Knocking on Heaven's Door
User preferences on digital cultural distribution

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Abstract

This paper explores the social, demographic and attitudinal basis of consumer support to a change from the status quo in digital cultural distribution. First we identify how different online and offline, legal and illegal, free and paying content acquisition channels are used in the Dutch media market using a cluster-based classification of respondents according to their cultural consumption. Second, we assess the effect of cultural consumption on the support to the introduction of a Copyright Compensation System (CCS), which, for a small monthly fee would legalize currently infringing online social practices such as private copying from illegal sources and online sharing of copyrighted works. Finally, we link these two analyses to identify the factors that drive the dynamics of change in digital cultural consumption habits.

Keywords— cultural consumption habits, copyright compensation system, discrete-choice analysis, clustering, digital consumption

1 Introduction

Copyright Compensation Systems (CCS) are legal instruments, which, for a small monthly fee legalize currently infringing online social practices, such as private copying from illegal sources and online sharing of copyrighted works. In this paper we examine whether the CSS idea enjoys public support in the Netherlands and try to identify how that support is structured.

A CCS idea was first floated in the years after Napster and its successors proved that enforcement alone cannot solve the digital copyright piracy problem. However, the context, in which the CCS idea was born (Eckersley, 2004; Fisher III, 2004; Grassmuck and Stalder, 2003; Netanel, 2003) has changed considerably. There is some evidence that low-cost flat rate legal streaming services are able to cannibalize illegal demand (Poort and Weda, 2015), and by now a plethora of streaming services offer free or low cost access to a wide variety of musical works. While the decline of recorded music revenues stopped in the early 2010's, and digital music revenues show a steady growth (IFPI, 2013, 2015), the piracy issue is still manifest for the audiovisual sector, and looming large over book publishing. Therefore we believe that while streaming services may offer a successful market-based approach to combat music piracy, the CSS-based alternative may still prove relevant in the audiovisual and publishing sectors, where the piracy is still a problem, and legal alternatives are lacking.

Addressing copyright infringement is not the only reason why CCS can be interesting. In recent years we witnessed a growing discontent with streaming services by rights holders and

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artists (Dredge, 2013; Geere, 2011; Knopper, 2014; Poort et al., 2013). The meager royalties that streaming services pay for each play seem to be the main source of complaints (Linshi, 2014). Low streaming revenues, coupled with the threat (Karp, 2014) that low value streaming substitutes other distribution alternatives with considerable higher revenue generating potential, prompted several successful artists to remove their catalog from streaming services. In addition, the level of control these new digital intermediaries enjoy over market access and pricing started a new round of conflicts. For example, ahead the launch of its streaming service, YouTube announced that artists cannot stay out of the streaming service without losing their other YouTube generated revenues (Peoples, 2015).

It has been demonstrated that a well designed CCS alternative has the potential to increase the welfare of consumers, producers, authors and artists by hundreds of millions of Euros a year in the Netherlands alone (Handke et al., 2015). The CCS alternative may not just offer a solution to the piracy problem, but it may also settle the debate about market control and the adequacy of the digital revenue streams to support the creative process in the continuously changing media consumption landscape in which digital and physical, illegal and legal, free, flat rate and pay-per-use channels substitute and complement each others in unforeseen ways.

This paper uses individual sociodemographic characteristics and our detailed data on the respondents' media consumption habits to identify the structure of media consumption habits in the Netherlands, as well as some of the factors that drive the change in those habits. Section 2 provides a review of the current state of the literature on digital consumption from legal and illegal sources, and presents the main research questions. In the subsequent section we present a model of consumption behavior and support for a change to the status quo in copyright compensation, and derive the main hypotheses. Afterwards, Section 4 describes the methodological apparatus of the paper and the data used to test the hypotheses. The main empirical results are presented in Section 5, which are further discussed in Section 6.

2 Review of literature

The runaway success of Napster and the subsequent peer-to-peer file sharing networks demonstrated that while consumers and the technology were ready for the digital distribution of cultural goods, rights holders were not. Cultural black markets emerge when legal markets fail to adapt to the changes in consumer demand and consumption habits (Bodó, 2011a,b): this thesis was supported both by the studies that documented the displacement between illegal downloading and physical sales (Barker and Maloney, 2012; Bodó and Lakatos, 2012; Bonneau and Fontaine, 2012; Leung, 2009; Bounies et al., 2012; Smith and Telang, 2009; Danaher and Waldfogel, 2012), and the more recent studies suggesting that well designed legal alternatives that offer a wide variety of content at a reasonable price are able to cannibalize piratical demand (Bahanovich and Collopy, 2009; Poort and Weda, 2015).

In the current era digital cultural consumption follows a hybrid pattern in which piratical consumption is still present, but only as a complementary practice to consumption through other, legal, free and paid consumption channels (Kantar Media, 2012; Poort and Leenheer, 2012). The latter study also found that people who download from an illegal source were more likely to use legal channels as well. While the digital legal services came a long way in terms of catalogue, price and ease of use, the continuous existence of piracy suggests that there are still some who feel that legal alternatives are lacking and turn to piratical services.

Consumers' choice of which (combination of) access channels they use of course depends on a wide variety of factors beyond unfulfilled demand. Legal channels are found to be preferred for legal certainty, convenience, their social networking functions, and for the fact that they provide compensation for authors (Cooper and Griffin, 2012; Warner Music Group, 2010; Kampmann, 2010; Swedish Performing Rights Society, 2009; Kantar Media, 2012). Piratical channels are chosen because they are free , offer speedy access (especially for audiovisual content) to a more complete catalogue and allow for the possibility to try before buy (British Music Rights, 2008; Swedish Performing Rights Society, 2009; Poort and Leenheer, 2012; Kantar Media, 2012; Bounies et al., 2012; Watson et al., 2014; Handke, 2015). Sociodemographic factors, such as age and education have also been demonstrated to have an effect on the channel choices of individuals (Rochelandet and Le Guel, 2005; Morris and Higgins, 2010; Poort and Leenheer, 2012). Attitudes, the legal environment, fear of enforcement, peer pressure and social control (Svensson and Larsson, 2012) have all been demonstrated to affect the channel choices of individuals.

Price and the availability of content thus push people towards piratical access channels, while a number of factors prevent them from engaging in piracy. Either decision (to be or not to be engaged in piracy) has significant associated costs: legal uncertainty, possible legal costs and penalties, social disapproval on the one hand, lack of access, peer pressure, social disconnect on the other. No wonder that proposals that promise to resolve that dilemma enjoy support. Studies that measured support for some version of a CCS demonstrated substantial demand for such a service (Grassmuck, 2009). Various studies conducted before the appearance of Spotify demonstrated substantial (75%-90%) support for a monthly levy based license, with a willingness to pay in the ∼€5-15 price range streaming services currently occupy (Bahanovich and Collopy, 2009; Entertainment Media Research, 2011; Renkema and Karaganis, 2012; SPEDIDAM, 2005; Swedish Performing Rights Society, 2009). Most of these study agree that even pirates support the CCS idea.

As rights holders realized that (even piratical) consumers are willing to use authorized services if the service quality and the price is right, their attention shifted to the revenue generating potential of the different legal alternatives. Despite the growing importance of the issue, few studies addressed the competition and subsequent sales displacement among different legal services. In a 2012 French study Dang Nguyen et al. (2014) found that free streaming had no effect on physical sales of recorded music, and had a positive effect on concert attendance for certain artists. In a pan-European study Aguiar and Martens (2013) found that a growth in the visits to streaming websites leads to very small growth in the visits to legal digital music purchases websites. Papies et al. (2010) used conjoint analysis to predict cross-channel effects of DRM, price, and catalogue size on paid download, flat-rate streaming and ad-supported free distribution channels. They find that advertising-based access channels have the potential to attract low value users to commercial services, and the danger of cannibalizing high value paid download channels is low. In certain consumer segments however, channel competition is more pronounced, especially among those who dislike advertising and consume the most digital content. More recent data, however, suggest that streaming is in fact replacing digital sales. The International Federation of the Phonographic Industry reported (IFPI, 2015) that the share of subscription revenues of the overall digital revenues nearly doubled (from 14% to 27%) between 2011 and 2014, while digital sales started to decline (Karp, 2014) in the same rate as physical sales. Subsequently, streaming faces more and more criticism from artists who are not content with the millions of streams generating only meager returns and fear that low value streaming actually substitutes high value sales.

Complex dynamics shape the development of the digital content marketplace. Huge digital intermediaries, such as YouTube, Netflix, Amazon control ever larger chunks of digital distribution, and are thus able to dictate the terms to artists and non-major institutional rights holders (Winkler and Smith, 2014; Michaels, 2014; Handke, 2015). Artists face the double challenge of having less and less control over the distribution *vis-à-vis* powerful intermediaries, and how to deal with the threat of dwindling revenues under the streaming model. Meanwhile consumers demand access to a wide variety of content, with the least possible restrictions at a reasonable price. Our study adds to the literature by addressing these closely interrelated questions in an integrated framework:

1. Given the variety of legal and illegal, free and paying, online and offline channels, how do Dutch individuals consume music, audiovisual works and books?
2. Within the context of hybrid consumption, can piracy still be seen as a separable and separate phenomenon, which can be addressed in itself?
3. What determines demand for a license-based access alternative? Can we identify specific sociodemographic and media consumption related drivers for the demand?
4. How would the introduction of such an alternative upset the currently observable media consumption patterns?

By answering the questions above, we assess the dynamics that drive change in the Dutch digital content markets via consumers' willingness to accept a completely new, CCS based content acquisition alternative.

3 Theoretical model and hypotheses

Our theoretical model attempts to shed light on the factors that explain support for a change in the status quo in copyright management specifically focused on digital consumption. As outlined in Figure 1, we model individual support for a change to the status quo largely as a function of their cultural consumption habits. By consumption habits we understand the frequency of use and the volume of content purchased through different consumption channels across different content types.

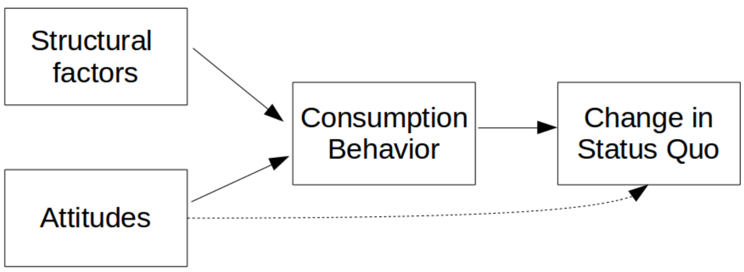

Figure 1: The basic model of cultural consumption and choice.

According to the rich stream of previous empirical research on the determinants of cultural behavior, cultural taste (Bourdieu, 1984; Peterson and Kern, 1996; Peterson and Simkus, 1992), behavior (Gayo-Cal, 2006; Widdop and Cutts, 2011) and digital habits (Poort and Weda, 2015) depend strongly on individual structural characteristics that include age, level of education, income, and place of residence. At the same time, these same factors have been found to determine the unequal distribution of skills and resources that explains the so-called "digital divide" (Norris and Inglehart, 2013). Given the relevance of the channel of consumption in our definition of cultural habits, in our first hypothesis (H_1) we expect to find that these factors are determinant in explaining patterns of cultural consumption. In particular, given the known effect of age and education in the ''digital divide" literature, *we expect to find that older people present more traditional patterns of consumption, while younger and well-educated respondents embrace mostly digital-based consumption habits.*

In addition to these structural factors, our model also contemplates that consumption habits are affected by preferences individuals hold on certain aspects of cultural consumption. For instance, music lovers interested in the continuous discovery of new things or in the ability to quickly access a musician's complete catalog may be strongly attracted to the search capabilities offered by digital music platforms and archives. In contrast, traditional bookworms may find an intrinsic value in the process of buying, reading or collecting physical books. In accordance, our second hypothesis (H_2) states that, apart from sociodemographic factors, preferences on specific aspects of digital consumption determine consumption behavior. In particular, *those having stronger preferences for elements associated with digital consumption—such as a wider range of user rights or access to artists' complete catalogs—will be more likely to adopt digitally-based cultural consumption, legal or illegal.*

Finally, our model predicts support for the establishment of a CCS (i.e., a change in the status quo) as a function of cultural consumption habits *and* preferences. As discussed in the previous section, several studies have found strong support to some form of copyright compensation system among those who already acquire cultural goods through non-traditional channels. These studies, however, are more than half a decade old, and reflect the state of digital markets of their time. We start from the naive assumption that the rapid development and adoption of a variety of legal access channels would be associated with a support for the status quo, given that their users may be satisfied with the new services. Accordingly, our third hypothesis (H_3) expects to find that, *both non-traditional and traditional consumers will be unlikely to choose an alternative to the status quo*, albeit for different reasons. In particular, we expect low support for a digital CCS among those who do not use digital access channels in the first place. Given the low level of enforcement in the Netherlands, those who acquire music, films or books through illegal sources may also find the fee based CCS option unappealing. We also expect those consumers who already use legal digital platforms to have few incentives to switch to a flat-fee based access alternative, if they find that the legal alternatives are satisfactory.

4 Methods and data

This study is based on the results of two surveys we conducted on the LISS panel[1], a representative sample of Dutch citizens aged 16+ (including those without internet connection) in November 2012. In the first survey we asked respondents to report their media consumption habits. We asked questions on the amount and frequency of purchases on various offline and online, legal free (ad-supported), subscription based and pay-per-use (PPU) as well as illegal content distribution channels for music, audiovisual content and books. In the second survey we conducted a discrete choice experiment. In the choice experiment, the payment mechanism of the CCS was defined as a surcharge to the Internet subscription fee, and respondents were informed that the functioning of the CCS (including the distribution of revenues) would occur under statutory regulation.

In the conjoint survey, CCS alternatives were defined by the combination of the following attributes:[2]

- *Allowed uses.* This attribute covers the rights that a CCS would provide participating

[1] `http://www.lissdata.nl/lissdata/` is administered by CentERdata, which is part-financed by the Netherlands Organization for Scientific Research (NWO).

[2] See Quintais (2014) for the overview and legal analysis on which the attributes of this survey were based.

users regarding the use of content, with three levels of use: (1) downloading only; (2) downloading and sharing, and (3) downloading, sharing and modification (including the right to create and disseminate derivative works).

- *Subject Matter*, which corresponds with the type of content that a CCS would make available. It also has three levels: (1) recorded music only; (2) recorded music and audiovisual works, and (3) recorded music, audiovisual works and books.
- *Catalog completeness* concerns the scope of a CCS license regarding artists' works. Its levels are: (1) complete catalog; (2) temporal restrictions; and (3) partial catalog—i.e. catalogs with permanent restrictions.
- *Monitoring.* The monitoring attribute had two levels: (1) any CCS participation is associated with anonymous monitoring; (2) there is a statutory guarantee of no monitoring.
- *Distribution of revenues.* This attribute has two levels: (1) the CCS would provide original creators with at least 50% of the CCS revenues; (2) original creators would be free to negotiate their revenue share with investors or intermediaries.
- *Price.* The choice experiment covered six 5-euro price points from €5 to €30

All the possible combinations of attribute levels would yield 648 different CCS alternatives, which cannot be tested while keeping sample size within a reasonable range. Through efficient factorial design (Addelman, 1962) we created 54 choice sets, 27 for each payment treatment option. Respondents were randomly presented with 12 choice-sets consisting of two utility balanced CCS options and a 'choose none' option.

In this paper we look at the data collected in the first survey together with the results of the second survey that concerns choosing the 'none' option only.

4.1 Classifying consumption habits

Our data set contains 28 questions related to the respondents' cultural consumption habits. Consumption is conceptualized in three dimensions: time since the last purchase or acquisition, the amount consumed, and the channel of consumption. Time is measured through six intervals, from "less than a week ago" to "more than a year ago", while the amount of consumption is measured in five categorical intervals from one unit (album, film, book) to more than 20.[3] The different channels of cultural consumption are dealt with in separate questions. The distribution of each type and dimension of consumption in the sample can be seen in Table 1. For the sake of readability, the table groups the temporal dimension into those who affirm to have never acquired a cultural good and those who have done so at least once; the amount consumed is the median amount reported by those who have acquired at least once.

The figures in Table 1 do not differ significantly from previous efforts to distinguish various channels of cultural consumption (Poort and Leenheer, 2012; Poort and Weda, 2015), but the separation between the temporal and quantitative dimensions of cultural consumption allows for a more complete picture. For instance, although downloading music or films from illegal sources is not widely spread among the population (one fourth and one fifth of the respondents, respectively), this type of consumption accounts for higher volumes of acquired goods.

In order to obtain a classification of all respondents according to their consumption, we apply a clustering algorithm to all 28 variables concerning cultural consumption habits. A clustering

[3]The amount of paid subscriptions for music is measured as the monthly household expenditure in paid online music services (e.g., Spotify or Deezer).

Table 1: Distribution of respondents' consumption habits (in time and amount).

	Time		*Amount*
	At least once	Never	Median consumption[a]
Music			
Physical buy	54.63	45.37	1 album
Paid download	16.55	83.45	1 album
Paid subscription	15.6	84.4	7.24€[b]
Free	47.24	52.76	1 album
Pirate	23.85	76.15	1-5 album
Film			
Physical buy	46.47	53.53	1 film/TV program
Paid download	9.3	90.7	1 film/TV program
Paid rental	10.24	89.76	1-5 film/TV program
Video on demand	22.58	77.42	1-5 film/TV program
Pirate	18.29	81.71	5-10 film/TV program
Books			
Physical buy	69.99	30.01	1-5 books
Paid download	11.04	88.96	1-5 books
Paid rental	3.00	97.00	1 book
Pirate	10.68	89.32	1-5 books

[a] Among those who have consumed at least once.

[b] Average monthly payment.

algorithm divides a collection of individuals into a set of similar groups, or clusters, so that individuals within a cluster are as similar as possible, and individuals in one cluster are as dissimilar as possible from individuals in other clusters (Manning et al., 2008). In order to define similarity, we use the standard Euclidean distance metric, that can be conceptualized quite naturally as distance (Greenacre, 2005). Regarding the specific clustering method, we use Hierarchical Agglomerative Clustering (HAC) (Manning et al., 2008), which compared to flat methods such as k-means clustering, does not need the prior specification of a number of clusters into which the data must be partitioned.

The method starts out considering each individual as one single cluster "and then successively merges pairs of clusters until all clusters have been merged into a single cluster that contains all [individuals]" (Manning et al., 2008). This "nested sequence of partitions" (Sandhya and Govardhan, 2012) is carried out on the dissimilarity matrix of all the individuals. In order to minimize the within-cluster variance we use Ward's minimum variance method (Ward, 1963). In the end, each respondent is classified exclusively into one cluster.

4.2 Model of cultural consumption habits

Once we get a classification of all respondents into clusters or typologies of consumers, we will test our first two hypotheses to explain cultural consumption through two types of explanatory variables: structural and attitudinal. On the one hand, our aim is to identify structural factors that shape cultural consumption habits, namely the respondents' main sociodemographic characteristics. Among these we test the effect of individual-level variables such as age, sex, income and level of education, and of contextual factors such as household size, and the respondents' city level of urbanization. On the other hand, we want to test whether respondents' preferences regarding certain aspects of cultural digital consumption affect their cultural consumption behavior. In particular, our data set contains questions regarding to what extent respondents have weak or strong preferences on the attributes of a copyright compensation system (CCS), concerning users' rights, the type of content included, completeness of the catalog, the distribution of revenues between artists and other rights holders, and the possibility of monitoring digital consumption.

Given that our response variable is a unordered polytomous measure (the different clusters representing types of consumer), we fit a multinomial logistic regression model on the type of consumer. The log-odds (η) that an individual i falls into the type of consumer k and not into the baseline (K) category can be formulated as

$$\eta_{ik} = \frac{log\pi_{ik}}{log\pi_{iK}} = \alpha_k + \beta_k \cdot X_i \tag{1}$$

where α_k is a constant, β_k is a set of regression coefficients associated with outcome k, and X_i is a vector of explanatory variables corresponding to individual i.

4.3 Model of willingness to change

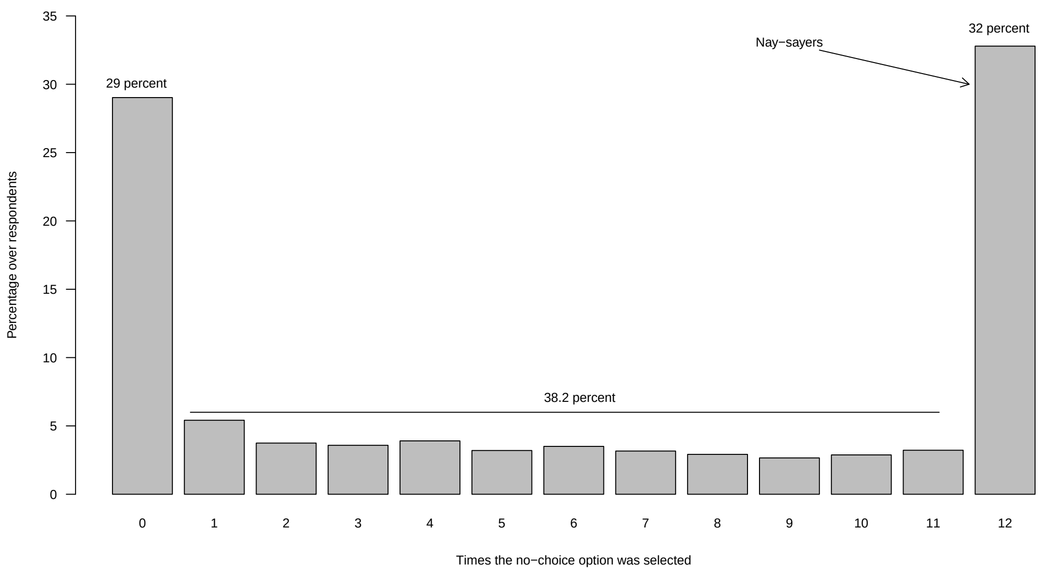

Figure 2: Distribution of times respondents chose the no-choice option in the discrete choice experiment on copyright compensation systems.

In our third hypothesis we want to test to what extent consumption behavior can explain respondents' readiness to change the status quo in copyright policy. We measure readiness to change through a continuous variable that measures the respondents' distance towards the status quo. This measure is derived from the discrete choice experiment results. In the experiment each respondent was faced with 12 choice sets, each of which containing three alternatives: two CCS alternatives containing a different combination of attributes, and a no-choice (or "none") option.

To operationalize distance, we take the number of times a respondent chose the “none” option as an indicator of her proximity to the status quo. Figure 2 shows the frequency distribution of respondents by the number of times the “none” option was chosen. 32 percent of respondents (referred to here as “nay-sayers”) opted for the no-choice option in all the choice sets they were faced with (12), and therefore they are closest to the status quo. In contrast, 29 percent always preferred some alternative to the status quo (i.e., they *never* chose the “none” option), thus being farthest from the status quo. In order to operationalize proximity as distance, we just subtracted the times each respondent chose the “none” option to 12.

To explain the respondents' readiness to change from their consumption behavior, we follow two different strategies. On the one hand, we fit a linear regression model (OLS) of the distance towards the status quo on the type of consumption controlling for the main sociodemographic factors. To ease interpretation, the distance measure has been normalized to have values between 0 and 10. We model the distance to the status quo as a function of the type of consumer, plus a number of sociodemographic and attitudinal control variables as follows:

$$y_i = \beta_1 \cdot X_{i1} + \ldots + \beta_k \cdot X_{ik} + \epsilon_i, i = 1, \ldots, n, \tag{2}$$

where y_i is the distance of the i^{th} individual to the status quo, β_k is a set of regression coefficients of length k, X_k is a set of predictors including the type of consumer and control variables, and ϵ_i stands for the unobserved error term.

On the other hand, although our raw measure of distance is a continuous variable (12 minus the number of times a respondent chooses the ‘none’ option), it is actually count data bounded to have integer values that can only range 0 to 12. Modeling variation of count data through straightforward linear models may cause estimation problems (Cameron and Trivedi, 1998), given that OLS assumes that values are normally distributed and that the response variable can take any real value (positive or negative). Count data can be better modeled through log-linear regression models that assume more realistic distributions in the response data, such as Poisson (Gelman and Hill, 2007). To that effect, we also fit a Poisson regression model to explain variation in distance to the status quo (through the raw, non-normalized measure of distance) as a function of the type of consumer (plus the same control variables used in the OLS model). In order to control for violations of the equality between mean and variance required by the Poisson distribution (Cameron and Trivedi, 1998), we compute robust, heteroscedasticity-consistent standard errors for the parameter estimates (Zeileis, 2004, 2006). Table 2 provides basic descriptive statistics of all the variables.

5 Main empirical results

5.1 Clusters of consumers

Table 3 shows average scores of each variable of media consumption for each of the five clusters provided by the algorithm.

Since consumption data are three-dimensional (time, amount, and channel) the interpretation of the results must take all three elements into account. Let's focus on the fourth numeric column of Table 3. Individuals in this cluster are characterized by very high scores in all time-related variables, indicating that their last consumption (whatever the amount and the channel) took place a long time ago (more than one year ago). Moreover, individuals in this cluster present the lowest average scores in all the amount-related measures, indicating that they acquired only a very small amount of cultural goods. In a nutshell, these are individuals that consume almost

Table 2: Descriptive statistics of the variables.

Statistic	N	Mean	St. Dev.	Min	Max
Distance to SQ (not normalized)	4,677	6.01	5.13	0	12
Distance to SQ (normalized)	4,677	4.99	4.27	0	10
Age	4,680	51.48	17.77	16	93
Education	4,668	3.39	1.50	1	6
Income (monthly, 1,000€)	4,680	1.42	1.00	0	10
Residence	4,639	3.01	1.27	1	5
Household size	4,680	2.56	1.28	1	8
Pref. users rights	4,612	3.21	2.36	1	7
Pref. types of content	4,610	3.49	2.42	1	7
Pref. catalog completeness	4,605	3.32	2.34	1	7
Pref. artists payment	4,604	3.25	2.31	1	7
Pref. monitoring	2,298	3.54	2.44	1	7

never and in very small amounts. We have therefore labeled them as "Non-consumers", and they represent 28 percent of the population.

The first cluster represents mainly the occasional cultural consumers (29 percent of the population). They are low-intensity consumers in both time and amount, but with a stronger preference for free music (e.g., radio or free Spotify accounts), and certain reliance on physical buy. In contrast, bookworms (20 percent) are defined by their low interest in music and audiovisual content, and by a rather high intensity of book consumption in both time and amount, which is almost exclusively focused on books in physical format. The third column in Table 3 represents the smallest group of consumers (6.4 percent), which are digital cultural omnivores that consume (especially music and films) through paid subscriptions, although they also rely on physical formats for all types of goods. Finally, the second cluster represents what we call pirates, who present similar cultural habits to the digital consumers (they are also cultural omnivores), but with high levels of consumption through illegal sources. They represent 16 percent of the respondents.

5.2 Determinants of cultural consumption

Once each respondent is classified as a particular type of consumer (i.e., in a cluster), we can explore what are the factors that correlate with the cultural consumption habits of each group. The response variable in this model will be the type of consumer, and the model a logistic regression with unordered response. Detailed tabular results are in Table 7 in the Appendix. Model A includes only controls for sociodemographic factors, while the effect of the intensity of preferences can be observed in Model B.To ease the readability of results, Table 4 presents the average values of each independent variable for each type of consumer.

Our baseline here are the non-consumers. The regression results show that age and education are important predictors of distinctive cultural consumption habits. Moreover, digital consumers and pirates present similar sociodemographic profiles. As expected, older respondents present lower chances of being pirates or digital consumers, and higher chances of being bookworms, than non-consumers. The first row of Table 4 shows that non-consumers and bookworms present much older average age profiles, while pirates and digital consumers are notably younger. Also, the chances of being any type of cultural consumer (compared to a non-consumer) increase with

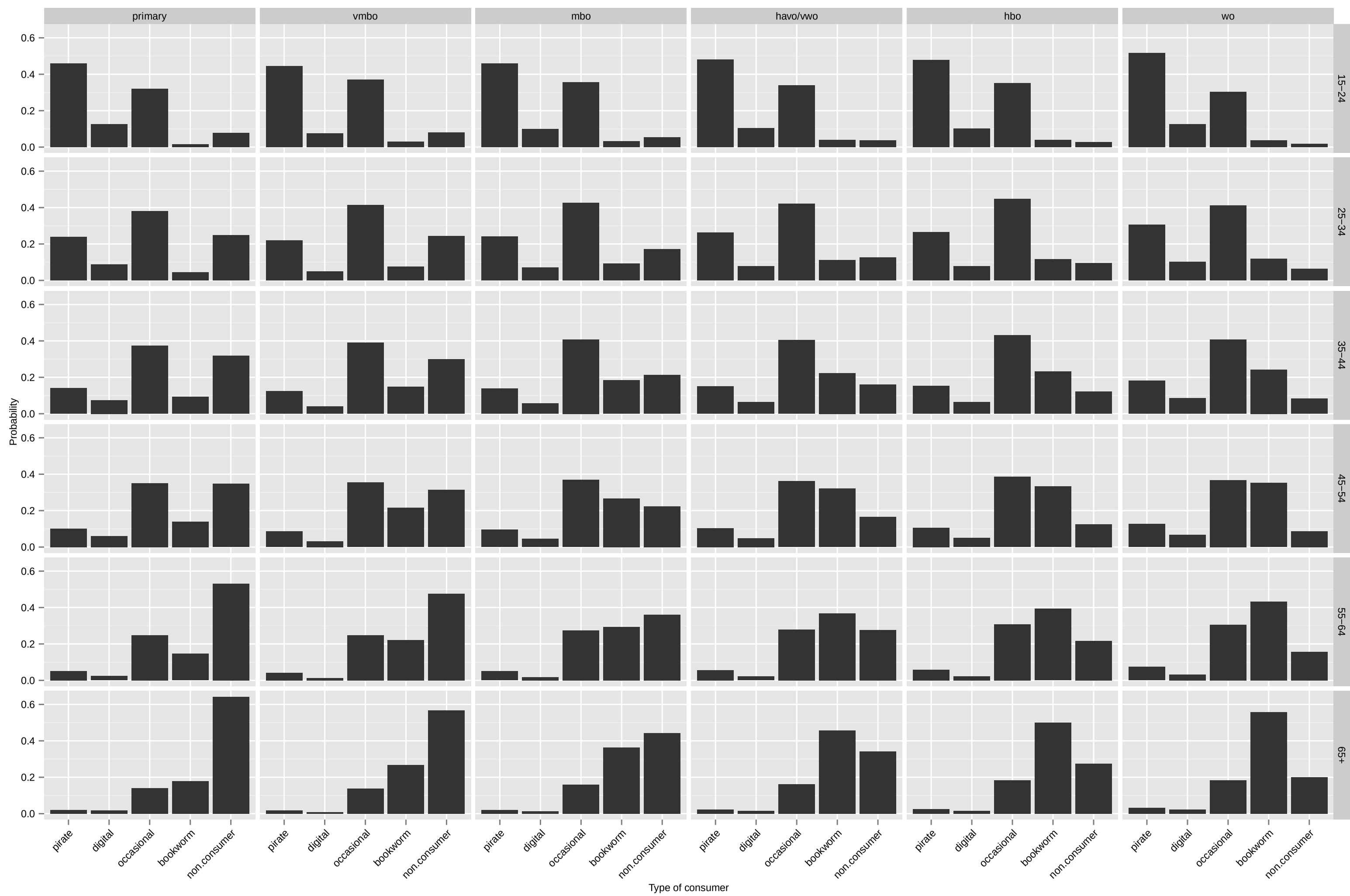

Figure 3: Probability of being each type of consumer by level of education and age.

Table 3: Cluster means of the Hierarchical Clustering results (Ward method).

	Occasional	Pirate	Digital	Non-consumer	Bookworm
Music					
Time					
Physical buy	5.97	6.00	5.72	6.84	6.05
Paid download	6.62	6.16	5.57	7.09	6.80
Paid subscription	6.56	6.24	1.92	7.13	6.88
Free	2.68	3.15	2.53	7.09	6.69
Pirate	6.50	4.00	5.69	7.12	6.96
Amount					
Physical buy	0.90	0.88	1.10	0.39	0.83
Paid download	0.23	0.46	0.91	0.03	0.16
Free	1.67	1.76	2.67	0.04	0.20
Pirate	0.36	2.08	1.04	0.02	0.11
Paid subscription	0.23	0.38	15.41	0.01	0.09
Film/TV					
Time					
Physical buy	5.80	5.25	5.50	6.85	5.89
Paid download	6.95	5.79	5.93	7.07	6.95
Paid rental	6.95	5.37	5.68	7.09	7.00
VOD	5.49	5.28	5.16	7.04	6.87
Pirate	6.97	3.13	5.44	7.08	7.00
Amount					
Physical buy	0.93	1.09	1.11	0.25	0.77
Paid download	0.08	0.49	0.67	0.03	0.05
Paid rental	0.07	0.75	0.89	0.02	0.03
VOD	0.81	0.83	1.15	0.05	0.13
Pirate	0.10	2.60	1.19	0.01	0.05
Books					
Time					
Physical buy	4.54	4.22	4.17	6.62	2.99
Paid download	6.82	6.07	6.38	7.08	6.59
Paid rental	7.02	6.42	6.81	7.09	7.01
Pirate	6.94	5.64	6.37	7.08	6.68
Amount					
Physical buy	1.65	1.63	1.82	0.53	2.32
Paid download	0.16	0.39	0.53	0.01	0.27
Paid rental	0.03	0.18	0.25	0.00	0.01
Pirate	0.12	0.88	0.66	0.01	0.40

education. For instance, at the same age and similar levels of income, the odds of being a pirate instead of a non-consumer will increase by 2.3 if moving from primary to secondary education (HAVO/VWO), and they will be 4.5 times higher if moving from primary to university education. The same pattern holds for the rest of types of cultural consumers, although of course the impact of education is highest among bookworms.

The significant combined effect of age and education on consumption habits, though, can be better observed in Figure 3. The plot represents the probability of being each type of consumer

Table 4: Average and most common values of each independent variable for each type of consumer. For education and type of residence, values are column percentages.

	Non-consumer	Pirate	Occasional	Digital	Bookworm
Age	60.99	37.24	47.31	40.56	59.00
Median income (€1000)	1.25	1.25	1.38	1.55	1.55
Average income (€1000)	1.36	1.26	1.39	1.56	1.61
Household size	2.28	2.85	2.72	3.05	2.34
Education (%)					
Primary	13.64	9.44	7.26	10.85	4.48
VMBO	39.45	16.09	21.64	12.88	23.02
MBO	22.19	22.61	25.24	23.73	21.04
HAVO/VWO	6.70	17.02	11.23	14.58	10.83
HBO	14.56	22.74	25.53	24.07	30.42
WO	3.47	12.10	9.10	13.90	10.21
Residence (%)					
Highly urbanized	11.09	14.67	13.25	17.18	12.05
Urbanized	24.10	28.94	25.97	29.55	26.00
Moderately urb.	23.94	24.05	24.14	22.34	23.38
Little urb.	23.40	19.57	20.53	17.53	23.27
Not urbanized	17.47	12.77	16.11	13.40	15.30
Preference intensity[a]					
User rights	2.22	4.40	3.52	4.48	2.83
Types of content	2.23	4.87	3.99	4.92	3.01
Catalog completeness	2.21	4.51	3.73	4.51	2.98
Artists payment	2.32	4.07	3.59	4.20	3.15

[a] Value range from 1 to 7.

at all combinations of education and age.[4] For instance, let's focus on pirates. At all levels of education the relative probability of being a pirate remains stable within age categories but changes dramatically across them. If, for instance, we focus on the younger group of respondents, the probability of being a pirate remains high regardless of their level of education, as it remains very low among older respondents at all educational levels. In contrast, the probability of being a book lover or a non-consumer changes across both age groups *and* education levels.

On the other hand, the model also includes the effect of the intensity of preferences on the type of consumption. In general terms, the inclusion of attitudinal questions does not change the coefficients of the structural factors while significantly improving the model fit, which serves as a robustness check.The attitudinal variables also behave as expected. Respondents with stronger preferences regarding the rights provided by copyright compensation system (CCS) are more probable to be a pirate or a digital consumer rather than a non-consumer. the preferences regarding the types of content are significantly associated with all types of consumer (as opposed to the non-consumers). In contrast, preferences on catalog completeness help distinguishing between all types of consumers from non-consumers except for bookworms, while stronger preferences on the specific way revenues from a CCS are distributed to artists are related with higher likelihood of being bookworms compared to non-consumers.

[4]For the sake of visualization, age has been recoded into a categorical variable with 10-year interval categories.

5.3 Users' readiness to change

Table 5 shows the results of both the linear and the Poisson regression models of readiness to change in relation to the type of consumer. The dependent variable is the distance to the status quo, normalized in OLS, not normalized in Poisson. For each type of model, the table shows three different specifications. Although coefficients are in different scale, the table shows that both modeling strategies arrive at basically the same results, serving as a robustness check for the analysis.

In the first specification we regress distance on the type of consumer without any other intervening factor. As expected, all types of consumers are on average farther away from the status quo compared to non-consumers. However, in sharp contrast with our naive hypothesis, digital consumers and pirates lead the way for change, followed by occasional consumers. In particular, digital buyers are on average 4.7 points (in the 0-10 scale, Specification 1, first column) farther from the status quo than non-consumers, while the distance differential is 3.8 for pirates and 2.5 for occasional consumers.[5] The Poisson model (second column of Specification 1) yields basically the same message: digital consumers are 2.6 times farther away from the status quo than the non-consumers, followed closely by pirates.These results may be better observed in Figure 4, which plots the predicted distance to the status quo of the five types of consumer (from the linear model), with 95 percent confidence intervals. The position of digital consumers and pirates is clearly away from the status quo, but the average position of occasional consumers is also significantly above the midpoint.

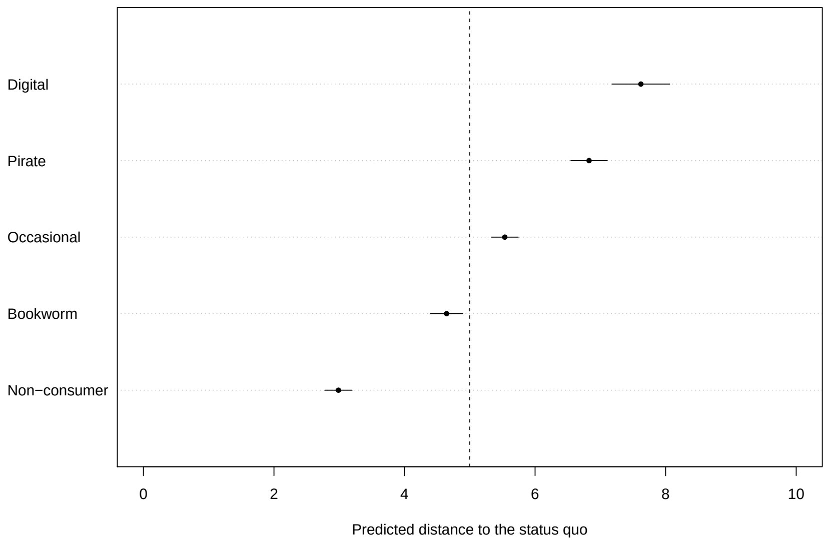

Figure 4: Predicted distance towards status quo by the different types of consumer, from the OLS model. Error bars correspond to 95% confidence intervals, and the vertical dotted line marks the midpoint in distance.

[5]In order to carry out a further check on the models given the extreme distribution of the data, we fit the same linear model of distance on the consumer clusters removing the individuals with extreme distance positions (i.e., 0 and 10) from the dataset. Results with the new data (38% of the sample) hold despite a variation in the levels of significance for occasional consumers and bookworms.

Table 5: OLS and Poisson regression models of distance towards the status quo on the type of consumer. Values are linear regression coefficients in OLS models (standard errors), and log of expected counts for the Poisson models (robust standard errors).

	Distance to the Status Quo					
	Specification 1		Specification 2		Specification 3	
	OLS	*Poisson*	*OLS*	*Poisson*	*OLS*	*Poisson*
Type of consumer [Ref. Non-consumer]						
Pirate	3.806***	0.822***	3.379***	0.736***	1.726***	0.422***
	(0.183)	(0.042)	(0.192)	(0.044)	(0.190)	(0.044)
Occasional	2.541***	0.616***	2.194***	0.546***	1.173***	0.339***
	(0.155)	(0.042)	(0.159)	(0.044)	(0.153)	(0.042)
Digital	4.705***	0.946***	4.198***	0.845***	2.639***	0.543***
	(0.259)	(0.044)	(0.265)	(0.046)	(0.253)	(0.047)
Bookworm	1.730***	0.457***	1.414***	0.394***	0.942***	0.292***
	(0.171)	(0.048)	(0.174)	(0.049)	(0.162)	(0.046)
Education [Ref. Primary]						
VMBO			−0.368	−0.094*	−0.331	−0.076
			(0.228)	(0.052)	(0.212)	(0.050)
MBO			0.256	0.061	−0.062	0.005
			(0.235)	(0.050)	(0.219)	(0.049)
HAVO/VWO			0.803***	0.155***	0.248	0.052
			(0.266)	(0.051)	(0.248)	(0.050)
HBO			0.979***	0.194***	0.334	0.073
			(0.238)	(0.049)	(0.223)	(0.048)
WO			1.167***	0.217***	0.326	0.061
			(0.292)	(0.055)	(0.274)	(0.053)
Income (log)			−0.029*	−0.006*	−0.022	−0.005
			(0.017)	(0.003)	(0.016)	(0.003)
Household size			0.147***	0.028***	0.062	0.015*
			(0.049)	(0.009)	(0.046)	(0.009)
Residence [Ref. Highly urb.]						
Urbanized			−0.260	−0.049	−0.120	−0.016
			(0.202)	(0.038)	(0.188)	(0.036)
Moderately urb.			−0.014	−0.0003	0.062	0.016
			(0.207)	(0.039)	(0.192)	(0.037)
Little urb.			−0.321	−0.060	−0.157	−0.025
			(0.211)	(0.041)	(0.196)	(0.039)
Not urbanized			−0.278	−0.054	−0.132	−0.021
			(0.226)	(0.045)	(0.210)	(0.044)
Female			0.087	0.015	0.221*	0.046*
			(0.122)	(0.024)	(0.114)	(0.024)
Preference intensity						
User rights					0.110***	0.023***
					(0.034)	(0.006)
Types of content					0.254***	0.054***
					(0.037)	(0.007)
Catalog completeness					0.067*	0.014**
					(0.039)	(0.007)
Artists payment					0.412***	0.080***
					(0.032)	(0.006)
Constant	2.987***	1.277***	2.613***	1.201***	0.882***	0.772***
	(0.111)	(0.037)	(0.283)	(0.064)	(0.270)	(0.066)
Observations	4,677	4,677	4,624	4,624	4,549	4,549
R^2	0.121		0.142		0.267	
Residual Std. Error	4.009		3.969		3.657	
Akaike Inf. Crit.		37,665.800		36,854.610		33,673.110
Note:						*p<0.1; **p<0.05; ***p<0.01

These same results hold in the second specification, where we control for the usual sociodemographic factors.[6] Of these factors, the effect of education, income and household size are significant, while place of residence does not have any significant effect on distance. On the one hand, we observe a significant relationship between distance and level of education: keeping the type of consumer constant, more educated respondents are more ready to change than respondents with lower educational levels. Larger households are also associated with higher distance to the status quo. On the other hand, higher levels of income are associated with lower distance to the status quo, although the effect is really small, the model predicting that a €1,000 increase in individual income would on average reduce distance to the status quo only by 6%.

The effect of the type of consumer on the readiness to change holds also when our third specification includes controls for preference intensity, increasing also the model fit substantially.Although the inclusion of preference intensity in the model mildens the effect of the type of consumer (coefficients are smaller), the same logic prevails. However, the inclusion of controls for the intensity of preferences dissipates any effect of sociodemographic factors, while preferences do make a difference. As expected, keeping the type of consumer and all the sociodemographic factors constant, preferences on artists payment and types of content present the stronger effect on readiness to change, while catalog completeness has only a very mild effect.

In sum, results support the hypothesis that different types of consumers hold significantly different levels of readiness to change the status quo in copyright enforcement, and that their openness to change is robust to controls on a varied range of sociodemographic factors and preference intensity variables. However, the naive assumption regarding the theoretical low incentives of digital consumers and pirates to support a change in the status quo given the existence of digital platforms and low copyright enforcement, respectively, is not supported by the data. On the one hand, the high level of support for change among digital consumers casts doubt on the assumption that current digital platforms actually cover their needs or aspirations so as to minimize their incentives to support a CCS. On the other, the significantly high level of support that pirates show for the implementation of a CCS is at odds with their widespread depiction as free-riders who take advantage of the low-intensity levels of copyright enforcement in the Netherlands.

Table 6: Average price of chosen compensation system (CS) alternatives by type of consumer.

Cluster	Price (€)
Digital	11.50
Pirate	9.87
Occasional	7.68
Bookworm	6.54
Non-consumer	4.12

A further test on the robustness of the support for change can be carried out taking into account the price of the CCS options voted by each type of consumer. In particular, if the naive hypothesis were true, we should observe that pirates systematically prefer CCS alternatives that maximize user's rights and cultural content at the minimum price. Table 6 shows the average price of the compensation systems chosen by each type of consumer (i.e. average price within each cluster). Digital consumers, who already pay for their cultural consumption, tend to choose alternatives at higher prices. Most significantly, though, pirates do not seem to be freeloaders,

[6]Due to the significant effect of some sociodemographic factors on the type of consumer reported in Table 7, a Variance inflation factor (VIF) test was conducted on the covariates of our linear regression model. Results suggested that age should be removed from the model due to multicollinearity.

but show systematic preference for compensation systems at prices only slightly lower than those chosen by digital consumers. In addition, a one-way ANOVA was conducted to compare the effect of type of consumer on average price of chosen alternative compensation systems. We found that average values of price are significantly different between types of consumers.[7] Results also indicate that average prices project the same order as the support for change: those more ready to change are willing to pay more.

6 Discussion and concluding remarks

Our research offers insights into how the emergence of a wide variety of legal digital consumption channels structured the media consumption landscape in the Netherlands. We also discussed some of the dynamics that drive future change.

We found that nearly half (48.72%) of our representative sample does not use digital access channels to consume music, audiovisual content or books. There are two major holdout groups: older, less educated people do not consume culture at all; older, more educated ones prefer to buy physical books only.

The division line between the digital holdouts and those who embraced the internet to consume culture is defined by age. The younger generations show promiscuous content acquisition strategies, in which legal and illegal, free and paying, online and offline channels are equally present. We distinguished three separate groups among them: digital consumers, pirates and occasional consumers. Both pirates and digital consumers are cultural omnivores: they often consume relatively high quantities of content through various free and paying channels. The main difference between these groups lies in their use of piratical access channels: digital consumers do not pirate, while pirates use illegal access channels alongside legal ones. Pirates tend to be much younger than digital consumers, but since income wasn't significant in any of our models in Table 7, we suspect the age effect not to be an indicator of the lack of disposable income. Digital consumers and pirates make up of 6.36%, and 16.02% of our sample, respectively, thus they are relatively few, but they are responsible for a relatively large share of the overall cultural consumption.

The third group, the occasional consumers is the largest of our 5 initial clusters, with 28.88% of the sample. This group is mostly characterized by infrequent and low intensity digital consumption in general. Their use of digital channels is still mainly focused on free sampling, which is complemented by the purchase of physical copies.

It is clear from our study, that though a substantial share of our sample uses piratical access channels, there are only a few who use them exclusively (around 1% for music and films, 0.6% for books), and thus, it is very hard, if not impossible to separate 'pirates from digital consumers. The use of piratical channels is only one aspect of the digital consumption landscape, and pirates are only a special subset of digital consumers, who happen to complement their legal consumption with illegal practices. This means that any intervention (such as the introduction of a CCS) that hopes to address the "piracy problem" will unavoidably affect the much wider domain of legal digital consumption.

In that context, the piracy-based argument in favor of a CCS seems not to be most important one. Our research found that against our expectations, there is considerable support for a CCS-based cultural distribution system, and this support is the strongest among those who already use legal access alternatives: pirates and digital consumers. In effect, the more someone uses the current legal alternatives, the more he or she is inclined to support the CCS idea. We interpret

[7] $F(4, 4863) = 147.4, p < 0.001$.

the support for the CCS alternative as a discontent with the status quo, with the currently available legal alternatives.

Our models offer an insight into the possible sources of that discontent. The main source of discontent is revealed by the third model specification in Table 5, which includes the preference intensities for two CCS components: user rights and types of content. Since all alternatives for both components included a baseline, we are safe to assume that a low preference intensity means the acceptance of the common denominator, namely downloading only and access to music only. In return, we associate a strong preference intensity with a preference for more than just the baseline.[8] Since both these variables demonstrate relatively large coefficients and are highly significant, we are safe to say that respondents who reject the status quo want access to content beyond music, and see the right to download as insufficient. Worth noting that piratical access channels have exactly these strengths compared to current legal alternatives: the freedom to share and access to a wide variety of content beyond music.

Finally, we can rule out the effect of a relatively low CCS price, i.e., that digital consumers and pirates prefer a CCS alternative because they see it as a chance to save on cultural spending. Table 6 shows that those who are the most willing to change are also the most willing to pay for the CCS alternative. Pirates, who actively use the free and unconstrained piratical access channels are willing to spend nearly as much as digital consumers for a CCS alternative (€9.87 and €11.5 respectively).

A CCS has less to offer for occasional consumers, to whom a flat rate would possibly raise the annual cultural spending beyond their current levels, and convert the internet as their free (i.e. ad-supported) access channel into a paying one. Nevertheless, even occasional consumers are more open to change than not. For them a CCS offers the chance to expand their explorative consumption (Bodó and Lakatos, 2012) beyond music into the audiovisual and book domains. Occasional buyers are not limited to low income/low education people, therefore, a CCS offers them a risk-free opportunity to explore and experiment with unknown cultural works, just as free music services before enabled them to sample music without risk. Occasional consumers are apparently ready to embrace this opportunity, even if somewhat hesitantly.

The last half decade radically transformed the ways consumers have legal access to cultural goods. The most visible change was the proliferation of the streaming model: the free and flat-rate access to wide catalogues of first music (with the likes of Spotify and Deezer), later movies (through Amazon and Netflix) and most recently books (via Kindle Unlimited or Oyster). These developments were first hailed for their capacity to cannibalize piratical demand, but more recently we witness an increasing level of push-back from rights holders. More and more creators feel that they are powerless *vis-à-vis* these newly emerged intermediaries who control an ever-larger share of the market (Streitfeld, 2014), have an increasingly exclusive access to consumers, but does not generate sufficient amounts of revenue.

Our study has shown that despite the widespread adoption of such services by consumers, there is a strong support for CCS-based alternatives. A CCS is preferred to the status quo both by occasional and frequent buyers of cultural goods. A CSS-based alternative would not necessarily increase the control of artists over distribution (though certain CSS configurations allow for that possibility), but at least it would increase the welfare of rights holders *and* consumers (Handke et al., 2015), and weaken the exclusive position of current digital intermediaries. All of these arguments seem to be in support of the CCS idea. Whether that is enough to initiate a change, is another question.

[8]Unless we assume theoretically that respondents have a strong preference for the option that offers them less.

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A Multinomial regression model of type of consumer

Table 7: Results of the multinomial regression model of type of consumer. Coefficients are in log-odds (standard errors within parentheses).

	Model A				*Model B*			
	Pirate	Occasional	Digital	Bookworm	Pirate	Occasional	Digital	Bookworm
Age	−0.111***	−0.015**	−0.075***	0.063***	−0.120***	−0.019**	−0.080***	0.068***
	(0.008)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)	(0.013)	(0.007)
Age squared	0.0002*	−0.0004***	0.00001	−0.001***	0.0004***	−0.0003***	0.0002	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Income (log)	0.013	−0.009	0.018	0.0002	0.008	−0.013	0.010	−0.001
	(0.015)	(0.012)	(0.018)	(0.014)	(0.015)	(0.013)	(0.019)	(0.014)
Education [Ref. Primary]								
VMBO	−0.093***	0.010	−0.617***	0.472***	−0.041***	0.028	−0.537***	0.466***
	(0.009)	(0.042)	(0.002)	(0.027)	(0.009)	(0.042)	(0.002)	(0.027)
MBO	0.301***	0.343***	0.042***	0.997***	0.222***	0.245***	−0.085***	0.935***
	(0.013)	(0.044)	(0.003)	(0.021)	(0.013)	(0.044)	(0.003)	(0.022)
HAVO/VWO	0.824***	0.709***	0.521***	1.543***	0.614***	0.547***	0.230***	1.459***
	(0.002)	(0.003)	(0.0004)	(0.002)	(0.002)	(0.003)	(0.0005)	(0.002)
HBO	0.964***	0.984***	0.708***	1.807***	0.731***	0.799***	0.449***	1.695***
	(0.010)	(0.040)	(0.002)	(0.028)	(0.010)	(0.041)	(0.003)	(0.029)
WO	1.513***	1.274***	1.343***	2.216***	1.101***	0.961***	0.869***	2.062***
	(0.002)	(0.005)	(0.001)	(0.003)	(0.002)	(0.005)	(0.001)	(0.004)
Household size	−0.128***	−0.071*	0.064	−0.054	−0.137***	−0.083**	0.051	−0.056
	(0.043)	(0.036)	(0.053)	(0.041)	(0.045)	(0.037)	(0.055)	(0.042)
Residence [Ref. Highly urb.]								
Urbanized	0.298***	0.172***	0.063***	0.151***	0.327***	0.178***	0.077***	0.152***
	(0.015)	(0.046)	(0.003)	(0.023)	(0.014)	(0.043)	(0.003)	(0.023)
Moderately urb.	0.069***	0.059	−0.312***	0.076***	0.055***	0.039	−0.342***	0.066***
	(0.015)	(0.047)	(0.003)	(0.024)	(0.014)	(0.043)	(0.003)	(0.023)
Little urb.	0.117***	0.045	−0.339***	0.125***	0.175***	0.072*	−0.284***	0.125***
	(0.012)	(0.047)	(0.003)	(0.029)	(0.011)	(0.041)	(0.003)	(0.025)
Not urbanized	−0.165***	0.008	−0.438***	−0.001	−0.122***	0.026***	−0.405***	0.005*
	(0.013)	(0.052)	(0.003)	(0.028)	(0.002)	(0.007)	(0.001)	(0.003)
Sex								
Female	−0.874***	−0.080	−0.622***	0.414***	−0.819***	−0.032	−0.542***	0.465***
	(0.019)	(0.053)	(0.003)	(0.025)	(0.018)	(0.054)	(0.005)	(0.027)
Preference intensity								
User rights					0.061*	−0.009	0.077*	−0.028
					(0.034)	(0.028)	(0.043)	(0.030)
Types of content					0.259***	0.190***	0.272***	0.063**
					(0.036)	(0.029)	(0.046)	(0.031)
Catalog completeness					0.122***	0.083***	0.090*	0.049
					(0.038)	(0.032)	(0.047)	(0.034)
Artists payment					0.014	0.029	0.048	0.078***
					(0.031)	(0.026)	(0.039)	(0.028)
Constant	4.619***	1.847***	2.516***	−3.052***	2.962***	0.903***	0.737***	−3.736***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Akaike Inf. Crit.	12,300.500	12,300.500	12,300.500	12,300.500	11,720.340	11,720.340	11,720.340	11,720.340
Note:								*p<0.1; **p<0.05; ***p<0.01