Distaste for Advertisements in Two-Sided Markets: Evidence from Free-to-Air TV*

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Abstract

This paper studies viewers' distaste for ads in a two sided-market. Using data from free-to-air TV permits us to observe the viewers' consideration set of alternatives and their characteristics. We first follow Wilbur (2008) to estimate both viewers' demand for content and advertisers' demand for advertising slots using channels' share data, advertisements' posted prices and content characteristics. We then exploit additional high-frequency data on individual choices to estimate viewers' heterogeneous distaste for ads without placing any distributional assumptions on how preferences change across consumers, following a similar strategy to Dubois et al. (2020). We find that distaste for ads is highly heterogeneous. Our approach also permits to disentangle pure distaste for ads from idiosyncratic preferences and inertia, which are relevant also for the advertisers' side of the market.

Key words: demand estimation, random utility discrete-choice model, heterogeneous consumers

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1 Introduction

A vast amount of services, including media content platforms, do not involve any monetary payments from consumers. Users of social media apps such as Facebook, TikTok, and Instagram pay with their attention that they give to the advertisements strategically placed throughout the service, and their individual data they provide through the service's use. Even Netflix, a traditionally ad-free platform is introducing a cheaper ad-supported version to compensate the decline in subscriptions. Offering an option with a limited number of ads could potentially be beneficial for advertisers, consumers, and platforms. To better understand how firms' trade off content quality with overall advertisements' quantity, it is crucial to adequately estimate consumers' heterogeneous distaste for ads.

In this paper we take advantage of comprehensive data available from the Free-to-Air TV market to estimate demand for media content and for advertisement slots. We also use high-frequency individual level data to further investigate consumers' ads distaste. We study how ad-avoiding behavior vary depending on individual characteristics such as socioeconomic status. This market provides multiple advantages to study consumers aversion to ads. Firstly, the media content choice set and the intensity of ads is observable and measurable. Second, around 75% of Spanish residents watch Free-To-Air television, which means the outcomes are highly representative of a typical (Spanish) consumer. Lastly, this setting permits us to have access to individual level high frequency data that allows us to study heterogeneous behavior without having to make distributional assumptions on demographic variables.

Just as for their digital counterparts, the main source of revenue for TV channels is the sale of advertisement slots to companies. This is a classical example of a two-sided market; on one side the individual channels compete with each other to create as many ad impressions as possible, and then on the other side they compete to sell these impressions to companies looking to inform and influence consumers.

There is a large theoretical literature on two-sided-markets (e.g., Rochet and Tirole (2003)), that has grown due to the prevalent presence of this type of markets in the Digital Economy. Within this literature, there is research studying specifically the two-sided nature of media content and advertising from a theoretical perspective. Regarding television advertising specifically, Anderson and Coate (2005); Anderson and Renault (2006) study the welfare outcomes of different equilibrium advertisement levels in the television industry.

From the seminal paper by Rysman (2009), the empirically literature on two-sided markets has also grown. Specifically for media markets, empirical research commonly estimates each side, advertisers' slot choice and consumers' content demand among the differentiated alternatives of media outlets. Argentesi and Filistrucchi (2007) study market power and network externalities among the four major Italian newspapers using a nested-logit model for readers and a logit for model for advertisers. Affeldt et al. (2021) study the same market allowing for multi-homing as ignoring it can lead to underestimation of demand elasticity. Newspapers readers' frequently multi-home, whereas in the case of TV, consumers choose from content that is shown simultaneously. Thus, multi-homing is not feasible unless viewers use devices that permit to postpone watching certain content.[1] Also focusing on newspapers, Fan (2013) studies the role of content characteristics as determinants of consumers' welfare in two-sided markets. She finds that changes in product characteristics can have a significant effect on consumer welfare after a merger.

Within the empirical two-sided market literature, a few focus on free-to-air television. Wilbur (2008) models the US TV two-sided demand using the heterogeneous agent discrete choice model developed in the seminal paper by Berry et al. (1995). Using market level data on an hourly frequency, Wilbur (2008) estimates both consumers and advertisers preferences. Specifically, the paper estimates an advertisement price elasticity for US TV viewers' of -2.9, which is a considerably more elastic demand than those below -1 found by Crandall (1972) and Bowman (1976). Ivaldi and Zhang (2022) and Ivaldi and Zhang (2021) estimate a structural model of the French television market in order to perform a counterfactual analysis on restrictions imposed on advertising sales hourses related to a recent merger. Unlike this paper, their analysis focuses on the advertiser side of the market, and uses data aggregated to the monthly level.

In this paper we estimate a discrete choice demand model, using consumer panel data to better control for consumer switching behavior as well as demographics. This model allows us to investigate how the distaste for ads changes across different demographics. This

[1] In our setting, the fraction of viewers' that used this type of devices is almost negligible.

improves our ability to study the relationship between demographics and viewer switching behavior. In addition, we estimate the other side of the market as well in order to perform counterfactual analyses on the market. In Section 2 we provide relevant background on the market, in Section 3 we give an overview of our data along with summary statistics, in Section 4 we explain and estimate demand models for both sides of the market, and in Section 5 we conclude.

2 Market Characteristics

The different free-to-air TV channels compete for viewers and then use their viewership to sell impressions to firms in the market for advertising. According to a report by an independent consultancy, there were 31,433,000 daily viewers in 2018, with each individual viewer averaging 234 min of watch-time per day Barlovento (2018).

The Spanish free-to-air TV market has both publicly run channels and private owned channels. The largest private channels are controlled by two media conglomerates, Atresmedia and Mediaset. The market is dominated by 5 channels: La 1, which is the main public channel; Telecinco and Cuatro, which is controlled by Mediaset; and Antena3 and La Sexta, which is controlled by Atresmedia. These three organizations together capture over three quarters of the viewership.[2] This competition structure allows for the analysis of effect of both channel market share and co-ownership on the programming decisions of individual channels.

2.1 The Spanish TV advertising market:

The TV advertising market is the side of the free-to-air TV market where channels receive their revenue. Broadcasters usually sell advertising based on viewer impressions (audience). Impressions count the number of unique consumer exposures an advertisement receives [3]. Media cost is the price advertisers pay to place their commercials on TV on a given time of day and it usually has a standard length (in Spain usually 20 seconds). There are different

[2] A detailed summary of yearly market shares from 2015 to 2018 can be seen in figure A.1 in the appendix.

[3] Viewers can receive several exposures over time. A total of 1000 impressions can be reached through different ways: for example: 100 targeted individuals watching a commercial 10 times or 1000 targeted individuals watching the commercial once.

usual ways to buy TV advertising spots in Spain. Most prominently based on Gross Rating Points (GRP) is a measurement of the audience size. Each GRP guarantees a number of impressions equivalent to 1% of the potential targeted universe[4]. A specific number of GRP can be obtained either through high audiences and low repetitions or through high repetitions and low audiences. This means that, to maximize impressions with lower number of frequency, the best advertisers can do is place their ads in channels with high audiences and specially during prime time[5]. The advantage of GRPs sale is that advertisers do not bear the risk of programs not being sufficiently popular because they pay for actual impressions. In addition, advertisers can also buy specific time slots. Under this scheme the broadcaster does not guarantee a specific audience, it only sells the slot at a specific price.

Advertisers have to fulfill market regulation which include, but are not limited to, content and timing restrictions. Channels are also not allowed to surpass a daily advertising threshold of 20% nor an hourly maximum of 17 minutes. In 2009, additional regulation imposed a new restriction on public channels, which were no longer allowed to have commercial breaks with few exceptions.[6] As a result of this regulation, it is possible for viewers to watch content without commercial advertisements.

The regulation affecting public channels also lead to the concentration of the market for advertising slots. The prohibition of advertisements on public channels increases the market power of the large private channels in the market for tv publicity. In November 2019, the CNMC imposed a considerable fine on Atresmedia and Mediaset for an infringement of article 101 of the Treaty of Functioning of the European Union (TFUE) and of Article 1 of 15/2007 Law (Spanish Defense of Competition Act) in the market for television advertisements. According to the CNMC, the two groups (Atresmedia and Mediaset) abused their market power by commercializing their advertising spots through vertical agreements that limited the ability of smaller channels to compete. Given that Atresmedia and Mediaset channels are essential for advertising agencies, these vertical agreements allowed them to prevent other channels from receiving advertising revenues. This had a foreclosure effect in the market,

[4]A potential targeted universe could be, for example, young people or homemakers.

[5]Prime time is considered to be from 10 pm to midnight and sometimes from 8:30 pm to midnight.

[6]Based on "Ley 8/2009" the public Spanish television can air commercial breaks only associated to the promotion of sports and cultural events.

since smaller channels were unable to produce revenue through selling their ad-slots.

3 Data

In our analysis we use two main data sets. The first set of data contains a minute by minute description of the top 5 channels[7] during the prime time hours of 8pm and 12:30am. One observation contains content and context information for one channel for one minute in time. A complete list of all the variables included in an observation is shown in the appendix The data set contains data on two weeks every month from March 2017 to March 2019, totalling in 535,941 observations. The market share for all remaining channels is calculated by subtracting the 5 channels viewership from total TV viewership and storing it under channel 10. Figure 8 in the appendix shows a summary of the market shares of the 5 channels included in the data. This data spans a large set of time and has more aggregate level market data.

Additionally, we use another, more detailed data set that covers the months of November and December for 2017 and 2018. This data set includes individual panel data on consumers, tracking 15,000 consumers' channel choice on a minute level. This data was collected by the data provider Kantar, using in-house tracking devices on people's remote controls and tv sets. Additionally, this data set included all programming information on a minute level for all of the channels, including channels with small market shares. Finally, this data includes the duration and timing of individual commercials.

The distribution of prime-time broadcasted programs into the main genres' categories is as follows:

There are over 100 different producers for the content shown. To simplify the producers are grouped into 5 different groups. The first three are if the shows are produced by the channel itself, (Altresmedia, Mediaset, and TVE). The remaining producers are sorted into two groups: small producers and large producers. To sort the producer by size, the aggregate minutes the producer was viewed was calculated[8]. This was then used to calculate the producers market share. Producers with a market share above a three percent were classified

[7]these channels capture half of the viewership

[8]this was done by aggregated the number of viewers across all minutes where that producer was used

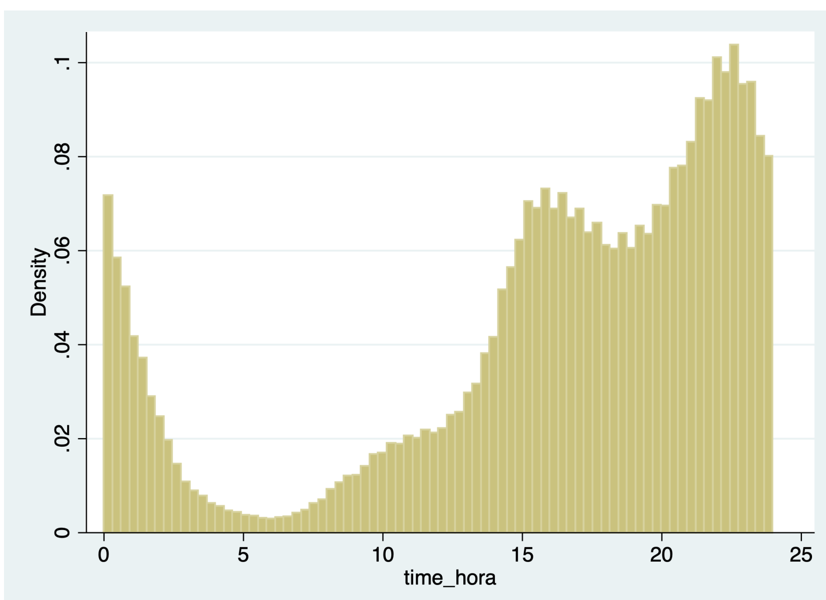
Table 1: Percentage of prime-time broadcast minutes by genre

Contest shows	13.19%
Cultural shows: documentaries, films, science shows, etc.	2.42%
Sports	2.05%
Entertainment: Reality shows, talk shows, comedy, etc.	27.76%
Fiction: movies, tv series, etc.	24.49%
Information: news, sports news, lottery results, etc	29.84%
Music	0.16%
Others	0.09%

as large, and the rest as small[9].

3.1 Descriptive Viewing Patterns

The total number of individuals watching TV has daily and weekly cycles. In the graphs below one can see the average viewership by the quarter hour and by the day of the week. Over the afternoon and night viewership slowly increases, until it peaks at 10:30pm, after which it decreases again. This pattern is in line with individuals turning on the TV to unwind after eating dinner and before going to bed.



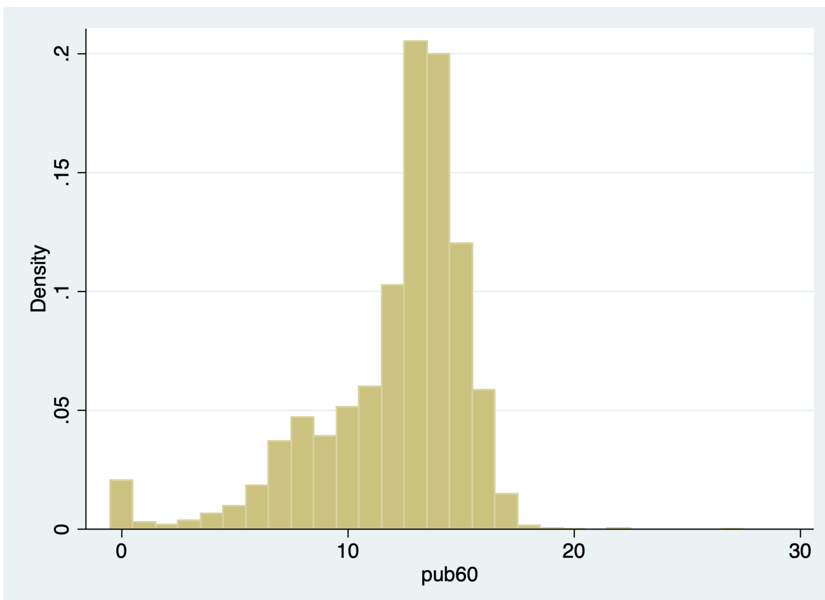
Averaging viewership over afternoons each day of the week, one can see that Sunday night has the highest viewership; then over the week the average number of viewers slowly

[9]robustness checks are performed on the cutoff percentage

goes down, with a significant drop Friday and Saturday night. This can be explained by people being more likely to have plans outside their homes, away from the TV, on a weekend night. This is depicted in Figure 3 in the appendix.

3.2 Channel Advertising Amounts

The amount channels choose to advertise is not the same every hour. Regulations limit ads to 17 minutes per hour, with a maximum daily average of 12 minutes per hour. The histogram below shows the distribution of the number of ads played per hour for the privately owned channels. It is clear that channels play more than 12 min of ads in some time periods, which then forced them to play less in others.



4 Two-Sided Market for Viewers and Advertisers

4.1 Demand Model for TV Viewers with Market-Level Data

We model demand based on a random utility discrete-choice model. Each television viewer i watches a maximum of one channel at a time. Viewers might also choose to watch none of the available channels (i.e., they choose the outside option).

We represent the individual i conditional indirect utility for alternative j at time t as:

$$U_{ijt} = \delta_{jt} + \epsilon_{ijt} \tag{1}$$

where

$$\delta_{jt} = \bar{X_{jt}} B_j + \alpha \mathrm{A}_{jt} + \xi_{jt} \tag{2}$$

The term $\bar{X_{jt}}$ represent the set of observed and common characteristics of the TV program broadcast on channel j at time t, captured by dummies (e.g, genre, day, hour). The term A_{jt} is the quantity of advertising on channel j at time t (blocks of 30 minutes), ξ_{jt} reflects the effect of unobserved characteristics of channel j at time t. The term ϵ_{ijt} is an individual specific component of utility. δ_{jt} is the mean utility and is common to all consumers. The mean utility of the outside good is normalized to zero , so δ_{0t}=0. this is necessary, since we never observe utilities, instead we observe quantities. Assuming ϵ_{ijt} to be an i.i.d and following a type 1 extreme value distribution would imply a logit model.

A limitation of the logit model is that the Independence of Irrelevant Alternative (IIA) Property may generate unrealistic substitution patterns between channels. To address this concern, we estimate demand using a nested logit model as developed in Berry (1994). Following a strategy similar to Ivaldi and Zhang (2022), we let Spanish households differentiate between choosing a mainstream channel (Antena3, Cuatro, Telecinco, LaSexta) or choosing among relatively newer less frequently watched channels as well as those with regional content. We also separate the public television in a separate nest due to the regulatory ban on commercial advertisements.

The nested logit model allows consumers' tastes for the choices within the same nest to be correlated. As shown in Berry (1994), the demand model can be specified as

$$\ln\Big(\frac{q_{jt}}{L - Q_t}\Big) = \bar{X}_{jt} B + \alpha \mathrm{A}_{jt} + \sigma \ln s_{j,t|g} + \xi_{jt} \tag{3}$$

The term q_{jt} represent the number of viewers watching channel j at time t. L is the potential market size represented by population having access to TV service in Spain (in 2018 was 44.6 million[10]) in time "t". Q_t is the total amount of viewers watching TV at time t. The term X_{jt} represent the observed characteristics of the program broadcast on channel j at time t. A_{jt} are the minutes of advertising on channel j at time t and ξ_{jt} represent the unobserved characteristics of channel j at time t. Finally, $s_{j,t|g}$ is the market share within each group. The parameter σ represents the correlation of the error term within each group. A σ of 0

[10]Barlovento (2018) considered this amount to be the consumption universe of TV in Spain.

would signify that consumers switch between products within the same group just as much as products outside the group. A σ closer to 1 would signify that consumer are more likely to switch to products within the same group.

We expect that advertising has a negative impact on viewers utility and that the number of viewers might decrease (increase) in response to a increase (decrease) in advertising.

Nevertheless, there are endogeneity problems caused by the fact that the more audience a channel has, the higher the advertising price. But, at the same time, the more ads a channel broadcasts, the higher the risk that viewers switch channels. In order to solve for this problem we use instrumental variables to estimate viewers demand. We use product characteristics as instruments as it permits to construct instrumental variables that vary across alternatives Berry et al. (1995). Program characteristics are presumed to influence audience receptivity to advertisements. Thus, for each channel we construct channel specific instrumental variables using the observable program characteristics (genre and producer) of the remaining channels. We sum the characteristics of the programs being broadcasted each half an hour and we compare them with other channels. We proceed the same way for program producers. Program characteristics are correlated with advertising level For instruments to be valid, program characteristics should be exogenous to the amount of advertisement in each time frame.

4.2 Viewers' Demand Results with Market-Level Data

Demand estimation results for the logit and nested logit model described above can be found in Table 1 below. For comparison, the results for the logit without nests are included as well. The estimate for the coefficient for advertising is negative and significant at the one percent level. This means that as the amount of advertisement in a given channel increases one would expect less consumers to want to watch that channel. The estimate for the nesting coefficient σ is also significant at a one percent level. This shows that consumers taste shocks for the channels within the same nest are correlated. However, the estimate is not very close to one, showing that outside channels as well as the public channel still put substantial competitive pressure on the four main privately owned channels.

The estimates for time fixed effects show an hour by increase in TV demand until 22:00, after which TV demand falls again. This is in line with the viewing patterns we described in section 4.1 above.

In order to see whether the instruments are helpful we compare the IV logit with estimates obtained using OLS. The distaste for advertisement became more negative with the instrumental approach, almost trippling in magnitude. This supports the use and need of our instrumental variables. Additionally, the Cragg-Donald Wald F-Statistic supports that we do not have weak instruments.

4.3 Individual Viewers' Heterogeneous Demand Choices

The specification of the logit demand model above assumes that the preferences for observed product characteristics are constant across consumers and time.

In their paper, Dubois et al. (2020) investigate whether sugar taxes effectively target the intended consumers. They use longitudinal micro data on on-the-go purchases to estimate unique coefficients for each consumer in their dataset. This allows the model to capture the heterogeneity of consumer preferences that often motivates the use of the random coefficients logit model from Berry et al. (1995). However, by estimating a unique coefficient for each consumer, they do not make any assumptions on the distribution of idiosyncratic preferences. Unlike Berry et al. (1995) and its extensions, they do not make any assumptions on how coefficients relate to different demographic characteristics, and therefore avoid the risk of mis-specification.[11] This limits these models when trying to capture complex relationships between consumer elasticities for different demographics. The flexibility of their model regarding demographics and price sensitivity, compared to a random coefficient logit model, makes it better suited for their research question, since their main objective was to study how price sensitivity varied across different demographic groups.

In a similar vain, we would like to be as parsimonious as possible in our assumptions regarding the relationship between demographics and advertisement distaste. In the market for advertisements, the demographics of channel audiences can have a large impact on the value of advertisement slots. Many companies value the ability to reach certain demo-

[11] Often this involves assuming a linear relationship between the mean of the coefficient distribution and demographic variables, and no independence in .

Table 2: Viewers' Demand

	Logit		Nested Logit
	OLS	IV	IV
	(1)	(2)	(3)
Distaste for ads	-0.016***	-0.043***	-0.034***
	(0.00)	(0.00)	(0.00)
Within nest share (σ)			0.581***
			(0.05)
day==1	-0.002	0.009	0.042***
	(0.01)	(0.01)	(0.01)
day==2	-0.025**	-0.012	0.030***
	(0.01)	(0.01)	(0.01)
day==3	-0.068***	-0.052***	-0.014
	(0.01)	(0.01)	(0.01)
day==4	-0.069***	-0.055***	-0.022**
	(0.01)	(0.01)	(0.01)
day==5	-0.242***	-0.233***	-0.204***
	(0.01)	(0.01)	(0.01)
day==6	-0.311***	-0.316***	-0.304***
	(0.01)	(0.01)	(0.01)
20h	-0.025*	-0.076***	-0.034***
	(0.01)	(0.02)	(0.01)
21h	0.272***	0.168***	0.207***
	(0.01)	(0.02)	(0.02)
22h	0.557***	0.489***	0.504***
	(0.01)	(0.02)	(0.01)
23h	0.424***	0.359***	0.367***
	(0.01)	(0.02)	(0.01)
Month and Year FE	Yes	Yes	Yes
N	15146	15146	15146
Weak IV		52.54	52.54

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include day of the week fixed effects; the third and fourth columns estimate the model with instrumental variables. The weak IV test is the Cragg-Donald Wald F-statistic.

graphic groups such as younger or wealthier consumers. If the distaste of advertisement is different across demographic groups, changes in advertising quantity could inlfuence viewer demographics. Additionally, the relationship between wealth and advertisement distaste is relevant in the pricing strategies of companies like Netflix, who plan to offer different subscriptions that vary in price and ad quantity. Since differences in ad distaste across demographics are so important to media markets, we will use a specification based on Dubois et al. (2020) in order to avoid any risk of mis-specifying the relationship between advertisement distaste and viewer demographics. We further build on their model by estimating consumer heterogeneity in a nested decision environment.

4.3.1 Demand Model

Similarly to Dubois et al. (2020), we use consumer level panel data to estimate preferences at an individual level. We assume that consumer i receives utility $u_{i,c,t}$ from consuming channel c at time t. To compare results between our two viewer demand approaches, we focus on viewer behavior during prime-time hours. At any given time during prime-time viewing hours, the consumer faces a choice set $\Omega_{i,t}$ that includes different free-to-air TV channels as well as an activity other than watching free-to-air TV.[12] The utility the consumer receives from watching one of the main channels is modeled as:

$$u_{i,c,t} = \beta_i^a I_{c,t}^a + \beta_d^g X_{c,t}^g + \eta_{d,c} + \tau_{d,t} + \epsilon_{i,c,t},$$

where $I_{c,t}^a$ is an indicator if channel c is showing advertisement at time t, $X_{c,t}^g$ is a vector of indicators of what genre channel c is showing at time t, $\eta_{d,c}$ are demographic group specific channel fixed effects and $\tau_{d,t}$ is a vector of time fixed effects that affects the valuation of all channels equally compared to the outside good of not watching TV[13]. This time fixed effects capture differences in the valuation of the outside good across time. The error term, $\epsilon_{i,c,t}$ is assumed to be i.i.d. and follow an extreme value distribution. As previously mentioned, the advertisement distaste is estimated on an individual level. However, to have a more parsimonious model the coefficients for channel, genre, and time fixed effects, are estimated

[12] This option includes related activities such as online streaming as well as something completely different, such as grabbing drinks with friends

[13] This vector includes time fixed effects for the year, month, weekend, and hour

for different demographic cohorts based on age, gender, and socioeconomic status.[14]

The original panel data set includes over 50 different channels. Of those channels, only 5 have a market-share above 3% [15]. For the analysis, we group all channels with a low market share into one composite channel with utility

$$u_{i,C,t} = \eta_{d,C} + \tau_{d,t} + \epsilon_{i,C,t}.$$

Finally, we normalize the utilities to the value of the outside good of not watching free-to-air TV,

$$u_{i,0,t} = 0 + \epsilon_{i,0,t}.$$

We again assume that the error terms, $\epsilon_{i,C,t},\ \epsilon_{i,0,t},\ \epsilon_{i,c,t}$, are independent and follow an extreme value distribution. Our other demand model and other models used in economic literate estimating television demand aggregate viewer choice on an hourly or monthly level, Wilbur (2008); Ivaldi and Zhang (2021, 2022). Aggregating data involves averaging viewership amount over a longer time span implicitly assuming that viewers choose one channel for a given time and watch all the advertising. This fails to capture consumers who switch away from channels to avoid advertisement. Additionally, consumers viewing behavior at the end of one hour may not be independent of their behavior at the beginning of the next hour. This makes the i.i.d assumption questionable when aggregating on an hourly level. We do not aggregate our data and consider minute level observations in order to avoid these concerns. By focusing on minute level observations, we are able to see if a viewer actually stayed to watch an advertisement, or switched to another channel. However, it is not realistic to assume that consecutive minutes are independent. Therefore, we focus on a subset of our data; for each viewer we select minutes that are separated by 30 min intervals[16]. In order to avoid, minute level biases, for each viewer, we randomly select which minutes are chosen for each day[17]. After creating our random subsample, we are left with 1220 observations per viewer over the four month period that our micro data spans.

[14]Viewers are grouped into 36 different cohorts by age, gender (male,female), and socioeconomic status (lower, middle, upper class).

[15]These are then same five channels that were included in the aggregate data.

[16]We also check the robustness of this method by considering spacing minutes by 60 min

[17]For example, for a given viewer one day minute 20 and 50 of every hour in primetime may be sampled, while the next day minute 7 and 37 of every hour in primetime are sampled.

One benefit of having such a large number of observations, is that we are able to identify individuals that have a strong distaste for advertisements, in that they are never observed watching a channel showing advertising. As done in Dubois et al. (2020), we set the ad coefficient to negative infinity for any viewer that was never observed watching an advertisement.

In addition to channel characteristics, a consumer may have additional motivations to maintain their current viewing behavior. We add an addition "consumer inertia" fixed effect, $\psi_{d,t}$, that captures any preference to make the same choice as in the previous period. This inertia coefficient can be interpretted as a switching cost that needs to be overcome in order for the consumer to change their behavior. As is discussed in Cardell (1997) and Shum (2004), one can specify a nested logit model by including nest specific random effects. Therefore, this specification can also be interpreted as capturing consumers with a nested decision where they first choose between continuing with their current channel or switching to another channel, and then choose between an alternative channel if they chose to switch. MacKay and Remer (2022) provide further motivation and discussion about the inclusion of a consumer intertia fixed effect and the implications it may have on market dynamics. We also estimate a model without

Now, given the assumption that $\epsilon_{i,0,t},\ \epsilon_{i,C,t}, \epsilon_{i,c,t}$ are all independent idiosyncratic shocks independently distributed type I extreme values, we can calculate the probability of choosing each channel, c, in the choice set using the multinomial logit formula:

$$P_{i,t}(c) = \frac{exp(\beta_i^a I_{c,t}^a + \beta_d^g X_{c,t}^g + \eta_{d,c} + \tau_{d,t} + 1_{c(t)=c(t-1)}\psi_{d,t})}{1 + \sum_{c \in \Omega_{i,t}} exp(\beta_i^a I_{c,t}^a + \beta_d^g X_{c,t}^g + \eta_{d,c} + \tau_{d,t} + 1_{c(t)=c(t-1)}\psi_{d,t})}$$

Let $y_{i,t}$ denote the choice of viewer i at time t. Let T_i be the set of minutes that make up the random sample of viewer i's watch time. Then the probability of observing the choices $y_{i,t}$ is:

$$\mathcal{L}(\beta, \eta, \tau) = \prod_i \prod_{t \in T_i} P_{i,t}(y_{i,t})$$

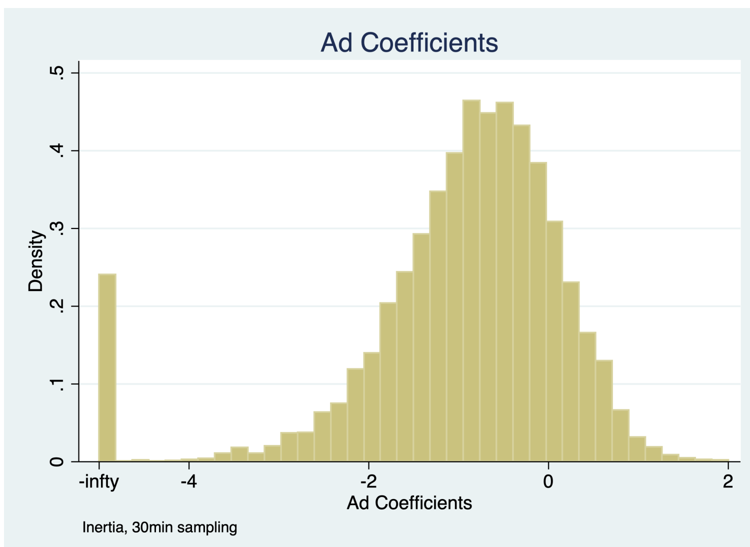
The log-likelihood function then becomes:

$$\mathbf{l}(\beta, \eta, \tau) = \sum_i \sum_{t \in T_i} log(P_{i,t}(y_{i,t}))$$

which is concave with respect to all parameters.

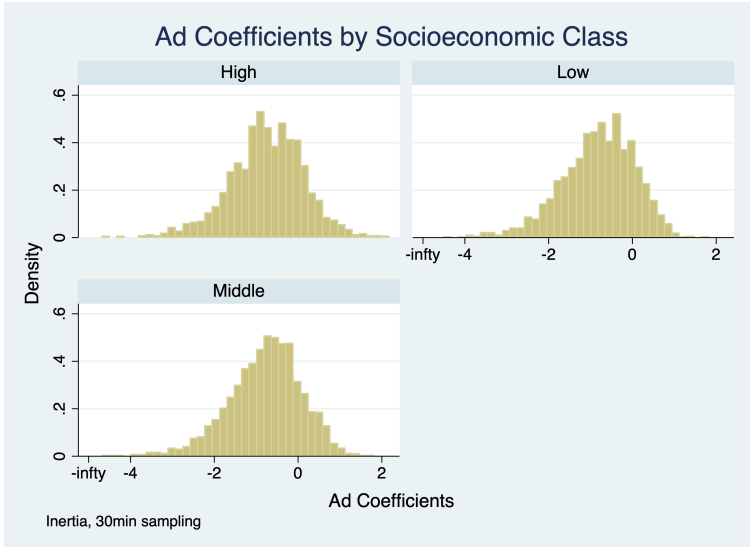
4.4 Heterogeneous Viewers Demand Model: Results

The model from the previous section was estimated using the maximum likelihood technique described. This provided individual ad coefficient estimate for each viewer. Less than 5% of viewers were never observed watching an advertisement, making their coef negative infinity. For the remaining viewers the average ad coefficient was -0.8. Overall over 83% of viewers had a negative estimated ad coefficient. These results go along with the intuition that the majority of viewers do not have a positive preference for advertising. The figure below shows the histogram for the advertising coefficient, showing a smooth slightly left skewed distribution.



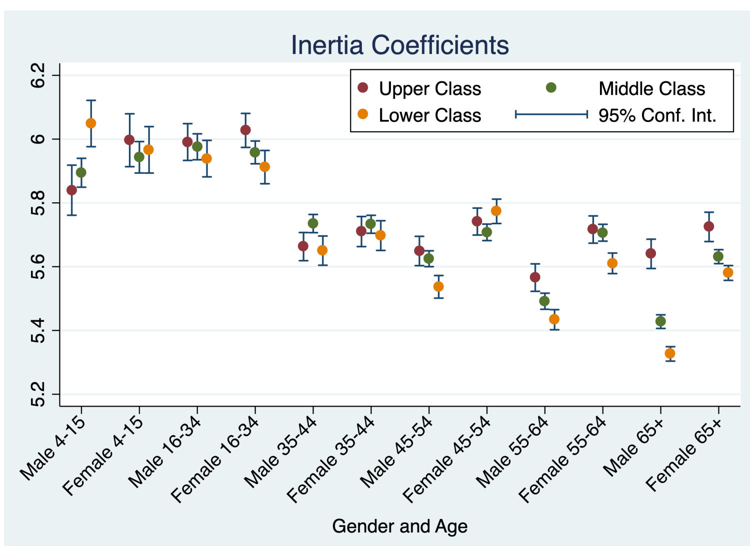
The way we specified our model allows us to compare the distribution of ad coefficient between different demographics, since the model should provide an unbiased estimate for each individual. Therefore, we can directly observe the possible relationship without any imposed predetermined structural assumptions on how ad distaste varies with regard to demographics. For example, in the figure below one can observe the distributions for different socioeconomic groups.

The box plots in the appendix show that the distribution for ad distaste does not appear to change with respect to other relevant demographic variables such as age and gender.



These results suggest that the distribution of ad distaste does not vary noticably across many relevant demographic variables.

However, if a channel wants to see which viewers tend to switch away from advertising, it is also relevant to look at the consumer inertia coefficient which captures differing switching cost. The figure below shows the estimated inertia coefficient for each of the 36 demographic cohorts. In the figure one can see that there is a downward trend in the inertia coefficient as



the age of the viewers increases. Additionally, differences between different age groups and differences between social classes become more pronounced in older cohorts, with lower-class males above the age of 64 having the lowest estimated inertia. Since ad adveristy is similar across cohorts, when a channel decides to play advertisements one would expect elderly lower-class males to switch away at a higher rate.

4.5 Advertiser Demand Side

We estimate advertisers' demand for ads slots adapting the model in Wilbur (2008). We study how ad prices are associated with audience share and advertising quantity, uence advertising prices, viewers in the free-to-air TV market do not pay for watching TV programs but audience is the main driver for advertising prices. We proxy actual prices with posted prices for the main TV channels. We aggregate data in 30-minutes blocks to measure audience shares and program characteristics. We control for day, time, channel, genre and producer.

The preliminary results using 8 months of data are shown in Table 2 below. An increase in advertising quantity decreases add price by 26 euros, while a 1% increase in audience share increases the add price by approximately 120 euros.

5 Conclusion

In this paper we study a two-sided market for media content. Consumers demand media content. Advertisers demand slots for commercial breaks. Our findings indicate that distaste for ads is highly heterogeneous. We also find evidence of non-monotonic relations between estimated consumer switching behavior and socioeconomic status. Our preliminary evidence also points out that advertisers' care about content. Overall, we find rich interactions between the two sides of the market.

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Table 2: Advertisers Demand

	(1) OLS	(1) IV
advertising	9.2692***	-26.4261*
audience share	89.7869***	119.8403
monday		2267.7***
tuesday		1847.2***
wednesday		2119.5***
thursday		1317.3***
friday		840.3***
saturday		-824.5***
20h		1917.4***
21h		3437.7***
22h		6768.0***
23h		6542.5***
_cons	5883.11***	7420.2***
N	4.856	4.856
R^2	0.65	0.63

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Figures/Appendix

Operators	2015	2016	2017	2018	Variation 2018/2017
Private operators	**66,2**	**65,9**	**65,2**	**65,1**	**-0,1**
Mediaset	**31,0**	**30,2**	**28,7**	**28,9**	**0,2**
Telecinco	14,8	14,4	13,3	14,1	0,8
Cuatro	7,2	6,5	6,2	6,0	-0,2
FDF	3,5	3,2	3,1	2,9	-0,2
Divinity	2,3	2,3	2,2	2,0	-0,2
Energy	1,5	1,9	2,0	1,9	-0,1
Boing	1,6	1,5	1,4	1,3	-0,1
Be Mad	n/a	0,4	0,6	0,6	0,0
Atresmedia	**26,8**	**27,1**	**26,5**	**26,8**	**0,3**
Antena3	13,4	12,8	12,3	12,3	0,0
La Sextan	7,4	7,1	6,7	6,9	0,2
Neox	2,6	2,5	2,5	2,4	-0,1
Nova	2,4	2,2	2,2	2,4	0,2
Mega	0,9	1,8	1,7	1,6	-0,1
Atreseries	n/a	0,8	1,1	1,2	0,1
G. Vocento (NET TV)	**3,4**	**2,9**	**3,1**	**2,9**	**-0,2**
Paramount Channel	2,0	1,8	1,9	1,7	-0,2
Disney Channel	1,4	1,1	1,2	1,2	0,0
U. Editorial (VEOTV)	**4,2**	**2,2**	**2,7**	**2,6**	**-0,1**
Discovery Max	2,1	1,9	1,7	1,6	-0,1
Gol	n/a	0,2	1,0	1,0	0,0
Trece TV	**n/a**	**2,1**	**2,1**	**2,0**	**-0,1**
Dkiss	**n/a**	**0,4**	**0,9**	**0,8**	**-0,1**
Ten	**n/a**	**0,3**	**0,4**	**0,3**	**-0,1**
Real Madrid TV	**n/a**	**0,2**	**0,4**	**0,3**	**-0,1**
Other Private regional channels[1]	**0,8**	**0,5**	**0,4**	**0,5**	**0,1**
Paid TV	**6,8**	**7,0**	**7,8**	**7,6**	**-0,2**
Public operators	**27,0**	**27,1**	**27,0**	**27,3**	**0,3**
CRTVE Group	**16,7**	**16,8**	**16,7**	**16,4**	**-0,3**
La 1	9,8	10,1	10,4	10,4	0,0
La 2	2,7	2,6	2,6	2,7	0,1
Clan TV	2,4	2,2	2,0	1,8	-0,2
24H	0,9	0,9	1,0	0,9	-0,1
Teledeporte	0,9	0,9	0,7	0,6	-0,1
Other (including regional channels)	**2,8**	**2,9**	**2,7**	**3,0**	**0,3**
Forta[2]	**7,5**	**7,4**	**7,6**	**7,9**	**0,3**
Total	**100,00**	**100,00**	**100,00**	**100,00**	

[1] Includes 8TV, CYL7, La 8, TV MEDITERRANEO, 8MADRID, RAC105, HIT TV.
[2] Forta is conformed by TV3, TVG, C.SUR, ETB2, ARAGON TV, EXTREMADURA TV, CMM, TPA, TVCAN, TELEMADRID, LA 7TV, IB3, ETB1, 3/24, A PUNT.

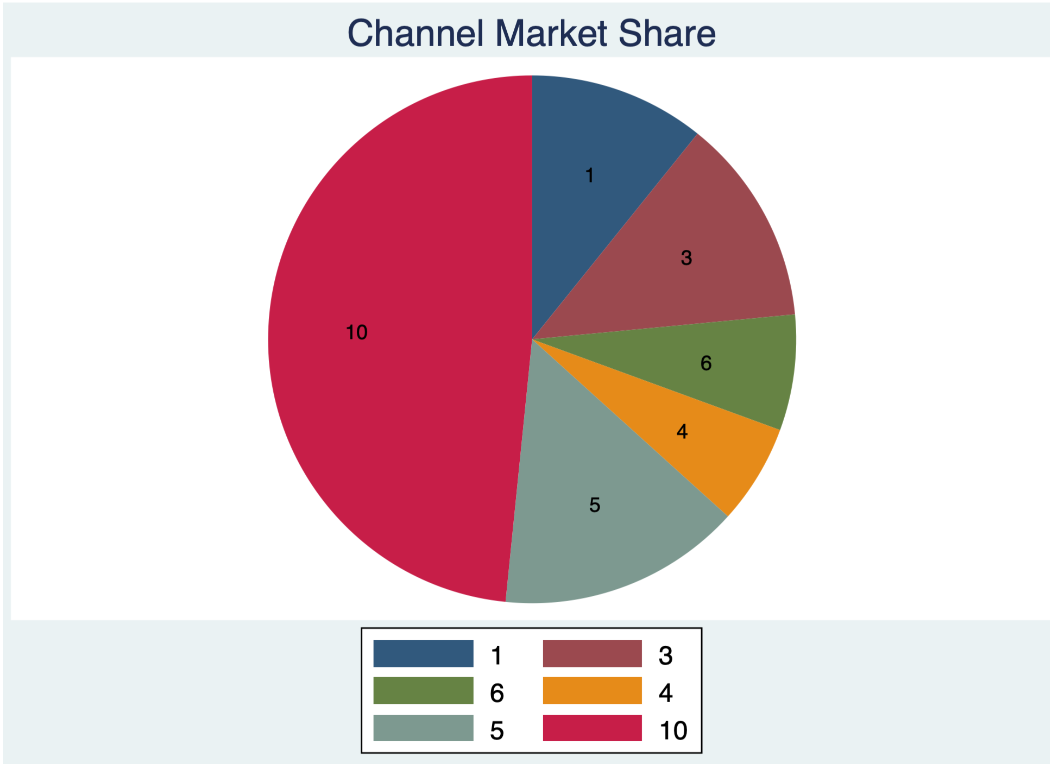

Figure 1: Market Share during prime time, Channel 10 is all other channels, Atresmedia owns channels 3 and 6, Mediaset owns channels 4 and 5, the public channel is channel 1

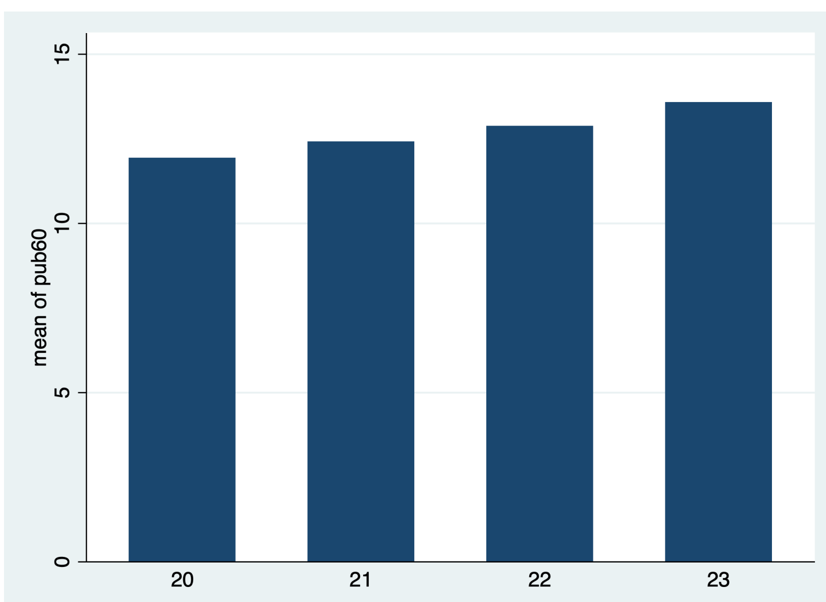

Figure 2: Average minutes of commercials for each hour

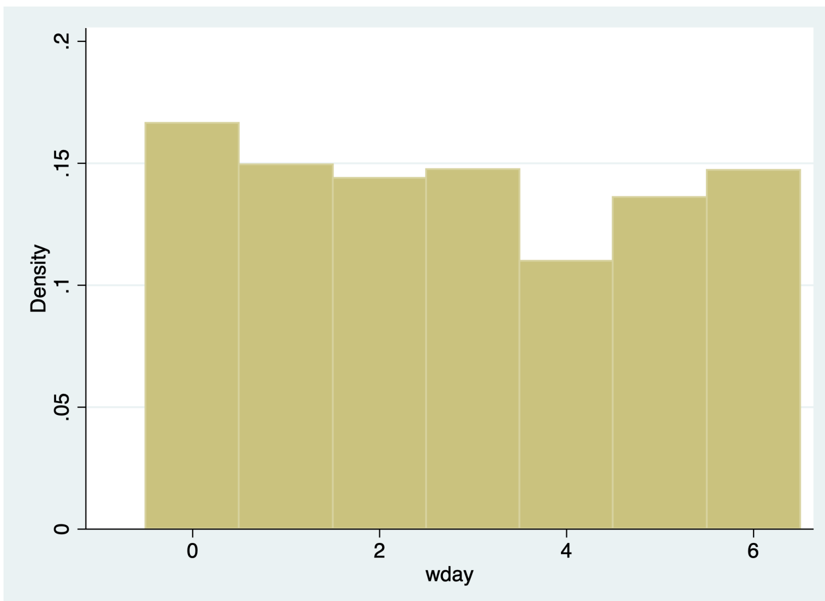

Figure 3: The proportion of watch time for each day of the week, where Sunday is 0 and Saturday is 6