Experimental evidence on demand for 'on-demand' entertainment*

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Abstract

This study applies stated-preference choice experiments and accompanying surveys to examine how Subscription Video on Demand (SVoD) has disrupted film and television consumption. We examine demand for a large set of traditional consumption alternatives, such as cinema and free-to-air TV, as well as newer internet-based subscription services, such as Netflix. We consider a range of alternative-specific product attributes—including price, viewing quality, and release delay—that allow us to quantify substitution effects and willingness-to-pay estimates. In addition, we also consider illegal viewing alternatives, with associated attributes related to (potential) punishment that inform on the efficacy of policy against digital piracy. Our primary results reveal that while some traditional alternatives remain important, consumers derive significant utility from SVoD, which provides a large surplus at current pricing. We also observe that marginal effects and willingness-to-pay estimates are sensitive to *ex-ante* interest in a film or TV series. Moreover, we provide evidence that consumers can be segmented in relation to (survey-reported) piracy experience, as well as perceptions of punishment risk and (industry) damage associated with piracy. We also find some evidence that increasing punishment probability and fines may discourage illegal consumption. Finally, we provide some validation of our results with a follow-up survey conducted six months after the experiment.

Key words: Subscription Video on Demand, stated preference, digital piracy.
JEL classifications: L82, Z10

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1 Introduction

The arrival of Netflix and, to a lesser extent, other Subscription Video on Demand (SVoD) services has significantly disrupted traditional media industries with interests in film and television. With SVoD increasing its global penetration, established pay-TV providers have had to reconsider their business and pricing strategies to remain competitive. For example, historic rivals Comcast and Netflix struck a deal in July 2016 to include Netflix in the Comcast X1 set-top box. In March 2018, Europe's Sky pay-TV announced a partnership with Netflix in a bid to retain customers. In November 2014, Australian pay-TV provider Foxtel halved the price of its basic subscription only months before Netflix's arrival.

Anecdotal evidence also suggests that digital piracy (both downloading and streaming) has reduced as a direct result of SVoD alternatives. In 2013, Netflix Chief Content Officer Ted Sarandos made the observation: "When we launch in a territory the Bittorrent traffic drops as the Netflix traffic grows".[1] A number of surveys have also attributed decreased illegal piracy levels to the arrival of Netflix. For example, a 2016 study by the UK Intellectual Property Office related decreased piracy levels to the rising popularity of Netflix.[2] Similar evidence has been found in Australia by the Intellectual Property Awareness Foundation.[3]

While few would deny the existence of a SVoD substitution effect against the incumbent providers (both legal and illegal), there have only been limited attempts to measure such effects. In large part, this is likely due to the dearth of data that researchers have access to on consumer activity in this space. Netflix is well known to be extremely protective of its data and, with the exception of the theatrical film industry, sales data from downstream content providers is also extremely difficult to access. Furthermore, obtaining reliable data on illegal piracy presents its own set of challenges, not the least of which being that many participants go to great lengths to conceal their activities.

Presented with these challenges, a revealed-preference analysis of consumer behaviour in these industries is extremely difficult. This study attempts to make headway into this area using laboratory-based stated-preference choice experiments as an alternate approach. Specifically, we investigate *how* SVoD affects traditional legal and illegal alternatives. Furthermore, our analysis also examines the efficacy of policy designed to curtail digital piracy. We develop a framework in which consumers face choices over viewing alternatives of film and TV, which (in addition to the important subjective differences) are defined by a common set of attributes related to price, viewing quality, and release delay. Within this set of

[1] Cited in *Stuff* interview on 1st May, 2013 (`https://www.stuff.tv/news/`).

[2] See `https://www.telegraph.co.uk/technology/2016/07/04/internet-piracy-falls-to-record-lows-amid-rise-of-spotify-and-ne/`.

[3] See `https://www.businessinsider.com.au/australian-internet-piracy-drops-29-2015-10`.

alternatives, we also consider illegal viewing options, associated with additional attributes related to potential punishment from this activity.

We estimate a variety of (related) discrete-choice models. Specifically, the multinomial logit (MNL), mixed multinomial logit (MMNL), and latent class (LC) models. While the MNL serves as a useful baseline model, it suffers from the well-known independence from irrelevant alternatives (IIA) assumption. The MMNL model avoids this problem and allows the estimation of more realistic substitution patterns and willingness-to-pay estimates, which permit inferences concerning the introduction of SVoD. We also harness the properties of the LC model to segment participants by observable characteristics, which further helps to understand how SVoD has disrupted the traditional media landscape.

Our stated-preference design is also novel in two important respects. First, we prime participants with a number of forthcoming film and TV series. For each respective title, we ask whether they would be i) 'highly likely', ii) 'fairly likely', or iii) not likely to view (default). This allows us compare substitution patterns and willingess-to-pay estimates across alternatives for *ex-ante* different-valued products. Second, we employ the 'availability design' methodology developed by Rose, Louviere and Bleimer (2013). As modern consumers face a relatively large set of viewing alternatives for film and TV, this allows us to present subsets of alternatives within an individual choice task, while maintaining an efficient global design. This minimises the potential for 'cognitively overburdening' participants, which may confound results when stated-preference choice tasks feature too many alternatives.

In addition to the stated-preference experiments, we utilise two distinct surveys to add depth to our analysis. First, and immediately following the stated-preference exercise, we conducted a 'post-experiment survey' of participants general viewing habits, attitudes towards piracy, and demographic information. We use this additional data to segment participants in the LC models. The second survey was conducted approximately six months after the laboratory-based experiments (and 'post experiment survey'). In this 'follow-up survey' participants were presented with the same film and TV titles from the laboratory experiments and asked *if* and *how* they actually viewed the various titles, of which almost all had been released for at least a few months.

This paper is structured as follows. Section 2 reviews literature related to our study. Section 3 outlines relevant stated-preference theory and provides specific details concerning our experimental design. In addition, this section describes the post-experiment and follow-up surveys that compliment our analysis. Section 4 discusses results. In addition to the MNL and MMNL model results, we report selected substitution effects and willingness-to-pay estimates. We also report results from LC model and the follow-up survey. Finally, Section 5 provides summary and concluding remarks.

2 Literature

Our study contributes to a growing literature that considers the effects of digital disruption in media industries. It is already relatively well established that illegal file sharing and online piracy results in at least some displacement of legitimate sales (Rob and Waldfogel, 2007; Hennig-Thurau, Henning, and Sattler, 2007; Bai and Waldfogel, 2012). As such, it should come as little surprise that more recent studies find evidence of similar displacement effects in the context of SVoD; both in terms of internet penetration leading to a reduction in time spent watching conventional television (Liebowitz and Zentner, 2016), and to the reductions in both legal and illegal forms of media consumption following the introduction of SVoD services (Aguiar and Waldfogel, 2018a; Godinho de Matos, Ferriera, and Smith, 2017). This displacement has been found to be particularly pronounced among low-income and younger households, who are more likely to cut subscriptions to other paid television services in the presence of SVoD services (Prince and Greenstein, 2017).

SVoD platforms such as Netflix, Hulu and Amazon Prime effectively constitute a type of club good, potentially requiring special consideration to be given to appropriate price, payment and revenue-sharing mechanisms compared with other forms of media consumption. In terms of pricing, evidence of the elasticity of demand for movie products is mixed. For example, Lang, Switzer and Swartz (2011) find evidence of relatively price inelastic demand for home movie consumption via DVD, while De Roos and McKenzie (2014) find evidence of relatively high price elasticity of demand at the cinema box office. Even among segments of consumers, Mukherjee and Kadiyali (2011) find evidence that those with stronger preferences for movies with higher theatrical revenues and advertising expenditures tend to be less price sensitive than average. Given varying evidence on the price elasticity of demand in this context, relatively simple strategies of price discrimination such as bundling and two-part tariffs have been advocated in the literature (Shiller and Waldfogel, 2011; 2013).

SVoD services are also likely to impact upon patterns of consumption via the timing of releases. Mukherjee and Kadiyali (2011) find evidence of low cross-channel availability elasticities between movie purchases and rentals. The authors argue that so-called 'windowing' strategies, involving the staggering of movie release across various channels, are ineffective since consumers prefer to watch older content on their preferred distribution channel rather than change channel in order to access newer content. Indeed, a number of other studies (e.g. Hiller, 2017; King and King, 2017) show that subscribers to SVoD services may be disproportionately likely to view older 'catalogue' titles compared with other forms of consumption, largely due to SVoD services helping to overcome the search costs associated with locating a movie over time. This pattern may also partly explain why consumers have been shown to be significantly more likely to view 'niche' titles as opposed to blockbusters via digital distribution channels (Zentner, Smith and Kaya, 2013). Lang, Switzer and Swartz (2011) further highlight that, while demand for home movie consumption is partly correlated with both the production budget and the performance of the original theatrical release, it is also comparatively less responsive to reviews from professional critics. SVoD services have also been shown to increase the availability of titles from other countries and promote non-US titles better than theatrical releases (Aguiar and Waldfogel, 2018b).

In the absence of comprehensive revealed preference data, studies investigating consumer demand for entertainment goods have made use of stated preference methodologies based around discrete choice and latent-class modelling. The aim of these approaches is to identify different willingness to pay (WTP) for content among consumers for products with different characteristics. A number of studies have employed these methodologies through surveying attendees at European theatre events (Grisolía and Willis, 2011; 2012; Baldin and Bille, 2018), highlighting how consumer preferences can be defined by characteristics such as age, gender, income and cultural capital, as well as the characteristics of output such as genre, timing of showing/release, critical reviews and word-of-mouth. To our knowledge, only one study has previously applied a stated-preference approach in the context of online movie streaming services, where consumer WTP is shown to be positively influenced by the amount (volume) of content offered and the timing of its availability relative to original release, while being negatively affected by the presence of advertisements and the sharing of non-identifying personal information (Glasgow and Butler, 2017).

Our work also has relevance to the literature on digital piracy and the effectiveness of anti-piracy policy. In theory, while Darmon and Le Texier (2016) argue that public enforcement of anti-piracy rules may be socially optimal compared with private enforcement, they also contend that supply-side policies may be counter-productive and damage social welfare. It is therefore somewhat unsurprising that the effectiveness of government policies designed to curtail piracy has been called into question by Orme (2014), who argues that very few anti-piracy policies adopted by the US over the last twenty years have any effect upon movie box office revenues. Those that are shown to have an effect are argued to ultimately harm the business in the long-run due to the loss of associated word-of-mouth promotion.

Similar findings have been shown in relation to more recent supply-side policy responses, such as the high profile shut-down of the popular 'cyber locker' site Megaupload.com. Although there is evidence to suggest that commercial revenues for film products increased in the wake of the Megaupload.com closure (Danaher and Smith, 2014), it has also been shown that the closure benefited only wide-release movies and that the net effect of the policy has been negative due to the loss of informational externalities created by file sharing (Peukert, Claussen and Kretschmer, 2017). Related results have also been shown in the case of music streaming services, whereby the removal of material from video streaming site YouTube is shown to increase album sales only among top-selling artists, whereas lesser-known acts suffer due to the loss of a vital promotional channel (Hiller, 2016).

An increasingly popular policy to tackle piracy in many countries over the last few years has been dubbed 'graduated response' due to the issue of warnings and sanctions of increasing severity issued by ISPs to consumers found to be repeatedly pirating digital materials. Danaher, Smith, Telang and Chen (2014) find evidence to suggest that the French graduated response policy (known as 'HADOPI') has led to a significant increase in legitimate music sales, especially among genres that are known to be more heavily affected by piracy. By contrast, a cross-country study by McKenzie (2017) finds no consistent evidence of any effect of graduated response policies upon movie box office revenues, which may be a consequence of the substitutability between the cinema experience and the illegal alternative.

In summary, the existing literature offers useful insight into the extent to which SVoD services bring about displacement of consumption via other legal channels. The literature also provides evidence of markedly different tastes and preferences among consumers in relation to price, variety, genre and timing of releases, as well as among distinct segments of consumers clustered according to age, gender, income, etc. In addition, there is inconsistent evidence concerning how SVoD may displace illegal consumption, which is particularly noteworthy given mixed evidence regarding the efficacy of supply-side policies. These issues have important managerial implications for SVoD platforms in the presence of piracy. Additionally, given the increased quantity and variety of output offered by digitisation, our study responds to a call for further research into the ways in which consumers identify suitable outputs from the vast array offered by platform such as Netflix (Waldfogel, 2017).

3 Stated-preference choice experiments

To investigate our primary research question concerning how the arrival of SVoD has disrupted established (legal and illegal) consumption of film and TV, as well as secondary questions concerning the efficacy of policies designed to curb illegal consumption, we develop a stated-preference choice experiment. This section begins by outlining basic theory underpinning the stated-preference approach before describing the specific features of our experimental design. A discussion regarding the selection of the film and TV alternatives and their attributes then follows. Finally, we detail two additional surveys used to support and help validate our stated-preference experiments.

3.1 Stated-preference theory

As has been well documented, discrete-choice models are based on random utility theory where a representative consumer's utility is derived from the product attributes (or characteristics), subject to some unobserved error term.[4] It is well known that the standard multinomial logit (MNL) model assumes that preferences are homogeneous/consistent across all consumers. In the simple MNL model, the utility a representative consumer i derives from alternative j can be expressed as $U_{ij} = \alpha_j + \beta' X_j + \varepsilon_{ij}$, where α_j is the alternative-specific constant for product j, β' is the parameter vector associated with the vector of product attributes X_j, and ε_{ij} is a random error term that captures unobservable contributions to utility. Under the assumption that ε_{ij} follows an extreme value type 1 (EV1) distribution, the MNL choice probability that individual i chooses alternative j from the available set of K alternatives, can be expressed as

$$P_{ij} = \frac{\exp(\alpha_j + \beta' X_j)}{\sum_{k=1}^{K} \exp(\alpha_k + \beta' X_k)}. \tag{1}$$

While the MNL model is useful to make preliminary inferences, the independence from irrelevant alternatives (IIA) property implies the estimated parameters are fixed amongst the population, which further implies there are no differences in individuals' preferences. While a convenient form, the IIA assumption places limitations on the MNL model.

A more advanced choice model that relaxes the assumption of IIA and permits heterogeneity amongst consumers is the mixed multinomial logit (MMNL) model. Assuming that utility can be succinctly defined $U_{ij} = \beta_i' X_j + \varepsilon_{ij}$ where $\beta_i = \bar{\beta} + \eta z_i$, the (expected) probability of individual i selecting alternative j can be defined

$$E[P_{ij}|\beta_i] = \int_{\beta_i} \frac{\exp {\beta'}_i X_j}{\sum_{k=1}^{K} \exp {\beta'}_i X_j} f(\beta_i) d\beta_i. \tag{2}$$

Note that z_i is a random draw from an underlying (multivariate) distribution, which we discuss further below. The MMNL has a number of important advantages over the MNL. In particular, it provides more realistic substitution patterns (e.g. marginal effects and elasticities) and willingness-to-pay estimates.

A further popular model that relaxes the IIA assumption and permits heterogeneity is the latent class (LC) model (Kamakura and Russell, 1989).[5] LC models offers an extension

[4] Although the origins of discrete choice theory can be traced back almost 100 years, the contributions of Daniel McFadden were pivotal in development of the area. See, in particular, McFadden (1986).

[5] The ability to identify market segments resulted in LC models being originally used in market research. See, for example, Gupta and Chintagunta (1994) and Wedel and Kamakura (2000).

to the standard MNL model by assuming a finite number of consumer classes account for preference heterogeneity amongst alternative choice. The LC model estimates Equation 1 for S classes and predicts the probability M_{is} that individual i belongs in class s. The unconditional probability of choosing alternative j becomes

$$P_{ij} = \sum_{s=1}^{S} P_{ij|s} M_{is} \tag{3}$$

given

$$P_{ij|s} = \frac{\exp(\alpha_{js} + \beta_s' X_j)}{\sum_{k=1}^{K} \exp(\alpha_{ks} + \beta_s' X_k)} \quad s = 1, ..., S \quad \text{and} \quad M_{is} = \frac{\exp(\gamma_s' Z_i)}{\sum_{s=1}^{S} \exp(\gamma_s' Z_i)},$$

where γ_s is the parameter vector associated with the class characteristics defined by Z_i. Determination of the appropriate number of latent classes requires the minimisation of a model selection index such as the Akaike Information Criterion (AIC) or the Bayesian information criterion (BIC), along with ensuring that the parameters of the classes are behaviourally valid.[6] Our primary interest in the LC model is in being able to segment consumer types in relation to answers given in the 'post-experiment' survey that we discuss below.

3.2 Experiments

Overview of design and choice tasks

A series of laboratory-based stated-preference experiments were conducted at a large Australian university during August and October, 2017. Each participant was provided with a set of instructions, as well as the appropriate ethics consent documentation.[7] Instructions were subsequently read to participants who were seated in partitioned booths. Each participant was paid A$20 (Australian dollars) for their time, which typically was 30-45 minutes. Approximately six months after these experiments, a follow-up survey was undertaken. Each participant was compensated with a A$5 gift voucher. This is described in more detail below.

In total, 151 participants completed the experiments (and post-experiment survey). The number of participants was selected to sufficiently exceed the largest S-estimate for each individual model parameter. The S-estimate is derived from the estimated prior parameters and standard errors. It represents the minimum sample size required to obtain a statistically

[6] The AIC and BIC criteria are respectively defined $AIC = -2LL + 2P$ and $BIC = -2LL + (ln(N))P$, where LL is the value of the log-likelihood function at convergence, P is the number of parameters in the model and N is the total sample size.

[7] Participant instructions and consent forms are provided in the Online Appendix.

significant estimate of each individual parameter at 95% confidence (Rose and Bleimer, 2013). In our experiments, the largest S-estimate was 87, which is significantly below our sample size of 151.

Participants were a mix of undergraduate and postgraduate students of the university. Although not representative of the entire population, the advantage of studying this demographic cohort are that they are well known to be among the most avid consumers of film and TV content across different platforms. However, given that our sample skews towards a younger tech-savvy cohort, and likely with lower disposable incomes, it is probable that the results are biased towards newer forms of content delivery, such as SVoD and illegal alternatives. Despite the limitations arising from the lack of heterogeneity in demographic characteristics (e.g. age, income), our post-experiment survey nevertheless reveals significant variation in attitudinal and behavioural traits that allow us to segment participants in the the LC model, which we discuss in detail in Section 4.5.

The first stage of the laboratory exercise presented participants with 15 forthcoming films across a range of genres. For each title, participants were provided an information sheet listing the genre, director, writer, cast, and brief synopsis.[8] Participants selected whether they were either 'highly likely', 'fairly likely', or (default) not likely to view each of the films. This design negated the need for a 'no (alternative) selection' option (as would be generally required without this conditioning stage) and allows for more nuanced estimates of utility, marginal effects, and willingness to pay. After selecting viewing intention for each film, participants completed a series of 10 choice tasks based initially on the films selected as 'highly likely' to view, followed by 10 choice tasks on films selected as 'fairly likely' to view. At the top of each 'choice task' screen, participants had a reminder list of the films they had selected with respect to their viewing intention.[9]

At the completion of the 10 film choice tasks, participants progressed to the TV stage of the experiment. As with the film stage, participants were initially presented with 15 upcoming TV series and asked to select which of these they were 'highly likely' or 'fairly likely' to view (or by default, not view). Following this step, they completed nine choice tasks for both viewing intention types. The difference between the film and TV sets is simply because 'cinema' is not relevant for TV viewing decisions. Again, their list of selected TV series was displayed to help frame the exercise.

[8]An example information sheet is provided in the Online Appendix (Figure A1).

[9]Example choice tasks are shown in the Online Appendix (Figure A2).

Alternatives and availability design

Satisfaction of the global utility maximizing rule that governs discrete choice experiments is dependent upon presenting all of the alternatives in the choice tasks to each respondent. This rule applies even if some of the alternatives are only available to a subset of respondents, or if some alternatives garner only a small share of the context being examined. With this in mind, a crucial first step in experimental design involves defining the universal but finite list of alternatives. In total, 10 viewing alternatives were considered for film and nine for TV as listed in Table 1. However, it is well known that such a large set of alternatives may cognitively overburden respondents. For example, Caussade et al. (2005) note that increases in the number of alternatives has a large influence on the error variance of the estimated utility function and suggest the optimal number of alternatives is around four.

There are various remedial measures to deal with problems arising from large (universal) sets of alternatives but typically the solution involves a subjective refinement of the set to include fewer options. Instead of proceeding this way, we make use of the recent innovative 'availability design' method developed by Rose, Louviere and Bliemer (2013). This design assigns a subset of alternatives from the universal list to each respondent. Practically, this means participants are presented with different subsets of alternatives in each completed choice task. In the context of our problem, out of the total 10 film (or nine TV) alternatives, each choice task contains a subset of only five of these. Over the course of the 10 (nine) choice tasks, each film (TV) alternative was presented exactly the same number of times to each participant, ensuring a balanced global design.

In order to determine the most efficient selection of choice tasks, a D-efficient experimental design was adopted.[10] Efficient designs predict the standard errors by determining the asymptotic variance-covariance matrix (AVC) of the underlying experiment, based on some prior information about the parameter estimates.[11] The efficiency of a design is determined by the minimisation of some 'efficiency error'. While a variety of efficiency measures have been proposed, one of the most common is the D-error, which calculates the determinant of the AVC matrix Ω_1 (that is to say, Ω_N is calculated for a single respondent). Hensher, Rose and Greene (2015) note that in practice it is difficult to find a design with the 'lowest'

[10]Efficiency in this context refers to reliable parameter estimates with small standard errors.

[11]Formally, the AVC matrix Ω_N is defined as follows:

$$\Omega_N(X,Y,\tilde{\beta}) = -[\ E(I_N(X,Y,\beta))]^{-1} \ = -\left[\ \frac{\partial^2 L_N(X,Y,\tilde{\beta})}{\partial\beta\partial\beta'}\right]^{-1} \tag{4}$$

where X represents the experimental design, Y the outcomes of the choice tasks, and β the associated parameter values. $I_N(X,Y,\beta)$ is the Fisher information matrix with N respondents, while $L_N(X,\tilde{\beta})$ is the log-likelihood function for N respondents.

D-error, known as a D-optimal design. Instead, researchers tend to settle for a 'sufficiently low' D-error, known as a D-efficient design.

As noted in Equation 4, efficient designs require some prior estimates of β. The priors used for the estimation of the D-efficient design were obtained using a pilot survey of 15 respondents. The location and structure of the pilot survey was identical to the one described above. Each respondent completed 10 choice tasks for each of the four branches of the experiment (i.e. film and TV, both 'highly likely' and 'fairly likely'), resulting in 150 observations per branch. This permitted the estimation of initial MNL models. The β parameters from each model were then used as priors for the D-efficient designs.

Attributes and attribute levels

Having defined the alternatives, the next step is to determine the attributes and associated levels of each attribute. This is not a simple task as each alternative in a labelled choice experiment may incorporate a mix of common and uncommon attributes. Furthermore, even if two alternatives have similar attributes, the levels associated with each of those attributes may differ from alternative to alternative.

When alternatives have shared attributes it is vital to ensure that the levels decision makers cognitively associate with each alternative are not different. Attribute ambiguity such as this will add to the unobserved variance in choice between alternatives. It is also important to avoid certain inter-attribute correlations that may result in cognitively unacceptable combinations within the design and bias results. For example, a decision maker may assume a strong correlation between the price and quality attributes. Presenting a choice task which does not represent this relationship (such as high price, low quality) may therefore cause the decision maker to stop taking the experiment seriously.

With these criteria in mind we define attributes related to price, viewing quality, release delay and (for the illegal options only) punishment probability and punishment fine. While other attributes could certainly be included, we focus on these as being the most relevant for consumers. This necessarily means that other (alternative-specific) attributes become part of the implicit choice process, which has important implications for the analysis as we discuss below. Furthermore, with some caveats, the selected attributes are firm-level strategic variables, which provide managerial implications for the analysis.

The next step is to define levels for each of the attributes listed above. There is no set number of recommend levels for each attribute (and the number of levels does not need to be the same for each attribute). It is worth noting, however, that each possible attribute level is mapped to a point in the utility space, therefore the more levels included, the more accurately we can map the utility function. Attribute levels must be carefully specified so they make sense to the participants. Ideally the extreme values of quantitative attribute levels should lie just outside the ranges of what the participant might consider reasonable in order to provide gain a better understanding of the trade-offs between choices and obtain more accurate estimation results. Furthermore, evenly spaced attribute levels (e.g. 1, 3, 5, 7 not 1, 4, 5, 7) are preferred when estimating the effects of quantitative attributes. With these considerations in mind, attributes and levels were selected as shown in Table 2.

One particular alternative/attribute relationship warrants further discussion. Specifically, the price of (bundled) SVoD (e.g. Netflix) and traditional pay-TV subscription services. Participants were explicitly told that the prices of these alternatives *did not* represent the cost of the subscription but an 'effective price per film (or TV series)' within that bundle. The instructions read: "For some viewing options this represents a proportion of the total fee paid for a service. It is important to note that the price listed does not represent the cost of a viewing option as a whole. Instead the price reflects the effective 'cost per film' or 'cost per TV series' of that particular service."[12] While in reality consumers do not make purchase decisions like this, we frame it this way to enable comparison between alternatives conditional on a film or TV series choice. Clearly, this formulation requires deeper thinking concerning the (subjective) value and cost of bundled content more generally.

In our study, it is implicitly assumed that selecting a bundled alternative will incur additional cost above the 'effective price' to meet the full price of a subscription. By design, when a participant makes any stated-preference choice they are required to make an assessment of the (net) benefits of each alternative based on their own preferences over product characteristics, which may or may not be completely reflected in the defined attributes. For example, in the context of the cinema alternative in our study, a participant may consider the appeal of a large screen, dynamic sound system, and candy bar as part of the implicit cinema experience—even though none of these things are explicitly included as attributes. Equally, costs (beyond the ticket price) might also feature in the decision-making process. For example, the cost of transport, parking, or candy bar items.

In a somewhat similar way, a subscription alternative implies benefits and costs beyond the specific film or TV series under consideration. Most relevant is the value of the additional (bundled) content relative to the total bundle price. This is in addition to whatever other (implicitly-valued) net benefits this alternative may provide (e.g. potential to watch on mobile devices).[13] Of course, some participants might misunderstand the instructions

[12]See participant instructions in the Online Appendix.

[13]We can apply simple bundling theory to demonstrate the decision process. In particular, a consumer will purchase a bundle containing product j if $v_j + v_{-j} + \epsilon_B \leq p_B$, where v_j denotes value of j, v_{-j} denotes value of other products in the bundle not equal j, ϵ_B denotes unobserved (net) benefits of bundle B, and p_B is the bundle price. Therefore, if the consumer selects the alternative with 'effective price' p_j, then

relating to 'effective price' and think of it as the price for the entire bundle. In this case, the willingness-to-pay estimates for the bundle are the same as those for the specific title. Alternatively, other participants might view SVoD content as part of a bundle purchase, and therefore not be willing to pay a positive price for any individual title if included as part of the bundle. We discuss these possibilities further in Section 4.4.

Post-experiment and follow-up surveys

Following the completion of the stated-preference choice tasks, each participant completed a 'post experiment survey' designed to capture information relating to attitudes and experience with piracy, as well as more general demographic information. The primary purpose of the post-experiment survey was to gather data for estimation of the membership functions of the LC model discussed in Section 3.1. There were five sets of questions that were used to capture information on the following: i) participant's history of illegal film and TV consumption; ii) perceived 'risk' of getting caught illegally accessing content; iii) perceived 'damage' that illegal consumption has on the content industry; and iv) general demographic questions.[14]

In order to help validate the experimental stated-preference approach, participants also completed a short online 'follow-up survey' approximately six-months after the laboratory-based experiments (and post-experiment survey) took place. The timing of this survey was chosen such that almost all of the titles had been released in the cinema (if applicable) as well as on video-on-demand (VoD) services and physical formats. Participants were contacted via email and directed to a website where they were shown the 15 films and 15 TV series from the original experiments. For each film/TV series, they were asked if (and how) they viewed each title. In order to prevent potential bias, participants were not reminded of the choices they made during the initial experiment while completing the follow-up survey. These responses were then cross checked with the viewing intention stated in the first stage of the experiments.

4 Results

4.1 Overview of design and selections

Table 3 provides details regarding the design and selections by participants. As described in Section 3.2, each participant completed 10 film choice tasks related to i) 'highly likely' and ii)

$v_{-j} + \epsilon_B \geq p_B - p_j$. That is, the value of other products apart from j combined with unobserved (net) bundle benefits exceed the difference between the bundle and effective price.

[14]The post-experiment survey questions are provided in the Online Appendix.

‘fairly likely’ selections, then completed 9 TV choice tasks related to i) ‘highly likely’ and ii) ‘fairly likely’ selections. These resulted in 1510 film observations, and 1359 TV observations.

With regard to films classified as ‘highly likely’, respondents selected cinema almost 30% of the time, and VoD options (both purchase and subscription) also featured prominently with a combined 25% of selections. This broadly confirms that cinema is still a strongly preferred alternative for highly-anticipated releases, but also that the new SVoD services provide a popular alternative to traditional viewing formats.

The evidence for films rated as ‘fairly likely’ reveals a much lower number of cinema selections (9.5%) and that free-to-air TV (32%) remains relevant for participants where advertising interruptions represent an implicit form of payment. Both purchased and subscription VoD were also much lower (combined 13%) relative to the highly-likely films, but DVD purchases and rentals both increased (12% to 18% combined). Interestingly, both illegal downloading and illegal streaming revealed themselves more attractive for *a-priori* less attractive films (21% to 14% combined). This suggests that respondents prefer implicit payment in terms of potential punishment and/or lower quality over monetary outlays, which is not inconsistent with implicit payment through advertising.

The observed choices relating to TV viewing alternatives reveals broadly similar evidence as films. In particular, the two VoD alternatives are popular with the ‘highly likely’ TV series and less popular with their ‘fairly likely’ counterparts (27% to 19% combined). Free-to-air is much more popular with the latter type of series (40% compared to 25%), again suggestive that participants are more willing to accept advertising as part of the viewing experience for less-attractive TV offerings. Overall, illegal consumption options were selected marginally more for TV shows of less appeal (19% compared to 17%) but the overall difference was not as apparent as it were for the different types of films.

4.2 MNL and MMNL results

The MNL and MMNL results are presented in Tables 4 and 5. In a number of respects, the results are similar and reveal the alternative-specific constants are markedly different for both films and TV series with respect to classification as ‘highly likely’ or ‘fairly likely’. For ‘highly likely’ films, both models support cinema as providing most utility. The SVoD alternative ranks strongly in terms of relative alternative-specific constant. For both models, the ‘fairly likely’ films suggest a lower relative utility from cinema (but still providing most utility), followed by SVoD. The free-to-air alternative is also relatively higher in the ‘fairly likely’ models. Illegal downloading also features as important in the ‘highly likely’ MMNL model, which is not observed in the MNL models. We believe this difference extends from modelling the punishment attribute variables as random, which reflects the heterogeneity in participants attitudes towards punishment of illegal activity.

All attributes in the film MNL and MMNL models have signage that accords with *a-priori* intuition. Specifically, quality improvements increase utility, whereas increased release delays and higher prices decrease utility. Both punishment probabilities and (potential) fine are negative in signage, as would be expected (but are insignificant in the MNL model). The implications of the estimated coefficients are discussed in the following sections with respect to substitution patterns (i.e. marginal effects) and willingness-to-pay estimates.

The results of the MNL and MMNL models relating to TV viewing confirm the popularity of SVoD, which provides the most utility for MNL and second highest utility for MMNL in terms of 'highly likely' series. As was observed with 'highly likely' films, illegal downloading is also highly relevant for 'highly likely' TV series in the MMNL model. As observed with film models, all attribute coefficients in the TV MNLs conform with *a-priori* intuition in terms of signage and all display statistical significance (with exception of the punishment attributes in the MNL and 'quality' in the MMNL model). Again, implications of the estimated attribute coefficients are discussed further in the following sections.

As already noted, the MMNL is able to provide more realistic substitution patterns as it does not suffer from the IIA property. We are most interested in examining relationships between alternative selections and attributes including price, viewing quality, release delay, and (potential) punishment for illegal viewing. Therefore, we model each of these as random parameters as reported in Table 5. In particular, all random parameters are assumed to be normally distributed, but we model price as a triangular distribution to ensure acceptable willingness-to-pay estimates (see Hensher, Rose and Greenee; 2015, p. 622).

4.3 Marginal effects

Due to the IIA property, the MNL produces unrealistic substitution patterns. Therefore, we report marginal effects of 'own' and 'cross' attributes from the MMNL model. These are respectively computed as

$$\delta^{P_{jn}}_{x_{jkn}} = \frac{dP_j}{dx_{jk}} = \frac{\int_{\beta_i} \frac{dU_j}{dx_{jk}} P_j \left(1 - P_j\right) f(\beta_i) d\beta_i}{\int_{\beta_i} P_j f(\beta_i) d\beta_i} \quad \text{and} \quad \delta^{P_{jn}}_{x_{j'kn}} = \frac{dP_j}{dx_{j'k}} = \frac{\int_{\beta_i} \frac{dU_j}{dx_{j'k}} P_j P_{j'} f(\beta_i) d\beta_i}{\int_{\beta_i} P_j f(\beta_i) d\beta_i}, \tag{5}$$

where P_j and $P_{j'}$ are choice probabilities of alternatives j and $j' \neq j$ and x_{jk} is the kth attribute of j. However, because the MMNL is non-linear, aggregation of the individual-specific elasticities may return biased elasticities. We follow Louviere, Hensher and Swait

(2000) and use probability-weighted sample enumerated marginal effects defined as

$$\delta^{\bar{P}_j}_{x_{j'k}} = \left(\sum_{n=1}^{N} \hat{P}_{jn} \delta^{P_{jn}}_{x_{j'kn}} \right) / \sum_{n=1}^{N} \hat{P}_{jn}, \qquad (6)$$

where $\hat{P}_{jn}$ is the estimated probability and $\bar{P}_j$ is the aggregate probability of j.

Own-attribute marginal effects

Table 6 reports own-attribute marginal effects for each alternative with respect to various attributes for both films and TV series, as well as by viewing intention. With respect to price, it is clear that marginal effects for 'highly likely' films and TV series are lower than their 'fairly likely' counterparts, which reflects the ex-ante popularity of such titles.

Both film and TV viewership is more likely with increased viewing quality and shorter release delays across all alternatives, which is observed across both 'highly likely' and 'fairly likely' types. However, there is no clear (own marginal effect) dominance with respect to viewing intention, as was evident with respect to price. This suggests participants respond differently to the various alternatives and that attributes are of different relevance for different alternatives. Finally, the marginal effects related to illegal downloading suggest both the probability of receiving a fine and amount of the fine if caught deter illegal consumption.[15]

Cross-attribute marginal effects

In this section, give our interest in understanding the disruption created by SVoD, we focus only a small subset of the most relevant cross-attribute marginal effects that we estimate.[16] In particular, we focus on cross marginal effects related to the SVoD and (illegal) downloading alternatives presented visually in Figures 1 and 2.

With respect to changes in the price of SVoD for film, it is clear that purchased VoD is the most likely substitute. However, for TV more traditional Pay-TV and DVD purchases options remain important. Free-to-air TV and (illegal) downloading also feature among the more likely substitutes alternatives. With respect to viewing quality and release delays of both SVoD film and TV, there is little evidence of substitution, i.e. most cross marginal effects are close to zero. Taken literally, these imply that SVoD consumers are not as sensitive to these attributes, which in some respects reflects the fact that such services continue to offer standard definition (SD) packages and specialise on a catalogue of older-release titles.

[15] Note that only the (illegal) download alternative is reported as the (illegal) streaming alternative is normalised in estimation.

[16] The full set of marginal effects are reported in the Online Appendix (Tables A1-A8).

The illegal download estimated cross marginal effects reveal that both increasing probability of a fine or the fine amount itself result in only limited substitution towards legal alternatives. This is particularly true for 'highly likely' types. For illegal downloads of TV series, there is some evidence that pay-TV purchases increase if either the probability of punishment or fine increases. However, in both cases, the size of the effect is limited.

4.4 Willingness to pay

Australian context

To provide context for the Australian dollar denominated willingness-to-pay (WTP) estimates discussed below, the 2017 average price for a cinema admission was A$14.30. However, it should be noted that this estimate is based on a measure of revenue divided by *all* admissions and includes concession and discounted tickets.[17] At most major city multiplexes, the full adult price is typically A$20-A$25. At the end of 2017, a Netflix subscription cost A$13.99 for a standard plan and A$17.99 for a premium plan. An iTunes purchase typically costs A$15-A$25 for a new-release film title. With respect to DVD purchase and rental, a variety of prices exist but typically cost A$20-A$30 for a new-release purchase, or A$6-A$8 for an overnight rental of the same title. A (pay-per-view) pay-TV movie purchase would cost A$5.95 (SD) or A$6.95 (HD) on the main pay-TV provider. Finally, base pay-TV subscriptions of the same provider cost A$26 with HD costing an extra A$10.

WTP estimates

Table 7 reports WTP estimates for both film and TV by viewing intention. The MNL values are directly calculated as the ratio of the estimated coefficient for alternative j (or attribute k) and the estimated price coefficient, as reported in Table 4. In order to obtain the MMNL values, we follow Hensher and Greene (2003) and derive WTP figures based on unconditional parameter estimates.[18] The standard deviation of each of the mean WTP values is also reported. Clearly 'highly likely' titles are consistently valued more highly than 'fairly likely' titles, which reflects the greater value consumers place on them. As described above, these estimates conform broadly with actual prices paid for content in the Australian market. As one example, assuming a A$20 cinema admission, a consumer would receive positive surplus for a 'highly likely' film but negative surplus for one considered 'fairly likely'.

[17] See `https://www.screenaustralia.gov.au/fact-finders/cinema/industry-trends/box-office/ticket-prices`.

[18] WTP figures based on conditional parameter estimates were also calculated and were comparable to the unconditional figures presented in Table 7.

With respect to SVoD, WTP for 'highly likely' films and TV series suggests considerable consumer surplus given the relative price of a typical subscription (e.g. Netflix). Recalling that participants selecting this alternative did so on the basis of 'effective price' per film (or TV series) implies WTP for the actual bundle is (possibly much) larger. Even if some participants misunderstood the instruction relating to 'effective price' and viewed it as inclusive of the bundle, the WTP estimates would then represent lower bound for the bundle. Another potential misunderstanding about SVoD price could occur if participants assumed an existing subscription, and attached zero marginal cost to (additional) bundled items. If such a misunderstanding occurred in our experiments, we would expect a significant proportion of participants not to select SVoD in any choice task given all SVoD were associated with positive prices (as provided in Table 2). However, of the 151 participants, we observe 132 (i.e. 87.4%) selecting SVoD at least once, which we believe alleviates concern about this particular type of misunderstanding. Therefore, based on our WTP estimates and comparison with the pay-TV (subscription) alternative, Netflix's current pricing appears low relative to the value derived by consumers even by providing only films and/or TV series that are 'fairly likely' to be consumed.

Beyond WTP estimates for the various alternatives, we are also able to measure WTP for incremental changes in the attribute levels implicit in the design. The WTP estimates related to quality and release delay reveal consumers are willing to pay more (less) for increased quality (release delay) for 'highly likely' relative to 'fairly likely' titles. This is true for both film and TV and reflects the importance of these attributes for more popular titles. In particular, in relation to the quality estimates the values are within a range that conform with industry practice as outlined above. For example, the relative price differences between standard definition (SD) and high definition (HD) films purchased via pay-TV equates to A$1. In terms of the difference in Netflix subscription costs of standard and premium (4K) this equates to A$4 (per month). Finally, we also observe a decrease in WTP for increased chance of being caught and the amount of fine if caught. However, relative to estimated WTP value placed on these illegal alternatives, the size of these decreases appears small. This raises some questions about the perceived efficacy of the punishments.

4.5 Latent class model

As outlined in Section 3.2, we conducted a post-experiment survey to collect data related to actual (illegal) piracy experience, attitudes towards piracy, and demographic information. The primary intention of this exercise was to generate accompanying data to be used in the LC model. Based on these questions, we investigated potential classes related to the following: i) number of films illegally downloaded or streamed, denoted 'FILMDL'; i) number of TV series illegally downloaded or streamed, denoted 'TVDL'; ii) risk perception of illegal consumption, denoted 'RISK'; iii) (industry) damage perception of illegal consumption, denoted 'DAMAGE'; iv) number of films/TV shows selected as 'highly likely' (out of 15), denoted 'FILMTOT'/'TVTOT'; and v) various demographic information, which were not ultimately included in the LC model due to lack of variation within our cohort (discussed further below).[19] Although we lack variation in the demographic variables, we note substantial variation in responses to the other survey questions permitting us to robustly estimate the LC model. For this exercise, we limited attention to 'highly likely' films and TV series.

As discussed in Section 3.1, the appropriate number of classes in the LC model is determined by the minimisation of a selection criterion such as the Akaike Information Criterion (AIC) or the Bayesian information criterion (BIC). In our case, increasing the number of latent classes from one to two leads to a decrease in both AIC and BIC. However, in both the film and TV models, as the number of classes was increased from two to three, the parameter estimates became unstable with large standard errors and very small class probabilities indicating an over-fitting of the model (Heckman and Singer, 1984). Subsequent analysis is therefore based on the presence of two latent classes of film viewers and two latent classes of TV viewers. In both the film and TV models, the estimated class sizes were approximately equal. The results are presented in Table 8.

Based on the parameter estimates of the LC models the following *ex-post* classification of film and TV viewers is proposed:

i. Film Class 1: Members of this class demonstrate a clear preference for watching highly-anticipated films at the cinema or via illegal downloads, as well as deriving a relatively high level of utility from a variety of other formats. They pay little regard to quality, but are sensitive to release dates. We define viewers in this class as *film buffs*.

ii. Film Class 2: Viewers in this class place an emphasis on the quality of the viewing experience. They are more price sensitive than the viewers in Class 1 and therefore show a desire to watch films on legal on-demand services, in particular SVoD, rather than in the cinema. We define viewers in this class as the *Netflix generation*.

iii. TV Class 1: Due to their willingness to view TV shows on a wide variety of both traditional and digital legal formats. Such viewers demonstrate a strong desire to watch TV shows as close as possible to their release date, prioritising this over the quality of the viewing experience. Members of this class are considered to be *TV junkies*.

[19] FILMDL, TVDL, RISK, and DAMAGE, were computed from (average) responses from the post-experiment survey Q1, Q2, Q3, and Q4, respectively. See Online Appendix.

iv. TV Class 2: Members in this class derive much less utility from their TV viewing experiences than Class 1. These viewers gain a similar level of satisfaction from viewing TV shows via F2A or SVoD services, but eschew other viewing platforms. These type are therefore be considered to be *casual viewers*

In relation to the two film classes, the positive coefficient on ‘risk perception’ suggests that the first class perceives illegal viewing to be more risky than the members of the second class (albeit not by much). Reconciling this with the fact that members of the first class receive a high utility of (illegal) downloading suggests they are aware of the risks but choose to partake in the activity nonetheless. The other variable of significance in the film context relates to the ‘number of films selected’. The negative coefficient suggests that the first class are more selective in their choices, particularly as they derive strong utility from cinema.

With respect to the TV LC model results, we were again able to identify ‘risk perception’ as a variable that separated the two classes. In this exercise, the second class perceived illegal viewing to be more risky, however neither class show a tendency to illegally view TV shows. The first class also selected more TV shows (of the 15) on offer than Class 2. This conforms with the observed higher utility they derive for all methods of viewing.

Finally, while we do believe there to be significant demographic effects that determine viewing preferences, our data do not exhibit enough heterogeneity to identify any of these effects in the LC models. This is almost certainly due to the fact that our participants were primarily students restricting the observed ranges of age, income, education, etc.

4.6 Follow-up survey results

The primary intention of the follow-up survey is to establish some credibility in the priming mechanism, which preceded the stated-preference choice experiments. Recalling that each participant was presented with 15 forthcoming films and 15 forthcoming TV series, we observe individual-specific viewing intention for each title as i) ‘highly likely’, ii) ‘fairly likely’, or neither. The follow-up survey took the same set of films and TV series and asked whether each title had been viewed and, if so, how it was viewed. The survey took place approximately six months after the experiment.

At the outset, it should be noted that due to the windowing and licensing effects, not all films and TV series had been released on all platforms at the time of the follow-up survey. For example, a number of cinema-release films had not been released on free-to-air TV and many TV series had only been licensed to one broadcaster after six (or less) months. Therefore, the intention of this exercise is not to compare alternative selections between the stated-preference experiments with the follow-up survey results. Rather, the intention is to examine how films and TV series reported *ex-post* viewed in follow-up survey (independent of viewing mode) correspond to the *ex-ante* stated viewing intention.

In this respect, the follow-up survey offers encouragement that the priming mechanism was highly effective. After quality-control questions, we had a response rate of 58% from the original 151 participants contacted six months after the experiments. Survey respondents were presented with the same set of 15 films and 15 TV series provided during the experiment and asked which titles had actually been watched at the time of the follow-up survey. Pooled across all respondents, 96.4% of films and 97.1% of the TV series identified matched with those selected as either 'highly likely' or 'fairly likely' to watch during the experiment six months beforehand. That is, of the TV series and films actually viewed from the full set, almost all of them had been nominated as either 'highly likely' or 'fairly likely', suggesting a strong link between stated intention and actual behaviour. The follow-up survey also permitted examination relating to the popularity of specific titles against those identified by the priming mechanism. To investigate this, we ranked each film and TV series by the number of participants who selected 'highly likely' and compared this against the ranking of specific titles from the follow-up survey. The Spearman rank-order correlation was found to be 0.94 for film and 0.65 for TV series.

In terms of (actual) alternatives reported in the follow-up survey, cinema was identified for 74.4% of films and SVoD for 59.4% of TV series viewed. However, as suggested above, this is not surprising given all of the films in our study had an initial (planned) theatrical release (i.e. windowing effect), and that nine of the 15 TV series were Netflix or other SVoD releases. Following cinema and SVoD, the next most popular alternatives in terms of observed choices were the illegal alternatives of streaming and downloading, respectively. The combined total of the illegal alternatives was 19.5% for film and 23.8% for TV series. With the passing of time, the distribution over alternatives would almost certainly alter.

5 Summary and concluding remarks

This study has applied stated-preference choice experiments in a setting where consumers consider film and TV alternatives against a set of broadly-defined product attributes. Based on our results, we are able to draw a number of inferences concerning the impact of SVoD on more established modes of film and TV consumption. In particular, while cinema and free-to-air programming still offer much appeal, it is clear that SVoD is creating significant disruption and is highly valued by consumers. This was particularly evident in the WTP estimates, which are substantially above current SVoD pricing. With the apparent surplus consumers are deriving from these services, it is not surprising that the adoption of Netflix (and other SVoD services) has been so pervasive across the world.

Our results also reveal a number of other interesting findings. First, all of the alternative/attribute marginal utilities, substitution effects, and willingness to pay estimates directly relate to the *ex-ante* appeal of a film or TV series. As would be expected, we observe a smaller (absolute) price marginal effects for film and TV of greater appeal. We observe that consumers suffer reduced utility from release delays (relative to the initial international release), and lower-quality viewing experiences also reduces utility. However, the relationship between quality and release delays *vis-à-vis* viewing intention varies across alternatives.

Second, we observe that consumers are heterogeneous in their consumption preferences and behaviour, even within homogeneous viewing intention groups. This is evident in the LC model results, where we identified two broad film consumer types ('film buffs' and 'Netflix generation'), and two broad TV consumer types ('TV junkies' and 'casual viewers').

Third, we find mixed evidence regarding the effectiveness of anti-piracy policy. In particular, while increasing punishment probabilities and fines decrease utilities, the implied (own and cross attribute) marginal effects are small. Furthermore, the willingness-to-pay estimates suggests only a relatively small decline in value associated with anti-piracy policies. While we cannot be certain about the precise origin of these findings, they may relate specifically to the participants we study.

More generally, we contribute to the applied stated-preference literature in two ways. First, the separation of experiments with respect to *ex-ante* interest allows comparison of utility, marginal effects, and willingness-to-pay. We are unaware of other research employing this approach. Second, it applies the novel 'availability design'. This method holds much appeal in settings (such as ours) where consumers face a relatively large set of alternatives.

We are also encouraged by the results of the follow-up survey. In particular, we observe a high correlation between actual titles viewed and stated viewing intention, as well as between titles ranked in terms of *ex-ante* and *ex-post* popularity. With accepted caveats, we believe this provides validation of both the priming mechanism and stated-preference approach more generally. Of course, the primary motivation for using such an approach relates to the general unavailability of revealed-preference data, so this validation is encouraging.

With the flexibility of stated-preference design, there is much scope for future work using these methods. For example, investigation of the specific attributes of SVoD that are most valued by consumers. This could include attributes related to content (e.g. back catalogue vs. new content), or technological dimensions of service (e.g. number of permitted devices). Another general question is whether similar results hold for other samples, in particular using a less-homogeneous sample in terms of age, income, etc. Alternatively, do the implications of this analysis hold for similar demographic cohorts in other markets, particularly those with different institutional environments.

Finally, there is further scope to evaluate the effectiveness of policies designed to curtail digital piracy. While this paper has implicitly examined policy related closely to the 'graduated response' approach, this type of approach has increasingly lost favour in key countries and alternative policies have been introduced to achieve the same objectives. For example, the blocking of websites supporting piracy has been applied in various territories. Given that illegal behaviour might be altered by the different policies, it is of interest to examine how this might impact consumption.

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Table 1: Alternatives

Abbreviation	Alternative	Definition	Repeat Viewing
CIN	Cinema	Standard seat in local cinema	No
F2A	Free-to-Air Television	Ad-supported network television	No
VODP	VoD—Purchase	One-off purchase (e.g. Apple iTunes)	Yes
VODS (SVoD)	VoD—Subscription	Monthly subscription (e.g. Netflix)	Yes
DVDP	DVD—Purchase	Outright purchase	Yes
DVDR	DVD—Rental	Physical rental from local vendor	No
PAYS	Pay TV—Subscription	Monthly subscription (e.g. Foxtel)	No
PAYP	Pay TV—Pay Per View	Online rental (e.g. Apple iTunes rental)	No
ILDL	Illegal—Download	BitTorrent download (e.g. Pirate Bay)	Yes
ILST	Illegal—Stream	Online streaming (e.g. Megaupload)	Yes

Table 2: Attributes

Abbreviation	Attribute	Attribute levels
PRICE	Price per film (AUD)	5, 10, 15, 20, 25, 30
	Price per TV series (AUD)	10, 20, 30, 40, 50
QUAL	Picture quality	HD, SD, Poor (illegal options)
RELEASE	Months since world premiere release	0, 3, 6, 9, 12
FINEPC	Probability of fine (%) (illegal options)	0, 25, 50, 75
FINEDL	Fine (AUD) (illegal options)	50, 100, 150, 200

Table 3: Summary of Design and Selections

Alternative	No. Times Presented	Film Highly Likely	Film Fairly Likely	TV Highly Likely	TV Fairly Likely
CIN	755	443	144		
F2A	755	168	482	334	548
VODP	755	175	84	191	165
VODS	755	208	110	174	98
DVDP	755	128	148	169	69
DVDR	755	54	118	33	14
PAYS	755	76	63	104	68
PAYP	755	51	43	117	141
ILDL	755	117	201	130	164
ILST	755	90	117	107	92
Total	7550	1510	1510	1359	1359

Notes: Each of the 151 participants was presented with 10 film choice tasks (total $n_{Film} = 151 \times 10 = 1510$) and 9 TV choice tasks (total $n_{TV} = 151 \times 9 = 1359$). In each choice task, a participant was presented with 5 alternatives, i.e. total number of alternative $N_{Film} = 151 \times 10 \times 5 = 7550$ and $N_{TV} = 151 \times 9 \times 5 = 6795$. The availability design ensured each alternative was presented 755 times during both the film and TV experiments.

Table 4: Multinomial Logit Results

	Film				Television			
	Highly Likely		Fairly Likely		Highly Likely		Fairly Likely	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Alternatives								
CIN	3.637***	(0.253)	2.784***	(0.270)				
F2A	1.634***	(0.196)	2.451***	(0.200)	1.690***	(0.168)	2.362***	(0.189)
VODP	2.385***	(0.227)	1.794***	(0.239)	1.622***	(0.203)	1.576***	(0.244)
VODS	2.715***	(0.217)	2.546***	(0.237)	2.048***	(0.223)	1.787***	(0.285)
DVDP	1.862***	(0.194)	1.938***	(0.193)	1.611***	(0.212)	0.975***	(0.285)
DVDR	1.345***	(0.242)	1.793***	(0.238)	0.316	(0.237)	-0.235	(0.337)
PAYS	1.565***	(0.209)	1.621***	(0.219)	1.185***	(0.196)	0.991***	(0.239)
PAYP	1.269***	(0.242)	1.028***	(0.239)	0.882***	(0.186)	1.048***	(0.195)
ILDL	1.507*	(0.779)	1.063	(0.698)	1.548***	(0.489)	1.151**	(0.472)
Attributes								
QUAL	0.322***	(0.107)	0.269**	(0.109)	0.202***	(0.075)	0.220**	(0.097)
RELEASE	-0.123***	(0.010)	-0.091***	(0.011)	-0.104***	(0.010)	-0.075***	(0.012)
PRICE	-0.096***	(0.007)	-0.169***	(0.010)	-0.058***	(0.004)	-0.080***	(0.006)
FINEPC	-0.010	(0.014)	-0.007	(0.013)	-0.020**	(0.008)	-0.020***	(0.007)
FINEDL	-0.005	(0.003)	-0.002	(0.003)	-0.005**	(0.002)	-0.002	(0.002)
Log likelihood	-1875.26		-1788.15		-1718.3		-1392.25	
AIC/N	2.502		2.387		2.548		2.068	
Obs	1510		1510		1359		1359	

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Mixed Multinomial Logit Results

	Film				Television			
	Highly Likely		Fairly Likely		Highly Likely		Fairly Likely	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Alternatives								
CIN	4.280***	(0.280)	4.228***	(0.328)				
F2A	2.092***	(0.222)	3.274***	(0.250)	2.339***	(0.211)	3.055***	(0.247)
VODP	2.959***	(0.249)	2.965***	(0.292)	2.759***	(0.251)	3.120***	(0.310)
VODS	3.434***	(0.242)	4.067***	(0.295)	3.422***	(0.282)	3.654***	(0.368)
DVDP	2.399***	(0.220)	3.359***	(0.246)	2.725***	(0.265)	2.560***	(0.359)
DVDR	1.793***	(0.266)	2.945***	(0.301)	1.377***	(0.267)	1.441***	(0.385)
PAYS	2.066***	(0.235)	2.887***	(0.268)	2.288***	(0.240)	2.580***	(0.303)
PAYP	1.758***	(0.263)	2.354***	(0.291)	1.341***	(0.228)	1.505***	(0.258)
ILDL	3.564***	(1.109)	2.895***	(1.006)	3.664***	(0.662)	2.566***	(0.620)
Attributes								
QUAL	0.610***	(0.132)	0.589***	(0.154)	0.162	(0.104)	0.157	(0.126)
RELEASE	-0.170***	(0.016)	-0.118***	(0.016)	-0.152***	(0.017)	-0.099***	(0.015)
PRICE	-0.124***	(0.009)	-0.302***	(0.019)	-0.114***	(0.009)	-0.209***	(0.017)
FINEPC	-0.079***	(0.028)	-0.050**	(0.021)	-0.058***	(0.011)	-0.067***	(0.012)
FINEDL	-0.015**	(0.006)	-0.012***	(0.004)	-0.016***	(0.004)	-0.010***	(0.003)
Dist. of RPs								
QUAL (N)	0.736***	(0.097)	1.075***	(0.105)	0.646***	(0.095)	0.675***	(0.107)
RELEASE (N)	0.128***	(0.013)	0.122***	(0.015)	0.151***	(0.016)	0.073***	(0.021)
FINEPC (N)	0.049***	(0.012)	0.039***	(0.008)	0.027**	(0.012)	0.053**	(0.011)
FINEDOL (N)	0.013***	(0.003)	0.013***	(0.003)	0.012***	(0.003)	0.008***	(0.003)
PRICE (T)	0.124***	(0.009)	0.302***	(0.019)	0.114***	(0.009)	0.209***	(0.017)
Log likelihood	-1772.3		-1565.8		-1563.6		-1233.5	
AIC/N	2.371		2.098		2.326		1.840	
Obs	1510		1510		1359		1359	

Notes: 'N' denotes normal distribution of random parameter (RP), 'T' denotes triangular distribution of random parameter (RP); Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 6: Own Marginal Effects

	Film		TV	
	Highly Likely	Fairly Likley	Highly Likely	Fairly Likley
Price				
CIN	-0.347	-0.459		
VODP	-0.230	-0.374	-0.189	-0.354
VODS	-0.255	-0.368	-0.300	-0.263
DVDP	-0.192	-0.413	-0.267	-0.242
DVDR	-0.092	-0.296	-0.070	-0.044
PAYS	-0.091	-0.170	-0.203	-0.288
PAYP	-0.068	-0.154	-0.177	-0.313
Quality				
CIN	0.188	0.193		
F2A	0.169	0.144	0.036	0.016
VODP	0.242	0.199	0.014	0.022
VODS	0.185	0.163	0.059	0.068
DVDP	0.098	0.098	0.055	0.071
DVDR	0.094	0.202	0.004	0.006
PAYS	0.071	0.018	0.028	0.033
PAYP	0.057	0.046	0.021	0.027
ILDL	0.125	0.085	0.020	0.013
Release Delay				
CIN	-0.065	-0.021		
F2A	-0.202	-0.186	-0.129	-0.105
VODP	-0.087	-0.014	-0.029	-0.022
VODS	-0.095	-0.047	-0.108	-0.063
DVDP	-0.053	-0.053	-0.017	-0.004
DVDR	-0.063	-0.150	-0.007	-0.009
PAYS	-0.005	-0.012	-0.006	-0.002
PAYP	-0.049	-0.086	-0.030	-0.040
ILDL	-0.056	-0.044	-0.047	-0.052
Fine Probability				
ILDL	-0.155	-0.127	-0.202	-0.165
Fine Dollars				
ILDL	-0.138	-0.108	-0.100	-0.097

Table 7: Willingness to Pay

	Film						TV					
	MNL		MMNL				MNL		MMNL			
	Highly	Fairly	Highly Likely		Fairly Likely		Highly	Fairly	Highly Likely		Fairly Likely	
	Likely	Likely	Mean	SD	Mean	SD	Likely	Likely	Mean	SD	Mean	SD
CIN	37.72	16.51	34.42	14.07	13.95	5.70						
F2A	16.94	14.53	16.82	6.88	10.80	4.42	29.14	29.54	20.44	8.39	14.54	5.97
VODP	24.74	10.64	23.80	9.73	9.78	4.00	27.97	19.71	24.10	9.89	14.85	6.09
VODS	28.16	15.10	27.62	11.29	13.42	5.48	35.32	22.35	29.90	12.27	17.39	7.13
DVDP	19.32	11.49	19.29	7.89	11.08	4.53	27.79	12.19	23.81	9.77	12.18	5.00
DVDR	13.96	10.63	14.42	5.90	9.72	3.97	5.46†	-2.94†	12.03	4.94	6.86	2.81
PAYS	16.23	9.61	16.62	6.79	9.52	3.89	20.43	12.40	19.99	8.20	12.27	5.04
PAYP	13.16	6.10	14.14	5.78	7.77	3.18	15.22	13.10	11.71	4.81	7.16	2.94
ILDL	15.63	6.31†	28.66	11.72	9.55	3.90	26.70	14.40	32.01	13.13	12.21	5.01
FINEPC	-0.10†	-0.04†	-0.64	0.26	-0.17	0.07	-0.35	-0.25	-0.50	0.21	-0.32	0.13
FINEDL	-0.05†	-0.01†	-0.12	0.05	-0.04	0.02	-0.08	-0.02†	-0.14	0.06	-0.05	0.02
QUAL	3.34	1.60	4.91	2.01	1.94	0.79	3.48	2.76	1.42†	0.58	0.75†	0.31
RELEASE	-1.28	-0.54	-1.37	0.56	-0.39	0.16	-1.79	-0.94	-1.33	0.54	-0.47	0.19

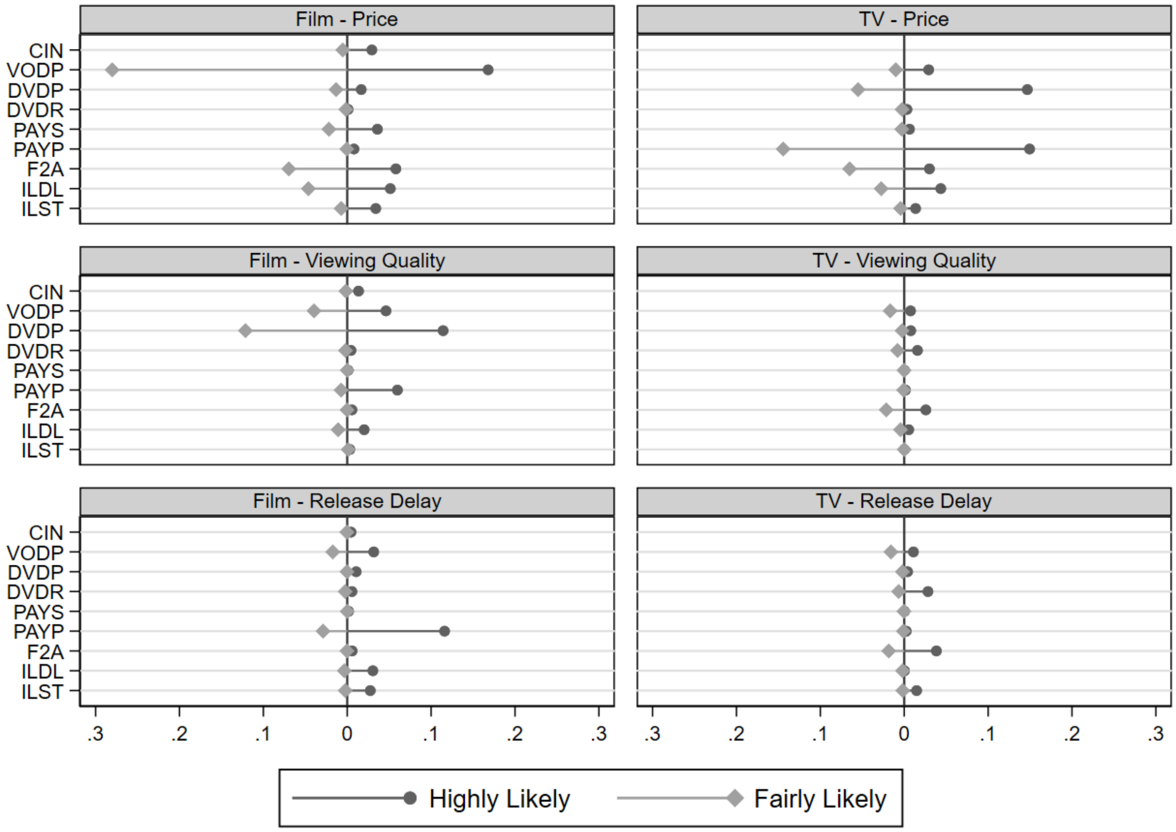
Notes: Willingness to pay measured in Australian dollars. † denotes statistical insignificance.

Table 8: Latent Class Model Results

	Film—Highly Likely				Television—Highly Likely			
	Class 1		Class 2		Class 1		Class 2	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Alternatives								
CIN	14.491**	(6.073)	2.061***	(0.500)				
F2A	7.053**	(3.241)	1.112**	(0.440)	9.438**	(3.696)	1.283***	(0.326)
VODP	1.966***	(0.762)	4.022***	(0.530)	11.249***	(4.043)	1.178***	(0.391)
VODS	1.456	(0.977)	5.670***	(0.684)	11.043**	(4.304)	1.749***	(0.482)
DVDP	7.237**	(3.055)	1.191***	(0.411)	10.604***	(3.742)	0.073	(0.488)
DVDR	1.980**	(0.807)	0.955**	(0.426)	7.956**	(3.121)	-0.317	(0.439)
PAYS	2.353***	(0.614)	2.953***	(0.591)	10.877**	(4.344)	-1.614	(0.880)
PAYP	5.019***	(1.921)	1.621***	(0.442)	5.147**	(2.275)	0.264	(0.383)
ILDL	23.533**	(11.413)	-2.853	(1.983)	9.122	(6.830)	1.438	(2.953)
Attributes								
QUAL	-1.792	(1.132)	1.406***	(0.268)	-0.461	(0.926)	-0.171	(0.232)
RELEASE	-0.381**	(0.173)	-0.221***	(0.042)	-0.936***	(0.301)	0.045*	(0.027)
PRICE	-0.107**	(0.044)	-0.159***	(0.022)	-0.235***	(0.071)	-0.045***	(0.009)
FINEPC	-0.080**	(0.036)	-0.049	(0.045)	-0.062	(0.091)	-0.088	(0.109)
FINEDL	-0.171**	(0.086)	0.041***	(0.009)	0.009	(0.013)	0.000	(0.009)
Membership								
RISK	0.219**	(0.112)			-0.278**	(0.132)		
DAMAGE	-0.063	(0.101)						
FILMDL	-0.036	(0.142)						
FILMTOT	-0.098**	(0.038)						
TVTOT					0.075**	(0.037)		
Class size	50.20%		49.80%		49.60%		50.40%	
Log likelihood	-1811.61				-1657.78			
AIC/N	2.443				2.482			
Pseudo R^2	0.479				0.445			
Obs	1510				1359			

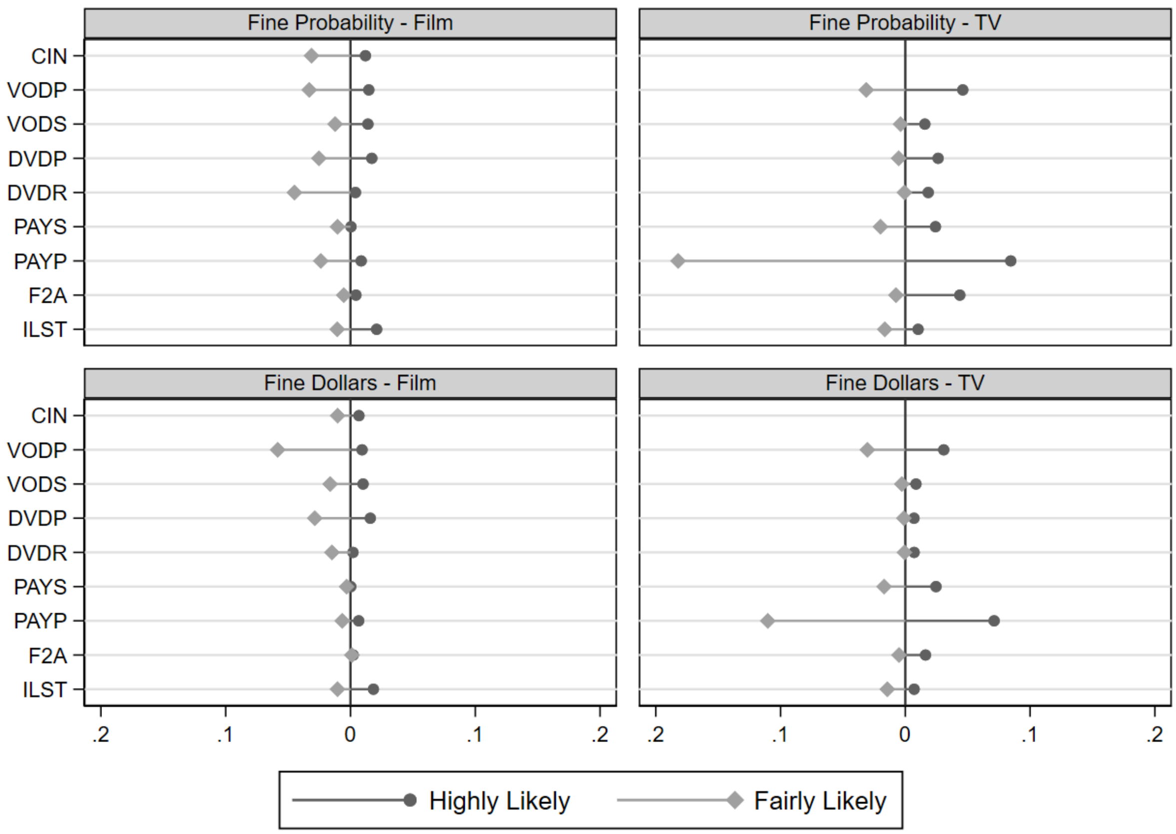
Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Figure 1: SVoD Cross Marginal Effects – Price, Viewing Quality, Release Delay



Notes: All figures refer to cross marginal effects of SVoD attributes (price, viewing quality, release delay) with respect to probability of listed alternative for either film or TV selection. Right hand side (horizontal) drop lines (round markers) represent 'Highly Likely' selections, and left hand side (horizontal) drop lines (diamond markers) represent 'Fairly Likely' selections. Price and release delay attributes marginal effects take positive values. Quality marginal effects take negative values.

Figure 2: Illegal Download Cross Marginal Effects – Fine Probability, Fine Dollars



Notes: All figures refer to cross marginal effects of illegal downloading punishment attributes (fine probability, fine dollars) with respect to probability of listed alternative for either film or TV selection. Right hand side (horizontal) drop lines (round markers) represent 'Highly Likely' selections, and left hand side (horizontal) drop lines (diamond markers) represent 'Fairly Likely' selections. Price and release delay attributes marginal effects take positive values. Quality marginal effects take negative values.

Online Appendix

Post-experiment survey *(comments in italics)*

The first set of questions related to piracy habits, where answers were grouped as 1) 0, 2) 1-10, 3) 11-100, 4) 101-200, and 5) 201+:

1. How many films have you downloaded or steamed from unauthorized file sharing sites?

2. How many TV series have you downloaded or steamed from unauthorized file sharing sites?

The following sets of questions addressed 'risk' and 'damage' perceptions, and took the form of answers on a five-point Likert scale (Agree Strongly to Disagree Strongly) and addressed the following:

3. The probability of being caught using an unauthorized file sharing site is smaller than:

   i. Getting caught shoplifting
   ii. Getting caught riding on public transportation without a valid ticket
   iii. Getting a parking ticket for parking illegally
   iv. Getting fined for speeding

4. For each of the following statements please state how strongly you agree or disagree.

   i. By using file sharing sites to watch films and TV series I may cause damage to actors and actresses
   ii. By using file sharing sites to watch films and TV series I may cause damage to writers, directors and producers
   iii. I can get caught and punished for using file sharing sites

The final set of questions related to demographic information. These were stated as follows:

5. Please tell us your gender.

6. What is your age?

7. What is your highest level of education?

8. What is your annual after-tax household income?

9. In which country were you born?

Participant Instructions and Consent Form

[redacted] Survey on Film and Television Consumption

Thank you for agreeing to participate in this survey.

The aim of this research project is to better understand the characteristics of consumption behaviour for television and films in Australia. This research is being conducted by [redacted].

Instructions

Please read this section carefully. If you have any questions about what is required from you please ask a member of the research team for assistance before beginning.

This survey consists of five sections:

1. You will first be shown a selection of upcoming **film** releases. For each of these releases you need to select how likely you are to watch the film in question.
2. We will then present to you a number of alternative **film** viewing experiences. Each of these film viewing experiences has a variety of format choices (cinema, free to air television, streaming video on demand, etc.), along with certain attributes (picture quality, time since first release, price, etc.) for each format choice. Given the attributes associated with each format you are asked to select the alternative you would purchase.
3. You will then be shown a selection of upcoming **television series** releases. For each of these releases you need to select how likely you are to watch the television series in question.
4. We will then present to you a number of alternative **television series** viewing experiences. Once again, each of these television series viewing experiences has a variety of format choices (free to air television, streaming video on demand, DVD, etc.), along with certain attributes (picture quality, time since first release, price, etc.) for each format choice. Given the attributes associated with each format you are asked to select the alternative you would purchase.
5. Finally we will ask you for some brief information about yourself.

It is estimated that the survey will take approximately 30 minutes to complete.

You will be paid $20 upon completion of this survey. A further $5 will be paid (in the form of a digital gift card) upon completion of a short (10 minute) online follow up survey which will be sent to your nominated email address around January 2018.
Please note

The ethical aspects of this study have been approved by the [redacted] Human Research Ethics Committee. If you have any complaints or reservations about any ethical aspect of your participation in this research, you may contact the Committee through [redacted]. Any complaint you make will be treated in confidence and investigated, and you will be informed of the outcome.

This survey is confidential and the analysis will be performed using de-identified data. At no point will the identity of participants form any part of the research output of this project. Participation in this survey is voluntary.

Further Information

Further information and updates on the survey, along with final results of this research project can be obtained from [redacted]. The anticipated completion date for the project is March 2018.

Consent

Completion of this questionnaire denotes consent to participate.

This information sheet is for you to keep

Viewing Option Definitions

During the course of the survey you will be presented with a number of alternative ways to view film and TV series. Details of these alternatives are listed below, along with information on whether or not your choice of alternative permits repeat viewing (i.e. if you can watch the same film or TV series more than once with a single purchase). Please ask a member of the research team if any items require further clarification.

Cinema
Definition - Standard seat to watch a film in a local cinema
Repeat viewings? – No, 1 viewing only, no recording permitted

Free-to-Air Television
Definition – Watching a film or TV series on a freely available Australian TV channel such as ABC, SBS, Channel 7, Channel 10, etc.
Repeat viewings? – No, 1 viewing only, no recording permitted

Streaming Video on Demand – Subscription
Definition – Monthly subscription to an online entertainment library such as Netflix, STAN, Presto, etc.
Repeat viewings? – Yes, unlimited viewings possible with working internet connection

Streaming Video on Demand – Purchase
Definition – One-off purchase from online store such as Apple iTunes, Google Play, etc.
Repeat viewings? – Yes, unlimited viewings possible, file downloaded to user device for offline use

DVD – Purchase
Definition – Outright purchase of physical disc
Repeat viewings? – Yes, unlimited viewings possible

DVD – Rental
Definition – 24-hour rental of physical disc from a local video store
Repeat viewings? – No, 1 viewing only, no copying of disc permitted

File Sharing Site - Download
Definition – Use of BitTorrent download sources such as The Pirate Bay, Torrentz, etc.
Repeat viewings? – Yes, unlimited viewings possible, file downloaded to user device for offline use

File Sharing Site – Stream
Definition – Use of websites such as 4Shared, Megaupload, etc. to view content via an online video portal
Repeat viewings? – Yes, unlimited viewings possible with working internet connection

Pay TV – Subscription
Definition – Monthly subscription to pay TV service that provides TV channels not available on free-to-air TV such as Foxtel, Austar, Fetch TV, etc.
Repeat viewings? – No, 1 viewing only, no recording permitted

Pay TV - Pay Per View
Definition – One-off rental purchase from an online store such as Apple iTunes rentals, Foxtel Store, Foxtel Box Office, etc.
Repeat viewings? – No, 1 viewing only, no copying of file permitted

Attribute Definitions

Picture Quality
Standard Definition – Baseline quality, standard video resolution
High Definition – High quality video resolution that shows finer detail than standard definition
Poor Definition – Low quality video resolution that may result in some pixilation of video when compared to standard definition

Number of Months Since Film's Worldwide Cinema Release / Number of Months Since TV Series' Worldwide Release
The amount of time (in months) that you would have to wait to watch the film or TV series via the chosen viewing option.

% Chance of Being Fined for Watching Without Paying / Fine (in AU$) if Caught Watching Without Paying
Lists the percentage chance of being caught by a copyright infringement agency for watching a film or TV series without payment. The fine amount is the subsequent punishment given to the viewer if caught.
Note: only applicable to the 'File Sharing Site – Stream' and 'File Sharing Site – Download' viewing options.

Price Per Film (in AU$) / Price for Entire Series (in AU$)
Price paid to watch a single film or all episodes of a single TV series.
Note: for some viewing options this represents a proportion of the total fee paid for a service. **It is important to note that the price listed does not represent the cost of a viewing option as a whole. Instead the price reflects the effective 'cost per film' or 'cost per TV series' of that particular service.**

Figure A1: Film Information Example

<table>
<tr><th colspan="2">Star Wars: The Last Jedi</th></tr>
<tr><td rowspan="4">
</td><td>GENRE
Action, Adventure, Fantasy</td></tr>
<tr><td>DIRECTOR
Rian Johnson</td></tr>
<tr><td>WRITTEN BY
Rian Johnson, George Lucas</td></tr>
<tr><td>CAST
Daisy Ridley, John Boyega, Mark Hamill</td></tr>
<tr><td colspan="2">SYNOPSIS
Having taken her first steps into a larger world in Star Wars: The Force Awakens (2015), Rey continues her epic journey with Finn, Poe and Luke Skywalker in the next chapter of the saga.</td></tr>
</table>

Figure A2: Choice Task Examples

Task 4 of 10

Keeping in mind the films you selected as being highly likely to watch are:

Ferdinand, Justice League, Polaroid, Suburbicon

If you had to **choose 1 of the 5 viewing options** in the table below in order to watch these films, which viewing option would you choose?

	Viewing Options				
	Streaming Video on Demand - Subscription	DVD - Purchase	Pay TV - Pay Per View	File Sharing Site - Download	File Sharing Site - Stream
	(e.g Netflix, STAN, Presto, etc.)	(outright purchase of physical disc)	(e.g. Foxtel Store, Foxtel Box Office, etc.)	(e.g. The Pirate Bay, Torrentz, or other BitTorrent sources)	(e.g. 4Shared, Megaupload, or other file streaming site)
Picture Quality	Standard Definition	Standard Definition	Standard Definition	High Definition	High Definition
Number of Months Since Film's Worldwide Cinema Release	9 Months	12 Months	6 Months	3 Months	3 Months
% Chance of Being Fined for Watching Without Paying	N/A	N/A	N/A	20%	60%
Fine (in AU$) if Caught Watching Without Paying	N/A	N/A	N/A	$100	$100
Price (in AU$)	$20	$5	$15	$0	$0

The viewing option I would choose is:

- Streaming Video on Demand - Subscription
- DVD - Purchase
- Pay TV - Pay Per View
- File Sharing Site - Download
- File Sharing Site - Stream

Task 6 of 10

Keeping in mind the films you selected as being highly likely to watch are:

Ferdinand, Justice League, Polaroid, Suburbicon

If you had to **choose 1 of the 5 viewing options** in the table below in order to watch these films, which viewing option would you choose?

	Viewing Options				
	Cinema	DVD - Purchase	DVD - Rental	Pay TV - Pay Per View	File Sharing Site - Download
	(standard ticket to local cinema)	(outright purchase of physical disc)	(24-hour rental of physical disc)	(e.g. Foxtel Store, Foxtel Box Office, etc.)	(e.g. The Pirate Bay, Torrentz, or other BitTorrent sources)
Picture Quality	High Definition	High Definition	High Definition	Standard Definition	Poor Definition
Number of Months Since Film's Worldwide Cinema Release	0 Months	6 Months	9 Months	9 Months	9 Months
% Chance of Being Fined for Watching Without Paying	N/A	N/A	N/A	N/A	60%
Fine (in AU$) if Caught Watching Without Paying	N/A	N/A	N/A	N/A	$50
Price (in AU$)	$25	$15	$5	$5	$0

The viewing option I would choose is:

- Cinema
- DVD - Purchase
- DVD - Rental
- Pay TV - Pay Per View
- File Sharing Site - Download

Table A1: Price Marginal Effects—Film

Film	Highly Likely to Watch									
PRICE	CIN	VODP	VODS	DVDP	DVDR	PAYS	PAYP	F2A	ILDL	ILST
CIN	**-0.347**	0.015	0.000	0.153	0.127	0.008	0.054	0.037	0.010	0.016
VODP	0.029	**-0.230**	0.084	0.000	0.001	0.001	0.005	0.070	0.008	0.034
VODS	0.000	0.168	**-0.255**	0.017	0.001	0.036	0.008	0.058	0.051	0.034
DVDP	0.052	0.000	0.002	**-0.192**	0.032	0.001	0.009	0.002	0.021	0.023
DVDR	0.028	0.006	0.007	0.050	**-0.092**	0.028	0.006	0.003	0.001	0.004
PAYS	0.016	0.011	0.018	0.011	0.002	**-0.091**	0.001	0.011	0.001	0.001
PAYP	0.011	0.007	0.017	0.007	0.009	0.019	**-0.068**	0.009	0.019	0.006
	Fairly Likely to Watch									
PRICE	CIN	VODP	VODS	DVDP	DVDR	PAYS	PAYP	F2A	ILDL	ILST
CIN	**-0.459**	0.002	0.000	0.117	0.161	0.030	0.032	0.094	0.059	0.023
VODP	0.005	**-0.374**	0.116	0.000	0.001	0.001	0.003	0.051	0.050	0.002
VODS	0.000	0.280	**-0.368**	0.013	0.002	0.022	0.000	0.070	0.046	0.007
DVDP	0.032	0.000	0.001	**-0.413**	0.100	0.006	0.024	0.018	0.048	0.191
DVDR	0.092	0.030	0.014	0.042	**-0.296**	0.020	0.087	0.001	0.045	0.008
PAYS	0.036	0.017	0.021	0.031	0.016	**-0.170**	0.002	0.032	0.021	0.013
PAYP	0.004	0.001	0.002	0.007	0.094	0.002	**-0.154**	0.019	0.009	0.002

Table A2: Price Marginal Effects—Television

TV	Highly Likely to Watch								
PRICE	VODP	VODS	DVDP	DVDR	PAYS	PAYP	F2A	ILDL	ILST
VODP	**-0.189**	0.029	0.003	0.007	0.081	0.000	0.030	0.015	0.034
VODS	0.029	**-0.300**	0.147	0.003	0.006	0.149	0.030	0.044	0.014
DVDP	0.001	0.056	**-0.267**	0.004	0.006	0.082	0.059	0.044	0.020
DVDR	0.029	0.001	0.010	**-0.070**	0.003	0.000	0.018	0.005	0.006
PAYS	0.040	0.009	0.008	0.000	**-0.203**	0.103	0.030	0.018	0.007
PAYP	0.000	0.016	0.017	0.000	0.010	**-0.177**	0.011	0.037	0.000
	Fairly Likely to Watch								
PRICE	VODP	VODS	DVDP	DVDR	PAYS	PAYP	F2A	ILDL	ILST
VODP	**-0.354**	0.007	0.001	0.003	0.134	0.000	0.017	0.024	0.115
VODS	0.010	**-0.263**	0.055	0.003	0.003	0.144	0.065	0.027	0.004
DVDP	0.000	0.016	**-0.242**	0.005	0.002	0.095	0.064	0.018	0.002
DVDR	0.017	0.001	0.008	**-0.044**	0.001	0.000	0.014	0.001	0.004
PAYS	0.068	0.005	0.003	0.000	**-0.288**	0.059	0.023	0.021	0.025
PAYP	0.000	0.014	0.014	0.000	0.004	**-0.313**	0.004	0.138	0.000

Table A3: Quality Marginal Effects—Film

Film	Highly Likely to Watch									
QUAL	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
CIN	**0.188**	-0.028	-0.009	0.000	-0.100	-0.064	-0.003	-0.026	-0.003	-0.004
F2A	-0.034	**0.169**	-0.052	-0.061	0.000	-0.001	-0.057	-0.009	0.000	-0.009
VODP	-0.014	-0.075	**0.242**	-0.107	0.000	0.000	-0.001	-0.005	-0.005	-0.021
VODS	0.000	-0.046	-0.114	**0.185**	-0.004	-0.001	-0.060	-0.006	-0.020	-0.003
DVDP	-0.035	0.000	0.000	-0.002	**0.098**	-0.022	0.000	-0.004	-0.023	-0.003
DVDR	-0.038	-0.001	-0.001	-0.001	-0.017	**0.094**	-0.004	-0.005	-0.001	0.000
PAYS	-0.004	-0.009	-0.006	-0.014	-0.002	-0.001	**0.071**	-0.001	0.000	0.000
PAYP	-0.016	-0.010	-0.008	-0.013	-0.002	-0.004	-0.012	**0.057**	-0.009	-0.001
ILDL	-0.004	0.000	-0.005	-0.009	-0.017	0.000	0.000	-0.006	**0.125**	-0.009
	Fairly Likely to Watch									
QUAL	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
CIN	**0.193**	-0.059	0.000	0.000	-0.066	-0.076	-0.003	-0.009	-0.013	-0.005
F2A	-0.039	**0.144**	-0.030	-0.072	-0.001	0.000	-0.022	-0.022	0.000	0.001
VODP	-0.002	-0.042	**0.199**	-0.077	0.000	0.000	0.000	0.000	-0.015	0.000
VODS	0.000	-0.040	-0.121	**0.163**	-0.002	0.000	-0.007	0.000	-0.011	0.001
DVDP	-0.019	-0.003	0.000	0.000	**0.098**	-0.059	-0.001	-0.004	-0.025	-0.015
DVDR	-0.073	0.000	0.000	0.000	-0.013	**0.202**	-0.003	-0.037	-0.014	0.000
PAYS	-0.003	-0.003	-0.006	-0.007	-0.005	-0.002	**0.018**	0.000	0.001	0.000
PAYP	-0.005	-0.018	-0.001	-0.002	-0.001	-0.020	-0.001	**0.046**	-0.001	0.000
ILDL	-0.011	0.000	-0.019	-0.007	-0.042	-0.006	0.001	-0.001	**0.085**	-0.003

Table A4: Quality Marginal Effects—Television

TV	Highly Likely to Watch								
QUAL	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
F2A	**0.036**	-0.001	-0.013	-0.011	-0.004	0.000	0.000	-0.016	0.005
VODP	-0.009	**0.014**	-0.003	-0.002	-0.001	-0.025	0.000	-0.001	0.006
VODS	-0.008	-0.008	**0.059**	-0.016	0.000	-0.001	-0.026	-0.005	0.000
DVDP	-0.013	-0.001	-0.013	**0.055**	-0.003	-0.002	-0.005	-0.005	0.003
DVDR	-0.003	-0.003	0.000	-0.008	**0.004**	-0.002	0.000	0.000	0.001
PAYS	0.000	-0.012	-0.001	-0.002	0.000	**0.028**	-0.002	0.000	0.000
PAYP	-0.004	0.000	-0.004	-0.003	0.000	-0.002	**0.021**	0.000	0.000
ILDL	-0.017	0.000	-0.002	-0.002	-0.001	0.000	-0.003	**0.020**	0.001
	Fairly Likely to Watch								
QUAL	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
F2A	**0.007**	0.000	-0.026	-0.023	-0.001	-0.001	0.000	-0.003	0.016
VODP	-0.005	**0.022**	-0.001	-0.001	0.000	-0.028	0.000	-0.002	0.002
VODS	-0.017	-0.002	**0.068**	-0.008	0.000	-0.001	-0.021	-0.004	0.000
DVDP	-0.019	0.000	-0.005	**0.071**	-0.004	-0.001	-0.011	-0.003	0.001
DVDR	-0.002	-0.001	0.000	-0.006	**0.006**	-0.001	0.000	0.000	0.001
PAYS	-0.001	-0.014	-0.001	-0.001	0.000	**0.033**	0.000	-0.001	0.000
PAYP	-0.001	0.000	-0.003	-0.003	0.000	0.000	**0.027**	-0.006	0.000
ILDL	-0.007	0.000	-0.001	-0.001	0.000	0.000	-0.010	**0.013**	0.000

Table A5: Release Delay Marginal Effects—Film

Film	Highly Likely to Watch									
RELEASE	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
CIN	**-0.065**	0.008	0.008	0.000	0.091	0.007	0.001	0.006	0.000	0.007
F2A	0.031	**-0.202**	0.038	0.043	0.001	0.001	0.091	0.005	0.001	0.063
VODP	0.005	0.035	**-0.087**	0.031	0.000	0.000	0.000	0.002	0.000	0.033
VODS	0.000	0.032	0.011	**-0.095**	0.006	0.002	0.116	0.006	0.031	0.028
DVDP	0.023	0.001	0.000	0.003	**-0.053**	0.005	0.000	0.006	0.041	0.015
DVDR	0.026	0.000	0.001	0.001	0.002	**-0.063**	0.000	0.004	0.001	0.000
PAYS	0.008	0.000	0.003	0.002	0.008	0.001	**-0.005**	0.000	0.000	0.001
PAYP	0.015	0.001	0.001	0.002	0.003	0.007	0.007	**-0.049**	0.013	0.005
ILDL	0.013	0.004	0.002	0.002	0.004	0.002	0.000	0.003	**-0.056**	0.016
	Fairly Likely to Watch									
RELEASE	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
CIN	**-0.021**	0.012	0.001	0.000	0.019	0.000	0.000	0.002	0.000	0.002
F2A	0.027	**-0.186**	0.013	0.034	0.002	0.000	0.079	0.012	0.001	0.044
VODP	0.000	0.013	**-0.014**	0.003	0.000	0.000	0.000	0.000	0.000	0.001
VODS	0.000	0.017	0.000	**-0.047**	0.002	0.000	0.029	0.000	0.003	0.002
DVDP	0.006	0.004	0.000	0.001	**-0.053**	0.018	0.000	0.005	0.026	0.014
DVDR	0.028	0.000	0.002	0.001	0.004	**-0.150**	0.001	0.048	0.008	0.000
PAYS	0.011	0.001	0.001	0.001	0.003	0.002	**-0.012**	0.000	0.003	0.000
PAYP	0.003	0.004	0.000	0.000	0.002	0.053	0.001	**-0.086**	0.004	0.001
ILDL	0.020	0.006	0.000	0.000	0.006	0.026	0.002	0.012	**-0.044**	0.008

Table A6: Release Delay Marginal Effects—Television

	Highly Likely to Watch								
RELEASE	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
F2A	**-0.129**	0.001	0.057	0.056	0.015	0.000	0.000	0.011	0.073
VODP	0.005	**-0.029**	0.000	0.000	0.001	0.037	0.000	0.002	0.003
VODS	0.011	0.004	**-0.108**	0.028	0.000	0.002	0.038	0.000	0.015
DVDP	0.018	0.000	0.000	**-0.017**	0.000	0.003	0.009	0.000	0.016
DVDR	0.001	0.004	0.001	0.009	**-0.007**	0.000	0.000	0.000	0.001
PAYS	0.000	0.000	0.001	0.002	0.000	**-0.006**	0.021	0.001	0.000
PAYP	0.000	0.000	0.005	0.011	0.000	0.000	**-0.030**	0.009	0.000
ILDL	0.000	0.014	0.003	0.005	0.000	0.019	0.052	**-0.047**	0.003
	Fairly Likely to Watch								
RELEASE	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
F2A	**-0.105**	0.000	0.071	0.095	0.008	0.000	0.000	0.002	0.028
VODP	0.002	**-0.022**	0.000	0.000	0.000	0.023	0.000	0.002	0.004
VODS	0.016	0.002	**-0.063**	0.007	0.000	0.001	0.018	0.002	0.002
DVDP	0.007	0.000	0.000	**-0.004**	0.000	0.001	0.002	0.000	0.001
DVDR	0.002	0.002	0.000	0.005	**-0.009**	0.000	0.000	0.000	0.000
PAYS	0.000	0.000	0.001	0.001	0.000	**-0.002**	0.005	0.001	0.000
PAYP	0.000	0.000	0.003	0.006	0.000	0.000	**-0.040**	0.015	0.000
ILDL	0.000	0.013	0.001	0.001	0.000	0.014	0.060	**-0.052**	0.007

Table A7: Punishment Marginal Effects—Film

Film	Highly Likely to Watch									
FINEPC	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.012	0.004	0.015	0.014	0.017	0.004	0.000	0.009	**-0.155**	0.021
	Fairly Likely to Watch									
FINEPC	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.031	0.005	0.033	0.012	0.025	0.045	0.010	0.024	**-0.127**	0.011

Film	Highly Likely to Watch									
FINEDOL	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.007	0.002	0.009	0.010	0.016	0.002	0.000	0.007	**-0.138**	0.018
	Fairly Likely to Watch									
FINEDOL	CIN	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.010	-0.001	0.058	0.016	0.029	0.015	0.003	0.007	**-0.108**	0.010

Table A8: Punishment Marginal Effects—Television

TV	Highly Likely to Watch								
FINEPC	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.044	0.046	0.016	0.026	0.018	0.024	0.084	**-0.202**	0.010
	Fairly Likely to Watch								
FINEPC	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.008	0.031	0.004	0.005	0.001	0.020	0.182	**-0.165**	0.016

TV	Highly Likely to Watch								
FINEDOL	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.016	0.031	0.009	0.007	0.007	0.025	0.071	**-0.100**	0.007
	Fairly Likely to Watch								
FINEDOL	F2A	VODP	VODS	DVDP	DVDR	PAYS	PAYP	ILDL	ILST
ILDL	0.005	0.030	0.003	0.001	0.001	0.017	0.110	**-0.097**	0.014