views than professional music videos (see table A.3 for an example).

3.4 Specification

We now detail the operationalization and model specification we use to estimate parameters of equation (4).

Sales Ranks indicate the position in the sales charts. Accordingly we observe discrete values from 1 to 300, where the top selling product has a value of 1.

Sampling is measured as the number of videos to a specific song that are available in other countries, but are blocked in the focal country. In the tables below, this variable is denoted as *Log(Restricted)*. To control for the effect of the denominator, i.e. the number of different search results appearing in other countries, we also report results of an alternative measure. *Share Restricted* is the number of restricted videos over the total number of unique videos for a song in all countries on a day. Before taking the logarithm, we add 1 to avoid losing observations.

Prices are included based on information about the *iTunes* retail price at time t. *iTunes* has a strict pricing policy, such that we only observe three price categories of songs (see table A.1). Prices of albums show more variation.[24] Because there is little variation in prices for songs, and the price categories are comparable across countries, we include a variable that has the value 1 in the low category, 2 in the medium category, 3 in the high category (see table A.1). In the album model, we include album prices as observed in the raw data. We control for currency-specific differences using country fixed effects.

Age: To control for the stage of the lifecycle of a product in a given country, we construct a measure of product age by computing the number of days since the release date. Sometimes products rank high in the sales charts although they are not yet on the market. This is the case when preordering is possible. For such products, we define age as zero before the actual release date. Because the distribution of age is skewed, we take the natural logarithm, but add 1 to avoid losing observations.

Fixed effects: Note that videos featuring popular songs are likely to be uploaded more frequently. With more draws from the urn, chances that the top 25 search results vary across countries increase. *YouTube*'s automatic filters capture the content of any uploaded video and almost immediately block it in regions where *YouTube* does not have an agreement with rights-holders.[25] By definition therefore, more variety raises the number of videos blocked in Germany. We solve this issue by controlling for song fixed effects in the regression below. Additionally, we include genre, month, calendar week, weekday, and country fixed effects. We report country-specific constants, where US is the omitted category. We adjust standard errors to account for correlation within observations of the same song.

[24] For example, in the US sample, we observe album prices of 1.29, 2.99, 3.96, 3.99, 4.65, 4.95, 4.99, 5.55, 5.94, 5.99, 6.99, 7.99, 8.99, 9.90, 9.99, 10.99, 11.99, 12.99, 13.99, 14.99, 15.99 and 16.99 USD.

[25] See `http://www.youtube.com/t/contentid`. See the discussion in footnote 19.

4 Results and Discussion

4.1 Baseline Results

Results of an OLS estimation of model (1) are given in Table 1. With fixed effects at the genre, month, calendar week, and weekday levels, the simple linear regression model fits the data reasonably well ($\overline{R}^2 = 0.62$). The coefficient signs of the control variables are as expected, the popularity of a song decreases over time and higher priced songs tend to sell less.[26] One interpretation of the country coefficients is that they represent a parameter for market size. According to equation (4), country fixed effects γ represent country-specific deviations from the parameter b. A positive coefficient then indicates a smaller market than the US (the omitted category). That is, in order to be at the top of the *iTunes* charts in Switzerland, an artist must sell fewer units than for a number one hit in the US. A second interpretation is one of controlling for country-specific sales patterns, because we are at the same time estimating parameters of the sales equation (1). The results reveal interesting similarities between countries with a common language (Canada, UK and US / Germany and Austria / Italy and Switzerland).

We report results for two different measures of video availability. In the first column we use the number of videos that appear in search results in other countries but are restricted in the focal country. In the second column we report results using the share of restricted videos as a measure.

Importantly, the coefficients of *Log(Restricted)* and *Share Restricted* are not significantly different from zero, indicating that there is no correlation between a song's popularity and its average availability on *YouTube*. In both cases, the interaction with the *Germany* dummy is positive but not significant. That is, even in Germany, where we observe completely different patterns of video restrictions for exogenous reasons, sales ranks are not affected differently.

Taken at face value, this may simply suggest that the availability of online music videos and digital song sales are not related. However, this could also be the result of two

[26] The estimated coefficients of product age (as a result of strategic product introduction timing) and price are of course potentially biased due to endogeneity. However, we include those variables to minimize a potential omitted variable bias rather than interpret their coefficients.

Table 1: Baseline Results

	Log(Restricted)		Share Restricted	
Germany	0.260***	(0.098)	0.274***	(0.092)
Log(Restricted)	-0.029	(0.022)		
Germany * Log(Restricted)	0.042	(0.028)		
Share Restricted			-0.291	(0.248)
Germany * Share Restricted			0.349	(0.269)
Log(Age)	0.178***	(0.019)	0.178***	(0.019)
Price Category	0.373***	(0.022)	0.373***	(0.022)
Australia	0.186***	(0.072)	0.184**	(0.072)
Austria	0.264***	(0.081)	0.264***	(0.081)
Canada	-0.005	(0.029)	-0.006	(0.029)
France	0.147*	(0.079)	0.146*	(0.079)
Italy	0.320***	(0.080)	0.320***	(0.080)
Spain	0.187**	(0.084)	0.186**	(0.084)
Switzerland	0.353***	(0.079)	0.352***	(0.079)
United Kingdom	0.112	(0.077)	0.110	(0.077)
Constant	2.803***	(0.246)	2.803***	(0.246)
Observations	503,028		503,028	
$\overline{R}^2$	0.616		0.616	

Dependent variable: Log(Rank) on *iTunes* Top 300 Songs.
Song, genre, month, calendar week and weekday fixed effects, United States is the omitted category. Standard errors clustered on the song-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

countervailing effects that cancel each other out on average. In what follows, we propose a number of corresponding tests. The basic idea is to look at conditions under which the relative importance of a displacement effect or a promotion effect varies.

4.2 Displacement vs. Promotion

We can think of music as horizontally and vertically differentiated products. Initially consumers are not perfectly informed about product characteristics, but they can gather information by sampling, i.e. consuming the product without paying a positive price. The closer the sample matches the product, the better informed are consumers about the quality of the product. Conversely, access to a sample can induce consumers to consume the sample instead of purchasing the product. The strength of this displacement effect will depend on consumers' perceptions about relative quality and cross-price elasticities.

Table 2: Varying Promotion and Displacement Effect

	Song Preorder		Album Sales Rank	
Log(Restricted)	-0.029	(0.022)	0.004	(0.026)
Germany * Log(Restricted)	0.042	(0.028)	0.100**	(0.040)
Preorder	0.159	(0.103)		
Preorder * Log(Restricted)	0.975***	(0.250)		
Germany * Preorder	-0.264	(0.230)		
Germany * Preorder * Log(Restricted)	-0.713***	(0.277)		
Log(Age)	0.180***	(0.020)	0.436***	(0.035)
Price Category / Log(Price)	0.373***	(0.022)	1.489***	(0.095)
Constant	2.787***	(0.248)	-2.005***	(0.338)
Observations	503,028		222,400	
$\overline{R}^2$	0.617		0.749	

Dependent variables: Log(Rank) on *iTunes* Top 300 Songs/Albums.
Song/Album, genre, month, calendar week, weekday and country fixed effects. United States is the omitted category. Standard errors clustered on the song/album-level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.1 Varying degrees of displacement

A specific feature of the music market helps us identify these countervailing effects. Products are usually pre-announced before their actual release to the market. Well before the actual release date, songs are played on the radio, music videos are shown on television, and of course uploaded to the Internet. Consumers use radio airplay, music television and the Internet to sample and then decide whether to purchase the song. Even before the release, consumers can preorder the product to be shipped on the day of the release. Preordering is not quite the same as purchasing a song after the release. We can think of this as an implicit increase in price, because the consumer has to bear the cost of waiting a couple of days before she can listen to the song. Accordingly, the cross-price elasticity of product and sample changes, while the information-gathering role of sampling in the purchase decision is not affected by the option to preorder. Consequently, more consumers will choose to stick with the free sample, i.e. watch the music video instead of preordering the song. We would therefore expect the displacement effect to dominate the promotional effect, and in contrast to the result we obtained when looking at all songs, a negative effect of sampling on sales.

This is tested in the first column of Table 2. We introduce a three-way interaction to investigate an additional difference in the difference-in-differences estimates. Preordering is measured as a dummy variable indicating whether the song has been released yet.
The insignificant coefficient of *Preorder* suggests that preordered songs do not show systematically different sales patterns compared to purchases after the release date. While the main effect *Germany*Log(Restricted)* remains insignificant and qualitatively unchanged, the coefficient of the triple interaction *Germany*Preorder*Log(Restricted)* is negative and significant. When it becomes less easy to substitute a purchase with watching a *YouTube* video, sales of pre-ordered songs increase. The effect is non-negligible with an increase of seven percent per ten percent increase in the number of restricted videos.

4.2.2 Varying degrees of promotion and displacement

Sampling can have external effects when consumers can indirectly gather information about related products with similar characteristics. For music, two closely related products are often on the market at the same time: songs and albums. Not only will albums usually feature songs of relatively similar style and quality, but by definition, one song is a subset of all songs on an album. Listening to a song on the radio or watching an online music video therefore lets consumers gather information about album quality. This channel is of course less direct and limited. Consider a highly stylized model to derive expectations in this case (see table 3 for a summary). In the following we think of songs as giving standalone utility to consumers, but also exhibiting externalities (displacement and promotion) that can be expressed in monetary units.
If there are n songs on an album, watching an online music video can perfectly inform the consumer only about $1/n$ parts of the album, but watching the video perhaps also shapes expectations about the quality of the other $n-1$ songs. In the extreme, one song may fully reveal the quality of the corresponding album. For example, sometimes *albums* that correspond closely to a song are so-called maxi-singles, with different versions or remixes of that song but no other, fundamentally different songs.[27] In most other cases where the album consists of many different songs, a single song carries less information about the

[27] In iTunes' (and our) terminology, this classifies as an album, as it is a collection of individual tracks.

Table 3: Theoretical Promotional and Displacement Effects

	Promotion (θ_p)	Displacement (θ_d)	Expected Net Effect (θ)
	$(1/n+\nu(n-1)/n)pn\delta$	$(1/n)pn\delta$	$\theta_p - \theta_d = p\delta v(n-1)$
Songs	$n=\delta=1$ $\Rightarrow \theta_p = p$	$n=\delta=1$ $\Rightarrow \theta_d = p$	$\theta = \theta_p - \theta_d = 0$
Song–Preorders	$n=\delta=1$ $\Rightarrow \theta_p = p$	$n=\delta=1, p' = p+x$ $\Rightarrow \theta_d = p+x$	$-x<0$ if $x>0$
Albums	$(1+\nu(n-1))p\delta$	$p\delta$	$p\delta v(n-1) > 0$ if $n>1$, $\delta>0$, $\nu>0$

rest of the album. We can think of this as a parameter ν, where $0 \leq \nu \leq 1$.

The total promotional effect can then be expressed in album price units and written as $(1/n + \nu(n-1)/n)p_a$, where p_a is the price of the album. Albums represent bundles (Elberse, 2010; Danaher et al., 2013), i.e. album prices are smaller than to the sum of individual songs prices.[28] We can express album prices as $p_a = pn\delta$ where p is the song price and $0 \leq \delta \leq 1$ is the bundling discount. Relative to the promotional effect of music videos on song sales, where $n = 1$ with a price $p \leq p_a$, we expect the promotional effect on albums to be smaller or at most equal.

While one song (or its corresponding music video) can potentially inform about album quality, consumers cannot directly substitute listening to the album with listening to just one song. Put differently, a music video at most replaces paid album consumption worth one song, i.e. $(1/n)p_a = p\delta$. Because of the relative lower price of a song in the album bundle, we also expect the displacement effect on albums to be relatively smaller or at most equal compared to the displacement effect on songs ($p \leq (1/n)p_a = p\delta$).

Adding up promotional and displacements effects, we can derive propositions about the net effect, i.e. $(1/n + \nu(n-1)/n)p_a - (1/n)p_a = p\delta v(n-1)$. The promotional effect always dominates the displacement effect if $n > 1$, $\nu > 0$ and $\delta > 0$. The intuition is that displacement is limited to one song (expressed in album price units), while a music video may inform about quality of more than one song. Accordingly, we expect the promotional effect to prevail for albums if the music video is informative about album quality at least

[28] In the strict regime of the *iTunes* store, album prices are a function of the number of songs on an album. See *iTunes Package Music Specification 5.0, Revision 1*, p. 187–188, `http://tinyurl.com/lo7gj2b`.

to some (arbitrarily small) extent.

Regression results are shown in the second column of table 2. Here the dependent variable is *Log(Album Rank)*, *Log(Age)* refers to the number of days since the album release and *Log(Price)* is the album price. The coefficient of *Log(Restricted)* remains insignificant, the coefficient of *Germany*Log(Restricted)* is positive and statistically different from zero. That is, the promotional effect prevails as expected given the *iTunes* pricing regime and at least some similarity between the song and the rest of the album. The effect magnitude is moderate, however. According to our estimates, album sales ranks decrease by one percent when the number restricted videos increases by ten percent. A back-of-the-envelope calculation suggests that the amount of information a song carries about the album is not very large. Under the assumption that the average album priced at 9.99 USD contains 12 songs, each individually priced at 0.99 USD, the implied discount is $\delta = 0.84$. Our estimates then suggest that the information parameter is $\nu = 0.011$, i.e. listening to one song informs about one percent ($\approx 0.011 * 11/12$) of the rest of the album.

Although the strict regime of the *iTunes* store limits the scope of pricing decisions, we emphasize that it is difficult to interpret those estimates given firms may set prices endogenously.

4.3 Quantifying the Effect on Sales

With information from additional regressions using external data we can shed light on country-specific coefficients of the assumed Pareto-relationship between rankings and sales in equation (2). This lets us infer estimates of the β's and give some indication about the effect on unit sales rather than ranks.

It is not possible to get data on unit sales directly from *iTunes*. We therefore rely on proxies obtained from two Internet sources. Our first measure comes from *digitalsalesdata.com* (DSD), a website which displays estimates of unit downloads based on a statistical model fitted with historical data obtained from *iTunes*.[29] Those figures are offered for the daily

[29] The website does not provide details about the statistical model. The owner of the website told us via email: "Basically, what I do is get the ratio of sales from the top seller to the bottom seller, then use exponential interpolation to fill in the gaps. I compare these to known data and modify where appropriate. The base sales are estimated using historical data (from when I received actual sales from iTunes) and use a separate model to handle the periodicity of sales over time and market growth trends. I used to periodically correct the model based on published data, but it's been 10 months since I last changed it and it seems to

Table 4: Digital Sales and Plays

Country	Correlation	Plays per Sale	
		Mean	Std. Dev.
Australia	0.93	0.96	0.40
Austria	0.98	3.02	1.41
Canada	0.90	1.85	0.66
France	0.91	1.81	0.45
Germany	0.94	3.61	1.47
Italy	0.93	3.58	1.08
Spain	0.86	8.17	2.09
Switzerland	0.98	1.34	0.47
United Kingdom	0.83	0.98	0.53
United States	0.93	0.75	0.33

Data from *digitalsalesdata.com* and *last.fm*.

top 100 songs for a large number of countries. Because the figures are predictions from a statistical model whose parameters do not change over time, we take a snapshot of one day for our purposes.[30]

Our second measure comes from *last.fm*, an music recommendation service that tracks listening of more than 30 million users worldwide. After a user has installed an application on her computer or mobile device, every song she listens to for at least 30 seconds is tracked. Among others, *last.fm* tracks songs played within the *iTunes* application on a desktop machine, or on an *iPod*, *iPhone* or *iPad*. Listening data from *last.fm* is therefore likely to be highly correlated with purchases on *iTunes*. Aggregate statistics about the music consumption of *last.fm* users can be directly accessed via the website. We obtained three snapshots of the international top 300 weekly song charts, including the total number of plays.[31]

Table 4 shows that both measures are highly correlated, although some differences between countries are evident. The correlation is highest in Austria and Switzerland with a Pearson coefficient of 0.98 and lowest in the United Kingdom with a Pearson coefficient of 0.83. The average number of plays per (estimated) sale is 2.61, again with cross-country differences. The highest coefficient by far is 8.17 in Spain, the lowest is 0.75 in the United States.

accurately predict sales most of the time now."

[30]Our data was obtained on September 17th, 2013.

[31]The data refer to calendar weeks 34, 36 and 37 of the year 2013.

Table 5: Parameter Estimates: Ranks and Sales/Plays

	Digitalsalesdata.com		Last.fm	
Log(Sales)	-1.096***	(0.038)	-2.685***	(0.033)
Log(Sales) * Australia	-0.007	(0.058)	0.041	(0.052)
Log(Sales) * Austria	0.091	(0.067)	0.077*	(0.046)
Log(Sales) * Canada	-0.116**	(0.050)	-0.174***	(0.048)
Log(Sales) * France	-0.240***	(0.049)	0.625***	(0.046)
Log(Sales) * Germany	-0.024	(0.066)	0.152***	(0.047)
Log(Sales) * Italy	-0.125**	(0.057)	0.348***	(0.051)
Log(Sales) * Spain	-0.094**	(0.045)	0.585***	(0.046)
Log(Sales) * Switzerland	-0.115*	(0.066)	0.179***	(0.050)
Log(Sales) * United Kingdom	0.149***	(0.050)	0.297***	(0.071)
Australia	-2.603***	(0.397)	-5.777***	(0.221)
Austria	-5.994***	(0.344)	-10.463***	(0.184)
Canada	-2.703***	(0.349)	-5.058***	(0.211)
France	-2.146***	(0.348)	-8.261***	(0.201)
Germany	-3.172***	(0.414)	-4.356***	(0.222)
Italy	-4.269***	(0.348)	-8.468***	(0.202)
Spain	-4.647***	(0.320)	-7.971***	(0.201)
Switzerland	-4.383***	(0.366)	-10.510***	(0.186)
United Kingdom	-2.280***	(0.390)	-3.713***	(0.336)
Constant	12.801***	(0.308)	19.182***	(0.177)
Observations	1000		9000	
$\overline{R}^2$	0.965		0.954	

Dependent variable: Log(Rank) on *iTunes* and *last.fm*.
Log(Plays/7) and week fixed effects in the *last.fm* model. United States is the omitted category.
Heteroscedasticity robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results from an estimation of equation (3) including country-specific coefficients for *Log(Sales)* and *Log(Plays)* are reported in table 5. The estimate of λ is -1.096 using DSD data, with a robust standard error of 0.038. The estimate obtained from the *last.fm* data is -2.685 with a robust standard error of 0.033. That is, controlling for country fixed effects, we predict average daily unit sales of 118,154 of a song on rank one, 649 for a song on rank 300 with DSD data. Because of the much steeper slope parameter, predictions based on *last.fm* data are very different at the top (1267 units for rank one), but more comparable in the tail (151 units for rank 300). Those parameter estimates translate the results above into a 8.0 or 19.6 percent increase in sales of preorders, and a 1.1 or 2.7 percent decrease in sales of albums with a 10 percent increase in restricted videos.

5 Conclusions

Using a rich data set collected from *iTunes* and *YouTube*, we use cross-country variation and a natural experiment in Germany to identify the effect of free sampling on digital sales of music. The results suggest that there is no effect of *YouTube* availability on digital sales of songs, whereas the effect on digital sales of albums is positive. At least for albums, this suggests that the promotional effect of *YouTube* videos outweighs a displacement effect.

The overall finding is that giving consumers access to free content is not necessarily hurting sales of the same content, but can actually increase sales. This may seem surprising at first glance. However, sampling was ever since considered an important mechanism to increase sales in the recorded music industry. In essentially every record store (including digital record stores such as *iTunes*, *Amazon*, and *Beatport*) consumers can listen to (parts of) songs before buying. Radio stations promote songs ever since, and music television is based on the idea that music videos create attention. The difference with streaming websites such as *YouTube*, *Soundcloud*, or *Dailymotion* is that firms cannot control how intensely consumers sample, i.e. it is not obvious that consumers may use such services as a substitute to actual purchases. Our contribution therefore is to show that sampling can still be an effective trigger of demand even if the firm cannot keep some consumers from sticking to the sample instead of purchasing the product.

A potential limitation is that we only observe album chart rankings when a song of the album is in the top 300 song charts at the same time. This may cause our album-level estimates to be biased, because the sample only includes relatively successful albums. If product characteristics of more successful albums are already known to more consumers, then the promotional effect of sampling may be less pronounced than for unsuccessful albums. This would mean that we are underestimating the promotional effect.

Instead of the reduced form approach we use, future research could study promotional and displacement effects in a structural approach, trying to separately estimate parameters for promotion and displacement. The main challenge would be to identify cross-price elasticity parameters, because song and album prices are determined endogenously.

Our study makes an important contribution to the literature on sampling and digital piracy. While it is relatively straightforward to conclude that free consumption increases consumer surplus, conclusions about overall welfare are more difficult. When positive externalities of unpaid consumption can offset forgone royalties income, sampling may be able to increase overall welfare. If confirmed in other studies and empirical settings, this finding may not only inform policymaking, but also firm attitudes to piracy.

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Appendix

Table A.1: iTunes Price Categories for Songs

Country	Currency	Low	Medium	High
Australia	AUD	1.19	1.69	2.19
Austria	EUR	0.69	0.99	1.29
Canada	CAD	0.69	0.99	1.29
France	EUR	0.69	0.99	1.29
Germany	EUR	0.69	0.99	1.29
Italy	EUR	0.69	0.99	1.29
Spain	EUR	0.69	0.99	1.29
Switzerland	CHF	1.10	1.60	2.20
United Kingdom	GBP	0.59	0.79	0.99
United States	USD	0.69	0.99	1.29

Table A.2: Top 20 Videoportals in Germany

Website	Visits
Youtube.com	34,000
Myvideo.de	5,600
Movie2k.to	2,900
Videos.t-online.de	2,400
Dailymotion.com	1,800
Clipfish.de	1,600
Rtl-now.rtl.de	1,600
Kinox.to	1,300
Vimeo.com	1,300
Ardmediathek.de	1,200
Mediathek.daserste.de	840
Rtl2now.rtl2.de	830
Maxdome.de	630
Videobash.com	620
Voxnow.de	520
Diziizle.de	470
Sevenload.com	390
Metacafe.com	360
Zatoo.com	290
Atdhenet.tv	290

Source: Google Ad Planner (meedia.de).
Unique monthly visits in thousands, March 2012, excluding porn.

Table A.3: YouTube Titles in Germany and the US

		Views	YouTube-ID	Gone
Germany				
1	Daft Punk - Get Lucky (Radio Edit) [feat. Pharrell Williams] (Official)	378819	Qhd5_JeRQYI	Yes
2	Daft Punk (feat. Pharrell Williams) - Get Lucky (Radio Edit) (PiaYes Cover)	931	-Rmt2I3JYmM	No
3	Daft Punk - Get Lucky ft. Pharrell Williams (1# Live Performance HTC live)	109453	ieSFGMkbkTc	No
4	Daft Punk - Get Lucky (Michael Jackson Edit)	301	S4mAORhFnCA	Yes
5	Daft Punk - Get Lucky (Ft. Pharrell & Nile Rodgers) (Radio edit) (Lyrics on description)	583	gDlAClawTT8	Yes
6	Daft Punk - Get Lucky (Michael Jackson Edit)	301	S4mAORhFnCA	Yes
7	Daft Punk - GET LUCKY Ft. Pharrell Williams (Exclusivite mondiale Fun radio) FAKE	66390	EFY9mdY-hK8	Yes
8	Daft Punk Get Lucky ft Pharrell Williams. Acoustic Cover.	1069	dW9KREPTfio	No
9	Daft Punk - Get Lucky feat. Pharrell Williams (Vijay & Sofia Zlatko Edit)	341	QDsx6g65Z1Y	Yes
10	Daft Punk - Get Lucky Feat. Pharrell Williams	532	5ev1G5548rM	Yes
United States				
1	Daft Punk - Get Lucky (Radio Edit) [feat. Pharrell Williams] (Official)	378115	Qhd5_JeRQYI	
2	Daft Punk - Get Lucky (Radio Edit) [feat. Pharrell Williams] [Official]	414052	M7VTByl6WqA	
3	Daft Punk - Get Lucky (Ft.Pharrell Williams & Nile Rodgers) - FAN EDIT	958972	4FRXLzw37-8	
4	Daft Punk - Get Lucky (Radio Edit) [feat. Pharrell Williams] (SONIC102.9 Leak)	103548	6o1fWlRyDtc	
5	Daft Punk - Get Lucky Feat. Pharrell Williams (Radio Edit)	98376	bYiYQXZRKBw	
6	Daft Punk ft Pharrell Williams & Nile Rodgers - Get Lucky (Official Radio Edit)	139393	FzyhpigFMKE	
7	Daft Punk - Get Lucky (Michael Jackson Edit)	6222	S4mAORhFnCA	
8	Daft Punk Get Lucky (Radio Edit) [feat. Pharrell Williams] HD 1080 Download!!!	26154	PTnNTxLBHso	
9	Daft Punk - Get Lucky (Radio Edit) [feat. Pharrell Williams]	19413	Dm2YD2AbZsE	
10	Daft Punk - Get Lucky (Radio Edit) [feat. Pharrell Williams] [Full Studio]	3136	KP7oc4EKp4c	

Note: Top 10 search results for "Daft Punk - Get Lucky (Radio Edit) [feat. Pharrell Williams]" on April, 24th, 2013. 'Gone' indicates whether the video is available in Germany on June, 12th, 2013.

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