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The Weekend Effect in Television Viewership and Prime-Time Scheduling

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Abstract The observed drops in the ratings of television programs on Fridays and Saturdays are likely a result of two factors: intrinsic contraction in demand for television watching and endogenous scheduling. I decompose the observed weekend effect into the effects from these two factors. To this end, I estimate a viewer choice model that uses aggregate Nielsen ratings data for prime-time network television shows over 11 years. The long span of the data enables me to control for television series qualities. The estimation results reveal that the estimated weekend effect is dampened as the empirical model accounts for variation in the program quality compositions. The counterfactual analysis that is based on the estimates of the preferred specification indicates that endogenous scheduling accounts for two-thirds of the rating drops on weekends.

Keywords Day-of-the-week effect · Prime-time television · Discrete choice model · Optimal scheduling

JEL Classification L82 · D22

1 Introduction

Periodic or cyclic variation, also known as seasonality, is nothing new to many time series variables. Retail sales in the US peak during the Thanksgiving and Christmas season. Movie ticket sales peak in summer, generating July's box-office that, on average, is twice as big as January's. Stock market returns tend to be larger on

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Fridays than Mondays. In this paper, I study the periodic variation in prime-time television viewership.

One stylized fact about television viewership is that viewership ratings fall on Fridays and Saturdays. It can be derived that people tend to engage in other activities rather than watching television on weekends. An economic model would capture such substitution as a result of a rise in the opportunity cost of, or a fall in the utility from, watching television. Therefore, in principle, one can easily estimate the weekend effect by projecting the differential in weekday and weekend ratings into the utility space. However, in practice, the observed weekend effect also includes an additional feature: The television program schedules are endogenous. This paper aims to separate the market contraction effect on weekends that arises as a consequence of endogenous scheduling from the demand-shift effect.

Understanding the periodic nature of television viewing is important to broadcasting companies to whom optimizing broadcast schedules is a key to maximizing advertising revenue. It may also be of policy makers' interest. Although traditional television is waning with the growing availability and popularity of online video streaming service, it is still the most popular mode of entertainment for Americans. According to a recent report by Nielsen, an average American spends 4 h and 32 min per day watching traditional TV, while Americans spend 30 min watching time-shifted TV.[1]

To estimate the day-of-the-week effects in television viewership, I formulate a discrete choice demand model for TV programs where a viewer's indirect utility from watching a particular program depends on the day of the week and the time slot. I estimate the model using Nielsen ratings data that span over 11 years. The long span of the data enables me to control for each television series' quality while the estimation method by Berry et al. (1995) allows me, despite the aggregate nature of the data, to incorporate viewer preference heterogeneity for TV program genres. The estimation results demonstrate the importance of controlling for the endogenous scheduling: The estimated weekend effect is dampened as the empirical model accounts for variation in the television series qualities.

The structural approach allows me, through counterfactual analysis, to decompose the observed weekend effect into the effect from demand contraction and that from endogenous scheduling. I first test whether the estimated broadcast day and hour effects justify the observed schedules; that is, whether the reshuffling of weekly broadcast schedules generates higher ratings for television networks. In most cases, the counterfactual rating falls below the actual one. It indicates that the estimates of the underlying broadcast day and hour effects are reasonably consistent with the television networks' rating maximization in the Nash equilibrium context. I then simulate two counterfactual scenarios: one with no day-of-the-week effects and the other with no endogenous scheduling. The results indicate that the intrinsic contraction in demand for television viewing accounts for only one-third of the observed rating drops on weekends.

The rest of this paper is organized as follows: Sect. 2 reviews related studies and Sect. 3 describes the data. I present the viewer choice model in Sect. 4, and discuss

[1] http://www.nielsen.com/us/en/insights/reports/2014/the-total-audience-report.html.

modeling issues and the identification strategy. I present the estimation results in Sect. 5 with robustness checks. Section 6 considers counterfactual scenarios to decompose the observed weekend effect into the intrinsic part and the endogenous part. Section 7 concludes.

2 Related Literature

This paper is most similar to Einav (2007) in that both study seasonality in media industries. Einav (2007) focuses on the seasonality in the movie industry, while this paper studies the weekend effect in TV viewership.

There is a strand of papers that estimates a viewer's program choice model. More recent examples include Shachar and Emerson (2000). They find that there is preference heterogeneity for show categories. I incorporate this, given the aggregate data, with random coefficients on show categories while they link the viewer preference for particular genres and shows with viewer demographics.

Some papers in the strand account for the weekend effect. Goettler and Shachar (2001) estimates a viewer's choice model with micro-level panel data over a week, accounting for the Friday effect. Because there is no variation in the programs offered on Friday, however, the estimated effect is likely compounded by the market contraction effect of endogenous scheduling. Other examples include Wilbur (2008) who estimates viewer demand for television programs with the use of aggregate viewer data over a four-week period. His estimation results indicate that viewers like watching television on Thursday and Friday nights, and notes that this contrasts with the broadcast networks' tendency to air low-quality programs on Friday nights.

While many papers in this strand have an edge against this paper in that their viewer choice models can examine how the viewer demographics are related to the television viewing patterns, they cannot separate the day-of-the-week effect from the market contraction effect—mainly because of the short span of the individual-level data.

One aspect of my viewer-choice model is to explicitly account for the so-called *lead-in effect*: A program with a big rating confers an advantage to the following program because viewers tend to stay with the channel that they were previously watching even after the program ended. The lead-in effect is well documented and studied in the literature on television audience flow (e.g, Rust and Alpert 1984; Rust et al. 1992; Shachar and Emerson 2000) and viewer inertia (e.g, Moshkin and Shachar 2002; Esteves-Sorenson and Perretti 2012).[2] The source of the lead-in effect, in my model, is the extra utility that a viewer receives from watching programs back-to-back on the same broadcast network channel.

This paper relates to another strand of papers on the broadcast network's scheduling and programming. Danaher and Mawhinney (2001) examine the rescheduling of television programs to maximize the total ratings for a network

[2] Shachar and Anand (1998) estimate a model of television viewing decisions to examine the sources of the viewership persistency. Shachar and Emerson (2000) incorporate the viewer inertia with switching costs that vary across show types and viewer demographics.

across a week using the results from a choice experiment in which television programs are rescheduled and presented to respondents. Kennedy (2002) tests for herd behavior in prime-time television programming. I add to these papers by considering reshuffling of the network channels' schedules to examine the estimated broadcast day and hour effects based on the revealed preference principle.

3 Data

The data encompass all TV shows that were broadcast on the four major networks—ABC, CBS, NBC, Fox—between January 1, 1999 and May 24, 2009 over 3797 days. They include each program's title, genre, broadcast time, Nielsen ratings, whether it's a new episode or a rerun, and the season and episode number if it's a new episode of a television series. The Nielsen ratings measure the share of television households who watch the given program, out of all television households.

The schedules and ratings are taken from two magazines. The ratings for programs that were broadcast from 1999 to March 25, 2007 are from *Broadcast & Cable*, and the remainder are from *TVWeek*. Because several issues of *Broadcast & Cable* contain no rating information, I have complete rating information for 3557 days. The season and episode information is mostly taken from http://epguides.com and www.tvtango.com. The program category variable was manually encoded based on each show's Wikipedia page or tv.com page. For cable/satellite channels beyond the four broadcast network channels, I only observe their combined ratings.

Among 3557 days with complete ratings information, I drop all observations from June to August, and Sundays. Most television series tend to run from September to May. Television networks tend to broadcast reruns of series or specials from June to August. As I treat most of the irregular, non-series programs as episodes of one series named "Others" , these observations would provide little, and noisy if any, information for the quality compositions that differ across the different days of the week. For the same reason, I also drop days during which at any time slot, all four TV networks broadcast sports or specials. The final sample includes 27,696 programs on 2329 days over 11 television seasons.

The top panel of Table 1 presents the ratings across the days of the week at the aggregate level. The average share of households using television (HUT) plunges on Friday and Saturday, obtaining only 83–90 % of the typical weekday ratings and the network television ratings drop to only 58–78 % of the weekday ratings. The bottom panel presents the average rating of the network television prime-time programs by their broadcast days of the week. The average rating is highest on Thursday and lowest on Saturday. Whereas the average rating is around 7.0–7.9 on weekdays, it is only 5.4 on Friday and 4.7 on Saturday.

In this study, television series play an important role in identifying the market contraction effects because the fact that they are repeatedly observed—although with different episodes—enables me to control for show qualities. The final sample include 573 network television series/title groups. There are an additional 20 title groups that are represented by dummy variables to estimate the constant quality

Table 1 Shares of television-watching households by broadcast days

	M	T	W	Th	F	Sa
Average shares of television-watching households						
HUT						
Obs.	394	385	388	386	393	383
Mean	63.69	62.99	61.04	61.36	54.78	53.17
SD	3.45	3.27	3.26	3.89	3.12	3.44
Network TV						
Mean	26.28	30.15	26.29	28.35	20.52	17.58
SD	4.63	5.26	5.49	6.55	4.70	4.78
Non-network TV						
Mean	37.41	32.85	34.75	33.02	34.25	35.59
SD	4.12	4.58	4.88	5.41	4.67	4.54
Average prime-time network program rating						
Obs.	4782	5067	4829	4877	4517	3624
Mean	7.39	7.16	6.98	7.86	5.44	4.67
SD	2.74	3.01	2.99	4.22	2.17	1.86

Households using television (HUT): share of households watching television out of all television households

measure within each group. They include groups of sports programs, such as "Olympic games" and "NFL games," several documentary series, and "Others" which includes movies, pageant and award shows, and any other special or irregular programs.

For 551 out of 573 series, I know whether each airing is a new episode or a rerun, and, if new, its broadcast season and episode number. The remaining 22 series lack such information because they are mostly news magazines. The longest running TV series in the sample is "Law & Order," whose 9th season to 19th season were broadcast during the sample period. Four hundred and sixty eight television series began their broadcasts during the sample period, and 458 series ended during the sample period. I observe the complete series from start to finish for 382 series. Out of these complete series, only 103 series were renewed after their first broadcast seasons.

In Table 2, I consider whether a television series was renewed or cancelled after its first season depending on the day of the week on which its premiere episode was broadcast. For this counting exercise, I consider only those, among 573 television

Table 2 Renewal/cancellation of TV series by broadcast days

	M	T	W	Th	F	Sa	S	Total
Day of the premiere episode								
Total	84	97	97	60	64	11	37	450
Renew	35	30	36	21	12	1	27	162
Renewal rate	41.67 %	30.93 %	46 %	37.11 %	23.08 %	9.09 %	72.97 %[a]	36.00 %

[a] Because the final sample does not include Sundays, Sunday is over-represented by series that were later moved to other days of the week and renewed

series included in the final sample, whose whole first season falls in the original sample. There are 450 such television series. While the average probability of renewal is 36 %, it is only 23 and 9 % for series that premiered on Friday and Saturday.[3] This exercise confirms the phenomenon that gave Friday evening slots a notorious nickname: "Friday night death slot" ; but it remains unclear whether the low renewal rate is due to the low quality of the programs that have been aired, or to the low demand for television viewing on Fridays.

Although the data span 11 years, if broadcasting companies tend to fix the broadcast day of each series, the variation in the combination in the qualities of TV shows offered on different days of the week can be limited. Table 3 presents the variation along this dimension by counting the number of different days of the week on which any episode of a series was broadcast. The second column counts the number over the entire series run for the 382 series for which both the series premiere and the finale were broadcast during the sample period. It shows that more than half of the series (198) were broadcast on the same day of the week through their entire series runs. For these series, I do not observe how their ratings varied depending on which day of the week they were broadcast, which thus limit the needed variation. Most of these series, however, lasted only one television season before cancellation.

When we consider the 103 series that lasted multiple seasons, the majority of the series were broadcast on two to four different days of the week. To see whether the changes in the broadcasting days occurred across television seasons, I consider (television series, television season) pairs so that a television series appears in the same number of pairs as the number of seasons it lasted. The 103 television series generate 918 series-season pairs. Among them, 66 % have the same broadcast day of the week, as shown in the third and last column respectively. This implies that a television network tends to fix the broadcast day of a series during its seasonal run, but usually explores several different days of the week throughout the series' lifespan.

Table 4 summarizes the distribution of program categories for 27,696 television programs in the data set. In my model, viewers are heterogenous in their preference for television program genres, which is captured by random coefficients on six show category variables. "Comedy" and "Action/Crime drama" are two most popular categories. Comedy includes sitcom such as *Friends*, comedy drama, comedy variety such as *America's Funniest Home Videos* as well as animation such as *The Simpsons.* Action/Crime drama include all action, police procedural, legal, military, and adventure dramas such as *CSI* and *Law & Order*.

The "Drama, Other" category includes drama other than action/crime drama, such as mystery/thriller, SciFi/fantasy/supernatural, teen/family and medical drama. A popular medical drama series *Grey's Anatomy* and a comedy drama series *Desperate Housewives* fall under this show category. The "Reality/Game Show" category includes reality television such as *Supernanny* and competition/dating/talent shows such as *Survivor*, *American Idol*, and *The Bachelor* as well as more

[3] Among the 450 television series considered, only 267 series were broadcast on the same day throughout its entire first season.

Table 3 Variation in broadcast days

No. of different days of the week	No. of series (complete, all)	No. of series (complete, multi-year)	No. of series-season pairs
1	198	26	609
2	118	38	235
3–4	55	33	61
≥ 5	6	11	13
Total	382	103	918

Sunday broadcasts are not counted. The sample includes 918 series-season pairs such that all new episodes of the television series in the season were broadcast over the sample period

Table 4 Distribution of program categories

Categories	No. of series	No. of programs
Comedy	201 (35.1 %)	8110 (29.3 %)
Action/Crime	76 (13.3 %)	5487 (19.8 %)
Drama, Other	152 (26.5 %)	4576 (16.5 %)
Reality/Game Show	131 (22.9 %)	4250 (15.4 %)
News Magazine	13 (2.3 %)	2500 (9.0 %)
Sports	–	831 (3.0 %)
Specials (non-series)	–	1942 (7.0 %)
Total	573	27,696

traditional studio game shows such as *Who Wants to Be a Millionaire?*. News magazine series, such as *20/20* and *Primetime*, are categorized as “News Magazine” ; this category also includes several documentary series. “Sports, Specials, and Others” includes all sports game broadcast shows and all non-series specials such as award and pageant shows, news specials, biography specials, and seasonal specials such as *Macy’s Thanksgiving Day Parade.*

Table 5 presents how program categories are related to the broadcast time slots by counting the number of TV programs in each category that were broadcast at each 30 min time slot. The reason why the number of drama, reality, and news magazine programs drop at the second 30 min of each hour is that most shows in these categories are 1 h long, whereas comedy shows are typically 30 min long. Television networks tend to schedule comedy and reality programs between 8 and 9 o’clock, whilst drama and news magazines are scheduled mostly after 9 o’clock, especially action/crime drama after 10 o’clock. This is most likely due to changes in the demographics of viewers along the prime-time hours.[4]

While *TVWeek* reports average ratings for each 30 min time slot, *Broadcast & Cable* reports average ratings over each program’s duration. To put the two data sets together, I take the average of 30 min ratings if a program runs longer than 30 min.

[4] Goettler and Shachar (2001) and Shachar and Emerson (2000) document changes in viewer demographics along the prime-time hours and incorporate them in their viewer choice models.

Table 5 Program categories by broadcast time

Time	Comedy	Action/Crime	Drama, Other	Reality/Game Show	News Magazine
8:00–8:30	2592	980	1366	2193	487
8:30–9:00	2218	4	66	548	3
9:00–9:30	1677	1713	1692	1130	726
9:30–10:00	1552	26	171	166	13
10:00–10:30	47	2748	1275	205	1256
10:30–11:00	24	16	6	8	15
Total	8110	5487	4576	4250	2500

Excludes Sundays

In reality, viewers can decide to start or stop watching television at any moment, and the rating of a program continuously changes.[5] To ensure that the model also predicts a constant rating during a program's run, I assume that the timing of viewer decision-making is discrete, and that no viewer can switch in or out of the program once it starts.

This assumption is restrictive, and taking the average rating is likely to cause a loss of information. For example, on one day, the rating for the first 30 min of a 1-h episode of an ABC series called *Extreme Makeover: Home Edition* was 3.1 and it was 6.3 for the second 30 min. While this could be due to a change in the plot, it coincides with the drop in the CBS's rating by 3.5 upon the end of a popular reality competition show, *The Amazing Race*, followed by *60 Min*, a news magazine show. A loss of information on such substitution could weaken identification of the random coefficients on television program genres.

Table 6, however, shows that the variation in ratings within a program is small for most programs. The average coefficient of variation of ratings for 30 min blocks within a program is only 5.5 %. Especially, for show categories such as drama that has a continuous, running plot, the average coefficient of variation is 4.5 %. Based on these results, it is reasonable to assume that the small amount of variation is not due to an equal amount of many switch-ins and switch-outs, but rather because only a few people switch in and out during a show.[6]

Finally, I present evidence for the lead-in effect. To this end, I run regression of the program ratings on the lead-in program's ratings while controlling for various other factors that can affect the ratings. Table 7 presents the estimate of the coefficient on the lead-in rating. The coefficient estimates are statistically and economically significant, and robust to the inclusion of the series (title group) fixed effects and the series-season pair fixed effects, which implies that the state-dependence is likely structural rather than spurious.

[5] Nielsen's minute-by-minute rating data are available for purchase.

[6] Shachar and Emerson (2000)'s estimation results show that the switching costs are higher during a program than between programs and especially when the program's category is drama.

Table 6 Coefficient of variation of 30 min ratings within a program (%)

	Obs	Mean	SD	Min	Max
All	4206	5.50	4.46	0	45.93
Action/Crime & Drama, Others	2484	4.46	3.64	0	24.96
Reality/Game Show	991	6.81	4.78	0	45.93

I compute the coefficient of variation of 30-min ratings for programs that take multiple 30-min blocks and whose ratings are taken from *TVWeek* which reports ratings over each 30 min block. *Broadcast & Cable* reports the average rating over each program's duration

Table 7 Lead-in effects

Dependent variable: ratings			
Lead-in rating	.514***	.430***	.367***
	(.006)	(.006)	(.005)
Rerun Dummy	Y	Y	Y
Year (TV season) FE	Y	Y	Y
Day FE	Y	Y	Y
Time Slot FE	Y	Y	Y
Genre FE	Y	Y	Y
Series (Title Group) FE	N	Y	–
Series-season FE	N	N	Y
Adjusted R^2	.551	.850	.944

*** $p < 0.01$

4 Model

Let $\mathbf{J}_t = \{\text{ABC, CBS, NBC, FOX, Cable, No TV}\}$ denote the set of TV programs available at time $t = (D, d, \tau)$ where D denotes the broadcast date, d indexes the day of the week, and $\tau \in \{8:00\text{–}9{:}00\,\text{p.m.}, 9{:}00\text{–}10{:}00\,\text{p.m.}, 10{:}00\text{–}11{:}00\,\text{p.m.}\}$ the 1 h-long time slot. Cable is a composite alternative that includes PBS, cable/satellite television networks such as WB and CNN, and all other channels besides the four broadcast networks.

Viewer i's utility from watching a program in series (title group) j on broadcast network $n_j \in N = \{\text{ABC}, \text{CBS}, \text{NBC}, \text{FOX}\}$ at time t is given by

$$u_{ijt} = x_j\beta_i + \beta_d d + \beta_\tau \tau + \alpha \cdot 1\left(n_{it-1} = n_j\right) + \zeta_j + \xi_{jt} + \epsilon_{ijt} \quad (1)$$

where x_j denotes observed attributes of program j and n_{it-1} indicates the network channel that viewer i watched in the previous time slot. Viewer i's utility from watching a program on any cable channel is given by

$$u_{ict} = \beta_d d + \beta_\tau \tau + \zeta_c + \xi_{ct} + \epsilon_{ict}.$$

The utility from the outside option—not watching television—is normalized to zero.

If a viewer watches programs back-to-back on the same channel, she receives extra utility α.[7] Notice that this extra utility exists only for the four broadcast

[7] Note that the extra utility term does not depend on the show categories of the previous and current programs. In the data, it is found that for comedy, the lead-in effect is greater if a program that is in the

network channels. It does not add to the indirect utility flow from repeatedly choosing the cable option. The reason is that the cable option includes many different channels, so even when its ratings appear to be state-dependent, it may not be a result of the viewer choice inertia as is defined for the broadcast network channels. Although a viewer's decision as to which channel (or, equivalently, which program) to watch has a dynamic consequence in this setting, I assume that viewers are myopic instead of forward-looking. I also assume that there is no heterogeneity in viewer inertia.[8]

The show attributes x_j include show category g_j and whether the show is a new episode or a rerun if j is an episode of some television series. All broadcast network programs are categorized as one of the following; comedy; action/crime drama; other drama; reality/competition shows; news magazine; and sports/specials. ζ_j captures the quality of program j that is constant within the same title group along its series run, apart from the preference for the show category. For example, if j is an episode of an action/crime drama series, this will capture the popularity of the main plot and characters of the series. If j is "*MLB games*," it will capture the average popularity of professional baseball games.

There are two unobservable variables: ξ_{jt} captures the time- (episode-) specific quality of show j that may be generated by, for example, the appearance of a celebrity cameo, or a dramatic turn in the plot. ϵ_{ijt} captures the idiosyncratic preference over the show at time t and is assumed to be drawn from an i.i.d. extreme value distribution.

With random coefficients on the show categories, I allow for flexible substitution patterns among the four network channels. As for the distribution of the random coefficients, I take the standard assumption in the literature that the vector of viewer type $\boldsymbol{\beta}_i$ is drawn from the multivariate normal distribution $\Psi(\boldsymbol{\beta}_i)$ with a diagonal covariance matrix.

I consider another specification where the mean coefficients on the show categories vary with the time slots. This is to control for the effects of changes in demographic compositions in viewers along the prime-time hours on the broadcast schedules. This specification assumes that $\beta_{ig\tau}$ is drawn from a normal distribution with mean $\overline{\beta}_{g\tau}$ and standard deviation σ_g. Note that the standard deviation is not specific to the time slot while the mean is. This parsimonious specification is mainly to confine the computational burden that result from an increase in the number of nonlinear parameters that need to be estimated.

Note that there is no random coefficient for the composite cable channel, to which no show category can be assigned. As a result, a viewer with a strong preference for, say, comedy shows is not more likely to substitute toward cable

Footnote 7 continued
same show category follows. For action drama and reality television, the lead-in effect is smaller if a program that is in the same show category follows. One could argue this is evidence that there is some diminishing marginal utility from watching shows in the same genre in a row for some genres.

[8] Shachar and Emerson (2000) allow viewers to switch channels every quarter hour, and also allow the switching costs to vary with show categories and viewer demographics. They find that the switching costs increase for female and older viewers, and for genres with a continuous plot such as drama.

television than turning off television when no comedy show is offered by the network channels. This is unrealistic, and can be relaxed by allowing viewer preferences for television programs to be correlated. The main difficulty with such an approach is that it is hard to find a valid instrument for the added non-linear parameter that captures the correlation among television channels, especially in addition to instrumental variables for the viewer preference heterogeneity terms. I instead estimate a standard nested logit model without random coefficients on program genres as a part of robustness check.

The probability of viewer i watching show j at time t, conditional on her watching network n_{it-1} at $t-1$, is given by

$$P_{it}^{j}(n_{it-1}) = \frac{\exp\left[\delta_{ijt} + \alpha \cdot 1\left(n_{it-1} = n_j\right)\right]}{\left(\sum_{k \in N} \exp[\delta_{ikt} + \alpha \cdot 1(n_{it-1} = n_k)] + \exp[\delta_{ct}]\right) + 1}.$$

where $\delta_{ijt} = x_j\beta_i + \beta_d d + \beta_\tau \tau + \zeta_j + \xi_{jt}$ and $\delta_{ct} = \beta_d d + \beta_\tau \tau + \zeta_c + \xi_{ct}$. The unconditional probability of viewer i watching TV show j at time t is $P_{it}^{j} = \sum_{k \in \mathbf{J}_{t-1}} P_{it-1}^{k} \cdot P_{it}^{j}(k)$. The recursiveness in the equation implies that $P_{it}^{j} = \sum_{m \in \mathbf{J}_0} P_{i0}^{m}(0) \cdots \sum_{l \in \mathbf{J}_{t-2}} P_{it-1}^{k}(l) \sum_{k \in \mathbf{J}_{t-1}} P_{it}^{j}(k)$ where time 0 denotes 8:00 p.m. when prime-time hours begin (before which I assume that no one watches television). The share (rating) is given by

$$s_{jt} = \int \sum_{k \in \mathbf{J}_{t-1}} P_{it-1}^{k} \cdot P_{it}^{j}(k) d\Psi(\boldsymbol{\beta}_i). \tag{2}$$

4.1 Discussion

The lack of information on each cable network's programs and ratings restricts the empirical model in several ways. All cable/satellite/independent channels are aggregated into one composite option of watching a television channel other than the four major networks. Moreover, the composite cable option faces the same day-of-the-week effects as the broadcast networks, but offers constant quality throughout the week. This assumption is critical in deriving the inherent weekly cycle in demand for television viewing from the ratings data. It almost works as another normalization by setting the weekly cycle in the *residual demand* for the broadcast networks to be the same as the weekly cycle in the *market demand* for television viewing. If cable networks in fact offered, for example, low-quality programs on weekends just as the broadcast networks do, the model would bias upward the underlying demand contraction.

The assumption, however, appears to be true for cable/satellite channels *as a whole*. Table 1 shows that the average ratings for cable channels together remain more or less constant throughout the week, whereas the broadcast networks' ratings drop sharply on Friday and Saturday. It indicates that cable networks are less susceptible, or less responsive to the weekend demand contraction than are the broadcast networks.

Two explanations can be offered: First, the weekend demand contraction may be smaller for each cable channel because those who subscribe to cable channels are the ones who really enjoy watching television and do so even on weekends. Second, the weekend effect appears to be less severe for cable channels as a whole because some cable networks gain their audience base on weekends while others lose.

The latter explanation is particularly sensible because many cable channels appeal to a narrow range of audience, in contrast to the broadcast networks that target a broader audience. For example, Friday and Saturday evenings are known to be for children and teenagers, and cable channels (such as Disney Channels, Cartoon Network, and WB) that target these demographic groups tend to broadcast their strong programs on weekends. Disney has aired a very popular, original series *Hannah Montana* and debuted the highly anticipated made-for-cable movie, *High School Musical 2* on Friday. ESPN is another example. Its ratings tend to rise when it broadcasts college football games on Saturdays.

The fact that the ratings of cable channels together exhibit no noticeable cycle whereas the broadcast networks show clearly visible cycles makes the latter more suitable for the estimation of market contraction effects of placing low-quality products in low business seasons. Even so, treating the cable television's strategy to offer constant quality through the week as exogenous may be viewed as problematic especially because they together garner the majority of viewers.

On the other hand, no cable/satellite channel alone attains ratings comparable to those of broadcast networks. For example, in the fall of 2000, 7.93 % of all television households on average watched a program on one of the four networks, whereas 2.53 % of cable/satellite households (which was only 80 % of all television households) watched a program on WB, which was one of the more popular cable channels. Given each cable/satellite channel's small share, it is unlikely that the four major networks consider each individual cable channel's scheduling strategy to the same extent as they consider each other's strategy. The most plausible scenario would be that the four major networks consider the other channels as a whole while paying close attention to the schedules of a few, highly popular original cable series such as ESPN's *Monday Night Football*.[9]

This paper attributes the driving force for broadcast networks to air low-quality programs on Friday and Saturday to the contraction in the audience base. Other explanations include changes to the audience composition and advertisers' demand for advertising during the week. For example, a convincing explanation for broadcast networks' tendency to air high-quality programs on Thursday is that many important purchases—such as for cars and furniture—are made on weekends and therefore advertising on Thursday may be most effective, whereas Friday may be too late. This explanation is well explored in Wilbur (2008) and Wilbur et al. (2013) .[10]

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[9] More recently, many original cable series became very successful. For example, AMC's *The Walking Dead* became the most popular cable series in cable television history. Its fifth season premiere retained 17.3 million viewers which would roughly correspond to a broadcast household rating of 6–8.

[10] Wilbur (2008) finds that viewers most prefer watching television on Friday evenings, followed by Thursday, and that advertisers most value Thursday evenings, followed by Friday. He then attributes the Thursday scheduling to the interaction between the two sides while providing explanations for the less intuitive results with regard to the Friday scheduling.

In relation to the changes in viewer demographics, the assumption that the day-of-the-week effects are additively separable from the program-specific mean utility can be questioned. Under the specification, all programs are affected by the weekly demand cycle in the same way. Therefore, the model will ignore any "synergy" between a television series and its broadcast day that may be set to target certain demographics. As a result, for example, if families are the majority of viewers, and consequently family drama series are usually offered on Friday nights, the model may over-estimate those series' qualities. Unfortunately, the aggregate ratings data make it impossible to have the day-of-the-week effects depend on viewer demographics.

4.2 Estimation and Identification

I estimate the model parameters using a two-level algorithm that has been proposed by Berry et al. (1995).

The inner level recovers mean utilities $\delta_{jt}(\alpha, \sigma_g) = x_j\overline{\beta} + \beta_d d + \beta_\tau \tau + \zeta_j + \xi_{jt}$ at every trial value of the non-linear parameters: α and σ_g. It starts with an initial guess of the mean utilities vector, computes the predicted ratings, compares them with the actual ones, and then updates the mean utilities vector according to the operator that has been proposed by Berry et al. (1995). The operator is contractive, so it converges to the unique fixed point at every value of α and σ_g.

The outer level solves for the linear parameter values $\overline{\beta}$ —given the mean utilities $\widehat{\delta}_{jt}(\alpha, \sigma_g)$ —that minimize a GMM sample criterion function and continues to loop until it finds the global minimizer of $\{\alpha, \sigma_g, \overline{\beta}\}$. Berry et al. (1995) propose a simulation method to compute the integration in Eq. (2). I draw 200 consumer types from the standard normal distribution as the first step.

The GMM criterion function arises from the usual orthogonality condition $E(Z'\xi) = 0$, where Z is a matrix of instrumental variables. It implies that the time-varying show quality ξ_{jt} is orthogonal to the day/time slot allocation conditional on the observables—particularly conditional on the series (title group) qualities. Since broadcast networks allocate day/time slots for their various shows before episode-specific shocks are realized and tend to fix their day-by-day line-ups, this is a reasonable assumption.

Television series qualities are, in principle, identified by observing the same show as it competes against different sets of programs and is broadcast on different days of the week. As shown in Table 3, a broadcast network does not frequently change the day/time slots for its series during the series' seasonal run, which dilutes the variation in the program compositions. The long span of the data enables me to exploit the variation generated across broadcast seasons: Many series are cancelled, new series are picked up, and renewed series are moved to different day/time slots to accommodate new series.

Relying on television series fixed effects to control for endogenous quality compositions restricts a series' quality to be constant throughout its broadcast cycle. This is unlikely to be true, since ratings of a "popular" television series tend to rise, hit a peak in a relatively early episode, and then fall before it is cancelled.[11] The broadcasting company may set the day and time based on the projected popularity of the series for each season. Therefore, the constant quality assumption could bias the underlying weekend effects upward. To mitigate this problem, I include a quadratic function of the total number of episodes of the series that have been aired up to each airing of a new episode.

The underlying day effects are identified from variations in the quality compositions of television shows that are available on different days of the week. There are several sources of the variations: The first is the rescheduling of the same series across its broadcast seasons. Second, the fact that a television network allocates the day/time slots among its set of series before the ratings are observed make it possible that the television programs that are scheduled on weekends are of high quality. However, it is unlikely that a television network broadcasts a widely popular television series on Friday repeatedly. If a series turns out unexpectedly to be successful ex-post, it can reschedule the series without incurring much cost. For example, *CSI* was originally scheduled to air at 9 p.m. on Friday when the series premiered, but later moved to Thursday during its first season.

Third, television networks are occasionally forced to shuffle their day-by-day line-ups. The occurrence of unexpected or irregular events—for example, a World Series broadcast—would make television networks reschedule regular programs during the affected weeks. Another example of such occasions include when they unexpectedly cancel a series and then replace it with another series in the mid-season. In such case, a network may put the newly picked-up series in the day/time slot of the replaced series to maintain the rest of its schedules, although this specific placement may be suboptimal.

The identifying assumption is that such rescheduling, both across and during broadcast seasons, is not correlated with idiosyncratic quality shocks. To evaluate this assumption, I consider 103 television series whose entire series from start to finish occur during the sample period and lasted more than one broadcast season. I sort them into four groups, depending on the (mode) broadcast days of their first and final seasons, and compare them in Table 8.

There is some difference in the first-season ratings between the series that remained to air on weekdays versus the series that were moved to weekends, but the difference is small. The average seasonal rating declines in the last seasons compared to the first season for both groups, but the drop is greater for the series that were moved to weekends. However, considering that they lasted longer on average (3.28 seasons versus 3.11), and that a part of the decline is due to the underlying demand contraction on weekends, the two groups seem little different. The same applies to the series that premiered on weekends, although the number of such series is too small to draw any meaningful conclusion.

[11] Sometimes a series is cancelled because of an increase in costs rather than a decline in ratings. Production costs tend to rise as television series stretch into several seasons—mainly because the actors and the others individuals who are involved in the production demand higher salaries. For an example, read http://www.today.com/id/10881944/ns/today-today_entertainment/t/th-heaven-canceled-due-cost-network/#.VhI7V_mqqko.

Table 8 Rescheduling of television series

First season	Last season	No. of obs.	No. of seasons	First season ratings	Last season ratings
Weekdays	Weekdays	75	3.11	7.13	4.50
	Weekends	18	3.28	6.90	3.83
Weekends	Weekdays	1	2.00	6.01	4.07
	Weekends	9	2.67	6.50	5.03

The comparison result in Table 8 ensures that the rescheduling of a television series toward its final season is unlikely to be correlated with the time-varying shock to the series' value—or at the least, less likely than the first-time scheduling—after I control for the time-invariant quality of each series and its decay over the lifespan of the series.

The random coefficients on the show category variables are identified from variation in the distribution of show types that are available at the time of decision-making and how viewers substitute among the available show types. As the viewer's choice is state-dependent due to the extra utility term α, the distribution of viewer types over the set of available show categories is also state-dependent. An initial condition is necessary to identify the random coefficients as well as α. I assume that at the beginning of prime-time (8:00 p.m.), no viewer has been watching any television, so that all types are available for the decision-making of what to watch.

The identification of the two sets of non-linear parameters—α and standard deviation of the random coefficients σ_g—requires instrumental variables. For the random coefficients on the show category variables, I use the number of available shows in each category at each time t. The offered composition of show categories is correlated with the level of the viewer preference heterogeneity because each broadcast network would consider the preference heterogeneity as well as rival programs' genres when assigning a day/time slot to the given program. Also it is unlikely to be correlated with the idiosyncratic quality shock of the given program.

The extra utility term is identified from the persistency/fluctuations in Nielsen ratings in comparison to the persistency/fluctuations in the observed variables. I use an indicator variable of whether the leading program is a new episode or a rerun of television series as an instrument. By requiring the lagged rerun variable to be uncorrelated with the unobserved idiosyncratic quality shock ξ_{jt} conditional on the extra utility term, the moment condition restricts the extent to which the unobserved term explains the observed persistency/fluctuations in the daily Nielsen ratings.[12]

5 Estimation Results

This section presents the parameter estimates of the baseline random coefficient model as well as those of the nested logit model. I consider three specifications that differ with respect to the inclusion of television series fixed effects and the show

[12] Yeo and Miller (2016) explain how the use of a lagged instrumental variable identifies a term that captures state-dependence of a choice, such as the extra utility term in this study or switching costs in their study.

category and time slot interaction terms. I also present the result from a counterfactual analysis that tests the optimality of the actual schedules given the parameter estimates.

5.1 Baseline Model

Table 9 shows that the estimated weekend effect is dampened as the empirical model accounts for variation in the television series qualities. The estimated weekend effect is most pronounced in specification I, which does not include the title group dummy variables. The negative coefficients on Friday and Saturday are 5–6 times larger than the coefficient on Thursday under this specification, but the differentials are much reduced in specification II and III—both of which control for television series qualities. This result indicates that the inherent contraction in television viewership in weekends are amplified by broadcasting companies' program scheduling choices.

The extra utility term α estimates are only statistically significant in specification II and III. To put the values in "utils" into perspective, I compute the average probability that a viewer who watches a network channel switches to a different channel at the end of a show, first, given the α estimate and then, when it is counterfactually set to zero. I simulate choices of the same set of 200 randomly drawn viewers to compute the counterfactual probabilities.

Under specification III, 43 % viewers instead of 50 % would switch if there were no extra utility from watching shows back-to-back on the same network channel. It is 47 % instead 49 % under specification II. These results imply a moderate lead-in effect. If the first prime-time show's rating increases by 1 %, the network will see an increase in the network's daily rating of around 2 %.

The estimates of α increase as the model includes more controls for program qualities. This may seem counter-intuitive if one expected that more controls would have the (serial) correlation in ratings among programs on the same channel on the same day explained less by the extra utility but more by their similar qualities. The subtle difference is that α is identified by how an increase in the utility from watching a program—more precisely, its unobserved part—is related to the utility from the proceeding program, and not by how the utility *levels* per se co-move along the days of the week.

All of the linear coefficients are negative as expected from the fact that the mean utility of the most popular option—not watching television—is normalized to zero. The "mean" viewer appears to prefer reality television shows the most in specification II and III. News magazine and comedy follow. Under specification I, reality television is a close second after news magazine.

The estimates of σ_g, which measure the viewer heterogeneity in preferences for television program genres, are only statistically and economically significant for comedy, action/crime drama, and sports and specials in specification I and II. Under specification II, the preference for "Sports, Special, and Others" is the most heterogeneous (1.635), while the preference for "Comedy" is the most homogenous (0.965). It is plausible that comedy appeals to a broader audience than any other

Table 9 Estimation results

Specification	I		II		III			
α	−0.227		0.820***		1.318***			
	(0.207)		(0.290)		(0.468)			
		σ_g		σ_g	8–9 p.m.	9–10 p.m.	10–11 p.m.	σ_g
Comedy	−2.964***	1.842***	−2.586***	.965***	−2.340***	−2.243***	−2.494***	0.165
	(0.031)	(0.090)	(0.098)	(0.092)	(0.333)	(0.642)	(0.766)	(0.719)
Action Drama	−2.398***	1.516***	−3.492***	1.424***	−3.005**	−3.060***	−2.979***	0.847
	(0.042)	(0.121)	(0.137)	(0.167)	(1.351)	(0.202)	(0.464)	(1.792)
Drama, Other	−1.872***	0.000	−2.893***	0.000	−2.950***	−2.960***	−3.061***	0.009
	(0.035)	(0.663)	(0.105)	(1.212)	(0.376)	(0.388)	(0.441)	(12.546)
Reality	−1.788***	0.000	−1.636***	0.000	−1.671**	−1.743***	−1.846***	0.000
	(0.053)	(2.631)	(0.104)	(1.997)	(0.677)	(0.323)	(0.530)	(16.539)
Newsmagazine	−1.756***	0.000	−2.381***	0.000	−2.395***	−2.362***	−2.454***	0.000
	(0.039)	(0.800)	(0.099)	(1.858)	(0.425)	(0.142)	(0.150)	(13.585)
Sports, Specials and Others	−2.408***	1.370***	−2.717***	1.635***	−2.621	−2.481*	−2.781*	1.497
	(0.078)	(0.201)	(0.435)	(0.348)	(1.803)	(1.439)	(1.484)	(1.966)
Tuesday	−.098***		−.081***		−0.087***			
	(0.010)		(0.009)		(0.017)			
Wednesday	−.159***		−0.087***		−.086**			
	(0.012)		(0.008)		(0.034)			
Thursday	−.100***		−0.140***		−0.137***			
	(0.013)		(0.021)		(0.030)			
Friday	−.489***		−0.392***		−0.382***			
	(0.016)		(0.018)		(0.026)			
Saturday	−.565***		−.457***		−0.434***			
	(0.021)		(0.038)		(0.093)			

Table 9 continued

Specification	I	II	III
Rerun	−.167***	−.521***	−0.484***
	(0.013)	(0.013)	(0.032)
No. of episodes	4.1e−3***	−1.5e−3***	−1.4e−3**
	(2.5e−4)	(1.3e−4)	(6.3e−4)
No. of episodes ˆ2	−7.4e−6***	1.1e−6***	9.8e−7
	(6.6e−7)	(2.9e−7)	(9.4e−7)
Series FE	N	Y	Y
Time Slot FE	Y	Y	Y
Year (TV season) FE	Y	Y	Y

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

Other controls include season premiere/finale dummy variables; whether a sports game is post-season or not; and wether the show is a pre/post game show rather than the game itself genre, and that sports or award ceremony broadcasts appeal to a narrower audience. On the other hand, it could have arisen from the fact that television programs that are categorized as "Sports, Special, and Others" are actually in various formats, themes, and contents whereas programs under the comedy category are mostly "sitcom" .

Under specification III, none of the standard deviation estimates are statistically significant, which implies no heterogeneity in viewer preferences for show categories. Though this is fairly common in the literature on random coefficient discrete choice models, it may be due to the restriction on the distribution of viewer types. Recall that I assume that the variance is constant while the mean preference changes across the prime-time hours in order to confine the number of non-linear parameters that need to be estimated.

The rerun variable yields the expected negative sign and is statistically significant in all three specifications. The coefficients in the quadratic function that accounts for decay of popularity of television series are mostly significant in all three specifications. Interestingly, the signs of the linear and quadratics terms flip once the model includes television series fixed effects.

The decay function estimates under specifications II and III point to a U-shaped relationship between the ratings of a television series and its age. Because of the much smaller coefficient value on the quadratic term, however, the series' quality decreases over its broadcast cycle for all series in the sample. Although a few popular television series in the sample that have lasted multiple seasons exhibit a rise in the ratings in their early seasons, the estimated decay function does not reflect it. I suspect that this is because most of television series in the sample were cancelled after their first seasons, and their ratings tend to decrease even in the first seasons.

In Table 10, I further examine the implications of controlling for program qualities. The first panel reports the average flow utility net of the day effect—$\delta_{jt} - \beta_d d - \beta_\tau \tau$—for a network television show over the sample period. This value reflects the overall extent that a program is liked. The results under specification I indicate that the programs aired on weekends are overall of higher quality than are the average shows aired on the other days. This counter-intuitive result highlights the importance of controlling for show qualities. Under specification II, the utility flow from the average Friday and Saturday show is respectively 4 and 11 % lower than that of the average show on weekdays. Under specification III, the difference in the utility levels between the average weekend program and the average weekday program further widens.

The second panel in Table 10 reports the mean value of the unobserved show qualities (ξ_{jt}). In principle, there should be little weekly cycles in the idiosyncratic quality shocks. The table clearly shows that as the empirical model controls for the endogenous scheduling, cyclicality in ξ_{jt} along the days of the week diminishes. For example, the average value of the idiosyncratic program quality is highest on Thursdays—the day with the highest average rating—under specification I, but only moderately high, and lower than the Wednesday's under specifications II and III. However, the weekend and weekday differentials are still present in these

Table 10 Average program qualities

	M	T	W	Th	F	Sa
Average program qualities						
Spec. I						
Mean	−2.5226	−2.5059	−2.4546	−2.4100	−2.4986	−2.4687
SD	.5968	.7074	.7261	.7686	.6996	.5882
Spec. II						
Mean	−2.1996	−2.1966	−2.2213	−2.1004	−2.3185	−2.4865
SD	.4700	.5207	.5322	.6256	.5271	.5484
Spec. III						
Mean	−2.0130	−1.9940	−2.0429	−1.9484	−2.1470	−2.3581
SD	.4372	.4429	.4466	.5778	.4531	.4671
Mean idiosyncratic quality shocks						
Spec. I						
Idiosyncratic Quality ξ_{jt}	.0365	.0235	.0131	.0506	−.0491	−.1053
Spec. II						
ξ_{jt}	.0217	.0144	.0242	.0217	−.0303	−.0723
Series Quality ζ_j	.6704	.7382	.6790	.7868	.6664	.4627
Spec. III						
ξ_{jt}	.0195	.0101	.0228	.0210	−.0288	−.0626
ζ_j	.6525	.7545	.6606	.7710	.6520	.4084

specifications. All in all, though imperfect, Specification III does a reasonably good job in controlling for the endogenous quality compositions.

5.2 Robustness Check: Nested Logit Model

Having random coefficients on the show categories in the model allows for flexible viewer substitution patterns amongst available television shows. However, because the random coefficients are on the categories for shows on the broadcast networks only, it restricts the substitution between a network channel and the composite cable option to be no different from that between a network channel and not watching television at all. This may be unrealistic as viewers on the broadcast networks are more likely to substitute toward a cable channel instead of not watching at all when the broadcast networks offer programs of low quality.

To allow preferences for television viewing to be correlated across available programs, I estimate a nested logit model of the television program choice. As before, viewer i's utility from watching a program in series (title group) j on television network $n_j \in N$ at time t is given by

$$u_{ijt} = \delta_{jt} + \alpha \cdot 1\left(n_{it-1} = n_j\right) + v_{it} + (1-\sigma)\epsilon_{ijt} \tag{3}$$

where $\delta_{jt} = x_j\beta + \beta_d d + \beta_\tau \tau + \zeta_j + \xi_{jt}$, group 1 is $\{\text{ABC}, \text{CBS}, \text{NBC}, \text{FOX}, \text{Cable}\}$, and group 0 is $\{\text{No TV}\}$. ϵ_{ijt} is the i.i.d. logit error term. v_{it} is common to all alternatives in group $g = 1$ and drawn from the unique distribution that leads $v_{it} + (1-\sigma)\epsilon_{ijt}$ to follow the type one extreme value distribution. As σ approaches one, the within-group correlation approaches one, and as σ approaches zero, the model collapse to a standard logit specification.

Conditional on viewer i watching network channel n at $t-1$, the probability of her watching show j at time t is

$$P_{it}^{j}(n) = \frac{\exp\left[\left(\delta_{jt} + \alpha \cdot 1\left(n = n_j\right)\right)/(1-\sigma)\right]}{V_g{}^{\sigma}\left(V_g^{(1-\sigma)} + 1\right)}, \tag{4}$$

where $V_g = \sum_{k \in N} \exp\left[\frac{\delta_{kt} + \alpha \cdot 1(n = n_k)}{1-\sigma}\right] + \exp\left[\frac{\delta_{ct}}{1-\sigma}\right]$. The probability of not watching television is $P_{it}^{0}(n) = \frac{1}{V_g^{(1-\sigma)} + 1}$.

If not for the extra term that captures the viewer inertia α, a regression equation could be derived in which the difference in the channel j's market share and the share of No TV in log is the flow utility δ_{jt} plus σ times the log of j's inside market share, as shown in Berry (1994) and Einav (2007). Then the model parameters including σ would be estimated by regressing the difference in the log market shares on the inside share and the observed attributes of program j, given an instrumental variable for the endogenous inside share term. This approach is not feasible here because the observed market shares are not equal to the conditional choice probabilities due to the state-dependence nature of the program choice.

Instead, I solve for the δ_{jt} that generates the observed market shares at each trial value of α and σ. As I assume that shows that begin at 8:00 p.m. $(t = 0)$ are not affected by viewer inertia, δ_{jt} for $t = 0$ can be analytically solved for:

$$\delta_{jt} = (1-\sigma)\left[\ln(s_{jt}) + \ln\left\{\left(\frac{1-s_{0t}}{s_{0t}}\right)^{\frac{1}{1-\sigma}} + \left(\frac{1-s_{0t}}{s_{0t}}\right)^{\frac{\sigma}{1-\sigma}}\right\}\right]. \tag{5}$$

I then numerically solve forward for δ_{jt} for $t \geq 1$ and evaluate a GMM objective function with the solution $\{\delta_{jt}(\alpha, \sigma)\}$.

The identifying condition is that the unobserved time-varying program quality is orthogonal to the broadcast day and hour conditional on the observed characteristics, and uncorrelated with instruments for two non-linear parameters. The lagged rerun indicator is once again used for the viewer inertia parameter α. As for the σ that determines how viewers substitutes amongst the available television channels, I use the number of programs in the same category as program j as an instrument.

Table 11 presents the estimation results. The estimates are qualitatively similar to those from the random coefficient model in Table 9. σ is economically and statistically significant in all three specifications, which implies that substitution patterns differ considerably in the choice of which channel to watch, and in whether to watch television or not.

One interesting observation is that as the extra utility from staying tuned to the same channel α increases, the within-group correlation of utility levels σ decreases. This result is intuitive: The larger is the extra utility term, the larger is the extent to

Table 11 Robustness check: nested logit specification

Specification	I	II	III
α	−8.304***	.387***	2.947***
	(.017)	(.010)	(.029)
σ	.726***	.554***	.472***
	(.004)	(.013)	(.005)
Tuesday	−.049***	−.046***	−.062***
	(.007)	(.013)	(.012)
Wednesday	−.095***	−.079***	−.079***
	(.013)	(.016)	(.007)
Thursday	−.074***	−.093***	−.128***
	(.014)	(.017)	(.009)
Friday	−.347***	−.331***	−.309***
	(.026)	(.046)	(.024)
Saturday	−.451***	−.408***	−.362***
	(.024)	(.045)	(.023)
Series FE	N	Y	Y
Time Slot FE	Y	Y	Y
Year (TV season) FE	Y	Y	Y

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

The linear part of each specification is the same as the previous random coefficient models

which continuous television viewing, which includes both switching to a different channel and remaining on the same channel, is explained by the extra utility term rather than by the within-group correlation.

The differentials in the estimated coefficients for the broadcast day dummy variables between weekdays and weekends tend to be slightly smaller under the nested logit model than under the random coefficient model. However, it does not automatically imply that the underlying weekend effects are biased upward in the previous random coefficient model because this should be evaluated in terms of predicted differentials in ratings between weekdays and weekends. I present these values in Sect. 6.

5.3 Optimality of Program Schedules

To examine the estimates from the demand model, I test whether each television network could have raised its ratings by reshuffling its weekly program schedule. The basic premise behind this exercise is that a television network schedules its programs to maximize its overall ratings in any given broadcast season. Although the relationship between ratings and advertising revenue is not exactly monotonic, the correlation between the Nielsen rating of a program and the advertising cost for a 30-second slot during its broadcast is known to be very high (Goettler 2012). Another critical assumption is that the decision to broadcast a television series is exogenous to the scheduling decision; that is, the set of available series and programs is fixed.

I adopt pairwise swaps as a reshuffling scheme. For example, consider two television series s and s' that are broadcast on, say, ABC, and suppose that s was broadcast on day d at time slot τ while s' was broadcast on d' at slot τ' during some broadcast season. I test whether ABC's overall ratings in that season would have risen if it had instead assigned series s to (d', τ') and s' to (d, τ) .

I select pairs of television series based on several criteria: First, for two series to be considered as a swappable pair, they should have the same duration in terms of the number of 30-min time slots that an episode of each series takes. Second, the smaller of the numbers of new episodes of the two series should be at least 10 and the difference between the numbers should be less than 30 % of the smaller. These restrictions are to ensure that the two series are sufficiently similar in terms of the number of days and hours that are needed to broadcast them during the season, and that the number of swaps generated is large enough to cancel the effect of idiosyncratic quality shocks on the counterfactual ratings. The algorithm returns a total of 1056 pairs of television series.

Last, I fix the utility levels that are offered by all of the other channels rather than the network that broadcasts the swapped pair. This treatment is consistent with the assumption that the observed program schedules are a Nash equilibrium strategy profile of a simultaneous scheduling game among the broadcast networks.

To see how this exercise helps validate the parameter estimates of interest, suppose that a broadcast network's ratings increase under some counterfactual schedule. Because the underlying demand for television viewing and the series' qualities are not affected by the rescheduling, the increase in the average weekly rating points to a *mismatch* between programs and their broadcast times in the actual schedule.

There are three paths through which the rescheduling can generate a better match: First is the exogenous weekly cycle in demand for television viewing. Second, each program in a pair now faces a different set of competing programs. A sitcom, for example, may do better than a crime drama against reality television shows that are on competing channels.[13] The third path is the lead-in effect as each program now has a different preceding and following program.[14]

Under the assumption that the actual schedule constitutes a Nash strategy profile, if many counterfactual schedules appear better than the actual schedule, one can raise suspicion about the parameter estimates that govern the three paths that are listed above. For this counterfactual exercise, I simulated the choices of 500 randomly drawn viewers. Table 12 presents the results.

As we expected, when the empirical model controls for the endogenous relationship between the series qualities and their broadcast days and hours, the actual scheduling is better rationalized. This reinforces the importance of controlling for television program qualities to separate the underlying day effects from the observed ones. However, the differences between the three specifications

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[13] Given the discrete choice demand system, program qualities are strategic complements, which implies that a broadcasting company will not put a strong program against its competitors' weak programs.

[14] Note that only the rating of a program affects the subsequent program's rating. The distribution of viewers from the preceding program matters only through the assumption about the timing of the decision because viewers of the preceding program automatically become available to watch the following program, whereas viewers on other channels may be stuck with continuing programs. Otherwise, the distribution would not matter because there is no correlation across preferences for show categories.

Table 12 Counterfactual analysis: optimality of program schedules

Specification	No. of pairs	I	II	III
ABC	228	194	193	176
NBC	275	199	203	217
CBS	455	367	370	416
Fox	98	50	60	69
Total	1056	810 (76.7 %)	826 (78.2 %)	878 (83.1 %)

are not large. This is likely a consequence of overfitting: The number of swapping pairs is small compared to the number of parameter estimates that governs the resulting changes in the ratings: eight linear and seven non-linear for specifications I and II; 26 linear and seven non-linear in specification III.

At most, 23 % of the rescheduling cases lead to an increase in the average weekly rating for the broadcast network. This does not immediately imply that the broadcast networks failed to maximize ratings or that the estimates are biased. There are several limitations to this exercise: First, many pairs of television series that are included in this exercise may not have been actually swappable at the time of scheduling due to the difference in the number of episodes in each series. Second, the numbers of swaps for some pairs are not large enough to neutralize the effects of idiosyncratic quality shocks.

Last, there can be other factors that are omitted from the model that make two television series undesirable for a swap. There may be synergies between a certain program genre and a certain day of the week—for example, a family drama and Friday—or some genre-specific synergies between two successive programs, such as that a crime drama that follows a sitcom is better than another sitcom that follows a sitcom. Though limited by a somewhat arbitrary selection of counterfactual schedules, this exercise shows that the estimates of the underlying broadcast day and hour effects are reasonably consistent with the revealed preference principle.

6 Decomposing the Observed Weekend Effect

In this section, I decompose the observed drops in the program ratings on weekends into the intrinsic demand contraction and the endogenous market contraction that is caused by broadcasting companies' scheduling low-quality programs on weekends. To this end, I consider two counterfactual scenarios: one with no underlying day-of-the-week effects and another with no endogenous scheduling. I simulate choices of 1000 randomly drawn viewers to document how ratings change, compared to the actual ratings, under each scenario. Table 13 reports the counterfactual ratings. The first panel presents the actual average ratings for comparison.

The first counterfactual scenario is that there is no underlying day effects in demand for television programs. I compute the predicted ratings under this scenario

Table 13 Counterfactual ratings

	M	T	W	Th	F	Sa	Mon–Thu	Fri–Sat
Average per-program rating								
Actual	7.39	7.16	6.98	7.86	5.44	4.67	7.35	5.10
Scenario 1								
RC Spec. II	7.29	7.02	6.89	7.90	6.06	5.44	7.27	5.79
RC Spec. III	7.40	7.12	6.96	7.99	6.15	5.47	7.37	5.85
NL Spec. III	7.39	7.16	7.04	8.12	6.21	5.46	7.42	5.87
Scenario 2								
RC Spec. II	7.49	7.02	7.06	6.88	6.37	6.45	7.11	6.40
RC Spec. III	7.41	7.12	7.11	6.91	6.41	6.68	7.14	6.53
NL Spec. III	9.08	7.16	7.38	7.12	6.43	6.83	7.67	6.61
Average HUT								
Actual	64.37	63.41	62.21	62.40	55.95	54.28	63.13	55.12
Scenario 1								
RC Spec. II	64.57	63.32	62.40	63.72	63.36	63.65	63.53	63.50
RC Spec. III	64.67	63.46	62.35	63.67	63.17	63.08	63.57	63.13
NL Spec. III	64.37	63.41	62.63	64.02	62.16	61.75	63.63	61.96
Scenario 2								
RC Spec. II	65.20	63.32	62.43	61.56	55.38	55.06	63.17	55.22
RC Spec. III	65.54	63.46	63.00	62.09	55.99	56.36	63.57	56.17
NL Spec. III	65.08	63.41	62.68	61.48	56.28	55.31	63.20	55.80

by setting the coefficients for the day dummy variables to be constant at the estimated coefficient for Tuesday. The simulation results predict that the average rating falls by around 21 % in weekends, both under the random coefficient (RC) and nested logit (NL) model. As the actual ratings fall by 31 % in weekends, it implies that the variation in the show qualities accounts for about two-thirds of the observed drop in weekend ratings.

The bottom panel reports the counterfactual ratings when there is no endogenous scheduling. To remove the effect of the endogenous scheduling, I keep the program-specific part of utility constant across the days of the week. Specifically, I set each program's broadcast day and hour invariant utility level— $x_j\beta_i + \zeta_j + \xi_{jt}$—in each broadcast year to be constant at the utility level of the network's average Thursday program in that year. Thus, given a network and a broadcast year, programs differ in utilities that they deliver only through the day- and time-slot-specific part: $\beta_d d + \beta_\tau \tau$. This approach directly alters the available utility levels at each time of decision-making, and hence is less comparable to the actual ratings than the first counterfactual scenario. Under this scenario, the average rating falls by 9 % under the RC model, which implies that roughly less than a third of the observed rating drops on weekends can be attributed to the intrinsic contraction in demand for television watching. It is 14 % under the NL model.

Note that, under scenario 1, the share of households who watch television (HUT) does not drop on weekends although the network channels still offer low-quality programs on weekends. This is because the removal of the day-of-the-week effects makes watching television more attractive than not watching, even on weekends, which causes the shares of the cable option (which delivers a constant level of utility throughout the week) to rise dramatically.

7 Conclusion

The observed decline in television program ratings on Fridays and Saturdays is likely a result of two factors: intrinsic shrinkage in demand for television viewing in weekends, and the market contraction effect that arises from endogenous scheduling. In this paper, I decompose the two effects: I model a viewer's problem as a discrete choice problem where the choices are whether to watch one of the four broadcast network channels, a cable channel, or not to watch television at all. The utility from watching a television program depends on the broadcast day of the week as well as the program's attributes (such as the show category) that interact with the viewer's type.

I estimate the model with the use of the method that has been proposed by Berry et al. (1995). The identifying condition is that idiosyncratic show quality shocks are orthogonal to the broadcast day/time slots conditional on the observables. The condition requires one to control for systematic or expected heterogeneity in program qualities that affect the television network's scheduling decision. The long span of the data that are used to estimate the model enables me to control for television series qualities using a fixed-effect approach. The estimation results reveal that the estimated weekend effect is dampened when the empirical model accounts for variation in the television series qualities.

To examine further the estimates from the demand model, I test whether the estimated broadcast day and hour effects justify the observed schedules as a Nash equilibrium strategy. To this end, I consider a reshuffling of the network's line-ups generated by pairwise swaps of the broadcast days and hours between two television series. The network rating decreases compared to the actual rating in more than 75 % of the counterfactual reshuffling cases. It implies that the estimates of the underlying broadcast day and hour effects are reasonably consistent with the television networks' rating maximization.

The results of counterfactual simulation indicate that the market contraction effect from endogenous scheduling accounts for two-thirds of the rating drops on weekends while the intrinsic contraction in demand for television watching accounts for only the remaining third.

It remains unanswered whether the estimated weekend effect in television viewership captures the disinclination for watching videos in general (which includes, for example, video streaming on Netflix) rather than engaging in more active leisure or outdoor activities in weekend, or simply the disinclination for more narrowly defined, linear television viewing. This question is worth investigating because it may reveal a central difference between the two alternative modes of entertainment—online video streaming and traditional television viewing, one waxing and one waning—and can be relatively easily answered. Because the set of available videos is more-or-less constant throughout the week, the observed weekend effect, if any, in the online video streaming service market is likely equal to the intrinsic demand contraction effect.

Also, industry stakeholders and policy makers may be interested in how the growing popularity of online television affects the market contraction effect and, consequently, broadcasting companies' program scheduling strategies. One can conjecture that the wide availability of online video streaming services amplifies the market contraction effect of broadcasting weak programs on weekends because viewers can more easily substitute away from low-quality television shows on weekends toward high-quality shows that were originally broadcast on weekdays. I leave this for future research.

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