Job market paper

Micro-costs: Inertia in television viewing*

Constança Esteves-Sorenson
Haas School of Business at UC Berkeley

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Abstract

Inertia, defined as persistence in the default option, affects outcomes from organ donations to enrollment in retirement plans. A leading explanation for inertia is the cost of switching to an alternative option. Can consumers display inertia in a setting where this cost is negligible? If so, is this behavior systematic and significant enough to affect the profit-maximizing strategies of firms? This paper finds inertia in a setting in which the switching cost is extremely small: click of the remote in the choice of which television program to watch. In the absence of a significant switching cost, the audience of a program should not depend on the audience of the prior show on the same channel, controlling for the non-random assignment of programs. I find, however, that despite the negligible cost of switching: (i) male and female viewership of the news depends on whether the preceding show appealed to men or women, (ii) a 10% increase in the demand for the prior show increases the demand for the current program by 2%-4%. I also find that viewer inertia decays over the duration of the subsequent show. These findings are consistent with quasi-viewer indifference towards programs, or procrastination in switching channels. Inertia in program choice affects the optimal program schedule and may influence as much as 20-40% of channels' profits.

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Airing immediately after the hit show Seinfeld, Frasier's initial time slot was Thursdays at 9.30 pm ... as good a scheduling slot as existed in prime-time television ... Steve Sternberg, an advertising executive, quipped that "you could read the phone book after Seinfeld and get a 25% viewer share."[1]

1 Introduction

Inertia, defined as persistence in the default option, affects outcomes in a variety of settings. Its impact has been documented in laboratory experiments (see Anderson, 2003, for a survey of some of these studies) and in the field, from organ donations (Abadie & Gay, 2006) to enrollment in retirement plans (e.g. Madrian & Shea, 2001).

One of the leading explanations for consumer inertia has been the switching costs associated with choosing an alternative to the default. If these costs are high, compared to the extra benefit from alternative options, consumers should rationally persist in the status-quo.

Consumer inexperience with the decision and the high number and complexity of alternatives increase these switching costs. For example, Madrian & Shea (2001) find that employees participated at a significantly higher rate – more than 50% – in a firm-sponsored 401k plan when enrolled in it by default, than when not. When not enrolled by default, employees could join the plan and start collecting the matching contributions from the firm by incurring the seemingly small direct cost of a phone call. Still, a substantial portion failed to do so. One explanation for this failure, replicated in other firms (Choi et al., 2004), is that employees faced an infrequent choice, over a vast and complex array of plans. The substantial indirect cost of learning how and where to invest could have inhibited their enrollment.

Would inertia exist in settings where the direct switching cost is negligible? And, moreover, the decision is frequent and the number of choices is limited? This paper provides evidence of inertia in one such environment – the choice of television programs in Italy. Television viewers are experienced in the decision of which program to watch: Americans and Western Europeans watch an average of four hours of television per day. Viewers choose from differentiated program offerings across channels. Switching channels requires only a click of the remote.

I test whether the micro-cost of clicking the remote induces significant channel persistence in program choice using a novel dataset of demand for television shows in Italy.[2] The Italian

[1] Harvard Business School case, "Frasier" (A), 2001, p.2

[2] Other studies have broached the topic of channel persistence on program choice. I will describe them later.

media environment is especially well-suited to study this question. Italy's sophisticated audience tracking system reduces the potential for measurement error. The concentration of 90% of viewership on six broadcast channels and the ubiquity of remotes lower the search costs and the complexity of the decision of which program to watch. The dataset contains two types of information: (i) minute-by-minute audience for men and women between 6:00 PM and 12:00 AM for 2002-2003, for Italy's six main channels; (ii) the demand, in audience and share, for every show aired on those channels between 6:00 PM and 12:00 AM, from 1990 to 2003.

The test is based on examining how variations in the audience of a show affect the audience of the subsequent show on the same channel, holding constant a set of controls. I use two distinct but complementary methodological approaches to address significant challenges to identification, such as endogenous scheduling by channels and weather shocks.

First, an event-study using minute-by-minute audience data for 2002-2003 exploits the variation in the appeal of programming to men and women before the late night news. When a male show, such as soccer, which appeals primarily to men, precedes the news, more men watch the news than women. In contrast, when a female show, such as a series on the romantic lives of doctors, precedes the news, more women watch the news than men. These results, which contradict the null of no channel inertia in program choice, are robust to calendar-day by minute-of-the-day unobservables that affect male and female viewership. The difference between male and female audience of the news erodes at each minute, suggesting inertia has a decay rate.

Second, for a larger sample of television programs aired between 1990-2003, I find that an increase in 10% in the demand for a show increases the demand for the subsequent show on the same channel by 2%-4%. An initial analysis using ordinary least squares (OLS) estimates the partial correlation between the demand for an episode of a show and the demand for the preceding program on the same channel. It includes an extensive set of controls that could be correlated with both variables. These controls are the appeal and type of competing programs to the episode of the current show as well as the interaction of current show, channel, year, month and half-hour slot unobservables. After the inclusion of this vast number of controls, I find a statistically significant OLS estimate of 3.8%.

The OLS estimate could, however, be biased by omitted shocks that are systematically correlated with the demand for adjacent programs on the same channel, such as weather, or by viewers tuning-in earlier to the channel to avoid missing the beginning of their preferred show. I address the potential omitted variables and simultaneity biases with two separate instrumental variables (IV) specifications.

First, for the sample of programs that air after movies, I instrument the *Demand for the prior show* with the theatrical movie audience of every movie shown on Italian movie screens and subsequently on television. I analyze how, within a program, the audience of its episodes varies with the popularity of the movie that plays prior to them. The resulting IV estimates are large, marginally significant, and not statistically different from the OLS estimates, despite the reduced number of observations induced by the smaller sample size. Second, I introduce an additional instrument for *Demand for the prior show* to conduct robustness checks requiring more observations: the average demand of the prior show in the preceding month. This alternative approach yields estimates that are not statistically different from the *Theatrical audience* instrument. In both instrumental variables specifications, I address the potential endogenous scheduling by channels, by restricting the dependent variable to *Demand for the news of the day*, whose daily popularity is arguably not susceptible to manipulation by channels. Finally, I use the latter instrument to rule out alternative explanations for channel inertia in program choice, such as advertising of the next show on the same channel, competing shows within a line-up not starting at the same time, and changes in the audience measurement system.

The OLS and IV estimates are consistent with substantial channel inertia in the choice of programs. As with the previous analysis of male and female audience during the news, I also find a decay rate to inertia here: the longer the length of the current program, the less the influence of the prior show on its audience.

The finding that the demand of a show is a significant determinant of the demand of the subsequent show on the same channel has been broached in prior studies. This research (Horen, 1980; Rust & Alpert, 1984; Shachar & Emerson, 2000; Goettler & Shachar, 2001; Moshkin & Shachar, 2002) attempts to predict, among others, the choice of television programs. One of most recent studies is Goettler & Shachar (2001). It uses a week of individual viewing choices for the major four U.S. networks to estimate a structural model of individual choices of television shows. It finds, among other things, that (i) over 56% of viewers of a show watched the end of the previous show on the same network, (ii) the parameters identifying whether a viewer watched the prior show are significant in predicting the choice of the current show on the same network.

Though these previous studies add much to the understanding of inertia in program choice, they are subject to three potential biases. First, correlated unobservable factors could affect the viewership of adjacent shows on the same channel. Bias arises if correlation in these factors – e.g. unobserved time invariant preferences for a channel, or weather shocks – is ignored.

I address this issue with fixed effects and instrumental variables. Moreover, inertia may be confounded with viewers tuning-in earlier to the channel to not miss the beginning of their chosen show, inducing correlation among adjacent shows. I address this reverse causality with instrumental variables. Second, since networks in the U.S. tend to air a clip of the show playing subsequently on the same channel, persistence in the default channel could also be due to this advertising (Moshkin & Shachar, 2002; Shachar & Anand, 1998). Advertising of the subsequent show on the channel with a clip is rare in the Italian setting. Third, measurement error could be confounded with viewer inertia. The most accurate data used in these studies is generated by the Nielsen Peoplemeter, which may measure viewership between adjacent shows on a channel where there is none. The Nielsen Peoplemeter asks viewers to confirm whether they are watching television after 70 minutes of inactivity. Therefore, if viewers fall asleep or leave the room without confirming they are not longer watching, the meter will record these viewers as watching the same channel up to 70 minutes. This issue is minimized in the Italian data, since the Italian meter requires viewers to confirm viewership after 15 minutes of inactivity.

The estimated inertia and its decay rate found in this study are consistent with two explanations, which I discuss in the context of a dynamic choice model with stochastic costs and the option value of switching channels. First, a portion of viewers have time-consistent preferences, but are almost indifferent between the show in the default channel and those of competing channels. They will persist on the default until they receive a utility shock that leads them to switch. This may cause delays in the status-quo channel. Alternatively, a portion of consumers may have quasi-hyperbolic preferences, whereby they discount the immediate future at a steeper rate than when discounting between two future adjacent time periods (Strotz, 1956; Phelps & Pollak, 1968; Akerlof, 1991; Laibson, 1997; O'Donoghue & Rabin, 1999). These preferences have explained the persistence in the default in retirement plans, 401k enrollment status (Samuelson & Zeckhauser, 1988; Cronqvist & Thaler, 2004; Madrian & Shea, 2001; Choi et al., 2004) and contractual choice in health clubs (DellaVigna & Malmendier, 2006). These preferences, especially when coupled with naivete about one's own behavior, lead consumers to procrastinate for longer spells in the status-quo, even when the extra-benefit of switching is significantly larger than the cost. The consumer believes she will change channels at some minute m in the future. However, at minute m, the steeper discounting between the present and immediate future leads her to persist in the status-quo.

Anecdotal evidence indicates that profit-maximizing channels anticipate viewer inertia and best-respond to this phenomenon. Books about the industry describe scheduling strategies that leverage viewer inertia. For example, the *lead-in strategy* – scheduling a weak or new show after a popular show to inherit its audience – and *hammocking* – placing a weak or new show between two popular shows, to inherit the audience of the prior show and garner those viewers tuning-in earlier to watch the subsequent show – are well-documented.[3]

Can we verify whether television channels respond strategically to viewer inertia? I investigate this question using the previously estimated magnitudes of viewer inertia. I find that viewer inertia affects the optimal schedule and may affect as much as 20%-40% of channels' profits. Under the assumption of no strategic interactions between channels and holding the schedule of other channels fixed, the gap in audience between the optimal schedule and the worst schedule, taking into account viewer inertia, ranges from 2%-4%. The average gap is roughly 2% for the larger channels. The program schedules for all six channels, however, are close to or at the optimum. I use the advertising prices for a 30-second commercial in prime-time for 2002-2003 for one of the larger channels to calibrate the value of changes in the audience on advertising revenues. I find that a change in 1% in audience changes the price of a 30-second commercial by 1.2%. A 2% change in audience represents a 2.4% change in advertising revenues, accrued directly to profits, since the costs of programming are sunk for the year. Hence, for the publicly traded channels, with profit margins of 11.3% in 2002 and 5.8% in 2003, the difference between the worst and the optimal schedules corresponds to 20-40% of profits.

This paper contributes to a growing literature of how firms may exploit potential non-standard features of consumer behavior (DellaVigna & Malmendier, 2004; Heidhues & Koszegi, 2008; Gabaix & Laibson, 2006), surveyed in Ellison, 2006. It also contributes to the discussions on the role of consumer inertia on choice (e.g. Tirole, 1988, p. 295; Cronqvist & Thaler, 2004). It also adds to the literature on the estimation of demand of television shows, and how channels compete to maximize audiences (Goettler & Shachar, 2001; Shachar & Anand, 1998). Decision-making in the consumption of television shows is a relatively under-studied phenomenon relative to the amount of resources allocated to this activity. The average viewer watches four hours of television shows per day and it is estimated that, in a lifetime, the average person will spend more time watching television than working.[4] A sizable industry supplies this demand: the

[3]These media scheduling strategies are common knowledge in the television industry and have been discussed extensively in many books. A leading book, *Ratings Analysis*, by Webster et al. in 2006 writes: *"... a lead-in strategy is the most common ..." ..."Another strategy that depends on [audience] inheritance effects is hammocking".*

[4]Estimated hours working in lifetime: (65 years-22 years) x 50 weeks x 5 days x 8 hours per day=86,000; Estimated hours watching television in lifetime: (75 years-15 years) x 365 days x 4 hours = 87,600 hours

broadcasting and cable TV market in the U.S. reached a value $125.7 billion in 2006, of which 57.5% is advertising, and is projected to grow by 27% to $159.8 billion by 2011.[5]

2 Background, audience measurement and data

2.1 Institutional background

The television environment in Italy consists of a duopoly: state-owned Rai competes mainly with publicly-listed Mediaset, partially owned and controlled by Italy's recurring prime-minister, Silvio Berlusconi.[6] Each group has three channels, and they jointly capture an average of 90% of television audience in Italy. Rai's three channels consist of Rai 1, its flagship with 25% average share, Rai 2 and Rai 3, which started operations in 1954, 1961 and 1979, respectively. Mediaset's three channels are: Canale 5, its flagship with 24% viewer share, which became a national channel in 1981; Italia 1, acquired in 1983; and Rete 4, acquired in 1985. The remaining market share is mainly split between MTV, LA 7 (which broadcasts mainly older movies), and local channels.

All six channels follow a generalist strategy. They air shows with broad appeal, not focusing on specific demographics, such as MTV with teens and pre-teens or topics, as the Discovery Channel with science. Nevertheless, each channel's programming appeals to somewhat different audiences. Figure 2 shows the line-up for a typical day, Monday, across the six channels and Table 1 describes the genres, such as news, sitcom and reality TV, in the line-up.

Advertising about the specific content of a show, during the preceding show on the same channel, is rare. It happens only in two instances. First, each of the flagship channels Rai 1 and Canale 5 advertises its 8:00 PM news during the prior show, with a clip. Canale 5 started this practice in 1995, to increase viewership of its news at 8:00 PM, strategically important due to its placement at the beginning of prime-time; Rai 1 followed suit. Second, the anchors for the 8:00 PM news in Rai 1 and Canale 5 announce verbally the next program. Rai 1 also announces the topic and guests of the news talk-show Porta-a-Porta which usually airs after the 11:00 PM news.

General information about the current and new program offers is substantial. Television schedules are published in all newspapers and television guides. Channels also advertise their

[5]Datamonitor, Broadcasting and cable industry in the United States, August 2007

[6]Prime-minister in 1994, 2001-2006, and 2008-present

own shows, for example, announcing a romantic movie in prime-time during the soap opera at 6:30 PM. Advertising of new series starts usually three weeks before the first airing. Cross-advertising, whereby channels advertise programs of other stations in the group, also occurs but is less frequent. Advertising of programs by channels is costly because it crowds out regular paid advertising due the regulatory cap on the amount of advertising per hour.

Like their counterparts in the U.S., Italians viewers are experienced. They watch more than 4 hours of television per day and viewership has been increasing from 4 hours and 22 minutes in 1997 to 4 hours and 43 minutes in 2006. Average viewership per person in the U.S. was 4 hours and 35 minutes per day in the 2005-2006 season, up 3 minutes versus the previous season.[7]

Similarly to the U.S., the Italian audience peaks at prime-time, from 8:00 PM to 11:00 PM. This is the time when most viewers are available to watch television and when stations compete more fiercely for viewer share. It is also the time at which advertising rates are the highest.

2.2 Audience measurement

The television audience in Italy is measured by a very sophisticated audience tracking system. Auditel, the audience monitoring organization is primarily owned by a consortium of stakeholders: broadcasters (e.g. Rai and Mediaset), the national advertisers association and media buyers affiliated with the three national associations for advertising. It monitors the viewership of a panel of 5,101 households, 14,000 viewers, with 8,000 meters (1 meter per television, and 1.6 televisions per household).

The panel is a stratified representative sample of the Italian television viewing population. Panel members are rewarded for participating in the panel with household goods. They are interviewed twice per year and their viewing behavior is monitored daily. Panel members' viewing choices are analyzed for abnormal patterns and they are called at random and asked whether they are watching television and what they are watching. Their answers are compared with the television meter measurements. Misbehavior, though rare, leads to expulsion from the panel. The panel is adjusted and refreshed every year with new members. Television show ratings and the corresponding prices for advertising are based on the viewership data from the panel. This paper uses the same data.

Viewers interact with the television meter using a remote. Most interactions require 2-3 clicks.[8] Once the television starts, the TV screen requests the identification of the viewers who

[7] Nielsen estimates, via Mediaweek, September 21st, 2006

[8] There are two types of remotes. Type I, the most prevalent, has one button for each member of the household.

are watching ("Registration prompt"). If viewers browse channels and settle on a channel for 30 seconds, they receive a prompt to confirm who is watching ("Action prompt"). The 30-second timing arises from observed browsing behavior: viewers evaluate programming in less than 30 seconds.[9] If there is no action for 15 minutes, viewers receive a prompt, asking who is watching ("No action prompt").[10] Viewers are not counted as watching until they answer the prompt. The prompt appears either as a translucent screen over the current programming or in a bar at the bottom of the screen. Before August 1997, only half the panel had the three prompts – Registration, Action and No Action. The remainder of the panel only had the Registration prompt. After 1997, the whole panel had the three prompts.[11]

The Italian audience measurement system differs from that in the U.S. in two ways. First, stakeholders in the Italian measurement system own the audience measurement company. This is not the case with Nielsen, the single provider of the audience measurement in the United States. Second, the company that provided the measurement technology for the Italian audiences during 1990-2003 – Audits of Great Britain (AGB) – has been a pioneer in enhancing the measurement of audiences compared to Nielsen. For example, Nielsen upgraded its measurement system to a similar system to the Italian, only after the threat of entry of AGB into the U.S. market in 1985.[12]

2.3 Data

The data consist of two related datasets on television viewership. The first dataset contains audience, for every minute between 6:00 PM and 12:00 AM for 2002-2003 for men and women

Type II has one button for all members of the household plus an upward and downward arrow to interact with the meter. For the most prevalent type I remote, pushing once the household member's button plus the OK button confirms that the person is watching; pushing twice plus OK indicates that he or she is not.

[9]This assertion is supported by a study on internet television watching by Cha et al. in 2008. It observed the browsing and viewing behavior of 250,000 consumers of internet television choosing over 150 channels. It concludes that: (i) Over 60% of users switch channels within 10 seconds, (ii) the average time before switching is 9 seconds, when viewers switch within one minute (iii) the average sampling time for news is 4 seconds, children's, music and sports programs is 7-8 seconds, cable-like shows is 9 seconds and documentaries and movies is 10-13 seconds, conditional on viewers switching within one minute (iv) viewers sample on average 4 channels before settling on a channel for one minute or longer.

[10]The most accurate data used in research that broaches inertia in television viewing is generated by Nielsen Peoplemeters in the U.S., where the No Action prompt only activates after 70 minutes.

[11]Later in the analysis, I show that this difference in measurement does not affect the estimates.

[12]The New York Times, October 8, 1990: Black Hole in Television; Nielsen's 'People Meter' Has Engendered A Revolution by Showing a Fall in Viewers.

for the six main channels and total television.[13] The unit of analysis is audience by channel, gender, calendar day and minute within the calendar day. The number of observations is about 2.5 million.

The second dataset contains the audience, market share (percentage of total television audience), genre (if a sitcom, reality show, etc.), starting time and ending time for each show aired between 6:00 PM and 12:00 AM, from 1990 to 2003, for the six channels. The audience for each show averages the recorded audience at each minute.[14,15] The unit of analysis is *episode of show* and it contains almost 200,000 observations, excluding shows that air on weekends. The largest proportion of shows are news (22% of total), followed by variety shows (11%), talk-shows (10%), TV series (9%) and movies (7%). The average length of a show is about 45 minutes and the average number of episodes per show is 16. These and other details appear in Table 1.

3 Empirical analyses and identification strategies

I start the analysis with mainly graphical evidence of inertia. An event-study using minute-by-minute data shows how the viewership of a given show among men and women varies with the appeal that the previous show on the same channel had for them. This analysis is constrained to one of Italy's main channels for 2002-2003. Later, I broaden the analysis to all six channels and the years between 1990-2003. I use OLS and IV to estimate the effect identified in the event-study across this larger sample of shows. This allows me, in the end, to calibrate the profitability of inertia for channels.

3.1 Event-study with minute-by-minute audience for men and women

Null hypothesis. I investigate whether the average viewership of a show is higher for men than for women when the prior program on the same channel appeals mainly to men; and if, conversely, the average viewership of the same show is higher for women than men when the prior show on the same channel appeals primarily to women. Absent inertia, the null hypothesis is that, all things equal, male and female viewership of a show should be insensitive to variations

[13] The dataset also contains audience data by age brackets for men and women (e.g. women 25-34 years old), audience by educational level and audience by socio-economic status that were not used in the analysis.

[14] Total show audience $= 1/M \sum_m$ Show Audience$_m$, m=1, ... M, $m \equiv$ *minutes*; Total show share $=$ Total show audience$/(1/M)\sum_m$ Total television audience$_m$, m=1, ... M

[15] A typical data point is "Show: 8:00 PM news Rai 1; Genre: news; Start of show: 8:00 PM; End of show: 8:30 PM; Audience: 4.5 million viewers; Share of total television viewers: 33%"

in the appeal to men and women of the prior show on the same channel. It should only reflect the intrinsic appeal of the show to men and women.

Sampling scheme and identification strategy. This analysis exploits variation in the appeal to men and women of a show that precedes the same program, the late news in Rai 1 in 2002 and 2003.[16] The daily late news, at the end of prime-time, starting at about 11:00 PM, follows soccer on 16 days, female shows (shows where every episode garners more female than male viewers) on 127 days and neutral shows (shows where the male audience exceeds female audience for some episodes but not others) on 53 days. Since the average duration of the late news is 8 minutes, I restrict the analysis to cases when daily news talk show Porta-a-Porta follows the late news, to gage whether channel persistence extends beyond 8 minutes. Porta-a-Porta covers political and current affairs and does not air during the summer. Table 2 details the sample construction and the mean time for the start of the late news on Rai 1.

Unadjusted audience analysis. Figure 3 shows the unadjusted audience analysis for soccer, female and neutral show days on Rai 1. The left panel represents the average male and female viewership on soccer days, starting one hour before the late news (-60). Soccer is followed by a short sports news program - Rai Sport with an average 13-minute duration – followed by a 5-minute commercial break and then by the late news. During soccer games, male viewership exceeds female viewership and this trend continues through the news and into the subsequent Porta-Porta talk-show. Male viewership, however, converges to the level of female viewership over time. The middle panel summarizes the days when female shows, such as Incantesimo, a series on the romantic lives of doctors, precede the late news. In contrast to the news viewership in soccer days, more women than men watch the news and the subsequent news talk show Porta-a-Porta. The right panel depicts the audience on neutral show days on Rai 1. Female viewership is higher than that of males both before and after the late news, though the difference between them is smaller than that in female show days.

Male and female viewers appear to choose between channels and not the outside option of not watching television. Figure 4 shows that the average total television viewership for men and women is fairly similar on soccer, female and neutral show days in Rai 1, both before and after the news.[17] This suggests, first, that women who would usually watch Rai 1 do not eschew

[16] Soccer is the only program where the audience of men consistently and significantly exceeds that of women. Though soccer games play on other channels, none of them preceded the same show on enough occasions to enable analysis of these channels.

[17] The total average female audience across all channels is always higher than that of males. The reasons for this gender imbalance in television watching could be two-fold: (i) Italy has 4-6% more women than men, (ii) its

television watching on soccer days in Rai 1; rather, they watch a different channel on another television set in the household. Otherwise, we would see a drop in total female audience in soccer days in Rai 1, both before and after the news. Second, it suggests that male viewers that persist into the news and Porta-a-Porta in Rai 1 after soccer do not increase the total number of male viewers. The same is true for women in female show days. This suggests that inert viewers trade-off watching Rai 1 versus other channels and not the outside option of not watching television.

Adjusted audience analysis. I now adjust the previous analysis by the mean viewership on neutral days in Rai 1 to take into account the baseline male and female viewership for Rai 1. Moreover, I also adjust the specification with minute-of-the-calendar-day by gender fixed effects to control for unobserved factors at each minute of the day that could influence the viewership of men and women on Rai 1. These factors include, for example, the unobserved appeal to men and women of competing shows on other channels at each minute (the competing five channels to Rai 1 aired about 370 distinct programs during the late news in Rai 1 for the 196 days of the analysis). Or, they could consist of unobserved shocks in the appeal to men and women of the outside option of not watching television. To facilitate the estimation of these fixed effects, I add audience by minute and gender observations from the other five channels for male show, female show and neutral show days on Rai 1.

The left panel of Figure 3, with the unadjusted male and female audience in Rai 1 on soccer days, is adjusted by the following specification:

$$\begin{aligned} Audience_{\tau,channel,day,min,gender} = {} & \alpha_{0,\tau} + \alpha_{1,\tau} Male.\mathbf{1}[channel = \text{Rai 1}] + \alpha_{2,\tau} Male.\mathbf{1}[channel = \text{Rai 1}]\mathbf{1}[day = \text{soccer}] \\ & + \beta_{1,\tau} Female.\mathbf{1}[channel = \text{Rai 1}] + \beta_{2,\tau} Female.\mathbf{1}[channel = \text{Rai 1}]\mathbf{1}[day = \text{soccer}] \\ & + \Gamma_{day}\Gamma_{minofday}\Gamma_{gender} \end{aligned}$$

where Male and Female are indicator variables for male and female, respectively, and $\tau \equiv$ Time from start of the late news in Rai 1 $= -60... + 60$.[18].

female labor participation rates are low (less than 40% in 2006, one of the lowest in Europe and two-thirds of that of the U.S. in 2006).

[18]This specification combines two specifications. The first specification adjusts the male audience in soccer days: $Audience_{\tau,channel,day,min,male} = \alpha_{0,\tau} + \alpha_{1,\tau} Male.\mathbf{1}[channel = \text{Rai 1}] + \alpha_{2,\tau} Male.\mathbf{1}[channel = \text{Rai 1}]\mathbf{1}[day = \text{soccer}] + \Gamma_{day}\Gamma_{\text{min of day}}\Gamma_{male}$ where $\alpha_{0,\tau}$=adjusted mean audience for all channels except Rai 1, on both soccer and neutral days in Rai 1; $\alpha_{0,\tau} + \alpha_{1,\tau}$=adjusted male audience for Rai 1 in neutral days and $\alpha_{0,\tau} + \alpha_{1,\tau} + \alpha_{2,\tau}$=adjusted audience for Rai 1 in soccer days. The coefficient of interest is $\alpha_{2,\tau}$, the adjusted gap in audience in Rai 1 in soccer days versus neutral show days. Similarly, the second adjusts the female audience in soccer days: Adjusted female audience for Rai 1 in female show days $Audience_{\tau,channel,day,min,female} = \beta_{0,\tau} + \beta_{1,\tau} Female.\mathbf{1}[channel = \text{Rai 1}] + \beta_{2,\tau} Female.\mathbf{1}[channel = \text{Rai 1}]\mathbf{1}[day = \text{soccer}] + \Gamma_{day}\Gamma_{minofday}\Gamma_{female}$

I run 120 regressions, one for each $\tau = -60, ...60$. For each τ, the time from the start of the late news in Rai 1, I pool the male and female audience for each of the 6 channels, by minute of the calendar day, for soccer and neutral show days in Rai 1.

The coefficients of interest are $\alpha_{2,\tau}$ and $\beta_{2,\tau}$: $\alpha_{2,\tau}$ is the adjusted gap in male viewership of Rai 1 on soccer days versus the baseline male viewership on neutral days; $\beta_{2,\tau}$ is the adjusted gap in female viewership versus the baseline female viewership in neutral show days.

The middle panel with male and female audience in Rai 1 in female show days, is adjusted by a similar specification. The coefficients of interest are $\alpha^0_{2,\tau}$ and $\beta^0_{2,\tau}$: $\alpha^0_{2,\tau}$ is the adjusted gap in male viewership on Rai 1 on female show days versus the baseline male viewership on neutral days; $\beta^0_{2,\tau}$ is the adjusted gap in female viewership versus the baseline female viewership on neutral show days.

Figure 5 shows the resulting adjusted coefficients for male and female viewership for soccer days and female show days. The left panel plots the adjusted coefficients for male and female viewership on soccer days: $\alpha_{2,\tau}$, $\beta_{2,\tau}$, the difference between them and the 95% confidence interval of the difference. The right panel depicts the adjusted coefficients for male and female viewership for female show days: $\alpha^0_{2,\tau}$, $\beta^0_{2,\tau}$, their difference and the 95% confidence interval for the difference. The standard errors are clustered on calendar day, to adjust for serial correlation within the day (Bertrand et al., 2004). It shows, as expected, that the adjusted average gap between male and female audience widens for soccer days and shrinks for female show days, reflecting the fact that on neutral show days more women than men watch Rai 1.

Calibration using the cumulative gap in audience between men and women. What is the magnitude of average difference between male and female audiences after the late news in Rai 1 relative to the average difference before the late news? How does it change over time? I use the adjusted difference between the viewership of men and women, at the bottom of Figure 5 to answer this question. I plot the sum of this adjusted difference, divided by the elapsed time since the event "start of late news". I perform a similar analysis for female show days. I focus on the post-news time, that is, after the start of the late news in Rai 1.

$$\text{Cumulative average gap after male show (soccer)} = 1/\tau \sum_i^\tau \beta_{2,\tau} - \alpha_{2,\tau}$$

$$\text{Cumulative average gap after female show } = 1/\tau \sum_i^\tau \alpha^0_{2,\tau} - \alpha^0_{2,\tau}$$

$\tau \equiv$ time since the start of the event "start of the late news in Rai 1"= 1,..., +60

The post-news cumulative gap is in Figure 6. It shows that the cumulative difference in audience between men and women converges over time, on both soccer and female show days, suggesting that inertia has a decay rate. Moreover, on both types of days, the magnitude of the average gap 30 minutes after the start of the news is 17-18% of the average gap before the news, and the magnitude of the average gap 60 minutes after the start of the news is 14% of the average gap before the news.

The prior analysis provides evidence of inertia and its decay rate. I conducted robustness checks in section four and these did not change the observed results. The evidence of channel inertia in program choice found so far is, however, restricted to the late news in Rai 1 and only for the years 2002 and 2003. It would be important to know if the inertia observed in this setting generalizes over a larger number of shows and across all channels. It would also be useful to estimate, on a larger sample, the average effect that variations in demand of a show have on the audience of a subsequent show on the same channel, in order to calibrate the profitability of viewer inertia for channels. I use the second dataset with audience data for each show aired between 6:00 PM and 12.00 AM, for Italy's six main channels, between 1990 and 2003, to conduct this analysis.

3.2 OLS and IV on panel of television shows

3.2.1 Main analyses and results

Null hypothesis. In the absence of inertia, demand for *Episode e of show i on channel c*, should not vary systematically with changes in demand for the prior show on the same channel. Demand for *Episode e of show i* should depend only on its characteristics – for example, cast and genre, year, month and time slot at which it plays – and those of competing shows on other channels.

OLS estimation. There is a high (0.66) simple correlation in the audience between adjacent shows on the same channel. Figure 8 shows, for example, that the audience of the 8.00 P.M. news in Canale 5 tracks closely that of the preceding Wheel of Fortune and that, similarly, the audience of Hitchcock Presents covaries with that of the previous movie. To ascertain the causal link between the *Demand for the prior show* and *Demand for episode e of current show i*, I exploit the (unbalanced) panel structure of the data: more than one episode per show, for most programs. This allows me to control for time invariant unobserved factors that influence the

Demand for episode e of current show i.

I postulate that demand, in log audience, for *Episode e of show i* should be a flexibly linear function of *Show i*'s (i) intrinsic attributes, such as, cast and genre (Γ_i) (ii) channel on which it airs (Γ_c), (iii) year and month at which it plays (Γ_y, Γ_m, respectively), (iv) half-hour time slot (Γ_s), and (v) intensity of competition, either by popular shows on other channels (*Competition on popularity*) or shows of the same genre (*Genre overlap*).[19] Once we account for these factors, variations in demand for the prior show on the same channel should not, in the absence of channel inertia, systematically affect the demand for *Episode e* of *Show i*. That is, the null hypothesis is α_1 =0 in:

$$\begin{aligned}\text{Demand}_{e\ of\ i,\ c,\ y,\ m,\ sl} = \alpha_0 + \alpha_1 \text{ Demand prior show, same channel}_{bi,c} + \alpha_2\text{Competition on popularity}+ \\ + \alpha_3\text{Genre overlap} + \Gamma_i\Gamma_c\Gamma_y\Gamma_m\Gamma_s + \epsilon_{si,c,y,m,sl}\end{aligned}$$

The dependent variable – *Demand for episode e of show i, in channel c, in calendar year, month and half-hour time slot* – and the main treatment variable – *Demand for prior show on the same channel* – are in log audience. The controls for show, channel, year, month and slot characteristics enter the estimation as time invariant characteristics. I assume that show characteristics are time-invariant within the calendar month and half-hour slot. *Competition on popularity* is the log of an index of the average audience that competing shows garnered in the past month. For example, during a 30 minute news show on Rai 1, Rai 2 airs a show that averaged 2.5 million viewers in the past month, Rai 3 airs a show that averaged 2.0 million viewers in previous month, and Rete 4, Canale 5, and Italia 1 air shows that garnered a 1.0 million viewers in the past month. The index is 1.5=(2.5+2.0+1.0+1.0+1.0)/(5 channels). Shows that air for the first time in the month, or have only one episode, are proxied with the audience of shows of the same genre, starting on the same half-hour slot, on the same channel, in the prior month. Table 3 describes summary statistics for this variable.

Genre overlap is an index with the fraction of time, while on the air, that a show faces competition from similar genres, weighted by the number of channels. For example, during a 30-minute news show on Rai 1, Rai 2 airs news, but Rai 3, Rete 4, Canale 5 and Italia 1 air non-news shows. The index is 0.2=(1+0+0+0+0)/(5 channels). Table 3 describes summary statistics for this variable.

[19] Audience does not vary significantly by day of the week, except on weekends, which are excluded from the analysis. Nevertheless, specifications including day of the week fixed effects produced equivalent results.

The unobserved show (Γ_i), channel (Γ_c), year (Γ_y) , month (Γ_m) and half-hour slot (Γ_s) time-invariant unobservables enter the estimation fully interacted. The interaction between channel and show is due to a few shows playing across different channels in the same group. For example, Walker Texas Ranger aired on Mediaset's Rete 4 in 1996 and on Mediaset's Italia 1 in 2003. The further interaction with year, month and half-hour fixed effects, accounts for unobservable factors that affect demand for that show within the calendar month and half-hour slot. As result, I only estimate the demand for shows that air at least twice within the same channel, calendar-month and half-hour slot.

The standard errors are clustered by day to account for correlation among the demand for shows in the same time slot.

The final estimate of α_1, conditional on the controls, is 0.38 and significant at the 1% level: a 10% increase in demand for a show increases the average audience of the subsequent show on the same channel by 3.8%. I arrive at this estimate by adding controls sequentially, as shown in Table 4. The coefficient of interest declines, in general, with the inclusion of the controls, stabilizing at 0.38-0.40. The log of the index of competition enters the specification as a proxy variable for the appeal of competing shows. Its inclusion as an instrument for the popularity these shows does not change the coefficient of interest, α_1. This will be true for the remaining specifications.

The estimates obtained via OLS may be biased, however, due to simultaneity and omitted variables bias. Bias due to simultaneity occurs because *Demand for prior show* may influence the *Demand for episode e of show i* but the converse may also be true: viewers may tune to the channel earlier in the expectation of watching a later program. Omitted variables, such as weather or other unobserved shocks that affect concurrently the demand for adjacent shows on the same channel, may also bias the estimate of the OLS coefficient α_1.

I use two instrumental variables specifications to address these biases and conduct robustness checks.

IV estimation using the theatrical audience of movies screened in Italy. The first instrument is the theatrical audience of all movies ($\sim$ 2000) released on Italian movie screens between 1990–2000 and subsequently shown on television. The theatrical audience of a movie is significantly correlated with its television audience on its first airing. It is also arguably uncorrelated with shocks in the demand for the show that airs after the movie. For example, if omitted weather variations are influencing the audience consecutive shows on the same channel, then shocks in the past theatrical audience of a movie are uncorrelated with weather shocks at the time of airing of the post-movie show. The instrument also addresses how simultaneity could be biasing the estimates. That is, the popularity of the current show may influence that of the prior show of the same channel, because viewers tune-in earlier to the channel to not miss the beginning of their selected show. Tuning-in earlier may affect the relationship between the television audience of a movie and its subsequent show, but not the theatrical audience of that movie and the television audience of its succeeding show.

Hence, this analysis restricts the sample to programs, with more than one episode in a given month and half-hour slot, that air after movies.

$$\begin{aligned}\text{First stage}: Demand_{Priorshow(movie)} &= \theta_0 + \theta_1 \text{Theatrical Audience} + \theta_2 \text{Competition on popularity} \\ &+ \theta_3 \text{Genre overlap} + \Gamma_i \Gamma_c \Gamma_y \Gamma_m \Gamma_s + \upsilon_{si,c,y,m,sl}\end{aligned}$$

$$\begin{aligned}\text{Second stage}: Demand_{si,c,y,m,sl} &= \beta_0 + \beta_1 Demand_{\text{Prior show(movie)}} + \beta_2 \text{Competition on popularity} \\ &+ \beta_3 \text{Genre overlap} + \Gamma_i \Gamma_c \Gamma_y \Gamma_m \Gamma_s + \eta_{si,c,y,m,sl}\end{aligned}$$

Table 5 shows the results for this specification. As shown in column (3), the first stage estimates imply that an increase in 10% in the theatrical audience of a movie, increases its television audience by 0.62% on its first airing.[20] This estimate is significant at the 1% level, with a t-statistic of 5.63, corresponding to an F-statistic of 31.7. This result suggests that the *Theatrical Audience* instrument is strong (Stock et al., 2002). The revised estimate for the sample of shows that play after movies is 0.48 and significant at the 1% level, as shown in column (2). This estimate is not statistically different from its OLS counterpart of 0.38.

One concern is that channels might endogenously schedule popular episodes of shows after high-demand movies and less popular episodes of shows after less appealing movies. Thus, I restrict the sample to the news that play after movies, since the daily popularity of the news is arguably not susceptible to manipulations by channels. As shown in column (5) of Table 5, the estimate on this subsample of 0.39 is marginally significant, at a 10% level, given that the number of observations in the sample declines to 143.

I use a second instrument for *Demand for the prior show* to conduct robustness checks that

[20]Movies tend to air on average three times on television. The partial correlation between a movie's theatrical audience and airings on television other than its first is not statistically different from zero.

require more observations: the average demand for the prior show in the preceding calendar month.

IV estimation using the average demand in the preceding calendar month. An advantage of this instrument is the increase in the number of observations for the analysis. Moreover, the average demand for a show in the preceding month is highly correlated with its current demand. It is also uncorrelated with weather and other concurrent shocks that affect the demand for adjacent shows. However, this instrument may not fully address unobservables that are both correlated with the current demand for a program and the average demand for the show prior to it in the preceding month, if those unobservables vary within the calendar month. For example, suppose that in the preceding month the news had a good anchor. She affected the demand for the news in the prior month but also the demand of the show prior to the news because some viewers tuned-in earlier to the prior show to watch the news with the capable anchor. Half-way through the current month, the channel switches from the capable anchor to a less capable one. The audience of the news during the current month is going to be affected by the unobserved anchor effect. However, this unobservable is also correlated with the instrument – the average demand for the show preceding the news in the past month – through the preceding month's tuning-in of viewers. This would bias the estimates. In contrast, if the channel had always used the capable anchor throughout the current month, the unobserved anchor effect would have been captured by the calendar-month fixed effects, and this bias would not arise.

I estimate how the demand for the main daily news shows at 6:30 PM, 7:00 PM, 7:30 PM, 8:00 PM and 8:30 PM varies with the demand for the shows that play prior to them (*pre-main news show*).[21] Restricting the outcome variable to demand of the main news shows has two advantages. First, it is difficult for channels to control the daily popularity of the news. Second, it allows me to test whether inertia holds on a different subsample of news shows. The daily news that follow movies tend to play late at night, at about 11:00 PM and be of shorter length. The daily main news shows play earlier in the day and tend to be of longer length.

The specification below yields results that are lower but not statistically different from those using the *Theatrical Audience* instrument. As shown in table 6 in column (2), a 10% change

[21] I differentiate between the daily main news and the daily short late night news. The daily main news have longer lengths, averaging 32 minutes, and start every day at the same time. The late night news average 11 minutes and usually air at the end of prime-time, but at no fixed time. This is the case of the eight minute news around 11:00 PM on Rai 1, discussed in the minute-by-minute estimation.

in the audience of the show that precedes the main daily news (*pre-main news show*) changes the main news audience by an average of 2.2%. The first stage in column (3) is strong with at t-statistic of 10.9 on the instrument, which corresponds to an F-statistic of 118.8 (Stock et al., 2002).

$$\text{First stage}: Demand_{\text{Prior show}} = \theta_0^0 + \theta_1^0 \text{Average demand for pre-Main News Show in preceding calendar month} \\ + \theta_2^0 \text{Competition on popularity} + \theta_3^0 \text{Genre overlap} + \Gamma_i \Gamma_c \Gamma_y \Gamma_m \Gamma_s + \upsilon^0_{si,c,y,m,sl}$$

$$\text{Second stage}: Demand_{Mainnews,c,y,m,sl} = \beta_0^0 + \beta_1^0 Demand_{\text{pre-Main News Show}} + \\ + \beta_2^0 \text{Competition on popularity} + \beta_3^0 \text{Genre overlap} + \Gamma_i \Gamma_c \Gamma_y \Gamma_m \Gamma_s + \eta^0_{si,c,y,m,sl}$$

3.2.2 Other findings of OLS/IV analysis on the panel of television shows

Decay rate on inertia. The decline in the point estimates from 0.39 in the movies-followed-by-news sample to 0.22 in the sample of show-followed-by-main news could be due, in part, to the length of the news. The news that play after movies average 11 minutes in length whereas the news in the main news sample average 32 minutes. The previous section comparing the effect of the preceding show on the audience of the news for men and women showed a decay rate to inertia. I therefore split the main news sample by news shows above and below the median length. The average duration of news below the median length is 28 minutes and above the median length is 38 minutes, as shown in columns (4) and (5) of Table 6. The impact of viewer inertia decreases in the duration of the news: an increase in 10% in the audience of the prior show increases the audience of the main news shows by 3.0% and 1.5%, respectively. However, it still persists to the program that plays after the news. As shown in column (6) an increase in 10% on the demand of the show preceding the news increases the demand of the show following the news by 0.9%.

Anticipation effect. The instrument can also measure the anticipation effect: how much a popularity of a given show affects the demand of the prior show on the same channel. This is a threat to identification not addressed in the previous research that broaches channel inertia in television viewing. Table 7, column (1), shows that an increase in 10% in the audience of a movie affects the demand of its preceding show by 4%. This estimate is slightly lower than the effect of the audience of the movie on that of the subsequent show of 4.8%, found previously. For the *Average demand of show in prior month* instrument, the effect of the audience of the *pre-main news show* on its preceding show is 4.3% as shown in column (4). This is higher than the 2.2% effect that the *pre-main news show* audience has on the main news audience, but this estimate is noisy and not statistically different from the 2.2%. Moreover, the 4.3% estimate may be inflated by channels endogenously scheduling popular episodes of shows before popular programs and low audience episodes of shows before low-audience programs. This is something that is arguably harder to manipulate with the news of the day, reducing the potential upward bias in the estimates.

4 Robustness checks on the event-study, OLS and IV analyses

4.1 Robustness checks on the event study

First, I investigated whether the topic of the news talk show Porta-a-Porta appealed more to men than women on soccer days and the reverse on female show days. Endogenous scheduling by Rai 1 could be generating the observed channel inertia for men and women. Inspection of a random sample of topics for soccer, female and neutral show days shows this is not the case. This is expected since the main focus of this Porta-a-Porta is news and current affairs. For example, on soccer days, Porta-a-Porta topics included a discussion on the hunt for Osama Bin Laden, Mad Cow disease and a review of the life and works of Pope John XXIII. On female show days topics ranged from corruption and politics, euthanasia, to an interview with the current prime-minister, Silvio Berlusconi. On neutral show days, topics spanned the U.S. attack on Iraq, the reform of pension law and labor markets, and remembering the kidnapped politician Aldo Moro and its kidnappers, the radical Red Brigades.[22]

Second, I investigated whether male and female inertia might stem from the announcement about Porta-a-Porta by the Rai 1 anchor at the end of the 8:00 PM news. If more men watch the 8:00 PM news than women on soccer days, then a higher proportion of men might be persuaded to watch Porta-a-Porta after the news at 11:00 PM. Similarly, on female show days, more women might watch the 8:00 PM news on Rai 1 and be exposed to the anchor's announcement

[22] A detailed description of the topics for the news talk-show Porta-a-Porta for a random sample of soccer, female and neutral show days is available upon request.

for Porta-a-Porta. An inspection of the patterns of viewership of Rai 1's 8:00 PM news in Figure 7 demonstrates that male and female audience for the 8:00 PM news on Rai 1 are the same for soccer and female show days: more women watch the news than men.

4.2 Robustness checks on the OLS and IV analyses

Placebo robustness analysis on the instruments. A test for the validity of the instrument is to verify its effect on samples where it is expected to have no influence. Hence, first I check whether the demand for a movie, instrumented by its theatrical audience, influences the audience of the shows that precede it by more than one show. Columns (2) and (3) in Table 7 show that the effect of the audience of the movie on two shows preceding it ($movie - 2$) is 2.3% and it disappears for the third show preceding it. Similarly, column (5) shows that changes in the audience for shows that play before the main news shows (*pre-main news show*), instrumented by their average demand in the preceding calendar month, do not affect the demand for second show preceding them (*pre-main news show*-2).

Effects of changes in the measurement system. Features of the measurement system can register channel inertia where none exists. Prior to August 1997, only half of the Italian panel had both the "Action prompt" – whereby the system asks viewers to confirm who is watching after they browse and then settle on a channel for at least 30 seconds – and the "No action prompt", in which the system asks who is watching after 15 minutes of inactivity. Hence, for this half of the panel, the estimated effect of inertia could be high due to viewers leaving the room or falling asleep while the television is on, potentially biasing the estimates upward.

I test this hypothesis by checking whether the estimated effect of demand for the shows prior to the main news shows, instrumented by their average audience in the past month, is lower for the subsample of years between 1998-2003.

As we can see in column (1) and (2) of Table 8, changes in the measurement system do not affect the estimates. The estimates for 1990-2003 and 1998-2003 are not statistically different.

Effect of information on subsequent show. Advertising of the subsequent show on the same channel could cause inertia if it persuades a significant portion of viewers to remain on the channel. In 1995 Rai 1 and Canale 5 started to advertise their 8:00 PM news during the previous show, with a clip.

I test and reject the hypothesis that asymmetric information between the subsequent news program at 8:00 PM in Canale 5 and Rai 1 versus competing shows on other channels significantly influences the estimates obtained thus far. Columns (3) and (4) of Table 8 shows the impact of inertia for the main news shows for channels Canale 5 and Rai 1 and for the remaining channels. The estimates are lower for Canale 5 and Rai 1 than for the other four channels, suggesting that advertising of the news on Rai 1 and Canale 5 does not bias average effect upwards. The lower channel inertia on the demand of these two news programs, despite the use of the clip to create channel retention, could be explained by the competitive environment. These news shows air at the start of prime-time and compete aggressively for viewers. Therefore, the potential viewer retention created by the clip during each of these news shows if off-set by the high level of competition between them and other shows at the beginning of prime-time.

Effect of unsynchronized starts. Differing timings for starts of programs might also generate channel inertia. Under the assumption that viewers experience disutility from not watching a show from the beginning, the estimated inertia may stem from a sub-sample of shows that face no competing shows starting at the same time. It could be that a significant portion of viewers remain on the default channel, until their preferred program starts on another channel.

I test this hypothesis by splitting the main news show sample into news that have one or more shows starting within 1 minute of the news versus not. The average difference between the time at which the news start on a channel and the start of competing shows on the other five channels is 22 minutes.

Unsynchronized starts do not affect the estimates. The coefficient of interest in column (5) of Table 8 is the interaction between *Demand for pre-main news show*, instrumented by its average audience in the prior month, and *Number of channels starting in the same 1 minute vicinity as the main news*. It is not statistically significant.

Effect of uncertainty about competing shows. Lower uncertainty about competing shows could also generate channel inertia. If there is high uncertainty about competing shows viewers can be rewarded by a much better show by switching channels. If competing shows turn out to be worse than that in the default, viewers can click back to the default channel. Hence, the upside of switching can be very high whereas the downside of switching is truncated at the cost of clicking.

I investigate this possibility on the subsample of cases in which the daily news show has a single competing show starting within one minute. I classify whether the competing show is a new program – in its first half of episodes – or if it is an established program, in its second half of episodes. The average number of episodes per show is 16.

Uncertainty about competing shows does not affect the estimates, as show in column (6) of Table 8. The coefficient of interest is the interaction between *Demand for prior show*, instrumented by its average audience in the prior month, and *Uncertainty about the competing show* is not statistically different from zero.

5 Calibration of value of consumer inertia for channels

5.1 A simple model

The previous empirical analysis established that viewer inertia affects the audience of television shows: an increase in demand for a show on a given channel by 10% increases the demand for the next show by 2%-4%. What is the optimal scheduling of shows given viewer inertia? How much can channels lose by not taking into account viewer inertia in their scheduling? The simple model below offers a framework to answer these questions.

Model setup. Assume that a channel has three consecutive time slots s_1, s_2 and s_3 of equal length. It wants to allocate three programs 1, 2 and 3 to these time slots. The programs vary in their intrinsic audiences: $a_1 < a_2 < a_3$, where $a_i \equiv$ intrinsic audience of program i. The audience of program 1 is normalized to 1 ($a_1 = 1$). There are no strategic interactions with competing channels. The channel's problem is to maximize average audience across the three time slots, since advertising revenues increase monotonically in audience.

Optimal scheduling in the absence of viewer inertia. In the absence of viewer inertia, any allocation of the three shows across time slots – the triplet (s_1, s_2, s_3) – yields the same average total audience $S(a_i, a_j, a_k) = 1 + a_2 + a_3$, for $i, j, k = 1, 2, 3$ and i $\neq j \neq k$.

Optimal schedule given viewer inertia. Given viewer inertia, the current show inherits a fraction ρ of the audience of the previous show. Of the six possible scheduling combinations of the three shows across the three time slots, the optimal one orders the programs in decreasing order of intrinsic audience: the higher intrinsic audience program 3 in the first slot, program 2 in the second slot and the weakest program 1 in third slot, yielding an average audience: $S(a_3, a_2, a_1)^{Optimal} = a_3 + (a_2 + \rho a_3) + (1 + \rho(a_2 + \rho a_3) = 1 + a_2 + a_3 + \rho(a_2 + a_3 + \rho a_3)$. The worst schedule orders the shows in reverse: the lowest intrinsic audience first to the highest intrinsic audience last, yielding $S(a_3, a_2, a_1)^{Worst} = 1 + (a_2 + \rho) + (a_3 + \rho(a_2 + \rho) = 1 + a_2 + a_3 + \rho(1 + \rho + a_2)$. The difference in average audience between the optimal and worst schedule corresponds to a difference in advertising rates, since rates are monotonic in the average audience for a given set of time slots (daypart).

Optimal schedule when show lengths are unequal. With varying show lengths, the schedule the maximizes the average audience across the three time slots depends on the relative ratio of intrinsic show audiences a_1, a_2, a_3, their lengths l_1, l_2, l_3 and the magnitude of the inertia parameter ρ.

Prime-time programming in Italy across the six main channels pools shows of different lengths. An analysis of the optimal schedule requires numerical optimization computing all possible combinations of shows and ascertaining which yields the highest and lowest average audiences during prime-time.

5.2 Optimal scheduling during prime-time

I focus the analysis on the flagship channels, privately-controlled Canale 5 and state-owned Rai 1, which concentrate 50% of the audience share, for 2003 and prime-time. I use the estimated inertia parameter of $\rho = 0.3$ for a 30 minute program to derive the audience, net of inertia, of each program in prime-time. Then I simulate the combinations of shows in prime-time – six combinations of the three shows – to calculate the audience inertia from one show to the next, and estimate the average audience for each combination. The optimal schedule is the combination of programs that yield the highest audience. Table 9 shows that the prime-time schedule for flagship channels Canale 5 and Rai 1 is close to the optimal: the percentage difference versus the optimum is 0.1% and 0.8% respectively. The percentage difference in average audience between the optimal and worst schedule is 1.9% and 2.6%.

The average difference in audience across the six different schedules in prime-time is dampened by the large weight of a two-hour program in prime-time which is less sensitive to variations in demand for the prior show. Canale 5 and Rai 1 usually have two half-hour shows, the news and a miscellaneous show, and one two-hour show, such as a movie or mini-series during the three hours of prime-time. The inertia parameter ρ for a half-hour show is 0.3, in line with estimates in the reduced form analysis. The parameter ρ for a two-hour show is only 0.106, due to the geometric decay in inertia, every half-hour, over the two hour period.[23] In the U.S. where prime-time comprises half-hour and hour shows, the difference in audience across different orderings of programs could be more pronounced.

[23]This magnitude is corroborated by an estimate of 0.12 when estimating the change in demand for a show, instrumented by its average demand in the prior month, on the demand for a show lasting 100 or more minutes.

The results for the analysis of the remaining four smaller channels (not shown) are similar. Channels are at the optimal or close to the optimal schedule and the percentage difference between the optimal and worst schedule ranges from 2-4%.

5.3 Relationship between audience and advertising rates

Using the advertising rates charged by Mediaset's Canale 5 for 2002 and 2003, for a 30-second commercial during prime-time, I find that an increase of 1% in the expected audience increases advertising revenues by 1.22%. This increasing returns to audience conforms with the relationship between audience and the price for a 30-second commercial in the U.S. in 2003, for all major networks, where an average increase in audience by 1% increase advertising revenues by 1.44% (Wilbur, 2008, Table 1, page 362).[24]

Estimation of the relationship between expected audience and advertising rates. Advertising rates are a function of the expected audiences for a part of the day, in this case, prime-time. I only observe, however, the realized ex-post audiences.

To estimate the relationship between the expected audience and advertising rates, I assume that the relationship between the rate of a 30-second commercial and expected audience is $\textit{ln rate} = \beta_1 \textit{ln expected audience} + v$, where $\textit{cov}(v, \textit{ln expected audience}) = 0$ and $\textit{ln realized audience} = \textit{ln expected audience} - \epsilon$, where ϵ is the deviation from the logged expected audience. Therefore, $\textit{ln rate} = \beta_1 \; \textit{ln realized audience} + \beta_1\epsilon + v$. If $\textit{cov}(\epsilon, \textit{ln expected audience}) = 0$, then $\textit{cov}(\epsilon, \textit{ln realized audience}) \neq 0$. Therefore, the estimate of β_1 will be biased towards zero. This is the attenuation bias in the classical errors-in-variables. The OLS estimate of β_1 will be a lower bound on the effect of an increase in 1% in audience on the percent increase in the price of a 30-second commercial.

Figure 9 plots the relationship between advertising rates for a 30-second commercial and its audience for Canale 5. The slope of the relationship between the *Advertising rate for a 30-second commercial* and *Audience (in thousands)* – not including a constant, since no audience yields no advertising revenues – is about 7 Euros per extra thousand viewers in prime-time. In the U.S. the cost per thousand viewers ranges from \$19-\$28 in prime-time (Wilbur, 2008, Table 1, page

[24] This table shows the average advertising rates for 30-second commercial and average audience for the six major networks in the U.S. during the April 24th-May 21st 2003 sweeps, from 8.00-10.00 PM. The audiences for UPN, WB, ABC, CBS, NBC and FOX in thousands of households were 2,793, 3,584, 5,693, 7,716, 7,361, and 8,058, respectively. The respective advertising rates for a 30" commercial in thousand of dollars, were 55, 71, 125,179, 212 and 241. Taking UPN as the baseline, an increase in audience versus UPN by 1% increases advertising rates by an average of 1.44%

362). The slope of the relationship between *Log advertising rate for a 30-second commercial* and *Log audience* is 1.22, not including a constant, suggesting that an increase in audience of 1% increases advertising rates by 1.22% (versus 1.44% in the U.S.).

5.4 Impact on channel's profitability

A change in audience by 2% changes Mediaset's channels' – Canale 5, Rete 4 and Italia 1 – profits by 20% to 40%. The impact is more pronounced for the Rai state-owned channels, because their profit margins are close to zero since they do not have the mandate to maximize profit. The average revenues for Mediaset in 2002 and 2003 were 2.280 and 3.029 billion Euros, respectively. Advertising revenues were 2.112 and 2.848 billion Euros, respectively. Profits were 309 and 244 million Euros, respectively. Profit as a percentage of revenue was 11.4% and 5.8%, respectively. Assuming that a change in 2% in audience due to scheduling could be achieved for the whole day, not just prime-time, and that the relationship between advertising rates and audience is valid across all channels, not just Canale 5, a 2% decrease in audience could decrease profits across Mediaset channels by 2.4%. This results in a decline in profits by 20% and 40% in 2002 and 2003, respectively. For the lower profit margin Rai 1 – 0.2% and 1.0% in 2002 and 2003 – a drop in audience would yield negative profits.

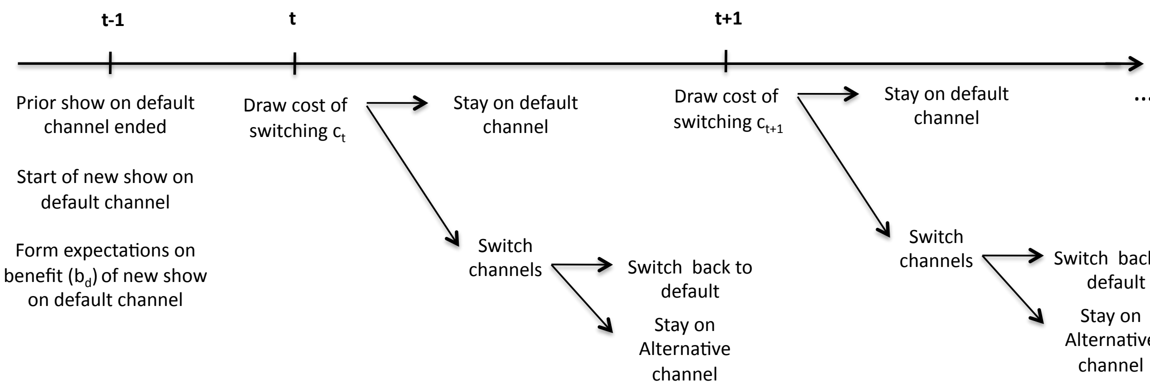
6 Discussion

6.1 Dynamic model of individual behavior

Which preferences are consistent with the observed inertia and its decay rate? The dynamic model below explains the relationship between small switching costs and the option value of switching that is consistent with long delays in the default. I discuss two main main models: time-consistent preferences with quasi-indifference between competing programs and quasi-hyperbolic preferences with naivete whereby consumers procrastinate in switching channels.

Model setup. Suppose consumers are on the default channel at the end of a program. The decision problem in whether to stay or switch to an alternative channel. The decision–making horizon is infinity. During minute $t-1$, a new program on the default channel starts and the consumer gathers information about it. The information gathered during minute $t-1$ allows the consumer to form unbiased expectations on the benefit $\hat{b_d}$ she will derive every minute thereafter from the show on the default channel. This is consistent with research showing that consumers

Figure 1 – Timing of game



need less than one minute to evaluate programming. They update their priors on the current programming almost instantaneously.[25]

At the beginning of minute t the consumer also draws a cost c_t of clicking to another channel. The cost of clicking c_t at each minute is stochastic, i.i.d, drawn from distribution $F(\cdot)$, known to the consumer. The consumer does not know ex-ante the benefit b_a she will obtain on the alternative channel. She has priors on it from previous experience or other information, but she only observes b_a by sampling the show.

She compares the benefits versus the costs of switching at each minute, discounting future time periods by δ. At minute t she can switch by incurring c_t, the cost of clicking at t. If the show on the alternative channel is better or the same as the show on the default, she stays on the alternative channel and gains b_a at minute t and at all the minutes thereafter, reaping $b_a + b_a \frac{\delta}{(1-\delta)}$. If the show on the alternative channel is worse than that on the default channel, she returns to the default channel, gaining b_a in minute t and $\hat{b_d}$ from $t+1$ onwards, reaping $b_a + \hat{b_d} \frac{\delta}{(1-\delta)}$. I assume that it is costless to switch back to the default channel, so the consumer has an even greater incentive to switch. Therefore, the upside of switching could be high compared to the downside, which is truncated below at $-c$.

The standard model. The payoffs, at time t, associated with the actions of switching

[25] Mediaset's viewer tracking system asks consumers to confirm who is watching when consumers browse channels and finally settle on a channel for 30 seconds. This is due to prior observation that consumers spend less than 30 seconds evaluating programs. These assertion is supported by a study on Internet television watching by Cha et. al, 2008. In a test with over 250,000 consumers of internet television over 150 channels it concludes that: (i) over 60% of users switch channels within 10 seconds, (ii) the average time before switching is 9 seconds, when viewers switch within one minute.

channels and not switching channels, are, respectively,

$$V(c_t) = \begin{cases} -c_t + E[b_a] + E[b_a|b_a \geq \hat{b_d}]P(b_a \geq \hat{b_d})\frac{\delta}{1-\delta} + \hat{b_d}P(b_a < \hat{b_d})\frac{\delta}{1-\delta} & \text{if switch} \\ \hat{b_d} + \delta E[V(c_{t+1})] & \text{if not switch} \end{cases}$$

Solving the model. Let $G \equiv E[b_a] + E[b_a|b_a \geq \hat{b_d}]P(b_a \geq \hat{b_d})\frac{\delta}{1-\delta} + \hat{b_d}P(b_a < \hat{b_d})\frac{\delta}{1-\delta}$, the gain associated with the option value of switching. The consumer switches if $-c_t + G \geq \hat{b_d} + \delta E[V(c_{t+1})]$. The solution to this problem is a cut-off c^* whereby the consumer is indifferent between switching and not switching channels:

$$-c^* + G = \hat{b_d} + \delta E[V(c_{t+1}, c^*)] \tag{1}$$

If the cost of switching at each period is less or equal to c^* the consumer switches the channel, and stays on the default channel otherwise. We can solve for c^* by first noting that

$$\begin{aligned} E[V(c_{t+1}, c^*)] &= \frac{1}{1-\delta+\delta P(c_{t+1} \leq c^*)}\{E[-c_{t+1}|c_{t+1} \leq c^*]P(c_{t+1} \leq c^*) \\ &+ GP(c_{t+1} \leq c^*) + \hat{b_d}(1 - P(c \leq c^*)\} \end{aligned} \tag{2}$$

since c^* is the solution across all time periods.[26]

Plugging equation (1) into (2), we solve for:

[26] To see this note that

$$V(c_{t+1}) = \begin{cases} -c_{t+1} + G & \text{if } c_{t+1} \leq c^* \\ \hat{b_d} + \delta E[V(c_{t+2})] & \text{if } c_{t+1} > c^* \end{cases}$$

Then $E[V(c_{t+1}, c^*)] = E[-c_{t+1} + G|c_{t+1} \leq c^*]P(c_{t+1} \leq c^*) + (\hat{b_d} + \delta E[V(c_{t+2}, c^*)]P(c_{t+1} > c^*)$. Since c_t, c_{t+1}, c_{t+2} is i.i.d. then $E[V(c_{t+1}, c^*)] = E[V(c_{t+2}, c^*)]$. We then solve for $E[V(c_{t+1}, c^*)]$.

$c^* = \frac{1}{1-\delta+\delta P(c_{t+1}\leq c^*)}\{G(1-\delta) - \hat{b_d} + \delta E[c_{t+1}|c_{t+1} \leq c^*]P(c_{t+1} \leq c^*)\}$.[27]

The cut-off c^* in increasing in G, the gain associated with the option of switching, and decreasing in the attractiveness of the show in the default channel $\hat{b_d}$.

I assume that $b_a - \hat{b_d} \sim \mathrm{U}[\Delta-\sigma, \Delta+\sigma]$, where Δ is the difference between the benefit of the show in the alternative channel and that of the default channel, with Δ any real number. And $\sigma \geq 0$, the variance around the difference in benefits Δ. For $\sigma = 0$, the difference in benefits is deterministic with $\Delta = b_a - \hat{b_d}$. There are three cases to consider. First is when $\Delta \leq -\sigma$. In this case the consumer never switches channels because the difference in benefits is negative. The second case is when $\Delta \geq \sigma$. In this case, the consumer knows that the program on the other channel is better, but has to incur the cost of switching. The third case is $-\sigma < \Delta < \sigma$. In this case, the alternative show may be on average worse that that of the default but the variance maybe high enough so that it is worthwhile to switch.

I focus on cases two and three which are the most interesting. Assume, for simplicity, that $c \sim U[0,1]$. For $\delta \simeq 1$, the cut-off in case two ($\Delta \geq \sigma$) is $c^* \simeq \sqrt{2\Delta}$. The consumer will delay switching is the difference in benefits $\Delta = b_a - \hat{b_d}$ is small, so that c^* is small. For the third case, where $-\sigma < \Delta < \sigma$, the admissible cut-off is $c^* \simeq \frac{\Delta+\sigma}{\sqrt{2\sigma}}$. For this latter case, the cut-off c^* is increasing in the variance σ of the difference in benefits, as option value theory would predict. It is also increasing in Δ, the difference the benefits. The higher the difference, the higher c^* and the higher the propensity to switch.

Case of quasi-indifference between channels. For case two, where the consumer knows for sure the alternative program is better, $c^* \simeq \sqrt{2\Delta}$, if Δ is small enough the consumer delays switching. Therefore, quasi-indifference between between channels could lead to long delays in the default. In case three, where $c^* \simeq \frac{\Delta+\sigma}{\sqrt{2\sigma}}$, the consumer may delay switching if both Δ and σ are very small, that is, the consumer believes that the other channel is only slightly better (e.g. the Δ is negative but the variance σ may render c^* slightly positive). In both case two and three a lower c^* leads consumers to persist longer in the default, since they have to wait longer

[27] To see this, note that:

$$\begin{aligned} -c^* &= -G + \hat{b_d} + \delta E[V(c_{t+1}, c^*)] \\ &= -G + \hat{b_d} + \frac{\delta}{1-\delta+\delta P(c_{t+1}\leq c^*)}\{E[-c_{t+1}|c_{t+1} \leq c^*]P(c_{t+1} \leq c^*) + GP(c_{t+1} \leq c^*) + \\ &+ \hat{b_d}(1 - P(c \leq c^*)\} \end{aligned}$$

Simplify by eliminating common terms with G and $\hat{b_d}$

for a draw c lower than c^*.

Case when consumer procrastinates in the default channel. Another behavioral model predicts delays in switching even if the variance of the difference in benefits is significant. In this model the consumer procrastinates in the default, because she continuously postpones the decision to switch. This model of behavior focuses on time-inconsistency of preferences, whereby the consumer plans to change the channel, incurring an immediate cost in order to start reaping the benefit of watching a better show. When the time to incur the cost arrives, the cost looms larger than the more distant benefit, and the consumer delays the decision, planning to switch in the future. She will do so repeatedly until a random shock in utility leads her to switch.

Time-inconsistent preferences, especially coupled with naivete about one's own behavior, have been used to explain persistence for long spells in the status-quo even when the reward of switching is seemingly much higher that the cost.[28] Failing make a phone call to enroll in an employer's 401k plan and therefore foregoing the employer's matching contributions or not canceling a gym membership after stopping attending the gym, are consistent with these preferences. The naive or partially-naive consumer will continually underestimate how much she will lose by procrastinating because she believes she will procrastinate less than what she actually will. She will therefore set a lower threshold c^* that the optimal, leading to long delays in the default.

A recent paper by McClure et al. in 2007 shows that time-inconsistency exists even when the delay in rewards is within minutes. In a lab experiment testing subjects sensitivity to immediate rewards, thirsty subjects preferred immediate squirts of juice or water versus waiting five minutes for those rewards. However, when choosing between squirts of juice and water in 10 minutes versus 15 minutes, or 20 minutes versus 25 minutes, there was no such preference for the earlier rewards, even though the lag between them was still five minutes.

I focus on the model for the fully naive consumer. A consumer with these types of intertemporal preferences postpones one-time tasks with immediate costs and delayed benefits. This

[28]Time-inconsistent consumers can be divided into two categories. Sophisticates, who know they have time-inconsistent preferences (Strotz, 1956; Phelps & Pollak, 1968; Laibson, 1997; O'Donoghue & Rabin, 1999). And naive or partially naive consumers (O'Donoghue & Rabin, 2001; Akerlof, 1991), who naively believe they are more time-consistent than they actually are. Both types of consumers will show longer delays in the status-quo than time-consistent agents, even when the variance in benefits is significant. The procrastination for naive or partially naive consumers is longer than for sophisticates because the latter understand they will procrastinate and therefore switch earlier.

is captured in a discount function 1, $\beta\delta$, $\beta\delta^2$, $\beta\delta^3$ .... where $\beta \in [0, 1]$. The fully naive consumer believes that she is time-consistent, that is, her belief about her β, defined as $\hat{\beta}$, is that $\hat{\beta} = 1 > \beta$. Therefore, she optimizes over future time periods as a time-consistent agent, not recognizing that she will procrastinate when the future becomes the present. The lower the β, the higher her procrastination. Her cut-off is:

$$-c^{*,naive} + E[b_a] - \hat{b_d} = \beta\{-G + E[b_a] + \delta E[V(c_{t+1}, c^*)]\} \tag{3}$$

In contrast the exponential consumer had solved, in the previous section,

$$-c^{*,exp} + E[b_a] - \hat{b_d} = -G + E[b_a] + \delta E[V(c_{t+1}, c^*)] \text{ where } -c^{*,exp} = -c^* \tag{4}$$

Plugging equation (4) into (3), I find that $c^{*,naive} = \beta c^{*,exp} + (1 - \beta)(E[b_a] - \hat{b_d})$ where $E[b_a] - \hat{b_d} = \Delta$ given the distributional assumptions of the difference in benefits. Therefore

$$c^{*,naive} = \beta c^{*,exp} + (1 - \beta)\Delta, \text{ where } c^{*,naive} < c^{*,exp} \text{ if } c^{*,exp} > \Delta$$

If $\beta = 1$, the consumer does not procrastinate and the cut-off is the same as that of the time-consistent consumer. As β gets smaller, she procrastinates more. The smaller β the smaller the $c^{*,naive}$, and therefore, the longer it takes her to draw a cost lower than the cut-off that will allow her to switch. In case two, in previous section, $c^{*,exp} \simeq \sqrt{2\Delta}$, so $c^{*,naive} \simeq \beta\sqrt{2\Delta} + (1 - \beta)\Delta$. In this case, $c^{*,naive}$ will be lower then $c^{*,exp}$ if $\Delta < 2$. This is always true for $c^{*,exp} \in (0, 1)$ which bounds Δ above by $\frac{1}{2}$. In case three, $c^{*,exp} \simeq \frac{\Delta+\sigma}{\sqrt{2\sigma}}$, $c^{*,naive} \simeq \beta\frac{\Delta+\sigma}{\sqrt{2\sigma}} + (1 - \beta)\Delta$, where $c^{*,naive} \leq c^{*,exp}$, especially when Δ is bounded above by $\frac{1}{2}$.

6.2 Concluding remarks

Do consumers show a consistent preference for the status-quo even when the direct costs of switching away from it are negligible? If so, is this behavioral regularity significant enough to affect the profit-maximizing strategies of firms which interact with consumers that exhibit this behavior?

This paper addresses these two questions in a particular setting – the choice of television programs – where the direct cost of switching, a click of the remote, is negligible. It analyses a novel dataset of television viewership in Italy, yielding several findings.

First, it finds that the viewership of the late news by men exceeds that of women when soccer, which appeals mostly to men, plays before the news. In contrast, viewership of the late news by women surpasses that of men when a program that appeals primarily to women airs before the news. It also finds, using OLS and IV estimation on a large sample of shows airing during a 14-year period that an increase in the demand of a show by 10% increases, on average, the demand of the subsequent show by 2-4%. Third, it finds that there is decay rate to inertia: viewer persistence from a program to the next declines with time, with viewers slowly switching to other channels. Other explanations potentially consistent with this phenomenon, such as, asymmetric information due to advertising of the subsequent program on the channel during the preceding program, unsynchronized timings in the start of shows, and potential mismeasurement of audiences were ruled out. Fourth, it finds that profit-maximizing channels seem to rationally anticipate inertial behavior by consumers and schedule their programs accordingly. Given viewer inertia, Italian channels are close to or at the optimal program schedule. Failing to take into account viewer inertia in program scheduling may affect as much as 20%-40% of profits.

The observed behavior is discussed in the context of a dynamic choice model with stochastic costs and the option value of switching channels. The behavior is consistent with quasi-viewer indifference towards programs or procrastination in switching channels.

These findings bear directly on the controversial trend in public television in Europe of using popular but lowbrow programs to nudge viewers into watching higher brow but more challenging educational content. The state subsidizes public stations in Europe due to their mandate to educate the public, under the belief that this generates several positive externalities. In the UK, the BBC's trend towards airing increasingly lower brow entertainment has drawn heavy criticism. The BBC's executives defended this policy on the grounds of viewer inertia, arguing that lowbrow programs increase the viewership of educational ones: *"[...] it is a revival of the old idea of hammocking difficult programs between entertainment[...]"*.[29]

A future area for research is the quantification of how much consumers are losing by not changing channels. Is the magnitude of the loss significant? Though viewers watch on average more than four hours of television per day, individual programs do not have prices. Hence, a first step is to calibrate the dollar value associated with different television shows. A future area for research is the calibration of this amount and the magnitude of the switching costs under different behavioral assumptions.

[29] Jana Bennet, BBC's director of Television, The Guardian, Media Section, February 2003

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Figures and tables

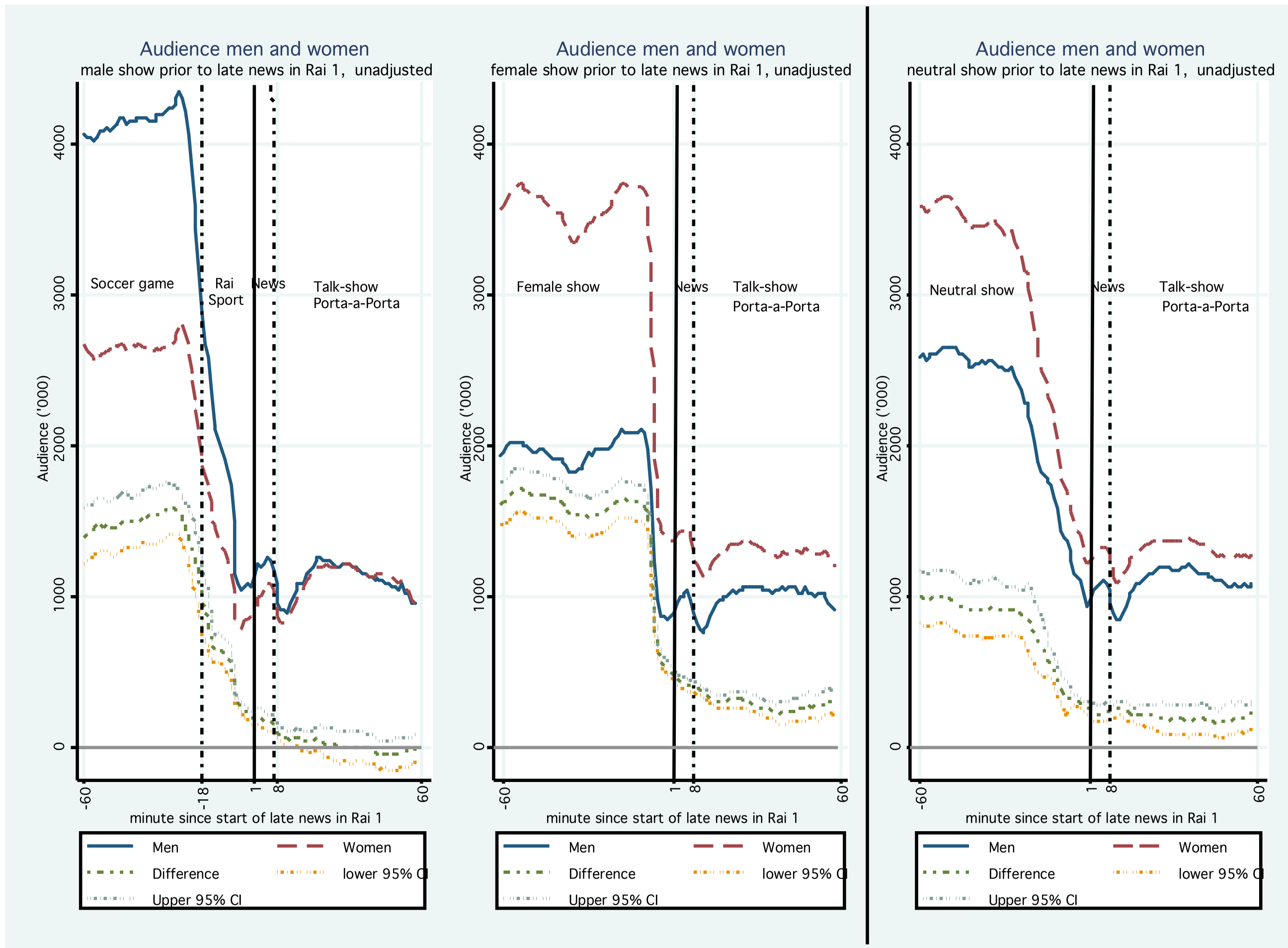
Figure 2 – Typical Monday night line-up; Italy's 6 main channels are generalist with a broad range of genres

Monday, October 7th, 2002

Starting at (PM): — Prime time: 8:00 PM to 11:00 PM

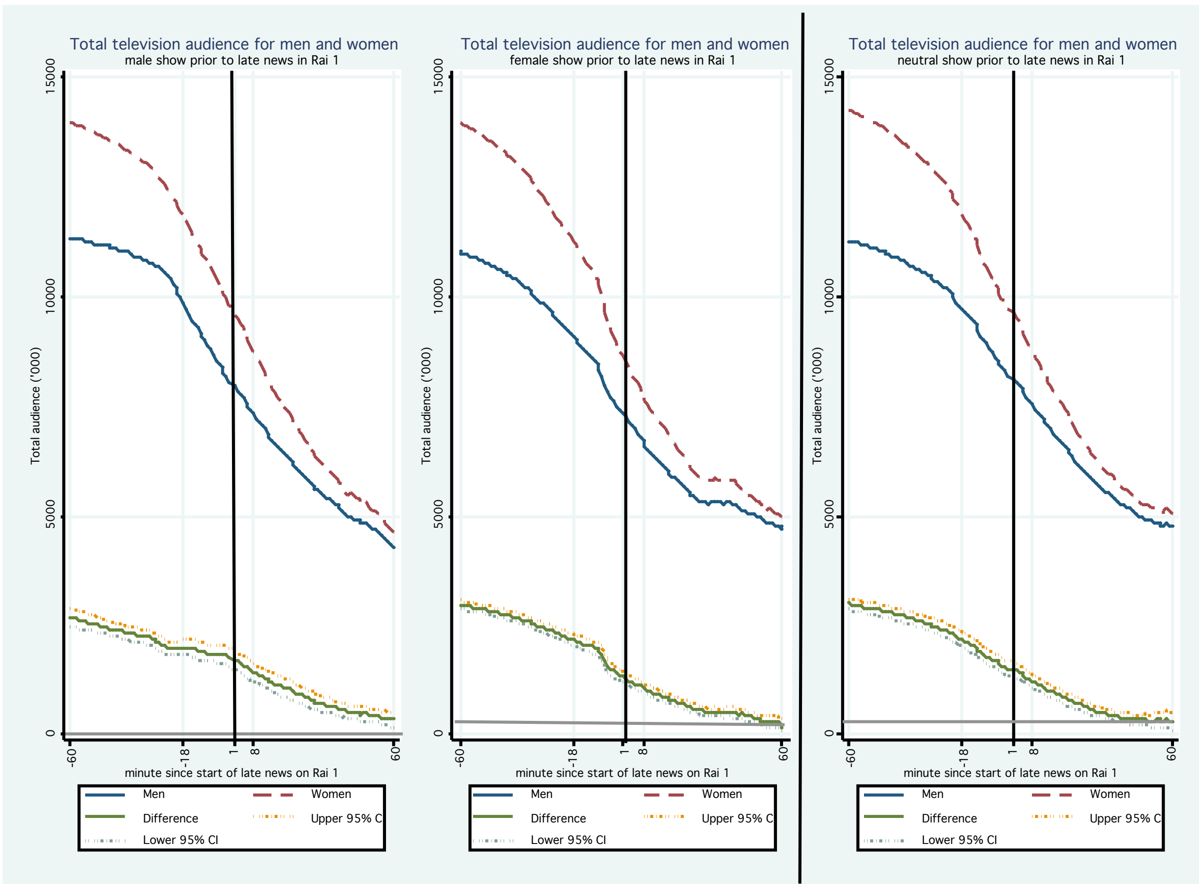
Channel	6:00	6:30	7:00	7:30	8.00	8:30	9:00	9:30	10:00	10:30	11:00	11:30	12:00
Rai 1	Variety La vita in diretta	Game show/Quiz L'eredita			News Rai 1	Max & Tuck; Variety Super-variety	Film Public Enemy					News Rai 1	News talk show Porta-a-Porta
Rai 2	Sport Sport sera; Vari e-ty	Soap Opera Cuori Rubati	TV series Cobra Special Squad		Cartoons Popeye	News Rai 2	Show Big Monday night					Variety Women stories	
Rai 3	Cultural Program Geo & Geo		News Rai 3	Regional News	Sport Rai Sport; Vari e-ty Blob di Tutt o Piu	Soap Opera Posto al Sole	Variety show Chi l'ha visto				News Rai 3	News magazine Primo-Piano	
Canale 5	Variety Verissimo	Game show Passaparola			News Canale 5	Variety Striscia	Miniserie Francesco				Talk-Show Maurizio Costanzo		
Italia 1	Sitcom Fresh Prince of Bel-Air	News Studio Aperto	Reality Show Operation Triumph	Sitcom Dharma & Greg	Game show/Quiz Sarabanda	TV series Carabinieri					Made for TV movie Da Cosa nasce Cosa		
Rete 4	Film		News Rete 4	Variety Sipario	Soap Opera Terra Nostra		Film El Dorado					Cultural program Travelling in the time machine	

Figure 3 – Unadjusted male and female viewership for Rai 1 in soccer days (left panel), female show days (middle panel) and neutral show days (right panel), 60 minutes before to 60 minutes after the event "start of the late news" in Rai 1



	SOCCER DAYS IN RAI 1 (N=16)		FEMALE SHOW DAYS IN RAI 1 (N=127)		NEUTRAL SHOW DAYS IN RAI 1(N=53)	
Viewers (millions)	**Before the late news (min -60 to min -1)**	**After the late news (min 1 to min 60)**	**Before the late news (min -60 to min -1)**	**After the late news (min 1 to min 60)**	**Before the late news (min -60 to min -1)**	**After the late news (min 1 to min 60)**
Male	3.40	1.12	1.90	1.00	2.20	1.10
Female	2.20	1.09	3.40	1.30	2.90	1.30
Difference	**1.20**	**0.03**	**-1.50**	**-0.30**	**-0.70**	**-0.20**

Figure 4 – Total television viewership for men and women, in soccer days in Rai 1 (left panel), female show days in Rai 1 (middle panel) and neutral show days in Rai 1 (right panel), 60 minutes before to 60 minutes after the event "start of the late news" in Rai 1



	SOCCER DAYS IN RAI 1 (N=16)		FEMALE SHOW DAYS IN RAI 1 (N=127)		NEUTRAL SHOW DAYS IN RAI 1(N=53)	
	Before the late news (min -60 to min -1)	**After the late news (min 1 to min 60)**	**Before the late news (min -60 to min -1)**	**After the late news (min 1 to min 60)**	**Before the late news (min -60 to min -1)**	**After the late news (min 1 to min 60)**
Viewers (millions)						
Male	10.30	6.00	9.70	5.90	10.20	6.30
Female	12.60	6.90	12.10	6.70	12.60	7.00
Difference	**-2.30**	**-0.90**	**-2.40**	**-0.80**	**-2.40**	**-0.70**

Figure 5 – Adjusted male and female viewership in soccer days (left panel, plot of $\alpha_{2,\tau}$, $\beta_{2,\tau}$) and female show days (right panel, plot of $\alpha^0_{2,\tau}$, $\beta^0_{2,\tau}$), from 60 minutes before to 60 minutes after the event "start of the late news in Rai 1"; adjustment with calendar dayXminuteXgender fixed effects to control for differential trends in male and female viewership by day and minute; τ is the time since the start of the event.

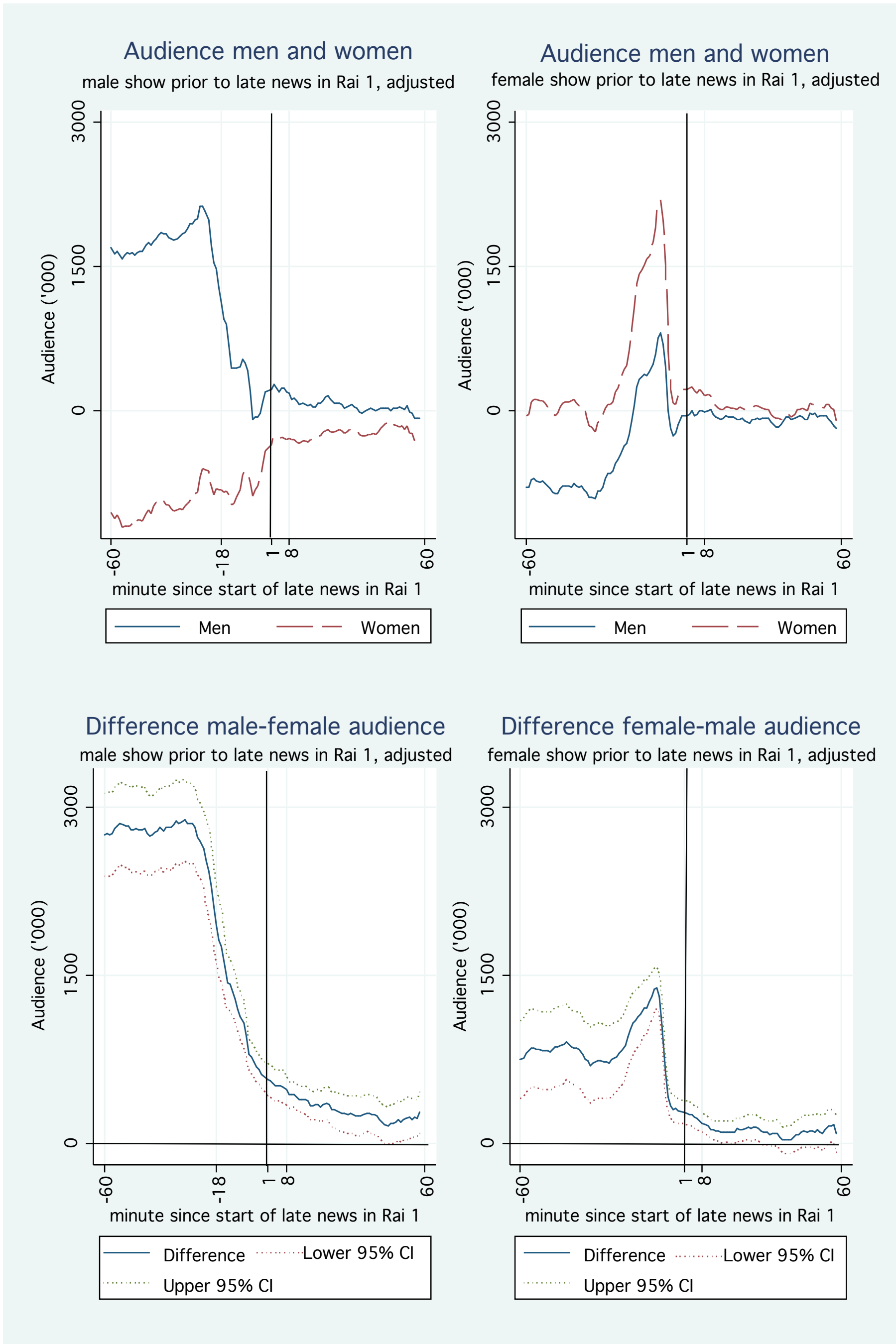


Figure 6 – Cumulative adjusted average gap in the audience between men and women after soccer (left panel) and after female show days (right panel); average estimated over the time elapsed since the start of the event (τ) –" start of the late news in Rai 1"

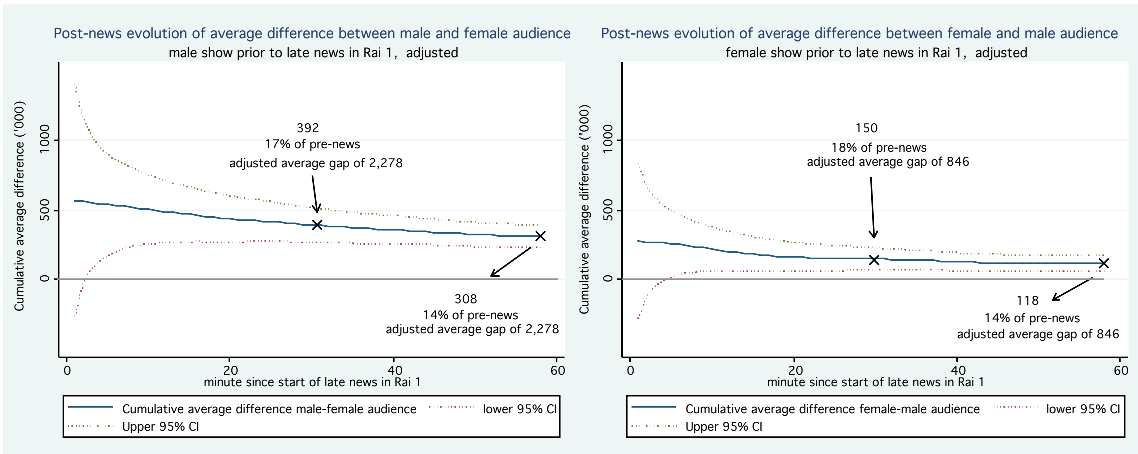


Figure 7 – Male and female audience during the news at 8:00 PM in Rai 1 in soccer, female and neutral show days. More women than men watch this news program across soccer, female and neutral show days and are exposed to the anchor's announcement of the news talk show Porta-a-Porta at 11:00 PM. Therefore, the higher viewership of the news talk show Porta-a-Porta by men than women in soccer days is not due to a higher number of male viewers watching the news at 8:00 PM in Rai 1 in soccer days.

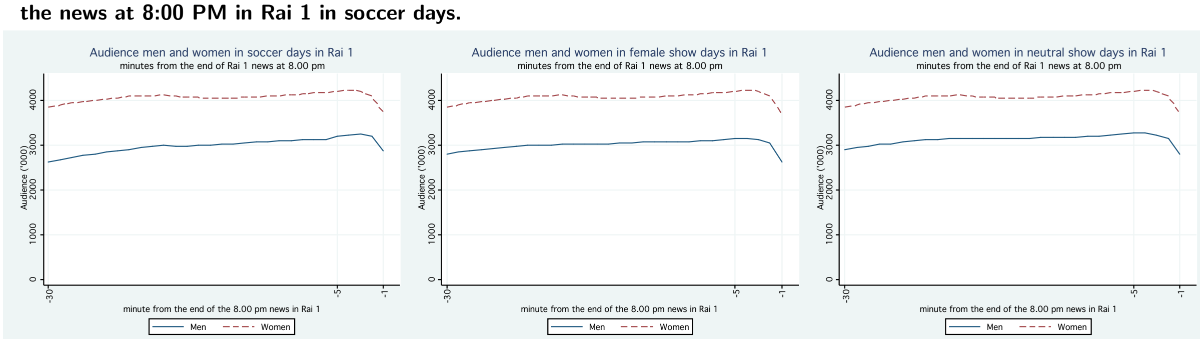


Figure 8 – Plot of audiences of consecutive shows on the same channel. Left panel: 8:00 PM news in Canale 5 preceded by Wheel of Fortune game-show. Right panel: Hitchcock Presents in Rai 1 preceded by movies

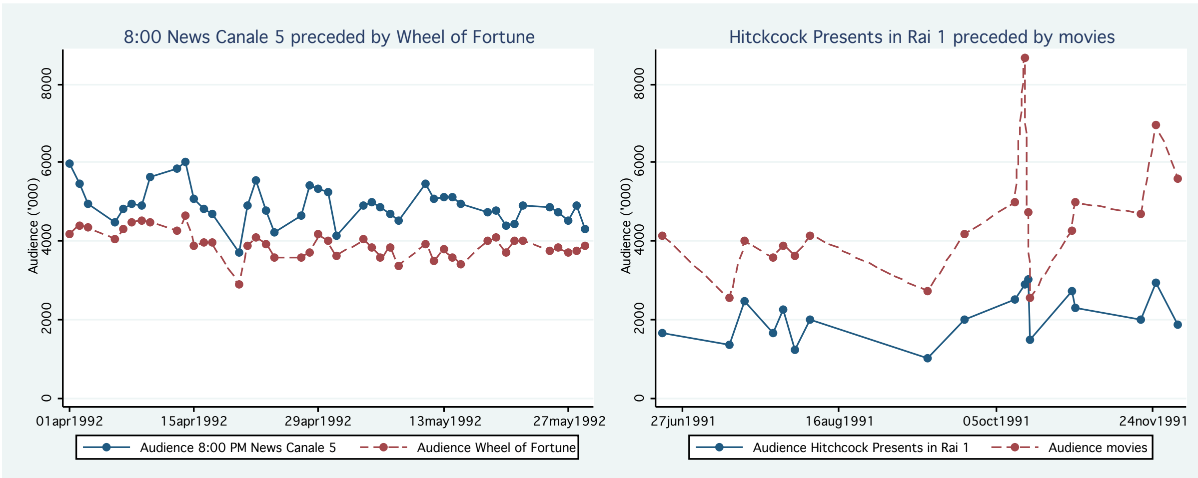


Figure 9 – Relationship between the rate for a 30" commercial and the monthly audience in prime-time, for flagship Canale 5, 2002-2003

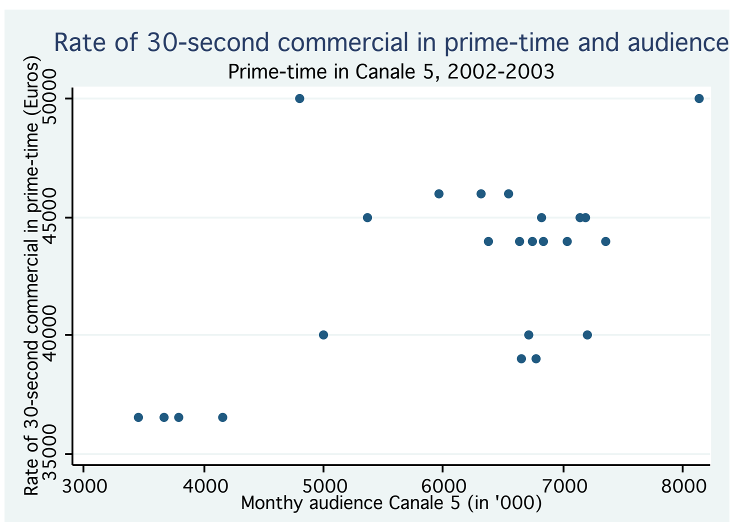


Table 1 – Overview of composition of television shows, 1990-2003, in Italy's 6 main channels

Show genre	Description	Freq.	Percent	length minutes (average)	number of episodes per show (average)
NEWS	Shows summarizing daily local and international news, such as 600 pm news in the US	43,602	22	22	206
VARIETY	Entertainment shows based on current events, such as mock news and missing persons misteries	22,462	11	36	28
SHOW	Mostly talk-shows	19,422	10	74	25
TV SERIES	Mainly TV drama series such as CSI, the X-files, ER or Xena Warrior Princess	17,547	9	55	45
FILM	All movies except made for TV movies	14,152	7	108	3
GAME SHOW	Games shows	14,064	7	46	177
SPORTS SHOW	Mainly shows about current, past or future sports events eg past Olympic games	13,608	7	19	55
NEWS MAGAZINE	Mainly feature on current news events, such as 20/20 or 60 minutes in the US	10,695	5	39	20
CARTOON	Mainly short animated features	7,056	4	16	38
SITCOM	Situational comedies, as in the US; includes shows such as Friends	6,606	3	29	67
CULTURAL PROGRAM	Programs designed to educate viewers, such as documentaries on science, history or the arts	6,426	3	53	11
SOAP OPERA	Daily drama shows, similar to soap operas in the US	5,956	3	43	109
SPORTS EVENT	Mainly the broadcast of sports events, such as soccer, basketball, tennis and volleyball	3,880	2	69	5
MADE FOR TV MOVIE	Movies made for television	2,828	1	102	2
MUSIC	Includes concerts, music festivals, and performances by well-know singers	2,320	1	65	4
PROMOTIONAL PROGRAM	Mainly short shows designed to sell a product, service	2,253	1	6	50
MOVIE COMMENTARY	Show commenting on movie	2,027	1	9	946
MINISERIE	TV series with usually fewer than thirteen episodes	1,230	1	101	5
REALITY TV	Non-scripted TV show based on real-life situations	1,212	1	42	34
Total		197,346	100	45	16

Note: Does not include weekends

Table 2 – Sample construction for minute-by-minute event-study analysis in 2002-2003

Table: Summary of days with soccer, female shows and neutral shows in Rai 1

January 1st 2002-December 31st 2003	Total	Average start (pm)	Standard deviation (min)
Days with late (11:00 PM news in Rai 1)[(1)]	498	11:08	16.8
Total days with late news followed by Porta-a-Porta[(2)]	253	11:12	13.9
Observations for analysis			
Total male show (soccer) days[(3)] + News +Porta-a-Porta	16	11:03	6.7
Total female show days[(4)]+News+Porta-a-Porta	127	11:17	13.5
Total neutral show days[(5)]+News+Porta-a-Porta	53	11:07	11.8
Total number of days for analysis[(6)]	196		

Notes: [(1)] Does not include weekends;[(2)] Drop due to Porta-a-Porta off the air in the summer months and not always playing after the 11:00 PM news in Rai 1; [(3)]Male show is a show that always has male audience higher than female audience, which is soccer;[(4)]Female show is a show where every episode has higher female audience than male audience (e.g., *Incantesimo*, a series on the romantic lives of doctors and nurses at a Roman hospital; *I Racommandati*, a singing talent show);[(5)]neutral show is a show where male audience exceeds the female audience in some episodes and the reverse in the remaining episodes (case when the talk-show *Porta-a-Porta* or the science show, *Superquark* air before the late news in Rai 1);[(6)]60 observations removed from the analysis because only air once and therefore with no criteria to classify them as male show (soccer) or female show.

Table 3 – Summary statistics for main specifications

Sample:	All shows					Movies followed by subquent show					Movie followed by News					Pre-main news show followed by main news show				
	N	**Mean**	**St. Dev.**	**Min**	**Max**	**N**	**Mean**	**St. Dev.**	**Min**	**Max**	**N**	**Mean**	**St. Dev.**	**Min**	**Max**	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Audience current show ('000 viewers)	133,258	2,434	1,881	44	23,543	307	1,890	717	519	6,284	143	2,051	777	662	6,284	16,695	3,875	2,459	219	13,989
Audience prior show ('000 viewers)	133,258	2,374	1,812	55	23,543	305	5,693	2,155	1,225	16,080	143	5,991	2,352	1,540	16,080	16,695	2,267	1,486	122	7,392
Current show																				
Index competition on popularity ('000)	133,258	2,560	1,078	284	8,058	307	1,995	863	547	4,411	143	2,373	803	991	4,411	16,695	2,720	797	461	5,774
Genre overlap	133,258	0.09	0.12	0.00	1.00	307	0.15	0.16	0.00	0.59	143	0.08	0.10	0.00	0.38	16,695	0.18	0.10	0.00	0.63
Start time (P.M.)	-	-	-	-	-	307	11.59	18.76	10.46	11.56	143	10.54	15.60	10.25	11.28	16,695	7.32	37.04	6.25	8.42
Length (minutes)	133,258	35	32	3	276	307	44	44	3	128	143	11	6	3	32	16,695	32	7	20	60
Observations and length by channel																				
Flagship channels																				
Rai 1	23,019	31.66	30.779	3	273	82	8	4	3	32	69	7	2	3	13	2,966	33	3	20	57
Canale 5	18,455	51.63	35.969	3	226	153	68	46	3	128	53	13	8	3	32	2,970	33	5	20	58
All others																				
Rai 2	28,246	30.21	27.303	3	219	20	48	24	5	90	2	19	1	18	20	3,025	28	4	20	57
Rai 3	29,737	29.08	28.793	3	276	19	16	4	7	22	19	16	4	7	22	3,147	37	11	23	60
Rete 4	14,425	37.41	33.609	3	199	6	6	2	3	8	-	-	-	-	-	2,147	35	5	20	60
Italia 1	19,376	38.15	29.998	3	225	27	42	33	5	112	-	-	-	-	-	2,440	26	5	20	59

Notes: does not include weekends; drop versus total observations in dataset due to inclusion of fixed effects: shows that air less than once in a calendar month and time slot are dropped.

Table 4 – OLS of demand for current show on demand for prior show using show log audience – all shows, 1990-2003

Sample[(1)]:	**All shows 1990-2003**						
Dependent variable:	**Ln audience of current show**						
OLS specifications:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Demand prior show (in ln audience)	0.674	0.595	0.583	0.400	0.501	0.406	0.380
	(0.002)***	(0.002)***	(0.002)***	(0.003)***	(0.003)***	(0.004)***	(0.004)***
Controls:							
Competition on popularity[(2)]	-	0.365	0.377	0.565	0.157	-0.018	-0.112
(ln index aud of competing shows in prior month)	-	(0.004)***	(0.004)***	(0.004)***	(0.004)***	(0.006)***	(0.007)***
Genre overlap	-	-	0.775	0.591	-0.001	0.010	-0.015
(% of time genre overlaps with other channels')	-	-	(0.013)***	(0.012)***	(0.010)	(0.013)	(0.011)
Channel FE	-	-	-	Yes	-	-	-
Channel X Show FE	-	-	-	-	Yes	-	-
Channel X Show X Year X Month FE	-	-	-	-	-	Yes	-
Channel X Show X Year X Month X 1/2 slot FE	-	-	-	-	-	-	Yes
R-squared	133,258	133,258	133,258	133,258	133,258	133,258	133,258
N (number of distinct show episodes)	0.43	0.48	0.50	0.58	0.89	0.95	0.96
Number of days (clusters)	3,630	3,630	3,630	3,630	3,630	3,630	3,630

Standard errors in parentheses; clustered by day; ***significant at the 1% level; **significant at the 5% level

Note: (1) Does not include weekends, and titles that play sequentially (e.g. Friends followed by Frieds in the subsequent time slot); [(2)]Using *index of ln audience of competing shows* in the prior month as an instrument for ln of average audience of show airing simultaneously with the current show (instead of using it as a proxy for simultaneous competition) does not change the coefficient on the variable of interest: Demand of prior show (movie).

Table 5 – Effect of movie demand on subsequent show and subsequent news show, 1990-2003

Sample[(1)]:	Any show after movies			News after movies		
Dependent variable:	Ln audience show after movie		Ln audience movie	Ln audience news after movie		Ln audience movie
Specification:	OLS	2SLS	1st stage: OLS	OLS	2SLS	1st stage: OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Demand of prior show (movie) - ln audience	0.566	0.483	-	0.695	0.388	-
(Instrumented with Ln Italian theatrical audience for movie)	(0.084)***	(0.107)***	-	(0.121)***	(0.205)*	-
1st stage: movie followed by news						
Ln Theatrical audience movies (in millions)			0.062			0.060
			(0.011)***			(0.015)***
t-stat 1st stage			5.636			4.050
Controls:						
Competition on popularity [(2)]	-0.075	-0.077	0.043	-0.008	-0.01	0.062
(ln index aud of competing shows in prior month)	(0.076)	(0.058)	(0.098)	(0.117)	(0.136)	(0.159)
Genre overlap	0.132	0.138	0.093	0.266	0.354	0.268
(% of time genre overlaps with other channels')	(0.127)	(0.097)	(0.171)	(0.210)	(0.226)	(0.298)
Channel X Show X Year X Month X 1/2 slot FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.83	-	0.82	0.79	-	0.82
N (Number of movie-show pairs)	305	305	305	143	143	143
Number of days (clusters)	268	268	268	129	129	129
Average length of show or news after movie (minutes)	44			11		

Standard errors in parentheses; clustered by day; ***significant at the 1% level; **significant at the 5% level; *significant at the 10% level
Note: [(1)] Does not include weekends[(2)]Using *index of ln audience of competing shows* in the prior month as an instrument for ln of average audience of show airing simultaneously with the current show (instead of using it as a proxy for simultaneous competition) does not change the coefficient on the variable of interest: Demand of prior show (movie)

Table 6 – Log audience of current main news on log audience of prior show, instrumented with the log of average audience in the prior month; log audience of show after the current main news show on log audience of the show that plays prior to the news, instrumented with the log of average audience in the prior month, 1990-2003

Sample[1]:	Main news shows [3], 1990-2003			Below median length	Above median length	
Dependent variable:	**Ln audience of news**		**Ln audience of show prior to news**	**Ln audience news Mean length: 28 minutes**	**Ln audience news Mean length: 38 minutes**	**Ln audience show after the news**
Specification:	**Pooled OLS**	**2SLS**	**1st stage: OLS**	**2SLS**	**2SLS**	**2SLS**
	(1)	(2)	(3)	(4)	(5)	(6)
Demand of prior show - in ln audience	0.353	0.220	-	0.298	0.147	0.091
(Instrumented with ln average audience in prior month in 2 SLS)	(0.012)***	(0.028)***	-	(0.044)***	(0.034)***	(0.046)**
1st stage: show followed by news						
Ln of average audience in prior month			0.218			
			(0.020)***			
t-stat 1st stage			10.90			
Controls:						
Competition on popularity[2]	-0.089	-0.089	0.001	-0.090	-0.094	-0.095
(ln index of audience of competing shows in prior month)	(0.025)***	(0.026)***	(0.024)	(0.027)***	(0.035)***	(0.017)***
Genre overlap	0.182	0.162	-0.147	0.091	0.236	-0.062
(% of time genre overlaps with other channels')	(0.061)***	(0.062)***	(0.068)**	(0.062)	(0.118)**	(0.024)**
Channel X Show X Year X Month X 1/2 slot FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.98	-	0.95	-	-	-
N (Number of show-news pairs)	16,695	16,695	16,695	9,708	6,987	15,050
Number of days (clusters)	3,589	3,589	3,589	3,528	3,020	3,583
Average length of main news show (minutes)	32			28	38	24

Standard errors in parentheses; clustered by day; ***significant at the 1% level; **significant at the 5% level; *significant at 10% level

Note:[1] does not include weekends; does not include news shows that play sequentially and news shows which are "Extraordinary Editions", like a news special on 9/11/2001; [2] Using *index of ln audience of competing shows* in the prior month as an instrument for ln of average audience of show airing simultaneously with the current show (instead of using it as a proxy for simultaneous competition) does not change the coefficient on the variable of interest: Demand of prior show (movie); [3] Main news shows are the standard daily half-hour (or longer) news shows scheduled at 6:30 PM, 7:00PM, 7.30 PM, 8.00 PM and 8.30 PM.

Table 7 – Effect of demand for movies and pre-main news shows on preceding shows, 1990-2003

Sample (1):	**Movie + 1st preceding show**	**Movie + 2nd preceding show**	**Movie + 3rd preceding show**	**Pre-main news show+1st preceding show**	**Pre-main news show+2nd preceding show**
Dependent variable:	**Ln audience show prior to movies (movie-1)**	**Ln audience two shows prior to movies (movie-2)**	**Ln audience three shows prior to movies (movie-3)**	**Ln audience show prior pre-main news show (pre-main news-1)**	**Ln audience show prior pre-main news show (pre-main news-2)**
Specification:	**2SLS**	**2SLS**	**2SLS**	**2SLS**	**2SLS**
	(1)	(2)	(3)	(4)	(5)
Demand of prior show (movie) - in ln audience	0.404	0.232	0.113	0.434	0.042
(Instrumented with Ln Italian theatrical audience for movie) **(Instrumented with ln average audience in prior month for pre-main news show)**	(0.081)***	(0.060)***	(0.094)	(0.099)***	(0.092)
Controls:					
Competition on popularity (2)	-0.040	-0.002	-0.242	-0.044	-0.043
(ln index aud of competing shows in prior month)	(0.107)	(0.067)	(0.097)**	(0.016)***	(0.024)*
Genre overlap	0.222	-0.24	-0.381	-0.051	-0.133
(% of time genre overlaps with other channels')	(0.123)	(0.149)	(0.315)	(0.030)	(0.046)***
Channel X Show X Year X Month X 1/2 slot FE	Yes	Yes	Yes	Yes	Yes
N (Number of movie-show pairs)	273	276	263	10,085	7,616
Number of days (clusters)	243	247	235	3,530	3,348

Standard errors in parentheses; clustered by day; ***significant at the 1% level; **significant at the 5% level; does not include weekends

Note: (1) Does not include weekends**;** (2)Using *index of ln audience of competing shows* in the prior month as an instrument for ln of average audience of show airing simultaneously with the current show (instead of using it as a proxy for simultaneous competition) does not change the coefficient on the variable of interest: Demand of prior show (movie)

Table 8 – Other robustness checks: (1)-(2) Effect with full panel with all prompts versus half the panel with all prompts; (3)-(4) of information about the upcoming news at 8:00 PM; (5) of competing shows starting in a 1 minute vicinity; and (6) of uncertainty about competing shows.

Sample:[(1)]	**Main news shows, 1990-2003**	**Main news shows, 1998-2003**	**Main news shows, 1990-2003**	**Main news shows, 1998-2003**	**Main news shows, 1990-2003**	**Main news shows, 1990-2003**
Dependent variable:	**Ln audience news**	**Ln audience news**	**Ln audience news Rai 1 and Canale 5**	**Ln audience news 4 other channels**	**Ln audience news**	**Ln audience news**
Specification:	**2SLS**	**2SLS**	**2SLS**	**2SLS**	**2SLS**	**2SLS**
	(1)	(2)	(3)	(4)	(5)	(6)
Demand of prior show - in ln audience	0.220	0.272	0.138	0.250	0.223	0.211
(Instrumented with ln average audience in prior month)	(0.028)***	(0.036)***	(0.037)***	(0.036)***	(0.028)***	(0.059)***
Demand of prior show X nb channels starting in same minute vicinity					-0.007	
(In ln audience: Instrumented ln of average audience in prior month)					(0.004)	
Demand of prior show X Uncertainty about competing shows						(0.004)
(In ln audience: Instrumented ln of average audience in prior month)						(0.008)
<u>Controls:</u>						
Channels starting in same minute vicinity					0.046	
(=1 if no shows starting in the same minute vicinity)					(0.030)	
Uncertainty about competing shows to current show						0.026
(=1 if competing shows into 2nd half of episodes)						(0.063)
Competition on popularity [(2)]	-0.089	-0.053	0.002	-0.115	-0.089	-0.117
(ln index aud of competing shows in prior month)	(0.026)***	(0.037)	(0.032)	(0.029)***	(0.026)***	(0.042)***
Genre overlap	0.162	0.332	0.166	0.164	0.164	0.082
(% of time genre overlaps with other channels')	(0.062)***	(0.104)***	0.087	(0.071)**	(0.062)***	-0.087
Channel X Show X Year X Month X 1/2 slot FE	Yes	Yes	Yes	Yes	Yes	Yes
N (Number of movie-show pairs)	16,695	8,273	5,936	10,759	16,695	5,341
Number of days (clusters)	3,589	1,555	3,434	3,575	3,589	2,852

Standard errors in parentheses; clustered by day; ***significant at the 1% level; **significant at the 5% level; *significant at the 1% level

Note: [(1)] Does not include weekends; [(2)]Using *index of ln audience of competing shows* in the prior month as an instrument for ln of average audience of show airing simultaneously with the current show (instead of using it as a proxy for simultaneous competition) does not change the coefficient on the variable of interest: Demand of prior show (movie)

Table 9 – Current optimal and worst schedule for flagship channels Canale 5 and Rai 1

Privately-controlled flagship Canale 5 - 2003 prime-time schedule

	Show id	Time (PM)	Average Audience (millions)	Ln average audience	Implicit Ln baseline audience (2)	Optimal Schedule	Average Audience (millions)	Worst Schedule	Average Audience (millions)
Pre-prime time									
Quiz show	s_0	**6:40-8:00**	3.753	1.323	-				
Prime-time									
8:00 PM News	s_1	**8:00-8:30**	6.422	1.860	1.463	**Half-hour variety show**	6.071	**Two-hour programs(1)**	5.370
Half-hour variety show	s_2	**8:30-9:00**	7.133	1.965	1.407	**8:00 PM News**	7.418	**Half-hour variety show**	6.760
programs(1)	s_3	**9:00-11:00**	5.750	1.749	1.540	**programs(1)**	5.774	**8:00 PM News**	7.662
Weighted average audience 8:00-11:00 PM			6.092	1.803			6.097		5.98
% Difference versus optimal schedule			0.1%						1.9%

Notes: (1) For example, Movies, Series, Miniseries; (2) Implicit Ln baseline audience=Ln average audience current show- ρ*Ln average audience show before, where ρ=0.3 for a half-hour show and $\rho=(0.3+0.3^2+0.3^3+0.3^4)/4=0.106$ for a 2-hour show.

Schedule simulations:	Current (s_0, s_1, s_2, s_3) (1)		(s_0, s_2, s_1, s_3) (2)		(s_0, s_3, s_1, s_2) (3)		(s_0, s_3, s_2, s_1) (4)		(s_0, s_1, s_3, s_2) (5)		(s_0, s_2, s_1, s_3) (6)	
	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)
s_0	1.323	3.753	1.323	3.753	1.323	3.753	1.323	3.753	1.323	3.753	1.323	3.753
s_i	1.463	6.422	1.407	6.071	1.540	5.370	1.540	5.370	1.407	6.071	1.463	6.422
s_j	1.407	7.133	1.463	7.418	1.463	7.150	1.407	6.760	1.540	5.652	1.540	5.686
s_k	1.540	5.750	1.540	5.774	1.407	7.367	1.463	7.662	1.463	7.261	1.407	6.877
Weighted average 8:00-11:00 PM	6.092		6.097		6.000		5.984		5.990		6.007	

Notes: Audience with inertia=exp[(Implicit log baseline audience)+ρ(log audience of prior show)] where ρ=0.3 for a half-hour show and $\rho=(0.3+0.3^2+0.3^3+0.3^4)/4=0.106$ for a 2-hour show. This latest estimate conforms with demand persistence found to show with more than 100 minutes.

State-owned flagship Rai 1 - 2003 prime-time schedule

	Show id	Time (PM)	Average Audience (millions)	Ln average audience	Implicit Ln baseline audience (2)	Optimal Schedule	Average Audience (millions)	Worst Schedule	Average Audience (millions)
Pre-prime time									
Quiz show	s_0	**6:40-8:00**	4.330	1.465	-				
Prime-time									
8:00 PM News	s_1	**8:00-8:30**	6.924	1.935	1.495	**Half-hour variety show**	4.621	**Two-hour programs(1)**	5.243
Half-hour variety show	s_2	**8:30-9:00**	5.319	1.671	1.091	**8:00 PM News**	7.060	**Half-hour variety show**	4.894
Two-hour programs(1)	s_3	**9:00-11:00**	5.359	1.679	1.501	**Two-hour programs(1)**	5.523	**8:00 PM News**	7.183
Weighted average audience 8:00-11:00 PM			5.613				5.656		5.508
% Difference versus optimal schedule			0.8%						2.6%

Notes: (1) For example, Movies, Series, Miniseries; (2) Implicit Ln baseline audience=Ln average audience current show- ρ*Ln average audience show before, where ρ=0.3 for a half-hour show and $\rho=(0.3+0.3^2+0.3^3+0.3^4)/4=0.106$ for a 2-hour show.

Schedule simulations:	Current (s_0, s_1, s_2, s_3) (1)		(s_0, s_2, s_1, s_3) (2)		(s_0, s_3, s_1, s_2) (3)		(s_0, s_3, s_2, s_1) (4)		(s_0, s_1, s_3, s_2) (5)		(s_0, s_2, s_1, s_3) (6)	
	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)	Implicit ln baseline audience	Audience with inertia (milions)
s_0	1.465	4.330	1.465	4.330	1.465	4.330	1.465	4.330	1.465	4.330	1.465	4.330
s_i	1.495	6.924	1.091	4.621	1.501	5.243	1.501	5.243	1.091	4.621	1.495	6.924
s_j	1.091	5.319	1.495	7.060	1.495	7.333	1.091	4.894	1.501	5.279	1.501	5.511
s_k	1.501	5.359	1.501	5.523	1.091	5.412	1.495	7.183	1.495	7.348	1.091	4.967
Weighted average 8:00-11:00 PM	5.613		5.629		5.619		5.508		5.514		5.656	

Notes: Audience with inertia=exp[(Implicit log baseline audience)+ρ(log audience of prior show)] where ρ=0.3 for a half-hour show and $\rho=(0.3+0.3^2+0.3^3+0.3^4)/4=0.106$ for a 2-hour show. This latest estimate conforms with demand persistence found to show with more than 100 minutes.