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Inertia and Earnings gaps: Essays in Behavioral and Labor Economics

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Inertia and Earnings gaps: Essays in Behavioral and Labor Economics

by

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Committee in charge:

Professor Steven Tadelis, Chair

Professor Stefano DellaVigna

Professor Catherine Wolfram

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Abstract

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Abstract for first essay: Micro-costs, inertia in television viewing. Inertia, defined as the persistent choice for 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: a click of the remote in the choice of television programs. 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%. The leading explanation, among the several considered for this and other findings, is procrastination: consumers continuously postponing switching channels. Inertia in program choice affects channels' optimal program schedule and may influence as much as 20-40% of their profits. The broader implications of these findings are discussed.

Abstract for second essay: The gender earnings gap for physicians and its increase over time. Studies comparing earnings of male and female physicians have traditionally shown that male physicians earn more than female physicians with similar characteristics. Recent research using data from 1990 (Baker, 1996, in the New England Journal of Medicine) has suggested, however, that the gap in earnings between male and female physicians at the onset of their careers has disappeared, hailing a new era of equal gender pay. This paper analyzes four rounds of the Community Tracking Study Physician Survey from 1997 to 2005. Contrary to recent research, the evidence suggests that even at the onset of their careers male physicians earn at least 13% more than their female counterparts. Moreover, as physicians age from their thirties into their forties, the gap in pay between male and female physicians more than doubles to at least 28%, stabilizing thereafter. The difference in our findings versus those of recent research lies in the latter use of a restrictive estimation equation which leads to flawed conclusions.

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Micro-costs: Inertia in television viewing

Abstract

Inertia, defined as the persistent choice for 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: a click of the remote in the choice of television programs. 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%. The leading explanation, among the several considered for this and other findings, is procrastination: consumers continuously postponing switching channels. Inertia in program choice affects channels' optimal program schedule and may influence as much as 20-40% of their profits. The broader implications of these findings are discussed.

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 the persistent choice for the default option, affects outcomes in a variety of settings. Its impact has been documented in laboratory experiments (see C. Anderson, 2003, for a survey) and in the field, from organ donations (e.g. Abadie & Gay, 2006, Johnson & Goldstein, 2003) to enrollment in retirement plans (e.g. Madrian & Shea, 2001).

A leading explanation for inertia is the switching costs associated with choosing an alternative to the default. They can be of two types. Direct costs, the costs of implementing the desired change. Or indirect costs, the costs of learning and evaluating alternatives before implementing the change. If the switching costs are higher than 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 generate significant indirect 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 where the decision is frequent and the number of choices is limited? This paper offers 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, on average, more than 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 for viewers' persistent choice of programs in the default channel using a novel dataset of demand for television shows in Italy.[2] The Italian media environment is especially well-suited to study this question. Italy's very sophisticated audience tracking system reduces the potential for measurement error. Moreover, the concentration of 90% of viewership on six broadcast channels and the ubiquity of remotes lower the search costs

[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.

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, which encompasses two distinct but complementary methodological approaches, 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. The two approaches establish a causal relationship between the demand for a program and the demand for the show that succeeds it by addressing significant challenges to identification, such as endogenous scheduling by channels and weather shocks. They also allow for testing of the mechanisms that could generate inertia.

The first approach consists of an event-study using minute-by-minute audience data for 2002-2003. It exploits the variation in the appeal of programming to men and women before the late night news. When a male show, such as soccer, 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 inertia in program choice, are robust to calendar-day by minute-of-the-day unobservables that affect male and female viewership.

The second approach consists of Ordinary Least Squares (OLS) and instrumental variables (IV) estimation of the demand for television programs aired between 1990-2003. In this larger sample of shows, I find that an increase of 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 prior 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 current show as well as the interaction of current show, channel, year, month and half-hour slot unobservables. Even including this vast number of controls, I still find a statistically significant OLS estimate of 3.8%. The OLS estimate could, however, be biased by omitted shocks that are correlated with the demand for adjacent programs on the same channel, such as weather, or by viewers tuning-in earlier to the channel to ensure seeing the beginning of a show.

I address the potential omitted variables and simultaneity biases with two separate instrumental variables (IV) specifications. 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. I introduce an additional instrument for *Demand for the prior show* to conduct robustness checks and test for mechanisms 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.

The event-study and IV estimations establish the causal effect of the demand for a show on the demand of its succeeding show. This causal effect decays over time: persistence in demand declines over the duration of the succeeding show.

The finding that the demand of a show affects 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 four major 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 choice of program on a network is predicted by whether a viewer watched the preceding 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 – are ignored. I address this issue with the event-study, fixed effects and IV estimation. 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 the event-study and IV estimation. 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 (Shachar & Anand, 1998; Moshkin & Shachar, 2002). 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 Nielsen Peoplemeter provided the most accurate data in these studies. This meter may measure viewership between adjacent shows on a channel where there is none. It only asks viewers to confirm whether they are watching television after 70 minutes of inactivity. If viewers fall asleep or leave the room without informing the system, the meter will record these viewers as watching 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.

I test for the main mechanisms underpinning inertia and its decay over time: (i) asymmetric information – advertising of the succeeding show during the current program, (ii) unsynchronized start times – competing shows within a line-up not starting at the same time, (iii) quasi-indifference – viewers who are nearly indifferent between the succeeding show and competing shows on other channels, and (iv) naive quasi-hyperbolic preferences – consumers continuously postponing switching the channel. Whether inertia is due to television's dampening effect on cognition is discussed at the end.

I narrow down the mechanisms to either quasi-indifference between the succeeding show and competing shows on other channels or quasi-hyperbolic preferences. I discuss them in the context of a dynamic choice model with stochastic costs and the option value of switching channels. First, a portion of viewers has time-consistent preferences, but is 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 has quasi-hyperbolic preferences and therefore continuously postpones switching the channel. These consumers 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, coupled with naïveté about one's own behavior, lead consumers to procrastinate in the status quo, even when the benefit of switching exceeds 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.

Two findings support the naive quasi-hyperbolic preferences mechanism. First, female viewers persistence in the default channel after a female show remains unchanged when competing channels offer female-oriented content. Under quasi-indifference, the demand of the news after a female show should decline with an increase in the number of channels offering female-oriented content. Second, inertia is unchanged when competing programs to the succeeding show are new and therefore the variance in their benefits to the consumer is higher. Under quasi-indifference, inertia should decline with novel programming on other channels since the option value to switching is higher.

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 – is well-documented.[3]

I verify that television channels respond strategically to viewer inertia. Using the previously estimated magnitude of viewer inertia, I find that viewer inertia affects the optimal schedule and may influence 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 percentage difference in audience between the optimal schedule

[3] This media scheduling strategy is common knowledge in the television industry and has 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 [strategy]..."*.

and the worst schedule, taking into account viewer inertia, ranges from 2%-4%. 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 conservative 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 on 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 demonstrates that inertia in program choices exists, estimates its magnitude and shows that firms best-respond to it. It also contributes to the discussions on the role of consumer inertia on choice (e.g. Tirole, 1988, p. 295; Cronqvist & Thaler, 2004). It shows that inertia can exist even when the cost of switching is extremely small (click of the remote), consumers are experienced with the decision and the choice set limited. 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). It estimates the effect on channels' profitability of ignoring viewer inertia in program scheduling. Finally, it adds the study of decision-making in the consumption of television shows, a relatively under-studied phenomenon relative to the amount of resources allocated to this activity. The average viewer watches more than 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 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 the 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

[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

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

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

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, such as the Discovery Channel with science. Nevertheless, each channel's programming appeals to somewhat different audiences. Figure 1 shows the line-up for a typical day, Monday, across the six channels and Table 1 describes the genres in the line-up, such as news, sitcoms and reality TV.

Advertising about the specific content of a show, during the preceding show on the same channel, is rare. It occurs 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 on Rai 1 and Canale 5 announce verbally the next program; Rai 1's anchor 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 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

Television audiences in Italy are measured by a very sophisticated audience tracking system. A consortium of stakeholders – broadcasters (e.g. Rai and Mediaset), the national advertisers association and media buyers affiliated with the three national associations

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

for advertising – own Auditel, the audience monitoring organization. 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 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 provider of Italy's audience measurement technology during 1990-2003 – Audits of Great Britain (AGB) – is an innovator in this field. 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]

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

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

[11] The difference measurement does not affect the estimates in the subsequent analysis.

[12] The New York Times, October 8, 1990: Black Hole in Television; Nielsen's 'People Meter' Has

2.3 Data

The data consist of two related datasets on viewership. The first dataset contains male and female audience, for every minute between 6:00 PM and 12:00 AM, for 2002-2003, 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 is 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 by showing graphical evidence of inertia. An event-study using minute-by-minute data demonstrates how the viewership of the news among men and women varies with the appeal of the previous show to 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 both to test for mechanisms underpinning viewer inertia and to calibrate the profitability of inertia for channels at the end.

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 whether, 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. The null

Engendered A Revolution by Showing a Fall in Viewers.

[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%"

hypothesis is no inertia. All things equal, male and female viewership of a show should be insensitive to variations 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 the variation in the appeal to men and women of a show that precedes the same program, the late news on Rai 1 in 2002 and 2003.[16] The daily late news, starting at about 11:00 PM, follows a male show – soccer – on 16 days. It follows female shows – shows where every episode garners more female than male viewers – on 127 days. And it follows neutral shows – shows where the male audience exceeds female audience for some episodes but not others – on 12 days. Since the average duration of the late news is 8 minutes, I restrict the analysis to cases when the daily news talk show Porta-a-Porta follows the late news, to gauge whether channel persistence extends beyond 8 minutes. Porta-a-Porta covers political and current affairs and does not air during the summer. Table **??** details the sample construction and the mean time for the start of the late news on Rai 1.

Unadjusted audience analysis. Figure 2 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-a-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 on 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 on female show days.

Outside option. Female viewers tuning into Rai 1 on female show days choose between Rai 1 and other channels, and not between Rai 1 and the outside option of not watching television. Female television viewership across all channels during soccer days on Rai 1 and female shows days on Rai 1 is the same before start of the late news, as shown in Figure 3.[17] Therefore, the number of female television viewers across all channels is not higher on female show days on Rai 1, as one would expect if women watching Rai 1 would be non-TV watchers otherwise. Most male viewers tuning into Rai 1 on soccer days seem to choose between Rai 1 and other channels, and not between Rai 1 and the outside option of not watching television. Male audience across all channels on soccer days on

[16]Soccer is the only program where both the audience of men consistently and significantly exceeds that of women and that alternates with female shows on the same slot before the same program.

[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 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).

Rai 1 is slightly higher, at 0.6 million, than on female show days on Rai 1. However, male audience before the late news on Rai 1 on soccer days is 1.5 million higher than that on female show days, suggesting that 0.9 million male viewers are choosing soccer on Rai 1 over programming on other channels.

Adjusted audience analysis. I now adjust the previous analysis by the mean viewership on neutral days on Rai 1 to take into account the baseline male and female viewership for Rai 1. 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 the unobserved appeal to men and women of competing shows or of the outside option of not watching television, at each minute. 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 2, with the unadjusted male and female audience on Rai 1 on soccer days, is adjusted by the following specification:

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

where Male, Female, Rai 1 and Soccer, are indicator variables for male, female, whether channel is Rai 1 and whether calendar day is a soccer day, respectively, and $\tau \equiv$ Time from start of the late news on Rai 1 $= -60... + 60$. [18]

I run 120 regressions, one for each $\tau = -60, ..., -1, 1, ..., 60$. For each τ, the time from the start of the late news on 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 on 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 on neutral show days.

The middle panel with male and female audience on Rai 1 on 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.

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

Figure 4 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 in minute-by-minute audiences 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.

Decay rate of inertia. The average difference between male and female audiences after the start of the late news on Rai 1 relative to the average difference before the late news decays over time. I use the adjusted difference between the viewership of men and women, at the bottom of Figure 4 and 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 period as of the start of the late news on Rai 1.

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

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

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

The evolution of the cumulative gap after the start of the news is in Figure 5. 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. The magnitude of the average gap 30 minutes after the start of the news is 20% of the average gap the hour before the start of the news on soccer days. On female shows days it is 18%. The magnitude of the average gap 60 minutes after the start of the news declines to 14% of the average gap the hour before the news. On female show days it declines to 16%. Appendix Table A.1 shows the details.

Insensitivity of inertia to competition on gender-specific content. I conducted two tests to ascertain whether variation in the number of competing channels offering female shows during the late news affects the rate at which female viewers remain on Rai 1 after the female show. I focus on female show days on Rai 1 since the high number of days allows me to split data to conduct the tests. Table 3 shows the test, based on difference-in-differences estimation. The null is that the gap in audience between men and women on Rai 1 during the news and Porta-a-Porta should decline with an increase in the number of competing channels to Rai 1 offering female shows. First, I test whether having one or fewer channels offering female shows during the news and Porta-a-Porta, versus more than one competing channel doing so, changes the rate at which women remain on the default Rai 1. The median is one competing channel offering a female show. In column (1) the coefficient of interest on the interaction *FemaleXAbove Median* measures the difference in female and male audience, during the news and Porta-a-Porta, between the two conditions. This coefficient, though negative, is not statistically different from zero. Second, I test whether having no channels starting a female show in the commercial break before the late news on Rai 1 or 5 minutes into the news, versus having one or more channels starting a female show in this time span, changes the rate at which women remain on Rai 1. Column (2) shows the coefficient of interest on the interaction *FemaleXat least one channel*. Though negative, this coefficient is not statistically different from zero. Both estimates are adjusted by day of the week unobservables.

The rate at which female viewers remain on Rai 1 after the end of a female show seems insensitive to female-specific content offered on competing channels.

Robustness checks. 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 to coverage of the elections. See Appendix Table A.2 for details.

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

Conclusion. The prior analysis provides evidence of inertia, its decay rate and insensitivity to competing channels' offerings. The evidence of channel inertia in program choice found so far is, however, restricted to the late news on Rai 1 in 2002 and 2003. I investigate whether inertia observed in this setting generalizes over a larger number of shows and across all 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. I estimate the average effect that variations in demand of a show have on the audience of the subsequent show on the same channel, to calibrate the profitability of viewer inertia for channels.

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 A.2 in the Appendix shows, for example, that the audience of the 8.00 P.M. news on 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 (Γ_c), (iii) year and month (Γ_y, Γ_m, respectively), (iv) half-hour time slot (Γ_s), and (v) intensity of competition, by either 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:

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

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,

[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.

and Italia 1 air shows that garnered 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). Audience for shows that air for the first time in the month, or have only one episode, is approximated 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 4 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 4 describes summary statistics for this variable.

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 a result, I only estimate the demand for shows that air at least twice within the same channel, calendar-month and half-hour slot. The total number of fixed effects is 16,965.

The standard errors are conservatively 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 5. 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, instead, as an instrument for the popularity these shows does not change the coefficient of interest, α_1. The remaining specifications in the paper use log of the index of competition as proxy instead of an instrument for competition. The results are identical with either.

The OLS estimates may be biased, however, due to simultaneity and omitted variable 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 address these concerns with two instrumental variable specifications.

IV estimation using the theatrical audience of movies screened in Italy. The first instrument is the theatrical audience of all movies – about 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 or 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, which air after movies.

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

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

Table 6 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 IV 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 0.57.

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 manipulation by channels. As shown in column (5) of Table 6, 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* – the average demand for the prior show in the preceding calendar month – for tests that require more observations.

IV estimation using the average demand in the preceding calendar month. An advantage of this instrument is the increase in the number of observations available for

[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.

the analysis. 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 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 early tuning-in of viewers. This would bias the estimates. In contrast, if the channel had 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 7 in column (2), a 10% change 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).

First stage:

$$\begin{aligned} Demand_{pre-MainNewsShow} = \theta_0^0 + \theta_1^0 &\text{Average demand pre-Main News Show in preceding} \\ &\text{calendar month} + \theta_2^0 \text{Competition on popularity} + \\ &+ \theta_3^0 \text{Genre overlap} + \Gamma_i \Gamma_c \Gamma_y \Gamma_m \Gamma_s + \upsilon_{i,c,y,m,s}^0 \end{aligned}$$

[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.

Second stage:

$$Demand_{Mainnews,c,y,m,s} = \beta_0^0 + \beta_1^0 Demand_{pre-MainNewsShow} + \beta_2^0 \text{Competition on popularity} + \beta_3^0 \text{Genre overlap} + \Gamma_i \Gamma_c \Gamma_y \Gamma_m \Gamma_s + \eta_{i,c,y,m,s}^0$$

3.2.2 Other findings on OLS/IV analysis

Decay rate of inertia. The decline in inertia 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 decay in inertia over 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. To test for the decay rate of inertia, I split the main news sample by news 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 7. 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. And it still persists to the program that plays after the news – 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% (column 6). This supports the finding in the event-study with men and women that inertia has a decay rate. Moreover, the magnitude of inertia in the event-study is 18-20% 30 minutes into the news, which is close to the 22% effect on the 32-minute news in the IV analysis mentioned above.

Effect of uncertainty about competing shows. Uncertainty about competing shows may affect viewer inertia. If there is high uncertainty about competing shows viewers can be rewarded by a much better show by switching channels. If competing shows are 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 is truncated at the cost of clicking. The next section models this process explicitly.

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 shown in column (1) 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*. It is not statistically different from zero.

3.2.3 Conclusion

This section establishes the causal effect of the demand of show on its succeeding show with different data from the event-study. It supports the same causal relationship found in previously. It also supports the finding that there is a decay rate to inertia. The magnitude of the decay rate is similar across both studies. It finds that inertia is insensitive to the novelty in programming on other channels. I discuss the several mechanisms that are consistent with inertia, its decay rate and the remaining findings the event-study, and OLS and IV estimation.

4 Mechanisms

Asymmetric information. Advertising of the subsequent show on the channel could cause inertia by persuading 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 preceding 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 (2) and (3) 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 the estimated inertia 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 persistence created by the clip during each of these news shows is off-set by the high level of competition between them and other shows at the beginning of prime-time.

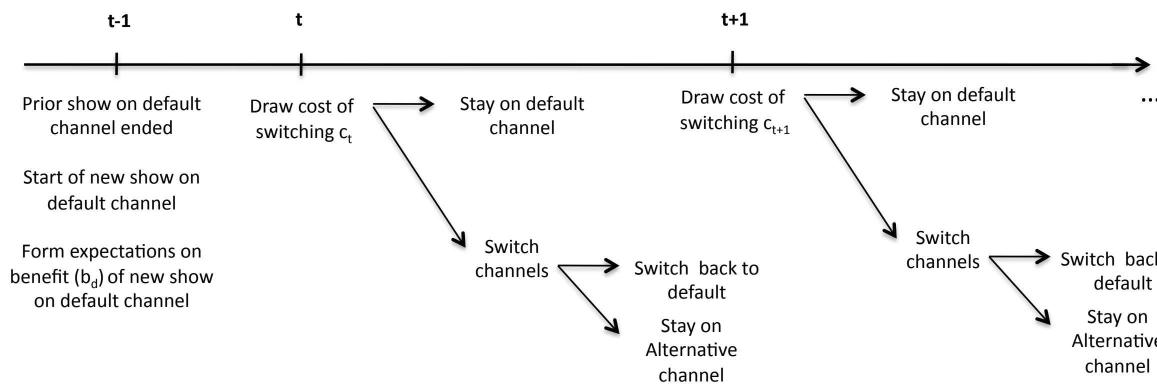
Unsynchronized start times for programs. Differing timings for starts of programs might also generate channel inertia. Under the assumption that viewers experience disutility from not watching a show from the beginning, the estimated inertia may stem from a sub-sample of shows that face no competing shows starting at the same time. A significant portion of viewers may 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 those that do 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 (4) of Table 8 is the interaction between *Demand for pre-main news show*, instrumented by its average audience in the prior month, and *No shows starting in the same 1 minute vicinity as the main news*. It is not statistically significant.

Quasi-indifference versus naive quasi-hyperbolic preferences. The most compelling mechanisms are time-consistent preferences with quasi-indifference between competing programs and quasi-hyperbolic preferences. The former lead consumers to stay in the default because they are nearly indifferent between the succeeding show in the default and programming on other channels. The latter, coupled with naïveté about one's procrastinating tendencies, causes consumers to postpone switching away from the default channel. To fix ideas, the dynamic model below describes the relationship between these two types of preferences, switching costs, the option value of switching and delays in the default.

Timing of game



Model setup. Suppose consumers are on the default channel at the end of a program. The decision problem is 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 need less than one minute to evaluate programming. They update their priors on the current programming almost instantaneously.[22]

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 $\hat{b_d}$

[22]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. This 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.

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 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 than 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.[23]

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

$$c^* = \frac{1}{1-\delta+\delta P(c_{t+1} \leq c^*)}\{G(1-\delta) - \hat{b_d} + \delta E[c_{t+1}|c_{t+1} \leq c^*]P(c_{t+1} \leq c^*)\}.$$[24]

[23]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 $E[V(c_{t+1}, c^*)]$.

[24]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 $\hat{b_d}$

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 $\hat{b_d}$.[25]

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. The variance around the difference in benefits Δ is $\sigma \geq 0$. 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 if 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 in 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 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 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. She chooses, in the short term, to postpone switching channels. This model of behavior focuses on time-inconsistency of preferences, whereby the consumer plans to change the channel, incurring an immediate cost to start reaping the benefit of watching a better show. When the time to incur the cost arrives, however, 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 naïveté 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.[26] Failing to make a phone

[25] This can be shown using implicit differentiation.

[26] Time-inconsistent consumers can be divided into two categories. Sophisticates, who know they have

call to enroll in an employer's 401k plan and therefore foregoing the employer's matching contributions or not canceling a gym membership when no longer using 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 set a lower threshold c^* than the optimal, leading to long delays in the default.

A recent paper by McClure et al. in 2007 shows that time-inconsistency exists 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 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

$$c^{*,naive} = \beta c^{*,exp} + (1 - \beta)\Delta$$

If $\beta = 1$, the consumer does not procrastinate – the cut-off is the same as that of the time-consistent consumer. It can be shown that $c^{*,exp} > \Delta$. This has two implications. First, $c^{*,naive} < c^{*,exp}$ for β in $[0, 1)$. Therefore, a naive consumer takes longer to draw a small enough cost to switch channels because her cut-off cost is lower. Second, the smaller β the smaller $c^{*,naive}$. Hence, the smaller β, the more a consumer procrastinates in switching the channel, delaying longer in the default.

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time-inconsistent preferences (Strotz, 1956; Phelps & Pollak, 1968; Laibson, 1997; O'Donoghue & Rabin, 1999) and naive or partially naive consumers (Akerlof,1991; O'Donoghue & Rabin, 2001) 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.

When the difference in the benefit of the alternative channel and the default channel is positive and the variance in this difference is significant, if β is small enough then one will still observe long delays in the default.

Discussion. Two findings support the hyperbolic preferences mechanism. First, the event-study of men and women in section 3.1. shows that women switch to Rai 1 to watch the female show. However, they persist at the same rate in Rai 1 through the news and the news talk-show Porta-a-Porta as the number of competing channels offering female-specific content during these news shows increases. A quasi-indifference mechanism would predict that female viewers would be sensitive to an increase in the number of channels offering female shows during these news shows. Second, the reduced-form test in section 3.2.2. shows inertia is insensitive to whether competing to shows the succeeding show are new, with potentially higher variance. A quasi-indifference mechanism would suggest lower inertia when the succeeding show competes against novel programs.

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 includes shows of different lengths. An analysis of the optimal schedule requires 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 0.9% respectively. The percentage difference in average audience between the optimal and worst schedule is 2.0% and 2.7%.

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.[27] 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.

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%.

[27]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.

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 return 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% increases advertising revenues by 1.44% (Wilbur, 2008, Table 1, page 362).[28]

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 $ln\ rate = \beta_1 ln\ expected\ audience + v$, where $cov(v, ln\ expected\ audience) = 0$ and $ln\ realized\ audience = ln\ expected\ audience - \epsilon$, where ϵ is the deviation from the logged expected audience. Therefore, $ln\ rate = \beta_1\ ln\ realized\ audience + \beta_1\epsilon + v$. If $cov(\epsilon, ln\ expected\ audience) = 0$, then $cov(\epsilon, ln\ realized\ audience) \neq 0$. 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 A.3 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 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., as previously estimated).

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. Their profit margins are close to zero since they do not have the mandate to maximize profit. The average revenues for for-profit Mediaset in 2002 and 2003 were 2.280 and 3.029 billion Euros, respectively. Advertising revenues were 2.112 and 2.848 billion Euros,

[28] 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%.

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 and conclusion

6.1 Television and cognition

Could viewers' persistent choice for the default channel be due to the hypnotic effect of television? The popular press (e.g. Scientific American, 2003) has claimed that television captures attention via frequent edits, inducing a hypnotic state of apathy, empty of cognition. This could, perhaps, curtail viewers' ability to actively choose.

The evidence from studies on television and cognition in adults, conducted mostly in the 1970s and 1980s, is mixed. Anderson and Burns (1990) reviewed this literature and concluded that, contrary to the popular press, "television viewing is a cognitively active behavior, sharing many characteristics of leisure time activities". They describe the limitations of popular studies. One such study (Krugman, 1971) compared electroencephalographic (EEG) activity of one subject exposed to television ads and magazine ads. Television generated a preponderance of slow waves – e.g. alpha frequencies – indicating low attention or involvement. Whereas reading showed high beta-wave activity, indicating higher mental effort. The conclusion that television content is processed in a mindless way, involving no cognition when compared to reading ensued. This study, however, comprised a single subject, limiting the generalizability of the findings. Weinstein et al. (1980) found that magazine ads generate more beta-wave activity than television ads, suggesting deeper mental processing when reading. However, subsequent research varying the content of television and reading materials (Radlick, 1980) found a reversal in the pattern of brain waves – higher mental processing when watching TV – when the content of television was more complex than that of books. Recent research (D. R. Anderson et al., 2000), using functional magnetic resonance imaging (fMRI), suggests that subjects' interpretation of montages of movies requires the coordinated activity of a large number of brain areas.

The evidence for children suggests they engage cognitively with television. In the above-mentioned review, Anderson and Burns (1990) conclude that, educational content "seems to educate in the manner intended (Bryant et al., 1983)". Violent content leads to more violent behavior (e.g. Bushman & Huesmann, 2001). And preschoolers' exposure to television has a positive effect on their later achievement (e.g. Gentzkow & Shapiro, 2008).

6.2 Conclusion

This paper shows that the persistent choice for the default option exists despite negligible switching costs, consumer experience and a limited choice set. It discusses the mechanisms underpinning this phenomenon, and its implications. It focuses on a particular application – the choice of television shows.

First, using a novel dataset of Italian television viewership between 1990-2003, it establishes the causal effect of demand of a show on its succeeding program. It does so by using an both an event-study exploring the appeal of shows to men and women, and OLS and IV estimation. The estimation addresses several threats to identification such as endogenous scheduling by channels, weather shocks, and reverse causality.

Second, it discusses and tests for mechanisms that could lead to this persistence, such as asymmetric information. The discussion between the two most compelling mechanisms – quasi-indifference between programs and quasi-hyperbolic preferences – is conducted in the context of a dynamic choice model with stochastic costs and the option value of switching channels. Quasi-hyperbolic preferences – leading consumers to continuously procrastinate switching the channel – are most consistent with the data.

Last, it shows that television channels respond strategically to viewer inertia: the prime-time line-up for Italian channels is close to optimal given viewer inertia. Ignoring viewer inertia in scheduling can affect 20-40% of channel's profits. In the United Kingdom, where the BBC is statutorily mandated to provide educational content, viewer inertia nudges viewers into consuming educational programs. BBC executives argue that popular but lowbrow programs increase the viewership of the less popular educational ones: *"[...] it is a revival of the old idea of hammocking difficult programs between entertainment[...]"*.[29]

Firms' behavior suggests that it is profitable to impose small costs for consumers to switch away from the default. Firms create a choice environment – "choice architecture" (Thaler & Sunstein, 2008) – to exploit procrastination. Automatic renewals with small cancellation costs, such as gym memberships and magazine subscriptions, are of no or low cost to firms. But they are a source of revenue from consumers that procrastinate canceling when faced with these small costs.

[29]Jana Bennet, BBC's director of Television, The Guardian, Media Section, February 2003; "hammocking" refers to scheduling a weak or new program between to popular ones, so that it inherits the audience of the preceding program and captures viewers tuning-in early to watch the succeeding program

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Figure 1: Typical Monday night line-up; Italy's 6 main channels are generalist with a broad range of genres

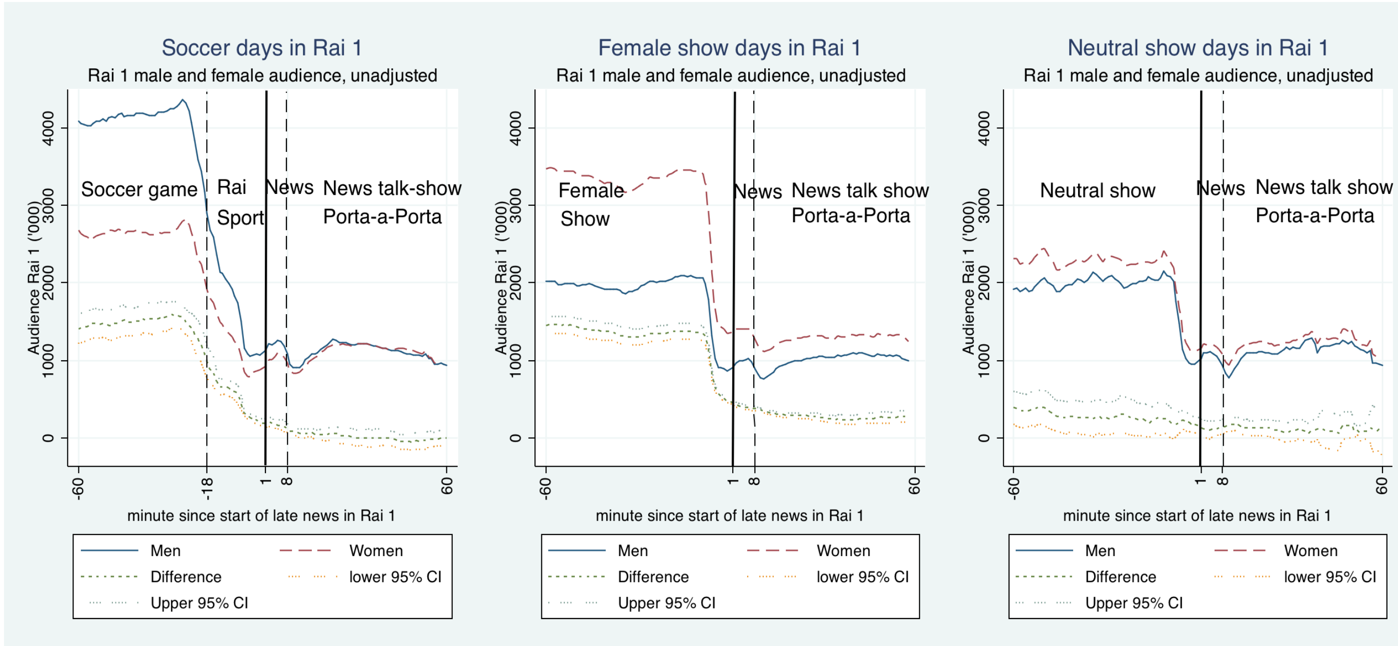
Date: Monday, October 7th, 2002

Starting at (PM): 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

Prime time: 8:00 PM to 11:00 PM

Channel									
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 show Sport sera	Varie-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 Rai 3	Sport Rai Sport	Varie-ty Blob di Tutto 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 Traveling in the time machine			

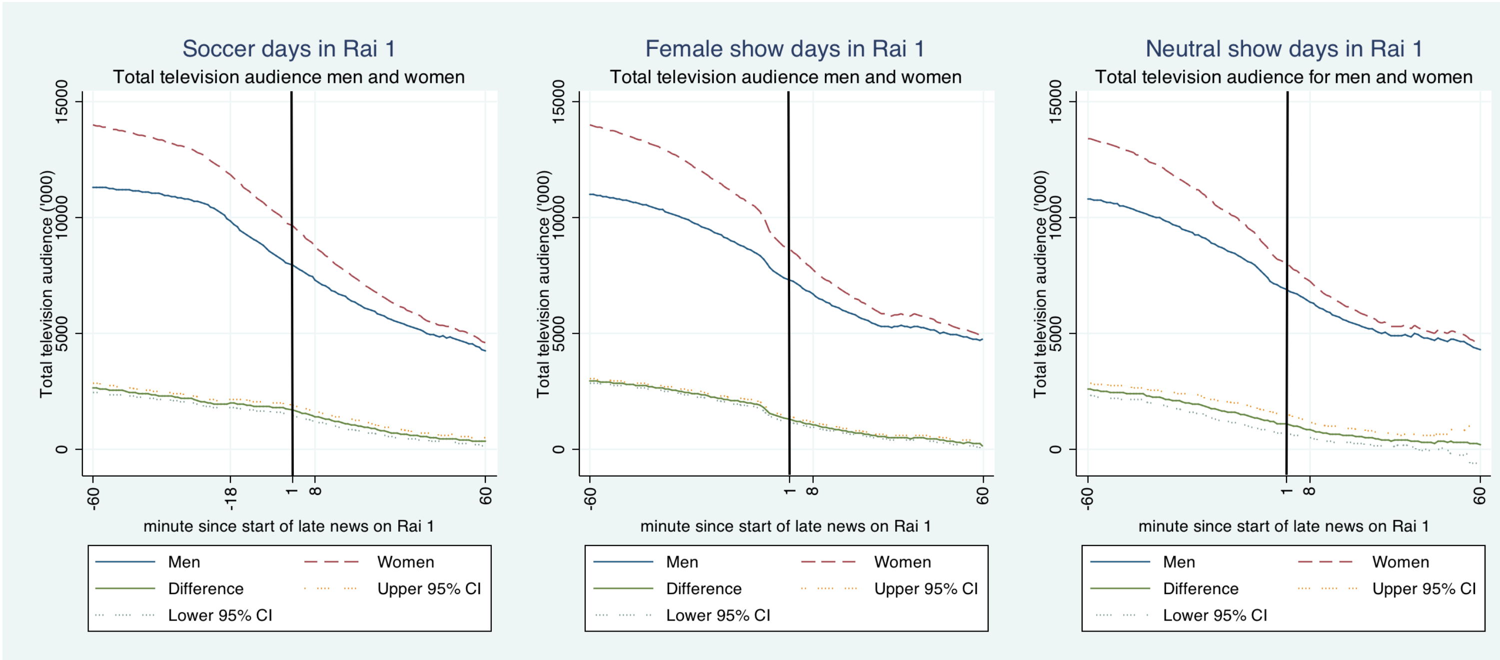
Figure 2: Unadjusted male and female viewership on Rai 1 on soccer days (left panel), female show days (middle panel) and neutral show days (right panel), 60 minutes before to 60 minutes after the event "start of the late news" on Rai 1



	SOCCER DAYS IN RAI 1 (N=16) Average viewership (millions)		FEMALE SHOW DAYS IN RAI 1 (N=127) Average viewership (millions)		NEUTRAL SHOW DAYS IN RAI 1 (N=12) Average viewership (millions)	
	Before the start of the late news (min -60 to min -1)	After the start of the late news (min 1 to min 60)	Before the start of the late news (min -60 to min -1)	After the start of the late news (min 1 to min 60)	Before the start of the late news (min -60 to min -1)	After the start of the late news (min 1 to min 60)
Men	3.41	1.12	1.88	0.98	1.91	1.09
	(0.20)	(0.05)	(0.05)	(0.03)	(0.13)	(0.06)
Women	2.21	1.09	3.18	1.29	2.18	1.21
	(0.07)	(0.06)	(0.00)	(0.03)	(0.00)	(0.07)
Difference	1.20	0.04	-1.29	-0.30	-0.27	-0.12
	(0.06)	(0.03)	(0.05)	(0.02)	(0.09)	(0.04)

The graph and table below summarize the audience for men and women for Rai 1 across the three types of days: soccer (16 days), female show (127 days) and neutral show days (12 days). The graph depicts the evolution of the audience of men and women, at each minute, one hour before and after the event "start of the late news in Rai 1": minutes -60 to 1 and 1 to 60, respectively, for the three types of days. The table shows the average viewership for men and women in Rai 1, one-hour before and one hour after the event "start of the late news in Rai 1" and their difference. Standard errors in the graph and table (in parentheses) are clustered by calendar day to account for the correlation between the audience of men and women across minutes of the day. The test of the equality of audience for men in soccer days and men in female show days is rejected both for the period before the late news (p-value of 0.000) and after the late news (p-value of 0.016). The test of equality of audience for women in soccer days and women in female show days is rejected both for the period before the late news (p-value of 0.000) and after the late news (p-value of 0.006).

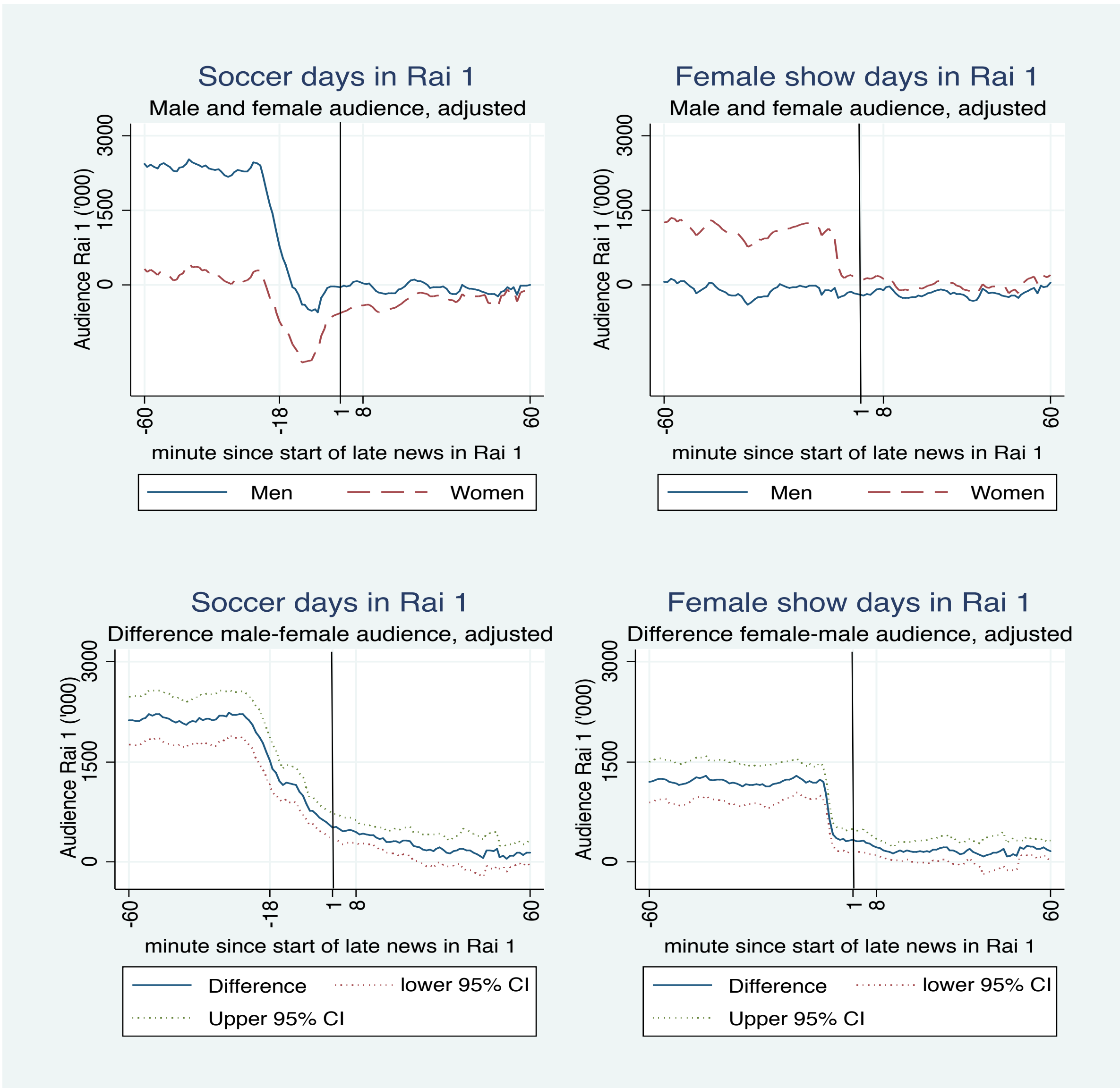
Figure 3: Total television viewership for men and women, on soccer days on Rai 1 (left panel), female show days on Rai 1 (middle panel) and neutral show days on Rai 1 (right panel), 60 minutes before to 60 minutes after the event "start of the late news" on Rai 1



	SOCCER DAYS IN RAI 1 (N=16) Average viewership (millions)		FEMALE SHOW DAYS IN RAI 1 (N=127) Average viewership (millions)		NEUTRAL SHOW DAYS IN RAI 1 (N=12) Average viewership (millions)	
	Before the start of the late news (min -60 to min -1)	After the start of the late news (min 1 to min 60)	Before the start of the late news (min -60 to min -1)	After the start of the late news (min 1 to min 60)	Before the start of the late news (min -60 to min -1)	After the start of the late news (min 1 to min 60)
Men	10.30	5.95	9.70	5.90	9.34	5.56
	(0.15)	(0.14)	(0.09)	(0.07)	(0.18)	(0.12)
Women	12.51	6.86	12.10	6.66	11.32	6.17
	(0.19)	(0.19)	(0.12)	(0.09)	(0.30)	(0.21)
Difference	-2.19	-0.90	-2.40	-0.76	-1.98	-0.61
	(0.08)	(0.07)	(0.05)	(0.04)	(0.15)	(0.13)

The graph and table below summarize the total television viewership (across all channels) for men and women across the three types of days in Rai 1: soccer (16 days), female show (127 days) and neutral show days (12 days). The graph depicts the evolution of the total television audience of men and women, at each minute, one hour before and after the event "start of the late news in Rai 1": minutes -60 to -1 and 1 to 60, respectively, for the three types of days. The table shows the average viewership for the total television audience of men and women, one-hour before and one hour after the event "start of the late news in Rai 1" and their difference. Standard errors in the graph and table (in parentheses) are clustered by calendar day to account for the correlation between the audience of men and women across minutes of the day. The test of the equality of the total television audience for men in soccer days and total television audience of men in female show days is rejected for the period before the late news (p-value of 0.001) but not for the period after the late news (p-value of 0.700). The test of equality of total television audience for women in soccer days and total television audience of women in female show days is not rejected both for the period before the late news (p-value of 0.067) and after the late news (p-value of 0.348).

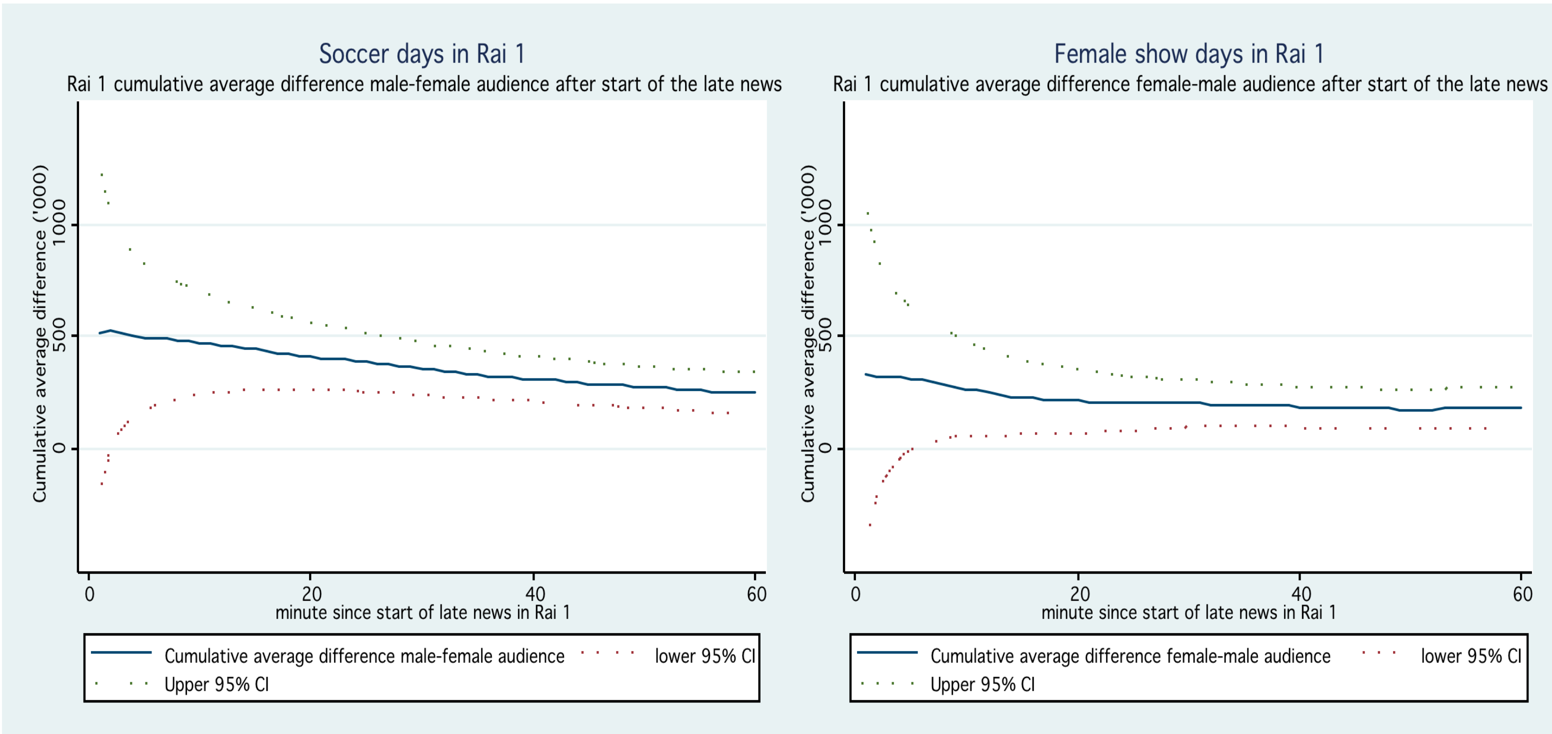
Figure 4: Adjusted male and female viewership on soccer days (left panel, plot of $\alpha_{2,\tau}$, $\beta_{2,\tau}$) and female show days (right panel, plot of $\alpha^0_{2,\tau}$, $\beta^0_{2,\tau}$), from 60 minutes before to 60 minutes after the event "start of the late news on Rai 1"; τ is the time since the start of the event.



The top left panel shows the adjusted male and female audiences on soccer days, before and after the event "start of the late news on Rai 1" - minutes (-60, -1) and (1,60), respectively. It adjusts the raw male and female audience for male and female audience in neutral show days and unobservable calendar dayXminute of the calendar dayX gender effects. The bottom left panel shows the difference between the adjusted male and female audiences and the 95% confidence interval around the difference. Standard errors are clustered by calendar day.

The top right panel shows the adjusted male and female audiences on female show days, before and after the event "start of the late news on Rai 1" - minutes (-60, -1) and (1,60), respectively. It adjusts the raw male and female audience for male and female audience in neutral show days and unobservable calendar dayXminute of the calendar dayX gender effects. The bottom right panel shows the difference between the adjusted female and male audiences and the 95% confidence interval around the difference. Standard errors are clustered by calendar day.

Figure 5: 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 on Rai 1"



The left panel shows the cumulative difference between the adjusted male and female audiences in the period after the event "start of the late news is Rai 1" - minutes (1, 60) - divided by the elapsed time since the start of the event. The 95% confidence interval around the difference is computed with standard errors clustered by calendar day.

The right panel shows the cumulative difference between the adjusted female and male audiences in the period after the event "start of the late news is Rai 1" - minutes (1, 60) - divided by the elapsed time since the start of the event. The 95% confidence interval around the difference is computed with standard errors clustered by calendar day.

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

Show genre	Description	Freq.	%	Average length minutes (minutes)	Average number of episodes per show
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 mysteries	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 e.g. 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

Time period: January 1st 2002-December 31st 2003	Total days	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
<u>Observations for analysis</u>			
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	12	11:16	11.4
Total number of days for analysis[(6)]	155		

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 where the male audience is higher than the female audience; this is the case with soccer; (4) Female show is a show where every episode has a 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 the male audience exceeds the female audience in some episodes but not in others (e.g. science show Superquark or Porta-a-Porta which air before the late news in Rai 1) and that last for at least one hour; (6) 57 observations removed from the analysis because only air once and therefore with no criteria to classify them as male show (soccer) or female show and an additional 41 observations removed because the duration of show before the late news is less than one hour.

Table 3: Test on whether female viewers persistence into the news on Rai 1 after a female show is sensitive to whether competing channel offer female shows

	Audience for Rai 1 after start of late news in Rai 1 (1, 60 minutes)	
	(1)	(2)
Constant	943.0	925.9
	(45.7)***	(39.7)***
Female (=1 if Female; =0 if Male)	304.7	305.7
	(17.9)***	(18.2)***
By competing number of channels showing female shows when the news on Rai 1 starts		
Above the median (=1 if two or more competing channels are showing female shows, = 0 otherwise)	6.9	
	(38.2)	
Female X Above the median	-10.5	
	(31.7)	
By competing number of channels starting female shows in the commercial break before the late news in Rai 1 or 5 minutes into the late news		
At least one channel (=1 if one or more competing channels start showing female shows during commercial break or 5 minutes into the news; =0 otherwise)		91.0
		(65.0)
Female X at least one channel		-23.0
		(46.4)
Day of the week dummies	Yes	Yes
N (calendar dayXminuteXgender observations)*	9,896	9,896
Number of clusters (calendar days)	127	127
Number of days with at least one competing channel showing a female show	51	18

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

*Note: (1,60) indicate the window, in minutes, from the start of the late news. Audience data ends at midnight. Therefore, for the days when the late night news in Rai 1 start after 11:00 p.m. there are fewer than 60 minute-observations to conduct the analysis. Hence the number of observations is 9896 instead of the potential 127x60x2=15240 observations.

Table 4: Summary statistics for main specifications

All shows				Movies followed by any show				Movie followed by news				Pre-main news show followed by main news show			
N=133,258				N=305				N=143				N=16,695			
Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Main variables															
Audience of prior show ('000)				Audience of movies ('000)				Audience of movies ('000)				Audience of pre-main news show ('000)			
2,434	1,881	44	23,543	1,890	717	519	6,284	2,051	777	662	6,284	3,875	2,459	219	13,989
Audience of current show ('000)				Audience of show after movies ('000)				Audience of news after movies ('000)				Audience of main news show ('000)			
2,374	1,812	55	23,543	5,693	2,155	1,225	16,080	5,991	2,352	1,540	16,080	2,267	1,486	122	7,392
Controls															
Index of competition on popularity for current show ('000)				Index of competition on popularity for show after movies ('000)				Index of competition on popularity for news after movies ('000)				Index of competition on popularity for main news show ('000)			
2,560	1,078	284	8,058	1,995	863	547	4,411	2,373	803	991	4,411	2,720	797	461	5,774
Genre overlap for current show				Genre overlap for show after movies				Genre overlap for news after movies				Genre overlap for main news show			
0.09	0.12	0.00	1.00	0.15	0.16	0.00	0.59	0.08	0.10	0.00	0.38	0.18	0.10	0.00	0.63
Other information															
Start time (P.M) for current show				Start time (P.M) for show after movies				Start time (P.M) for news after movies				Start time (P.M) for main news show			
-	-	-	-	10.59	18.76	10.46	11.56	10.54	15.60	10.25	11.28	7.32	37.04	6.25	8.42
Length of current show (minutes)				Length of show after movies (minutes)				Length of news after movies (minutes)				Length of main news show (minutes)			
35	32	3	276	44	44	3	128	11	6	3	32	32	7	20	60

Notes: does not include weekends

Table 5: 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 hour 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 Friends 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.

Table 6: 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)*	-
<u>1st stage: movie followed by news</u>						
Ln Theatrical audience movies (in millions)			0.062			0.060
			(0.011)***			(0.015)***
t-stat 1st stage			5.636			4.050
<u>Controls:</u>						
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 hour 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 7: 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					
Dependent variable:	Ln audience of news		Ln audience of show prior to news	Ln audience news below median length	Ln audience news above median length	Ln audience show after the main 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 the preceding month for 2SLS)	(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; [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 8: Effect of uncertainty about competing shows in column (1); Effect of information about the upcoming news at 8:00 PM in columns (2) and (3); Effect of competing shows starting in a 1 minute vicinity in column (4)

Sample:[1]	Main news shows, 1990-2003	Main news shows, 1998-2003	Main news shows 1990-2003			
Dependent variable:	Ln audience news	Ln audience news	Ln audience news Rai 1 and Canale 5	Ln audience news other channels (non Rai 1 and Canale 5)	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 the preceding month)	(0.028)***	(0.036)***	(0.037)***	(0.036)***	(0.028)***	(0.059)***
Demand of prior show X no shows starting in same minute vicinity					-0.007	
(In ln audience: Instrumented ln of average audience in the preceding month)					(0.004)	
Demand of prior show X Uncertainty about competing shows						(0.004)
(In ln audience: Instrumented ln of average audience in the preceding 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 hour 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

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

Panel A: 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**	5.981	**Two-hour programs**[(1)]	5.376
Half-hour variety show	s_2	**8:30-9:00**	7.133	1.965	1.407	**8:00 PM News**	7.502	**Half-hour variety show**	6.754
programs[(1)]	s_3	**9:00-11:00**	5.750	1.749	1.540	**Two-hour programs**[(1)]	5.780	**8:00 PM News**	7.632
Weighted average audience 8:00-11:00 PM			6.092	1.803			6.101		5.98
% Difference versus optimal schedule			0.1%						2.0%

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 (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**
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	5.981	1.540	5.376	1.540	5.376	1.407	5.981	1.463	6.422
s_j	1.407	7.133	1.463	7.502	1.463	7.256	1.407	6.754	1.540	5.669	1.540	5.712
s_k	1.540	5.750	1.540	5.780	1.407	7.265	1.463	7.632	1.463	7.242	1.407	6.762
Weighted average 8:00-11:00 PM		6.092		6.101		6.004		5.982		5.983		6.005

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. Program audiences are also adjusted for the average, for 2003, of total television audience during the time slot in which they play; variation in average total television audience across prime-time slots is no higher than 16%.

Panel B: 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**	4.567	**Two-hour programs[1]**	5.248
Half-hour variety show	s_2	**8:30-9:00**	5.319	1.671	1.091	**8:00 PM News**	7.149	**Half-hour variety show**	4.890
programs[1]	s_3	**9:00-11:00**	5.359	1.679	1.501	**Two-hour programs[1]**	5.530	**8:00 PM News**	7.155
Weighted average audience 8:00-11:00 PM			5.613				5.662		5.506
% Difference versus optimal schedule			0.9%						2.7%

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 (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**	**Implicit ln baseline audience**	**Audience with inertia (millions)**
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	4.567	1.501	5.248	1.501	5.248	1.091	4.567	1.495	6.924
s_j	1.091	5.319	1.495	7.149	1.495	7.325	1.091	4.890	1.501	5.297	1.501	5.536
s_k	1.501	5.359	1.501	5.530	1.091	5.334	1.495	7.155	1.495	7.329	1.091	4.904
Weighted average 8:00-11:00 PM		5.613		5.639		5.609		5.506		5.514		5.662

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. Program audiences are also adjusted for the average, for 2003, of total television audience during the time slot in which they play; variation in average total television audience across prime-time slots is no higher than 16%.

A Appendix figures and tables

Figure A.1: Robustness check on whether male and female audience of the 8:00 PM news on Rai 1 on soccer, female and neutral show days is different. The graph below shows they are not different.

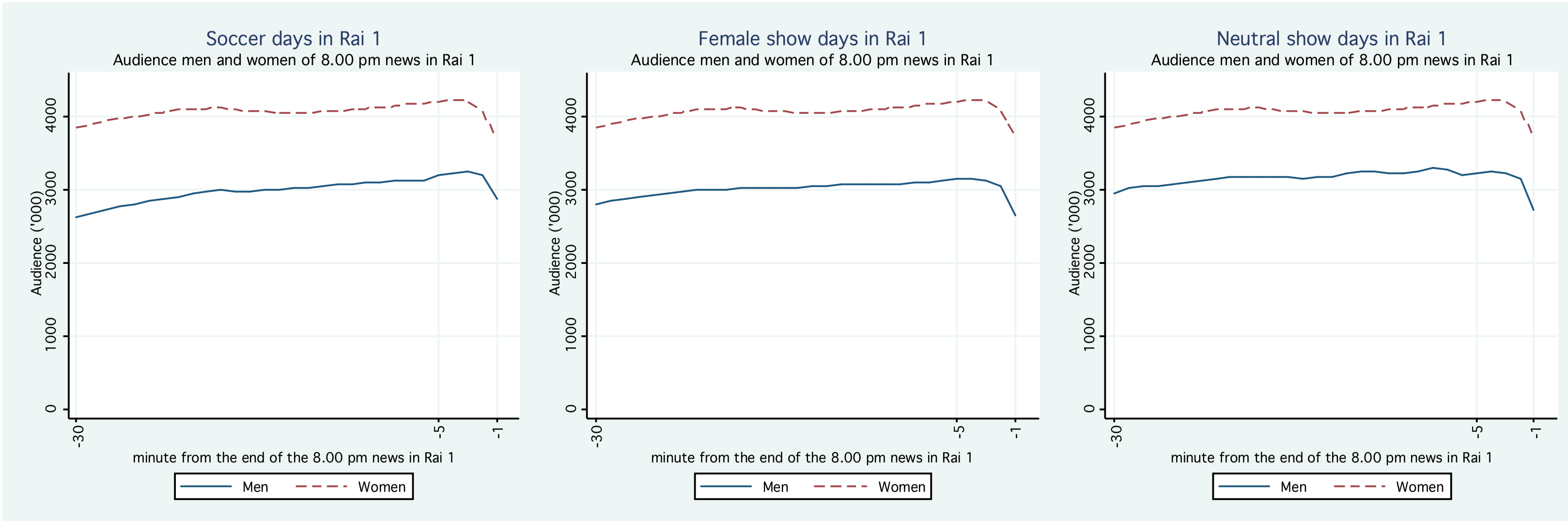


Figure A.2: Plot of audiences of consecutive shows on the same channel. Left panel: 8:00 PM news in Canale 5 preceded by Wheel of Fortune game-show. Right panel: Hitchcock Presents on Rai 1 preceded by movies

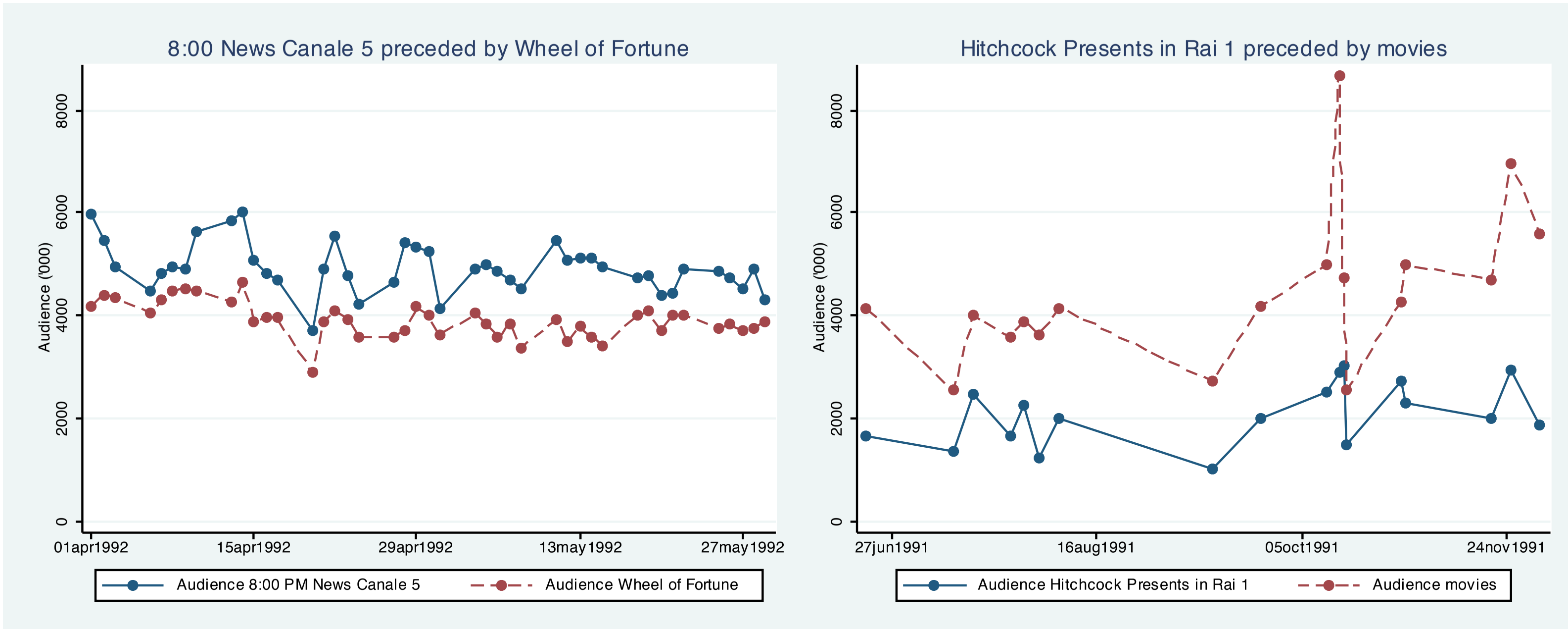


Figure A.3: Relationship between the rate for a 30" commercial and the monthly audience in prime-time, for flagship Canale 5, 2002-2003

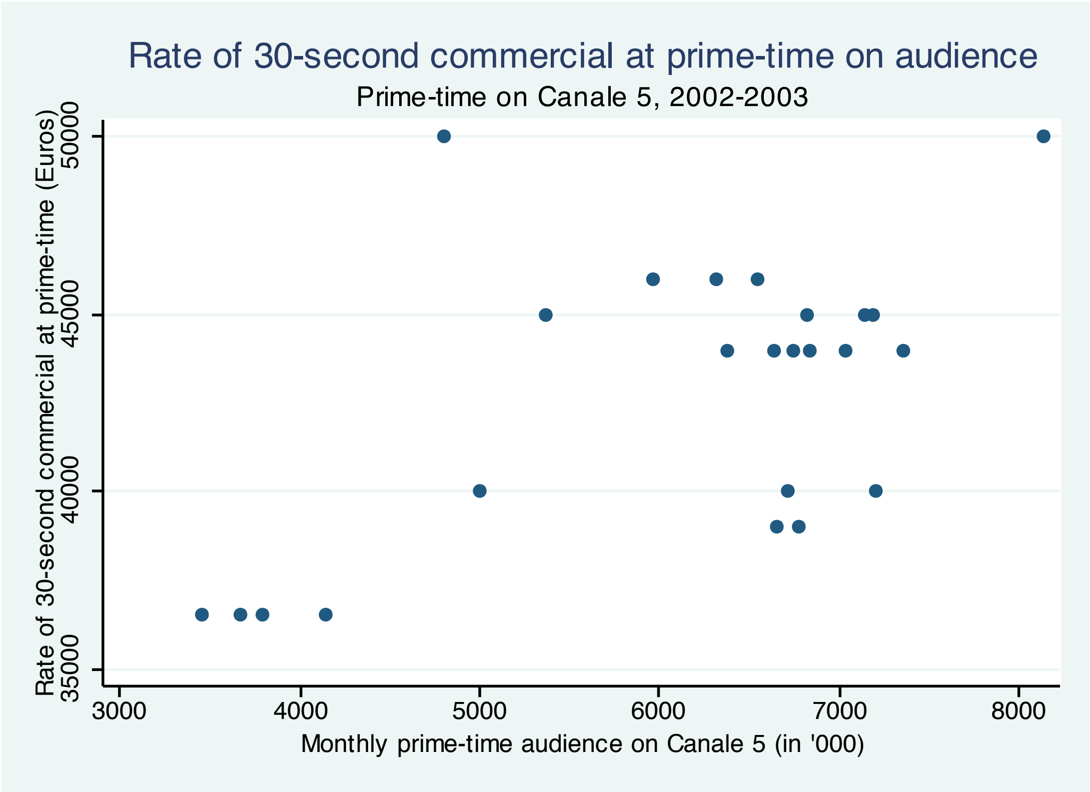


Table A.1: Backup the graphical analysis in Figure 4 on soccer days (left panel of Figure 4) and female show days (right panel of figure 4). Panel A shows the male and female average audience before and after the start of the late news on Rai 1 on soccer days. Panel B shows the male and female average audience before and after the start of the late news on Rai 1 on female show days. Estimates are adjusted for the audience on neutral show days and for unobservable time invariant shocks by calendar day-minuteX minute of the calendar dayXgender.

Panel A: Soccer days

	Male and Female Audience in Soccer days in Rai 1 Adjusted for Male and Female Audience in Neutral Show Days in Rai 1			
	Before the start of late news in Rai 1: (-60, -1)		After the start of late news in Rai 1: (1, 60)	
	(1)	(2)	(3)	(4)
Constant	1,910 (132)***	-	1,088 (63)***	-
Rai 1 x Male	-	679 (170)***	-	392 (72)***
Rai 1 x Soccer x Male	1,497 (242)***	1,560 (294)***	38 (83)	-17 (100)
Female	273 (92)	-	118 (44)***	-
Rai 1 x Female	-	583 (131)***	-	375 (82)***
Rai 1 x Soccer x Female	28 (187)	-226 (222)	-116 (100)	-269 (126)**
Rai 1 x Soccer x Male - - Rai 1 x Soccer x Female	1,469 (113)***	1,787 (145)***	154 (55)***	252 (81)***
Gender x Calendar day x Minute of Calendar day Fixed effects	No	Yes	No	Yes
Augmented sample	No	Yes	No	Yes
N (Number of Gender x Channel x x Calendar day x Minute observations)	3,360	2,804	20,160	16,864
Today number of days	28	28	28	28
Number of channels	1	6	1	6

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

Note: Audience in thousands of viewers; (-60,-1) and (1,60) indicate the window, in minutes, from the start of the late news: (-60,-1) is the hour before start of the news and (1,60) is the hour after the start of the news. [1] Augmented sample consists of all six channels, instead of just Rai 1; Number of observations after the start of the late news is lower than the number of observations before the start of the late news because audience measurements end at midnight and the late news in Rai 1 may start after 11:00 PM. Does not include weekends. The coefficient for column (4) would have been a statistically significant 354 if we were considering the window (1,30): time up to 30 minutes after the start of the late news.

Panel B: Female Show days

	Male and Female Audience in Female Show days in Rai 1 Adjusted for Male and Female Audience in Neutral Show Days in Rai 1			
	Before the start of late news in Rai 1: (-60, -1)		After the start of late news in Rai 1: (1, 60)	
	(1)	(2)	(3)	(4)
Constant	1,910	-	1,088	-
	(130)***		(61)***	
Rai 1 x Male	-	679	-	392
		(167)		(71)***
Rai 1 x Female Show x Male	-25	-104	-107	-180
	(140)	(182)	(66)	(76)**
Female	273	-	118	-
	(90)		(43)***	
Rai 1 x Female	-	583	-	374
		(129)***		(81)***
Rai 1 x Female Show x Female	993	1,015	81	6
	(132)	(157)***	(80)	(90)
Rai 1 x Female Show x Female - - Rai 1 x Female Show x Male	1,019	1,119	188	186
	(102)***	(128)***	(46)***	(64)***
Gender x Calendar day x Minute of Calendar day Fixed effects	No	Yes	No	Yes
Augmented sample(1)	No	Yes	No	Yes
N (Number of Gender x Channel x x Calendar day x Minute observations)	16,680	100,080	11,732	70,392
Today number of days	139	139	139	139
Number of channels	1	6	1	6

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

Note: Audience in thousands of viewers; (-60,-1) and (1,60) indicate the window, in minutes, from the start of the late news: (-60,-1) is the hour before start of the news and (1,60) is the hour after the start of the news. (1) Augmented sample consists of all six channels, instead of just Rai 1; Number of observations after the start of the late news is lower than the number of observations before the start of the late news because audience measurements end at midnight and the late news in Rai 1 may start after 11:00 PM. Does not include weekends. The coefficient for column (4) would have been a statistically significant 200 if we were considering the window (1,30): time up to 30 minutes after the start of the late news.

Table A.2: Topics of Porta-a-Porta talk-show on soccer days, female show days and neutral show days on Rai 1

Soccer days (N=16, all days)	**Female show days (N=16, random sample of 127 days)**	**Neutral show days (N=12, all days)**
The hunt for Osama Bin Laden and Mullah Omar	Program on famous Italian film producer and politician	Interview with television personality
The new custody law for children of separated parents	Corruption and politics	Love, loneliness and other issues for the elderly
No description	The effects of power and who rules the home, men or women?	Domestic and workplace violence
Crisis in Argentina, what it means for its Italian population	Euthanasia	Discussion of the elections
Mad Cow disease	Interview with the current prime-minister, Silvio Berlusconi	Not available
The unsolved mystery of who killed little Samuel	Love and war: reporters that die while covering war zones	The U.S. attack on Iraq
Anti-obesity drugs and dieting	Interview with the president of Democrats for the Left	Not available
Pope John XXIII, his life and works	The crisis of Fiat and the economic policies of the Government	Reform of pensions and labor markets
Not available	Interview with the Minister for the Economy	A review of pope John Paul II
Prostitution and its links to celebrities	The radical group that tried to derail the G8 summit	How do single people live in Italy
Interview with high-level political personality	Discussion of the prostitution law	The arts of seduction
Discussion on new law to increase labor market flexibility	Whether television should be regulated to protect children	India and its progress
Not available	The UN security council reaction to George Bush's Iraq ultimatum	
Law that forbids smoke in offices	The return of the exiled Savoy royal family to Italy	
Not available	Not available	
Broadcasting reform law	The soul and life after death	

Source: Porta-a-Porta archive at Rai 1 (2002-2003)

The gender earnings gap for physicians and its increase over time

Abstract

Background: Studies comparing earnings of male and female physicians have traditionally shown that male physicians earn more than female physicians with similar characteristics. Recent research using data from 1990 (Baker, 1996, in the New England Journal of Medicine) has suggested, however, that the gap in earnings between male and female physicians at the onset of their careers has disappeared (Baker, 1996, New England Journal of Medicine), hailing a new era of equal gender pay. Whether the gap in pay increases as physicians age is unknown.

Materials and Methods: We analyze four rounds of the Community Tracking Study Physician Survey from 1997 to 2005. They cover representative samples of the U.S. physician population. We estimate the gap in earnings between male and female doctors using regression analysis adjusting for several physician characteristics.

Results: Male physicians earn on average 23% more than female physicians (95 percent confidence interval, 21% to 25%), after adjusting for several physician characteristics. The adjusted earnings gap for young physicians (at most 40 years old with 2-5 years of experience) is significantly lower at 13% higher pay for men (95 percent confidence interval, 9% to 17%). For the cohort of physicians between the ages of 30-37 in 1997, the adjusted earnings gap is 13% higher pay for men (95 percent confidence interval, 7% to 19%). The adjusted earnings gap for this cohort, however, grows to 28% eight years later (95 percent confidence interval, 22% to 34%). Older cohorts of physicians in 1997 show no change in their adjusted earnings gap eight years later.

Conclusions: Even at the onset of their careers male physicians earn more than their female counterparts. Moreover, as physicians age from their thirties into their forties, the gap in pay between male and female physicians more than more than doubles, stabilizing thereafter.

1 Introduction

A large number of studies over the past thirty years have documented a statistically and economically significant earnings premium of male physicians relative to female physicians with similar characteristics.[1−10] An earnings gap persists despite adjusting for factors that could explain it, such as women selecting into lower paying specialties than men.

Recent research, using physician earnings data from 1990 (Baker, 1996) has found, however, that the gender earnings gap has disappeared for physicians at the early stages of their careers physicians at most 40 years old with 2-5 years of experience. We will henceforth label these physicians as young physicians.[11] This raises two questions regarding the current state of the profession: (i) Do we still observe equal pay for men and women in recent samples of young physicians, confirming the pay equalization trend identified by Baker? (ii) Does pay remain equal across genders as young physicians age? This study addresses these questions using a multi-year survey of physicians between 1997-2005.

2 Materials and methods

We use data from the Community Tracking Study Physician Survey, which covers four survey rounds 1997,[14] 1998,[15] 2001,[16] and 2005.[17] This survey was conducted via telephone by the Center for Studying Health System Change and was sponsored by the Robert Wood Johnson Foundation. The core group of physicians interviewed originated from a set of 51 randomly selected metropolitan and 9 non-metropolitan areas. Physicians provided patient care for more than 20 hours a week, and could not be federal employees, fellows, or residents. The sample design used stratification, clustering and oversampling. The survey documentation includes variables and instructions to account the sample design when estimating the statistics of interest. In each year, the total number of completed interviews was approximately 12,000, except in 2005 when the sample included 6,000 completed interviews. The response rate was 65.4% in 1997, 60.9% in 1999, 58.6% in 2001, and 52.4% in 2005.

The survey covered physicians earnings, hours and weeks worked, demographics, practice setting, specialty, and geographic location. Practice settings were coded as solo practice, group practice partial owner, group practice employee, HMO employee, hospital employee, free standing clinic employee, medical school employee, government employee, or other. The survey focused on major specialties, which we grouped into Family Practice, Internal Medicine, Pediatrics, Psychiatry, General Surgery, Ophthalmology, Orthopedic Surgery, Cardiology, Obstetrics, Emergency Medicine, Dermatology and Other.

We excluded from the sample physicians who worked less than an average of 20 hours a week in the survey year, worked less than 26 weeks, earned less than $10 an hour, or resided but did not practice in one of the 60 sites 51 metropolitan and 9 non-metropolitan covered in the survey.

We used ordinary least squares to estimate the effect of gender on earnings. The earnings measure is yearly physician earnings. We regressed the logarithm of yearly earnings on a binary (1-0) gender variable equaling one if the physician is male and zero if the physician is female. The coefficient on this binary gender variable can be interpreted as a lower bound on the estimate of the percent difference in male earnings versus female earnings.[18,9] We further adjusted the estimate of gender on earnings by several factors: (i) yearly hours worked because we want to compare the earnings of men and women that work the same number of hours, (ii) specialty and practice setting because male and female physicians may select into them at different rates, (iii) year of the survey and for the metropolitan area where the physician practices, to account for differences in pay across years and across metropolitan areas for male and female physicians, (iv) age and experience quadratics to control for non-linear age and experience effects.

We conducted the analysis in Sudaan 10. Sudaan 10 is the only software that takes into account the complex design of the survey when estimating the variance of the estimated coefficients. Correct estimation of the average percent difference in male earnings relative to female earnings would require that we adjust the coefficient of the binary gender variable by its variance,[18,9] which, in our case, would increase the magnitude of the male wage premium. However, the variance of this new estimate the coefficient on the binary variable adjusted by its own variance can only be estimated by sample bootstrapping taking into account the complex design. This is beyond Sudaan's current capabilities. By foregoing the adjustment on the coefficient on the binary gender variable, the average male wage premium estimated in this paper is a lower bound of the true premium. Therefore, our results conservatively understate how much male physicians earn relative to their female counterparts.

3 Results

Table 1 presents summary statistics of the sample 24,718 male physicians, which correspond to a representative sample of 999,329 male physicians. As well as a sample of 7,747 female physicians, which correspond to a representative sample of 269,314 female physicians. Average yearly earnings are approximately 49% higher for male physicians. Female physicians are more likely to work in Pediatrics, Psychiatry, and Obstetrics. Female physicians are less likely to be part-owner in a group practice and more likely to be employees. They are also almost five years younger and five years less experienced than male physicians. Table 1 also presents summary statistics for a representative sample of 95,477 young male physicians and 44,935 young female physicians. Average yearly earnings are approximately 39% higher for young male physicians.

Table 2 shows how the earnings premium of male physicians changes as we adjust for factors that could be creating it. We pool the whole sample of physicians across the four survey years. In column (1) we find that men earn, on average 40% more than women. This estimate is lower than 49% mentioned in the preceding paragraph because, as we discussed previously, our specification conservatively underestimates the male wage premium. In column (2) we adjust for hours worked, which reduces the earnings gap to 33%. Since male physicians work, on average, about 8 more hours per week than female physicians, part of the gender earnings gap is explained by men working more hours. In column, (3) we adjust for the year the survey was taken, which does not change the estimates. In column (4) we adjust for specialty to account for differences in earnings potential across specialties that men and women chose. This lowers the male earnings premium to 26%. In column (5) we adjust for practice setting, which lowers the male earnings premium slightly to 24%. The analysis in columns (6)-(8) adjusts for the area where physicians practice, their age and experience and other characteristics, to address systematic differences across male and female physicians along these dimensions. The inclusion of this last set of variables leaves the estimated male earnings premium almost unchanged. Column (8) shows a stable 23% earnings gap after all the adjustments.

In column (9) we analyze the earnings gap for young physicians only, using the full set of controls. For this sample of young doctors, the male earnings premium decreases to 13%, significantly less than the 23% for the entire population in column (8). These magnitudes hold not only when aggregating all four survey years 1997, 1998, 2001 and 2005 but also when analyzing each survey year individually. The analyses for each individual year are not reported but are available upon request.

In columns (10)-(13) we investigate how the earnings gap varies with specialty for young physicians. We focus on four specialties that tend to aggregate most male (42%) and female (68%) young doctors: Family or General Practice, Internal Medicine, Pediatrics, and Obstetrics and Gynecology. We find a significant earnings gap of 10% in Family and General Practice, 12% in Internal Medicine and 8% in Pediatrics. In Obstetrics and Gynecology, however, the male wage premium in not significantly different from zero.

Table (3) shows the evolution of the male earnings premium for a cohort of physicians as they age. We grouped physicians by 8-year cohorts since the time between the first survey and the last survey is 8 years (1997 and 2005, respectively). Column (1) shows that the male earnings premium for physicians aged between 30-37 years old in 1997 is 13%. Column (2) shows that this gap more than doubles to 28% in the ensuing 8 years when the cohorts age increases to 38-45 years old. No such increase in the male premium as physicians age is found for older cohorts of doctors. Specifically, columns (3)-(4) show that the 23% earnings gap for physicians between the ages of 38-45 in 1997 is not statistically different from that 8 years later, when they reach 46-53 years of age. Likewise columns (5)-(6) show that the 26% earnings gap for physicians between the ages of 46-53 in 1997 does not grow in 2005, when they reach 54-61 years of age.

4 Discussion

Contrary to recent research documenting the equalization of earnings between young male and female physicians, we find a persistent gender gap in pay despite controlling for many confounding factors. Moreover, this gap increases as physicians age. Specifically, our study finds that (i) young (40 or less years of age with 2-5 years of experience) male physicians earn on average 13% more than female physicians when pooling all young physicians surveyed between 1997 to 2005, (ii) male physicians aged 30-37 in 1997 earn

13% more than their female counterparts but eight years later, when aged 37-45 years, are earning 28% more. Though some confounding factors such as hours worked and specialty explain part of the male wage premium, a large portion remains unexplained.

A range of different mechanisms could explain why male physicians earn more than female physicians at the early stages of their careers and why this gap increases with time. First, female physicians may be more likely, early on and throughout their careers, to engage in activities where pay is lower in exchange for more flexible schedules to care for dependents, such as children. If, in contrast, their male counterparts pursue increasingly higher paying activities, this could explain the initial and growing gender wage gap. Second, caring for children may also lead female doctors to reduce their labor force participation, depreciating their skills relative to those of their male counterparts. This may cause female doctors to earn less than male doctors when they fully return to the labor force, generating the widening of the wage gap. Third, women may be less willing to negotiate for higher salaries than their male counterparts when starting and throughout their careers. Fourth, female physicians may be subject to discrimination both at the onset of their careers and when vying for higher-paying practice management positions later in life.

This study differs from recent research in significant ways. Baker (1996)[11] using data from 1990, found no statistically significant earnings gap between young male and female physicians after adjusting for specialty and practice setting. In contrast, our study, covering 1997 through 2005, finds a statistically and economically significant earnings gap for this group, after adjusting for these variables and many others.

The main reason for the difference between our results and Baker's is due to the definition of the earnings variable. Bakers study uses the log of hourly earnings the log of the ratio of yearly earnings to hours worked as the dependent variable. Our study uses a more flexible specification using the log of yearly earnings as the dependent variable and subsequently adjusting for the log of hours worked. Bashaw and Heywood[12] replicated Baker's paper and also found that Baker's specification using the log of hourly earnings was too restrictive, concealing the pay differential between men and women. Baker's specification assumes that the relationship between physician earnings and hours worked is one-to-one, that is a 1% increase in hours worked leads to a 1% increase in earnings. In reality, the increase in earnings for an extra hour of work diminishes as men and women work more hours. The coefficient on the logarithm of hours worked, ranging from 0.2-0.4 indicates that a n increase in 1% increase in hours worked only increases earnings by 0.2%-0.4%. As shown in Figure 1, for every category of hours worked per week 20-40, 40-60, 60-80, and more than 80 hours per week men earn more per hour than women, though average hourly earnings decline as both work more hours. However, more women than men work fewer hours per week. Specifically, most women work 20-40 and 40-60 hours per week whereas most men work 40-60 and 60-80 hours per week. Therefore, more women than men are at the higher earnings per hour range. Hence, women's average hourly earnings for the whole sample approaches that of men, masking the existing pay differential, which exists for all levels of hours worked.

Our more flexible specification, which does not force the relationship between earnings and hours worked to be one-to-one, accounts for the re-emergence of the earnings gap for young physicians in 1997-2005 vis-à-vis 1990. Using a similar specification to ours, Reyes[13] found, however, no gender earnings gap for young Obstetricians and Gynecologists. We also find this result. The demand for female physicians is, however, plausibly higher than that for male physicians for Obstetrics and Gynecology, especially when compared to the demand for male and female doctors in other specialties. It could account for the absence of the gender gap in pay in Obstetrics and Gynecology.

Our study does concur with of one of Baker's (1996) key findings: that the gender earnings gap exists for older physicians. This raises the important issue of structural changes in the environment and their influence on physicians earnings. An open question from Bakers paper was whether the existence of the wage gap for older physicians physicians with at least 10 years of experience but not for young physicians stemmed shifts in the environment in favor of female physicians. For example, older cohorts may have operated in an environment with more discrimination towards female physicians, less patient willingness to consult female doctors, and differential quality in medical education. This environment could have changed over time to become more hospitable to female physicians over time, leading to a permanent disappearance or narrowing of the wage gap at early stages of physicians careers and its stability thereafter. Our evidence for 1997-2005, however, shows that the gap on earnings exists for young doctor cohorts and widens as they age. Therefore, if these structural shifts in the environment have occurred they have not been sufficient to offset the effects of other mechanisms discussed previously e.g. differential responses by male and female doctors to the care of dependents that generate the existing wage gap between young male and female physicians and its widening over time.

Further work should focus on developing a deeper understanding of the mechanisms that create the gender earnings gap among physicians. This study suggests that studying differential responses to the care of dependents, negotiation patterns and discrimination could be explanations for the significant pay differences between male and female physicians both at the early and later stages of their careers.

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Table 1: Summary statistics for whole sample of physicians and "young" physicians, by gender - 1997-2005

	Male Physicians	Female Physicians	Male Physicians 40 or Younger with 2-5 years of experience	Female Physicians 40 or Younger with 2-5 years of experience
Average Yearly Income	199,637	133,863	166,440	119,571
Average Weeks Worked per Year	48	47	48	46
Average Hours Worked Per Week	57	49	59	50
Total Hours Worked per Year	2,719	2,310	2,836	2,328
Specialty				
Percentage in Family or General Practice	15%	16%	13%	16%
Percentage in Internal Medicine	14%	16%	17%	22%
Percentage in Pediatrics	7%	20%	6%	20%
Percentage in Psychiatry	6%	9%	3%	4%
Percentage in OB/GYN	6%	9%	6%	10%
Percentage in General Surgery	5%	2%	4%	2%
Percentage in Ophthalmology	5%	2%	3%	2%
Percentage in Orthopedic Surgery	5%	1%	3%	0%
Percentage in Emergency Medicine	5%	4%	7%	3%
Percentage in Cardiology	4%	1%	4%	1%
Percentage in Dermatology	2%	3%	1%	3%
Percentage in Other Specialty*	26%	17%	33%	17%
Practice setting				
Solo Practice	28%	20%	11%	9%
Group Practice Part Owner	33%	20%	29%	13%
Group Practice Employee	7%	11%	17%	18%
HMO Employee	4%	7%	5%	6%
Hospital Employee	9%	12%	9%	16%
Free Standing Clinic Employee	2%	3%	2%	4%
Medical School Employee	8%	11%	12%	12%
Government Employee	2%	4%	2%	4%
Other Practice Setting	8%	12%	13%	18%
Age	49.98	45.21	35.68	35.04
Experience	17.65	12.4	3.54	3.48
Total Raw Observations	24,718	7,747	2,452	1,448
Total Weighted Observations (Representative Sample)	999,329	269,314	95,477	44,935

*Other specialties, not detailed because they represent 2% or less of male and female doctors, include: Urology Dermatology, Gastroenterology, Otolaryngology, Neurology, Pulmonary Diseases, Plastic surgery, Medical Oncology, Physical medicine and Rehabilitation, Nephrology, Occupational Medicine, Allergy & Immunology, Infectious diseases, Neurosurgery and Other Specialties

Note: Summary statistics created using survey weights in Sudaan. The standard errors are extremely small.

Table 2: Earnings premium of male physicians versus female physicians, 1997-2005. Columns (1) through (8) show how the male wage premium for all physicians changes with progressive adjustments. Column (9) shows the male wage premium just for young physicians with all the adjustments. Columns (10)-(14) show the male wage premiums for young physicians by major specialty, also including all the adjustments.

Dependent variable:	Log (Yearly Income)									Log (Yearly Income)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Male[1]	.40 (.01)***	.33 (.01)***	.33 (.01)***	.26 (.01)***	.24 (.01)***	.23 (.01)***	.23 (.01)***	.23 (.01)***	.13 (.02)***	.10 (.02)***	.12 (.02)***	.08 (.03)**	.02 (.05)
Log (Yearly Hours Worked)	-	.41 (.02)***	.43 (.02)***	.35 (.02)***	.34 (.02)***	.33 (.02)***	.29 (.02)***	.29 (.02)***	.28 (.04)***	0.34 (0.04)***	0.30 (0.04)***	0.21 (0.06)***	0.19 (0.08)**
Year Adjustment	-	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-	-
Specialty Adjustment	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Practice Setting Adjustment	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Practice Location Adjustment	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age and Experience Quadratic	-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other adjustments[2]		-	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All Physicians								Physicians 40 Years Old and Younger with 2-5 years of experience	Family or General Practice	Internal Medicine	Pediatrics	OB/GYN
										Physicians 40 Years Old and Younger with 2-5 years of experience			
R-squared	0.10	0.15	0.17	0.31	0.35	0.37	0.39	0.40	0.48	0.49	0.39	0.38	0.65
Raw Observations	32,465	32,348	32,348	32,348	32,348	32,348	32,348	32,348	3,900	746	1,070	628	178
Total Weighted Observations (Representative Sample)	1,268,643	1,264,268	1,264,268	1,264,268	1,264,268	1,264,268	1,264,268	1,264,268	140,411	19,494	26,028	15,101	10,618

[1] Denotes the coefficient on the binary variable Male: Male=1 if the physician is male and Male=0 if the physician is female. The coefficient on male multiplied by 100% represents a lower bound on the percent amount by which earnings of male physicians exceed those of female physicians.

(2) Includes region of physicians' medical school (US, Canada, Puerto Rico or Other) and whether physician is a primary care physician

Note: * significant at 10% confidence level, ** significant at 5% confidence level, *** significant at 1% confidence level. Observations change from column (1) to (2) because of a small number of missing observations for hours worked

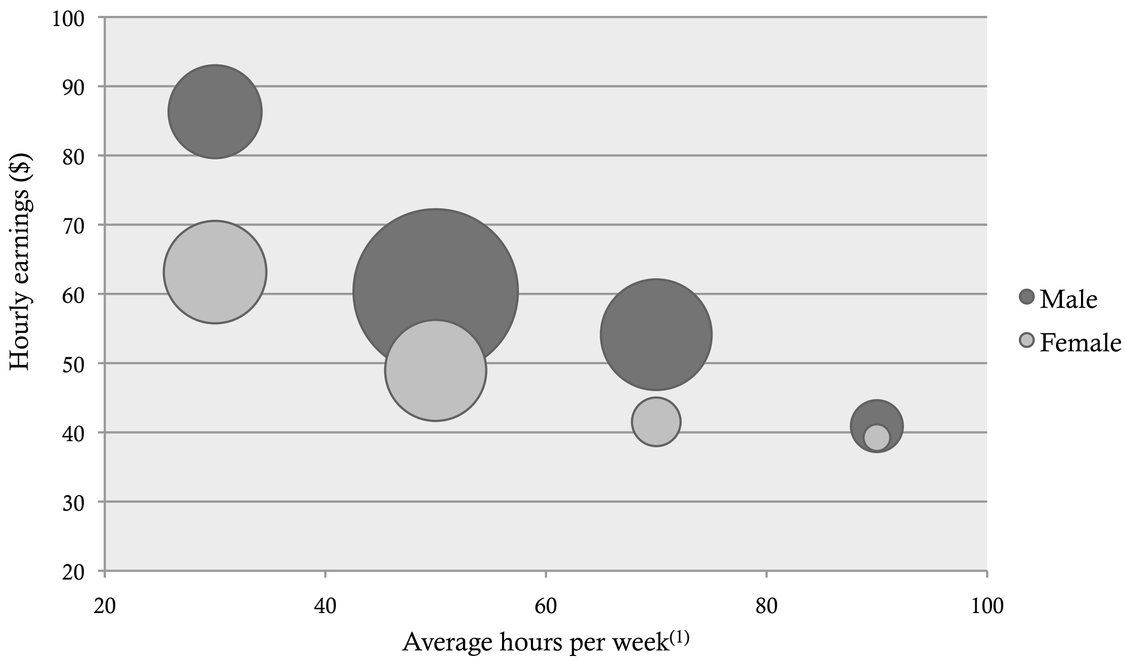
Table 3: Evolution of the male physician earnings premium between 1997-2005 — by age cohort of physicians.

Dependent variable:	Log(Yearly Income)					
	(1)	(2)	(1)	(2)	(1)	(2)
Male[(1)]	.13 (.03)***	.28 (.03)***	.23 (.02)***	.25 (.04)***	.26 (.03)***	.26 (.03)***
Year	1997	2005	1997	2005	1997	2005
Log (Yearly Hours Worked)	.29 (.04)***	.24 (.05)***	.31 (.03)***	.33 (.07)***	.27 (.03)***	.28 (.05)***
Sample	Physicians Between 30 & 37 in 1997	Physicians Between 38 & 45 in 2005	Physicians Between 38 & 45 in 1997	Physicians Between 46 & 53 in 2005	Physicians Between 46 & 53 in 1997	Physicians Between 54 & 61 in 2005
R-squared	0.51	0.57	0.46	0.46	0.39	0.49
Raw Observations	1,141	1,112	3,133	1,371	2,596	1,018
Total Weighted Observations (Representative Sample)	31,964	74,390	101,412	100,810	85,726	68,798

(1) Denotes the coefficient on the binary variable Male: Male=1 if the physician is male and Male=0 if the physician is female. The coefficient on male multiplied by 100% represents a lower bound on the percent amount by which earnings of male physicians exceed those of female physicians. This estimate is adjusted for the full set of controls: log of yearly hours worked, specialty, practice setting, practice location, age and experience quadratics and other adjustments such as the region of the physician's medical school and whether the physician is a primary care physician.

* significant at 10% confidence level, ** significant at 5% confidence level, *** significant at 1% confidence level

Figure 1: Number of "young" male and female physicians working 20-40, 40-60, 60-80, and more than 80 hours per week, and respective hourly earnings at each of these hours-per-week ranges. The size of bubble represents the number of "young" physicians (male in black and female in grey) working at each bracket of hours worked per week: 20-40, 40-60, 60-80 and more than 80 hours per week. For any bracket of hours-per-week men earn more per hour than women, on average (center of the each ball). A higher proportion of women work 20-40 and 40-60 hours per week, whereas a higher proportion of men work 40-60 and 60-80 hours per week.



Note: (1)Average hours per week=total hours per year divided by 52 weeks