Targeting Viewers' Heterogeneous Ad Aversion: Evidence from a Two-Sided Market*

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Abstract

This paper studies the role of viewers' heterogeneous ad aversion on media content demand and advertisers' willingness to pay. High-frequency individual-level data on broadcast media content allows us to track viewers' minute-by-minute choices within the set of available alternatives. We estimate ad aversion using high-frequency data on individual content choices exploiting per -minute discrete decisions of what content to watch. We estimate viewers' heterogeneous ad aversion adapting the demand model in Dubois et al. (2020) to media content. With this approach, we prioritize estimating heterogeneous preferences without placing distributional assumptions on individuals' ad aversion or on how it correlates with observable demographic characteristics. We find that ad aversion is highly heterogeneous and not strongly correlated with observable socioeconomic characteristics such as economic status or gender. We are also able to disentangle ad aversion from idiosyncratic inertia/state dependence and demographic-cohort content preferences. For the advertisers' side of the market, our findings indicate that advertisers' willingness to pay per impression is positively associated with the content's ability to reach audiences with high (estimated) ad aversion. We find robust evidence of a per-impression price premium for ad slots that are able to target individuals with higher levels of ad aversion.

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

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1 Introduction

Consumers' ad aversion and ad avoidance behavior is a core concern for ad-supported business models.[1] With the expansion of the digital economy, an increasing number of content creators and service providers are now funded through more precisely targeted advertising. Even traditionally ad-free platforms have introduced cheaper ad-supported versions to increase revenues.[2] Survey evidence indicates that consumers exhibit aversion to advertisements, though the magnitude of this aversion varies significantly depending on the context and the framing of the question.[3] Using revealed preferences from actual discrete content choices permits to recover consumers' disutility from ads. How heterogeneous is consumers' ad aversion? To which extent is advertisers' willingness to pay associated to hard-to-reach ad averse individuals?

Platforms' ability to engage viewers with high ad aversion is likely to play an increasingly pivotal role in two-sided markets' business models. Further research is needed to better understand the determinants and implications of ad avoidance behavior, especially in two-sided markets.[4] Assessing ad aversion poses challenges because content quality matters. Depending on their heterogeneous preferences, viewers face an idiosyncratic trade-off between their aversion to ads and their preferences for content. A decomposition of this trade-off can contribute to the growing empirical and theoretical literature on the role of advertisements

[1]Notably, platforms showcasing video content, ranging from free-to-air TV to social media video hosting services (e.g., TikTok, Youtube), heavily rely on advertising revenue.

[2]E.g., CNN Business November 3, 2022, "Netflix launches 'Basic with Ads' — its much anticipated commercial-supported plan." In the US the "Basic with Ads" option was announced as including an average of four to five minutes of commercials per hour played before and during TV series and movies. The shift towards an ad-supported business model may provide an opportunity for advertisers to reach individuals with higher ad-aversion relatively to those in other platforms. Given that the streaming platform expanded to 243 countries in 2016 (Aguiar and Walfogel, 2018), the adequate pricing strategy likely depends on the idiosyncratic ad-aversion levels country by country.

[3]From a sample of 3000 US adults in Nielsen (2023), the majority of individuals say they tolerate 1-15% of advertisements per hour of free content/services, whereas up to 44% of individuals report that they are not willing to tolerate any advertisements per hour of paid content/services. In contrast, Hub-Entertainment (2024), based on a similar sample of US individuals, finds that the percentage of people who said they "can't tolerate any ads in their content" dropped from 17% in 2021 to 12% in 2024. The report also found that the percentage of respondents who reported that content affected their ad tolerance went up from 26% to 35%.

[4]Previous literature studies ad nuisance due to concerns on ad blocking technology potentially generating inefficiencies and quality downward spirals (Anderson and Gans, 2011; Shiller et al., 2018; Gordon et al., 2021) or misalignment between advertisers and consumers' interests (Anderson and Peitz, 2020)

in two-sided markets.[5]

We contribute to the literature by estimating viewers' demand for video content and idiosyncratic ad aversion. We also study whether viewers' estimated ad aversion relates to advertisers' willingness to pay per impression. Advertisers (and, therefore, platforms) particularly value being able to target those not previously exposed to the specific ad or to ads in general (Sahni et al., 2019; Gentzkow et al., 2023). Viewers with a heightened ad aversion are likely to be a valuable but elusive and harder-to-reach audience for advertisers (and platforms).

Our analysis aims to better understand how two-sided markets trade off consumers' preferences for content quality and ads aversion in order to optimize advertising revenue. We disentangle the drivers of consumers' choices such as ad aversion, inertia/state-dependence, and idiosyncratic content preferences. Understanding how two-sided markets balance content quality against the quantity of advertisements is pivotal. To unravel the factors guiding consumers' choices, we take advantage of comprehensive data available from the Free-to-Air TV market to estimate demand for both media video content and advertisement slots. We first provide descriptive evidence on the factors associated to ads exposure. In line with Wilbur (2008), we find that ads exposure varies considerably across channels, which could be due to unobserved content characteristics or to selection effects. Then, making use of high-frequency data at the individual level, to estimate demand for content, inertia and viewers' ad aversion. We also study the role of variation in audiences' ad aversion on advertisers' willingness to pay. Adjusting Dubois et al. (2020)'s empirical strategy to media content demand (rather than to food demand), we model consumer preferences as individual level parameters that we can estimate (rather than as random coefficients). This approach permits us to study heterogeneous behavior without having to make distributional assumptions on demographic variables.

We find that ad aversion is highly heterogeneous and only partially correlated to inertia and commonly used socio-demographic characteristics. With these estimates we can study

[5] For empirical research see, for instance, Wilbur (2008); Bel and Domenech (2009); Fan (2013); Joo et al. (2014); Berry and Waldfogel (2015); Wilbur (2016); Lambrecht and Tucker (2019); Sahni et al. (2019); Ivaldi and Zhang (2022); Gentzkow et al. (2024); Brynjolfsson et al. (2024) and for theory, for instance, Kaiser and Wright (2006); Bergemann and Bonatti (2011); Athey et al. (2018); Shiller et al. (2018).

how consumers trade-off content quality with ad aversion. Looking at the advertisers' side of the market, we contribute to the literature that studies empirically ad avoidance behavior (Zigmond et al. 2009; Schweidel and Kent 2010; Wilbur et al. 2013; Wilbur 2016) and price premiums for certain demographic groups (Gentzkow et al. 2024). We find that advertisers' willingness to pay is associated not only to viewers' commonly observed socio-demographic characteristics (e.g., age, gender, income, education, TV watching time) but also to programs' capacity to engage high ad aversion viewers.

There is a large theoretical literature on two-sided-markets and advertising (seminal theory papers are Rochet and Tirole 2003 and Becker and Murphy 1993, respectively). This area of research has grown due to the prevalence of ad-funded platforms 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 (2004) on the market for Yellow Pages directories, the structural literature on two-sided markets studies how platforms provide value by connecting consumers' and advertisers. The main focus of this literature is determining how the externalities between both sides of the market affect market outcomes (Rysman, 2009). Within the structural two-sided market literature, our paper is particularly related to those that study 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 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.

Methodologically, our paper also connects with the structural literature on how to adequately model two-sided markets. Structural models in media markets have pointed out the crucial role of including key features such as endogenous product characteristics and multi-homing for identification. 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 key effect, measuring consumer welfare after a merger. Also focusing on newspapers, Argentesi and Filistrucchi (2007) and Affeldt et al. (2021) study market power and network externalities among four major Italian newspapers. Affeldt et al. (2021) argue that allowing for multi-homing prevents the underestimation of demand elasticity as newspapers readers frequently multi-home. We contribute to this literature by pointing out at the importance of estimating inertia and viewers' heterogeneous preferences, especially when they might not necessarily correlate with observable socio-demographic characteristics.

In Section 2 we provide relevant background on the market and data characteristics, in Section 3 we provide reduced-form evidence to motivate the use of individual choice data, in Section 4 we model and estimate demand for viewers and advertisers, and in Section 5 we conclude.

2 Market Characteristics and Data

The broadcast industry provides granular, high-frequency data on consumers' demand for news and entertainment video content. As a two-sided market where the different channels compete for both viewers and advertisers, it provides an ideal setting to empirically study the role of ad aversion in this type of markets. Due to the advertisers' interest in monitoring the impact of ad campaigns, there is a long-standing tradition of rigorously monitoring viewers' choices without having to rely on platforms' own data. Audimeter devices track viewership at the individual level with measurement standards that facilitate comparability across countries. In addition, the well-defined choice set of alternatives allow the identification of heterogeneous preferences, substitution patterns and responses to advertisements. Viewers make choices between the differentiated products, watching only one channel at a time, making it possible to use discrete-choice demand models.[6]

Television remains a major advertisement and entertainment market worldwide. In Spain, around the period of analysis, free-to-air TV had more than 30 million viewers each day (more than 65% of the Spanish population), with each individual viewer averaging 234 minuntes of watch-time per day Barlovento (2018). The Spanish free-to-air TV market has both publicly run and privately owned channels. The largest private channels (Telecinco, Cuatro, Antena3 and LaSexta) 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.[7]

In the advertisement side of the market, there exists even further market concentration of Atresmedia and Mediaset. In November 2019, the National Commission for Markets and Competition (CNMC) sanctioned the two conglomerates for anti-competitive practices. The CNMC determined that Atresmedia's and Mediaset's advertising guidelines reduced competition and excluded smaller television channels through vertical agreements with marketing agencies. During the period of analysis, Atresmedia and Mediaset jointly account for 89% of free-to-air television advertising revenues.[8]. This particular market structure could be a concern in terms of external validity. However, platforms' market power concentration in advertising markets is also a feature commonly present in digital markets in (Decarolis and Rovigatti, 2021; Ferrer et al., 2023). Another common feature shared in both the market we study and digital markets is that advertisers commonly delegate tasks to marketing agencies. In order to decide the allocation of resources into specific ad slots, advertisers in digital and television markets hire expert intermediary marketing agencies Decarolis and Rovigatti

[6] Viewers' watching several channels simultaneously (i.e., similarly to multi-homing) is not feasible in our setting as channels broadcast content simultaneously. Viewers could use devices that permit to postpone watching certain content with delay ("en diferido") . However, during the period of analysis, the fraction of minutes watched with delay is almost negligible as it accounts for less than 3% (Barlovento, 2018).

[7] With the implementation of the Digital Terrestrial Television system in 2010, there was a temporary increase in the number and diversity of national operators and local television channels (Bel and Domenech, 2009; Gil and Gutierrez-Navratil, 2017); however, the decrease of market power concentration did not consolidate.

[8] CNMC, Advertising revenue of private DTT operators, "Telecommunications and Audiovisual Sector Economic Report," p. 129, https://www.cnmc.es/sites/default/files/2750388_4.pdf

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%

(2021).

Advertisement in our setting has to fulfill market regulation which include content and timing restrictions. Channels are 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 (with few exceptions) were no longer allowed to have commercial breaks.[9] As a result of this regulation, content without commercial advertisements is available in national public television.

We focus on audience data for Spain's prime-time (8pm and 12:30am). We use two main data sets. The main data set consists of individual choices over the set of possible channels during four months per year (September to December) during 2017-2019. This data set includes individual panel data on consumers, tracking 15,000 consumers' channel choice on a minute level. It was collected by the audimeter data provider in Spain (Kantar) based on in-house tracking devices on individuals' remote controls and tv sets. For each minute of content, we combine this data with programming information and genre information. The distribution of prime-time broadcast programs into the main genres' categories is shown in Table 1. Finally, the data includes the duration and timing of the ads being aired in each channel, which we aggregate at the minute level.

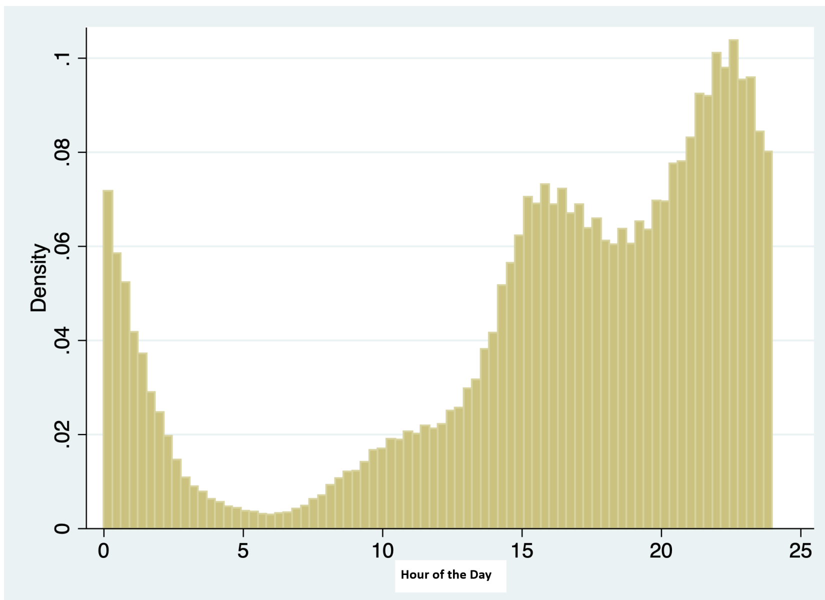
We complement our main data set with aggregate data on the number of viewers per minute for each of the 5 main TV channels. For each minute, we also observe the total TV viewership across all free-to-air channels. This data is available for a longer period of time as it includes the two last weeks of every month between March 2017 to March 2019,

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

resulting 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 6 in the appendix provides a chart of the market shares of the 5 main channels included in the data as well as of the composite Channel 10.

As common in other countries, the total number of Spanish individuals watching TV has daily and weekly cycles. As illustrated in Figure 1, over the afternoon and night viewership slowly increases, until it peaks at 10:30pm, which aligns with the popular perception of late dinner time in Spain relative to other countries.

Figure 1: Viewers' frequency per hour of the day



Regarding the amount of advertisement content watched, Table 2 reports descriptive statistics of individual viewers' average proportion of watch time consisting of advertising. We observe substantial heterogeneity, where at the 5th percentile 3.5% of viewers' content consists of advertising, whereas at the 95% percentile 19% of viewers watched content is advertisements. Comparing the descriptive statistics by gender and socioeconomic status based on income and education level, we find significant differences. Both females and individuals with lower socioeconomic level (Soc. Statuses 4, 5, 6 and 7) are more likely to watch ads. Even though these differences are significant their magnitude is rather small in size. Gender differences account for a quarter of the overall standard deviation (.0488) with

Table 2: Descriptive statistics on viewers' average fraction of time watching advertisements

	Obs	Mean	Median	SD	5th pctile	95th pctile
All	18,937	.1132	.1130	.0488	.0354	.19
Females	9,560	.1193	.1207	.4852	.0403	.1944
Males	9,377	.1070	.1054	.4834	.0324	.1870
Sociecon status 1	1450	.1013	.0982	.0554	.0232	.1873
Sociecon status 2	2675	.1055	.1044	.0476	.0309	.1859
Sociecon status 3	2266	.1111	.1100	.0463	.0380	.1861
Sociecon status 4	4888	.1153	.1158	.0490	.0391	.1923
Sociecon status 5	2772	.1168	.1156	.0468	.0430	.1922
Sociecon status 6	3488	.1168	.1180	.0486	.0357	.1933
Sociecon status 7	1398	.1209	.1232	.0480	.0373	.1971

Notes: Each observation represents a viewer's average share of advertisement minutes watched relative to the total TV minutes watched on the same day, conditional on having watched any TV that day.

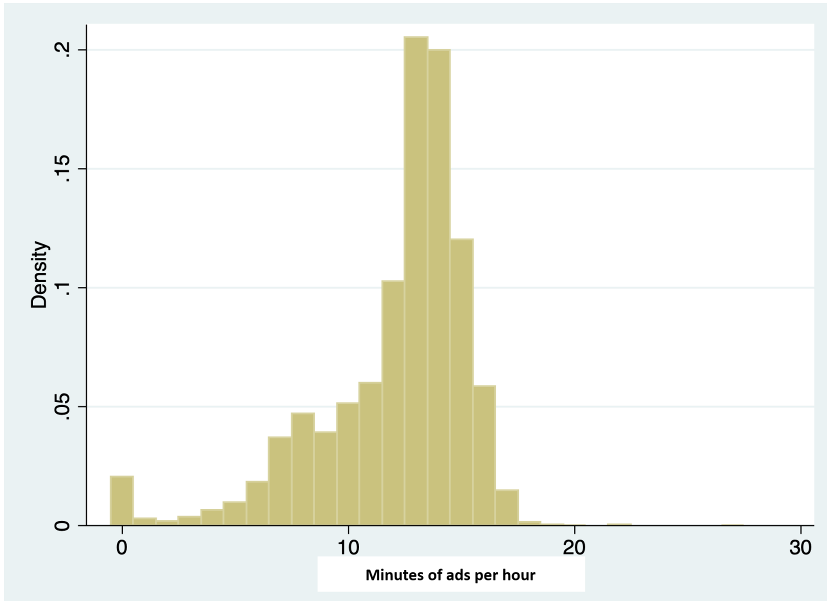
females significantly watching on average 1.2% more ads. Socioeconomic status accounts for similar variation than gender. The group with highest socio-economic level (Soc. Status 1) watches on average 11.32% minutes of ads, whereas the group with lowest socioeconomic (Soc. Status 6), 12.09%.

Figure 2 illustrates that the number of minutes of ads minutes varies per hour. Regulations limit ads to 17 minutes per hour, with a maximum daily average of 12 minutes per hour. Figure figure:ad-minutes below shows the distribution of the number of ads played per hour for the privately owned channels. We observe considerable variation in the number of advertisement minutes. Specifically, channels often choose to go over the 12-minutes average limit, which then forces them to show less advertisements during other hours within the same day.

3 Individual vs. Market-level data: Selection challenges and heterogeneity

In this section, we conduct reduced form regressions to provide descriptive evidence on factors affecting viewers' ads exposure. An additional goal of these exercises is to illustrate the contribution of using data on individual choices relative to aggregate data on the number of viewers. We study how exposure to ads vary by channel, day of the week, month, and

Figure 2: Number of advertising minutes per hour



year. In addition, we control for daily weather conditions since previous research finds that avoidance behavior increases on certain days of the week and depending on weather conditions Wilbur (2016).

As the dependent variable measuring ad exposure, we use viewers' daily proportion of watch time consisting of advertising. In the absence of individual choice data, we would only observe the number of viewers per channel and minute. We could measure the exposure to ads by obtaining the share of ads minutes watched per channel by all viewers relative to the daily number of minutes watched of that channel by all viewers. Thus, the dependent variable per channel j would be the fraction y_{jt} ads minutes watched by viewers on day t over the number of channel j's minutes watched by viewers.

Thus, at this aggregate level, we would not be able to distinguish if on a given day and channel, there is relatively higher exposure to ads; however, it would not be possible to disentangle the underlying mechanism taking place. Specifically, a lower exposure to ads on a given day and channel could be driven by individuals deciding to watch.

With individual level, it is possible to compute the share of ads minutes separately for each of the individuals. Therefore, per channel j and viewer i,the dependent variable is the fraction y_{ijt} of ads minutes over the number of channel j's minutes watched by viewer i on day t.

Therefore it is possible that differences in the fraction of ads' minutes watched across channels or days of the week are driven by selection bias. Specifically, with aggregate data, we cannot rule out that Antena3 or Telecinco have a higher coefficient because their content is simply able to engage individuals with lower ad elasticity. To address selection Columns (3) and (4) include individual fixed effects in the regressions. In addition, in Column (4) the sample is restricted to individuals whose fixed effects are below the median individual fixed effect. This specification shows that the coefficients vary throughout the distribution. As shown in the table the coefficients for channel fixed effects are lower when in the individual level regression. Also, whereas Channel 4 is associated to the larger ads exposure in Column (1), it is no longer the case in the individual level regressions. specifically,

4 Two-sided Markets with Heterogeneous Viewers' Content Choices

In this section, we introduce and estimate a discrete choice demand model for content. The main objective is to model viewers' trade-offs when facing commercial breaks while watching broadcast content. Viewers' ad avoidance behavior has been shown to vary as a function of content and advertisements' characteristics (Siddarth and Chattopadhyay, 1998; Zigmond et al., 2009; Schweidel and Kent, 2010; Wilbur, 2016; McGranaghan et al., 2022).

In order to estimate heterogeneous individual ad aversion and address concerns associated to market level data, we adapt the model in Dubois et al. (2020) to demand for media content. In their paper, they 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). In contrast with the random coefficients approach, this method avoids having to make independence assumptions to integrate out the parameters' density. Preferences are treated as consumer level parameters to be estimated, such that there is a unique coefficient for each consumer and no need to make assumptions on the distribution of

Table 3: Descriptive evidence: Share of Advertisements

	Agg. shares (y_{jt})	**Indiv. shares** (y_{ijt})		
		All indiv.		Below median
	(1)	(2)	(3)	(4)
Daily mean temperature	-0.0004	-0.0000	-0.0004***	-0.0003***
	(0.0007)	(0.0001)	(0.0001)	(0.0001)
Daily min temperature	-0.0023***	0.0003***	-0.0000	-0.0000
	(0.0008)	(0.0001)	(0.0001)	(0.0001)
Log daily rainfall	-0.0010**	-0.0013***	-0.0008***	-0.0008***
	(0.0004)	(0.0001)	(0.0001)	(0.0002)
Channel 3	0.1669***	0.1440***	0.1411***	0.1104***
	(0.0016)	(0.0003)	(0.0003)	(0.0004)
Channel 4	0.1793***	0.1422***	0.1394***	0.1084***
	(0.0016)	(0.0003)	(0.0003)	(0.0004)
Channel 5	0.1559***	0.1261***	0.1215***	0.0924***
	(0.0016)	(0.0003)	(0.0003)	(0.0004)
Channel 6	0.1560***	0.1213***	0.1219***	0.0894***
	(0.0016)	(0.0003)	(0.0003)	(0.0004)
Female		0.0071***		
		(0.0002)		
Constant	0.0697***	-0.0056***	0.0174***	0.0146***
	(0.0105)	(0.0008)	(0.0008)	(0.0010)
N	1815	4173770	4173770	2085587
R^2	0.9087	0.0871	0.0800	0.0589
DoW, Month and Year FE	Yes	Yes	Yes	Yes
Socio-demographic and gender FE	No	Yes	No	No
Individual FE	No	No	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All specifications include month, year, and day of the . week fixed effects. The omitted categories are “Channel 1” for channel, “Sunday” for day of the week, ’Year 2007’ for year, and “Socioeconomic status 1” (i.e., the highest socioeconomic status) the idiosyncratic preferences; specifically, allowing for dispersion of preferences to vary across demographic groups. Additionally, this approach allows us to study the role of viewers' (estimated) preferences on the advertisers' side of the market and potential ad premiums for content able to target viewers with certain preferences.

Our model builds upon Dubois et al. (2020) in order to be as parsimonious as possible in our assumptions regarding the relationship between demographics and ad aversion. In the market for advertisements, the demographics of channel audiences can have a large impact on the value of advertisement slots. Advertisers value the ability to reach demographic groups that are hard to reach. Viewers with high ad aversion would naturally be hard to reach. However, based on previous literature we cannot rule out that ad aversion is orthogonal to observable socio-demographic characteristics. Our model permits to estimate heterogeneous ad aversion without making assumptions on its relationship with demographics commonly used in the literature, such as age, gender and socio-economic status.

4.1 Demand Model with Individual Heterogeneous Content Choices

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. Additionally, we only consider viewers who watch at least one minute of TV[10]. 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.[11] The utility the consumer receives from watching one of the main channels is modeled as:

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

The coefficient of the first term, β_i^a, captures an individual viewers taste for advertisements; $I_{c,t}^a$ is an indicator of whether channel c is showing advertisement at time t. The coefficient of the second term, β_d^g, captures preferences for different observed channel programming

[10] This is similar to other discrete choice demand settings where the consumers choice is only observed when the consumer makes a purchase (e.g., supermarket transactions in scanner data).

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

characteristics, $X^g_{c,t}$, such as genre; this also includes an end-of-show indicator, controlling for people switching away during the ad-break between shows. In addition, we include demographic group specific channel fixed effects, $\eta_{d,c}$, capturing additional unobserved preferences for the different channels. The second to last term, $\tau_{d,t}$, is a vector of time fixed effects that affects the valuation of all channels equally compared to the outside good of not watching TV.[12] These time fixed effects capture differences in the valuation of the outside good compared to all channels across time. The error term, $\epsilon_{i,c,t}$, is assumed to be i.i.d. and follow an extreme value distribution.

Ad aversion is estimated at the individual level. However, to have a more parsimonious model, the coefficients for channel, genre, and time fixed effects are estimated for different demographic cohorts based on age, gender, and socioeconomic status.[13]

The original panel data set includes over 50 different channels. Of those channels, only 5 have a market-share above 3%.[14] 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.

Models commonly used in the literature to estimate TV demand, aggregate viewer choice over time periods blocks (e.g., hourly as in Wilbur (2008), monthly as in 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 avoid advertisements by switching channels during breaks. Additionally, consumers viewing behavior at the end of one hour may not

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

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

[14] These are then same five channels studied in the aggregate data. Namely, TVE1, Antena3, Cuatro, Telecinco and LaSexta

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 randomly selected subset of our data; for each viewer we randomly select minutes from 30 minutes intervals.[15] We perform a random selection of minutes that varies daily and by individual.[16]

One benefit of having such a large number of observations, is that we are able to identify individuals that have a strong ad aversion, 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. Despite the low cost of switching channels, empirical research finds strong inertia effects in TV watching behavior (Esteves-Sorenson and Perretti, 2012; Richter, 2025). We add an additional "consumer inertia" fixed effect, $\psi_{d,t}$, that captures any preference to make the same choice as in the previous 30-minutes interval. This inertia coefficient can be interpreted as a switching cost that needs to be overcome in order for the consumer to change their behavior.

Now, given the assumption that $\epsilon_{i,0,t}$, $\epsilon_{i,C,t}, \epsilon_{i,c,t}$ are 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:

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

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:

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

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

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

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.

4.2 Estimation of Viewers' Heterogeneous Ad Aversion

The model from the previous section was estimated using the maximum likelihood. This provided individual ad coefficient estimates for each viewer. Roughly 5% of viewers were never observed watching an entire minute of advertisements in our sample, making their coefficient negative infinity. For the remaining viewers the average ad coefficient was -0.8, which implies an average ad aversion of 0.8. Overall, over 83% of viewers had an estimated ad coefficient $-\beta_i^a > 0$. These results go along with the intuition that the majority of viewers do not have a positive preference for advertising.

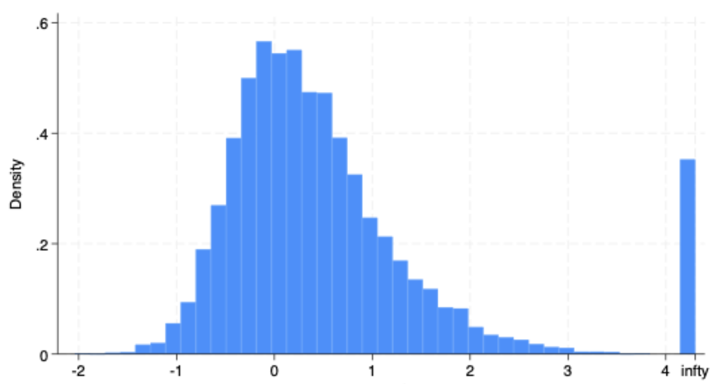


Figure 3: Viewers' Estimated Ad Aversion, (β_i^a), associated to the viewer-level idiosyncratic value obtained from watching advertisements

Our empirical strategy allows us to compare the distribution of ad aversion between different demographic groups, 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 aversion varies with regard to demographics. We indeed find the ad coefficient to be highly heterogeneous. Figure 3 shows the histogram for the advertising coefficient, showing a slightly right skewed ad aversion distribution. In addition, the infinity bar at the extreme represents the 5.45% of viewers that in the sample did not view more than an entire minute of advertisements.

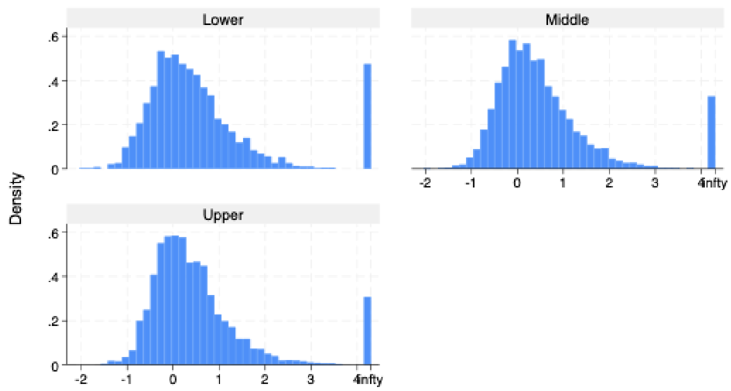
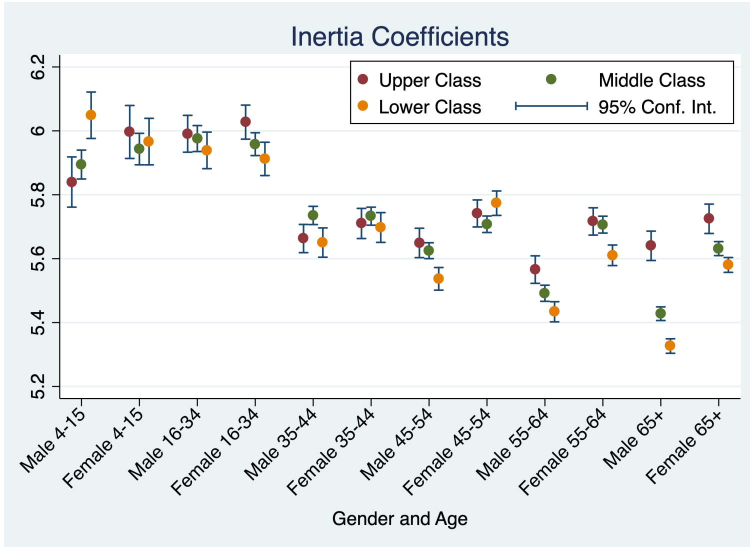


Figure 4: Viewers' Estimated Ad aversion, (β_i^a), grouped by viewers' socio-economic status

In Figure 4 one can observe the distributions for the three different socioeconomic groups. The distribution for ad aversion does not appear to vary considerably with socio-economic status. We also do not find it to vary considerably with other relevant demographic variables such as age and gender. These results indicate that substantial variation in ad aversion is driven by other factors than commonly observable demographic variables.

In addition, we study how consumer inertia/state dependence's coefficient relates to demographics. 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 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. Given that the average ad aversion is similar across age cohorts, we would then expect elderly lower-class males to switch away at a higher rate when exposed to ads. The interpretation of the inertia and ad aversion coefficients must keep under account that larger coefficients do not always imply more actual ad viewing. Specifically, McGranaghan et al. (2022) find evidence that older viewers are more likely to avoid ads by changing channels whereas younger viewers are more likely to avoid ads by leaving the room or diverting their visual attention (e.g., shifting their focus to mobile devices).



4.3 Advertisers' Demand Side

In this section, we study the advertisers' side of the market to analyze the determinants of advertisers' willingness to pay. Outlets jointly compete for viewers and advertisers. Because we are studying free-to-air TV, advertisers are the primary source of channels' revenue with the only exception being the fully-subsidized national public TV network. Therefore, advertiser decisions are key drivers of content profitability.

We estimate how advertisers' willingness to pay depends on the characteristics of the other side of the market (viewers), including their estimated ad aversion. Previous literature, has studied how advertisers' willingness to pay depends on the ability to reach audiences with observed socio-demographic characteristics that are hard to reach on TV (Wilbur 2008; Gentzkow et al. 2024). We contribute to this previous literature by studying how advertisers' willingness to pay is associated to the audience's ad aversion preferences estimated in the viewers' demand side. Taking advantage of ads prices and our granular viewership data, we focus on estimating the determinants of the actual price per impression.

To measure advertisers' willingness to pay we use publicly available posted prices for the main TV channels, which vary by hour, day of the week, and trimester, as illustrated in Figure 5. Advertising posted prices in Spain are made public on corporation's website, which commonly publish updated rates each trimester. For a given ad price, a larger number of viewers implies a larger number of impressions. Advertisers' willingness to pay may vary

Table 4: Advertisers' market descriptive statistics

Channel	Viewers (000s)	Ad price (euros)	Price per impression (euros per 1000 imp.)	Avg Audience's Ad Aversion per minute of content
3	1532.3	13850	0.92	0.072
4	742.4	11992	0.82	0.085
5	1780.4	19519	1.31	0.175
6	795.6	8737	0.58	0.009

depending on time, content and viewers' characteristics. In Table 4 we find considerable variance of price per impression and on the average taste for ads. There is considerable variation across channels in the relationship between ad prices and number of viewers. In particular, the price per impression is particularly high in Channels 3 (Antena3) and 5 (Telecinco), which are the channels with higher market share. The last column provides the average ad aversion (i.e.,) of the actual audience watching each minute of content

In two-sided markets, a common measure of advertisements' performance is the number of impressions. Impressions count the number of unique consumer exposures an advertisement receives. In order to explore how variation in the willingness to pay per impression relates to viewers' characteristics and ad disutility, we use price per impression as the dependent variable in order to estimate:

$$P_{jt}/V_{jt} = \beta \mathrm{X}_{jt} + \gamma W_{jt} + \xi_{jt} \tag{1}$$

where P_j is the price of an ad during the time in channel j, V_j is the number of viewers (share) watching the channel j, X_j are the program characteristics and W_j are the audience characteristics of j, specifically moments of the actual audience's estimated ad aversion, and fraction of the audience belonging to each sociodemographic group. Also, ξ_{jt} is the error term. We control for day of the week, hour of the day, channel, genre and producer fixed effects.

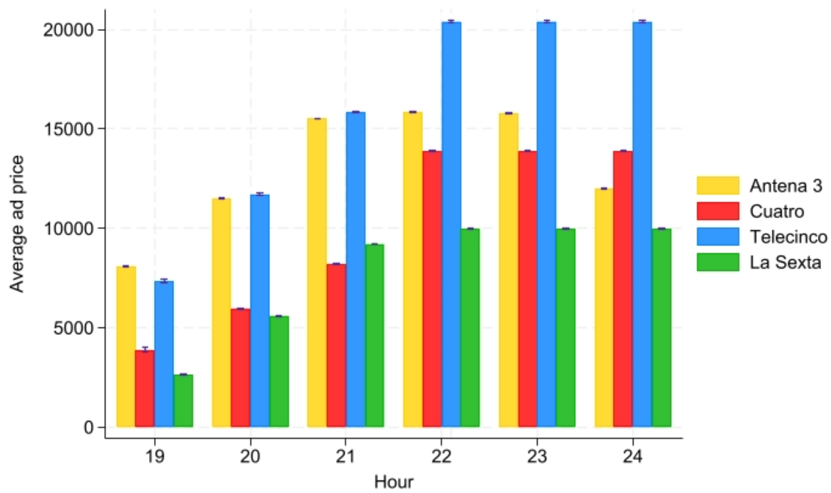


Figure 5: Average posted advertisement prices for a standard 20 seconds commercial by hour range, 2017-2019

In Table 5's analysis we study the determinants of price dispersion in the market for advertising slots. We find a relation between programs' capacity to engage certain social demographic groups; however, demographics explains only part of the variation. Interestingly, we find that being able to engage consumer's with a high estimated ad aversion increases the advertisers' willingness to pay per impression. Using percentiles of the ad aversion distribution, in Columns (3) and (4) show that this is mostly driven by individuals at the top tail of the ad aversion distribution. The higher the value of the audience's top ad aversion quartile, the higher the advertisers' willingness to pay Notice that as we are controlling for hour of the day, day of the week and channel fixed effects, our results are associated to within channel and time slot variation.

The results appear to indicate that advertisers are able to identify content appealing to high ad-aversion individuals. This targeting ability is striking although aligns with the prevalent use of advertising intermediary agencies Hristakeva and Mortimer (2023). The use of data analysis is widespread and growing, particularly with the rise of online advertising Decarolis et al. (2020).

In Table 6 we show the robustness of the results after introducing further control variables. We find that our results are robust to controlling for audience's overall TV viewership and multihoming behavior. Previous literature finds evidence of ad price premium for television

Table 5: Advertisers' Demand

	Log (Price per Impression)			
	(1)	(2)	(3)	(4)
Audience Avg Ad Aversion	0.480***	0.407***		
	(0.02)	(0.03)		
Audience's Median Ad Aversion			0.360***	-0.192***
			(0.03)	(0.06)
25th Percentile Ad Aversion				0.306***
				(0.05)
75th Percentile Ad Aversion				0.307***
				(0.04)
Audience's Demog. Concentration		-4.918***	-4.812***	-4.985***
		(0.41)	(0.41)	(0.41)
First emission 1 year	0.197***	0.192***	0.189***	0.196***
	(0.03)	(0.03)	(0.03)	(0.03)
First emission 2 years	0.086**	0.073**	0.075**	0.079**
	(0.03)	(0.03)	(0.03)	(0.03)
First emission 3 years	0.166***	0.142***	0.148***	0.145***
	(0.04)	(0.04)	(0.04)	(0.04)
First emission 4 years	-0.037	-0.057**	-0.056**	-0.061**
	(0.03)	(0.03)	(0.03)	(0.03)
First emission 5-9 years	0.061***	0.047**	0.042*	0.052**
	(0.02)	(0.02)	(0.02)	(0.02)
First emission 10-20 years	0.213***	0.182***	0.183***	0.183***
	(0.02)	(0.02)	(0.02)	(0.02)
First emission >20 years	0.164***	0.150***	0.148***	0.152***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-0.396***	-0.756*	-0.767*	-0.898**
	(0.02)	(0.45)	(0.45)	(0.46)
N	12569	12569	12569	12569
Audience's demog. bins	Yes	Yes	Yes	Yes
Content Genre FE	Yes	Yes	Yes	Yes
DoW HoD Year FE	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is the price per impression calculated as the ratio between the posted price of a standard 20 seconds ad in Channel j in time t divided by Channel j's audience at time t. The default for years since first emission corresponds to having less than 12 months of time on air. The *Audience's Socio-Demographic Bins* are defined as the audience's share of individuals belonging to each of the 36 bins (3 socioeconomic categories x 2 gender x 6 age groups). The regressions include channel, hour, day of the week, year and genre fixed effects.

programs with relatively larger audiences Phillips and Young (2012), or with less active viewers. Gentzkow et al. (2024) also find evidence of a premium in price per impression for slots with audiences that are less active in visiting competing outlets (i.e., lower multi-homing activity). Building on these previous studies, we control for the average amount of TV minutes watched, which permits measuring to which extent each content is appealing to heavy (light) TV users. To control for multi-homing activity, we also measure the share of different channels watched by each individual and compute the sum of squared shares (i.e., equivalent to individual viewers' channels concentration). Looking at gender, we find a price premium for content be able to engage a more diverse gender audience. Our results are also robust to controlling for the actual audience's average range of channels watched as well as with the audience's average daily viewing minutes watched. Finally, we find that the advertisers' willingness to pay per impression decreases as the concentration of the audience demographics increases, which is in line with the advertisers' preferring a more diverse audience.

Table 6: Advertisers' Demand - Robustness

	Log(Price per Impression)					
	(1)	(2)	(3)	(4)	(5)	(6)
Audience Average Ad aversion	0.455***					
	(0.03)					
Audience's Median Ad Aversion		0.399***	-0.188***	-0.195***	-0.195***	-0.156***
		(0.03)	(0.06)	(0.06)	(0.06)	(0.06)
25th Percentile Ad Aversion			0.343***	0.325***	0.325***	0.390***
			(0.05)	(0.05)	(0.05)	(0.05)
75th Percentile Ad Aversion			0.324***	0.323***	0.323***	0.331***
			(0.04)	(0.04)	(0.04)	(0.04)
Audience's Gender Concentration				-2.451***	-2.451***	-3.046***
				(0.34)	(0.34)	(0.35)
Audience's Mean Channel Range						1.164***
						(0.18)
Audience's Demog. Concentration	-5.098***	-4.953***	-5.169***	-4.528***	-4.528***	-4.666***
	(0.41)	(0.41)	(0.41)	(0.42)	(0.42)	(0.42)
Constant	-0.795*	-0.801*	-0.927**	-1.540***	-1.540***	-1.923***
	(0.45)	(0.45)	(0.45)	(0.46)	(0.46)	(0.46)
N	12569	12569	12569	12569	12569	12569
Audience's socio demog bins	Yes	Yes	Yes	Yes	Yes	Yes
Audience's Average Watching time	Yes	Yes	Yes	Yes	Yes	Yes
Program's Years on Air FE	Yes	Yes	Yes	Yes	Yes	Yes
Audience's socio dem FE	Yes	Yes	Yes	Yes	Yes	Yes
Content Genre FE	Yes	Yes	Yes	Yes	Yes	Yes
DoW HoD Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Channel FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the logarithm of the price per impression calculated as the ratio between the posted price of a standard 20 seconds ad in Channel j in time t divided by Channel j's audience at time t. The *Audience's Demographic Concentration* is defined as the average sum of the squares of the shares corresponding to each of the 36 demographic bins. *Gender concentration* measures for each minute of ad content the sum of the square of the gender share in Channel j at time t. The *Audience's Average Channel Concentration* is defined as the average sum of the squares of the time share allocated by the viewer to each channel. The default for years since first emission corresponds to having less than 12 months of time on air. The regressions include channel, hour, day of the week, year and genre fixed effects.

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 ad aversion is highly heterogeneous. We also find evidence of non-monotonic relation between estimated consumer switching behavior and socioeconomic status. Our evidence also points out that advertisers' willingness to pay per impression is increasing for programs able to engage audiences with a higher ad aversion. Overall, we find rich interactions between the two sides of the market.

In further extensions we are assessing the robustness of the results to account for ad content. The content of advertisements may play a role in shaping viewers' ad tolerance. Higher quality ad campaigns can retain viewers more effectively. By introducing advertisers' and ad campaign fixed effects we will also test whether the higher willingness to pay for targeting ad averse individuals is driven by a small group of advertisers.

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Appendix

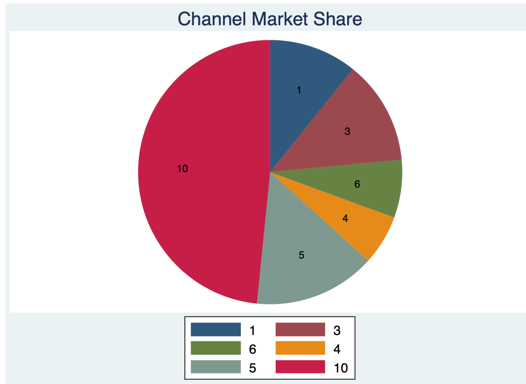

Figure 6: Market Share during prime time, Channel 10 is all other channels, Atresmedia owns Channels 3 (Antena 3) and 6 (LaSexta), Mediaset owns Channels 4 (Cuatro) and 5 (Telecinco), the public channel is Channel 1 (La1)

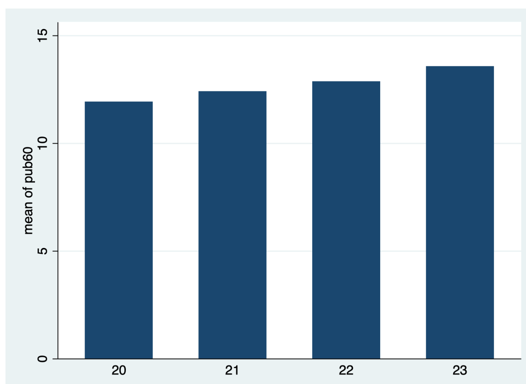

Figure 7: Average minutes of commercials per hour