Spatial Competition in Cable News: Where Are Larry King and O'Reilly located in Latent Attribute Space?*

Bharat Anand† — *Harvard Business School*
Dmitri Byzalov‡ — *Harvard University*

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Abstract

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†banand@hbs.edu, (617)-495-5082.
‡byzalov@fas.harvard.edu, (617)-529-3805.

1. Introduction

There has been a growing public debate around the existence and consequences of bias in the media. Accompanying this has been a recent explosion in the academic literature on media bias. Starting with Mullainathan and Shleifer's analysis of factors that can result in news "slant", there have been various theoretical papers that try to explain why bias might even arise as an equilibrium phenomenon (see Baron 2004 and 2006; Stromberg 2004, Gentzkow and Shapiro 2006, Anand et al 2007). Various papers examine both supply-side reasons and demand-side forces.

At the same time, the data on which this debate, and literature, is grounded has until recently remained rather anecdotal. Some books describe a liberal bias (*Bias* [Bernard Goldberg, 2001], *Slander: Liberal Lies About the American Right* [Ann Coulter, 2002], *South Park Conservatives: A Revolt Against Liberal Bias* [Brian Anderson, 2005]), others a conservative bias (*What Liberal Media* [Eric Alterman, 2005], *Lies and Lying Liars who Tell Them* [Al Franken, 2007], *Blinded by the Right* [David Brock, 2007]). Interestingly, even these authors of best-selling books acknowledge the lack of any hard data on the subject[1]. Empirical work, however, confronts a serious challenge in measuring bias. The reason this is hard is that bias is both unobserved and hard to define. This creates two problems in turn. The first concerns the choice of data: specifically, what data is both appropriate for constructing a measure of bias, *and* systematically collectable? The second challenge concerns the choice of "anchor" for any measure of bias: specifically, what constitutes "unbiasedness"?

Two recent papers take an important step forward on measurement. Groseclose and Milyo (2004) and Gentzkow and Shapiro (2007) rely on "content analysis" to measure bias in news coverage by particular media outlets. Their data are in each case previously hard-to-gather records of the actual textual content in the news stories of each outlet. Furthermore, rather than trying to measure bias directly, they do so indirectly. Specifically, they correlate content of a media outlet news stories with the content of politician's speeches. Correlation allows one to anchor the measure of bias in measures of politician's ideological rankings.[2] For example, a media outlet whose news content appears most similar to that of, say, Senator Kennedy, will have an estimated ideological ranking closest to his.

These studies look to measure bias as the degree of right-left ideological differentiation re-

[1] Eric Alterman: xxx.

[2] Groseclose and Milyo measure this as a congressperson's adjusted ADA scores, and Gentzkow and Shapiro as the share of the 2004 two-party presidential vote total going to George Bush in the congressperson's constituency.

vealed in the textual content of news outlet stories.[3] In general, the overall message of a news outlet is a combination of verbal content together with pictures and other non-verbal aspects, all of which are under the control of news outlets. Indeed, the sources of bias that are commonly described in public debate include various factors beyond textual content: for eg., "bias by headline" (two stories with the same textual content may elicit different responses regarding bias because their headlines differ), "bias by photos, captions, and camera angles", "bias through placement" (the ordering of news content within stories and across news pages matters), "bias through tone", or "bias through omission.[4] For newspapers, focusing on verbal content is probably accurate enough to capture right-left differentiation. For television, however, capturing the non-verbal content is probably much more important.

In this paper, we study product differentiation in the market for cable TV news, adopting a different empirical approach than prior studies. We rely on consumer choices, rather than content analysis, to infer product attributes of media programs. In other words, we don't impose a priori what the relevant attributes are, or what they mean, but instead use consumer choices and a revealed preference logic to identify what these unobserved attributes are. Specifically, we rely on correlations in consumer choices across different TV news programs to reveal the latent product attributes of these programs. The simplest logic is as follows: for example, if one group of consumers consistently watched shows A and B only, and another group usually watched shows shows C and D, then such choice data would reveal the existence of some attribute dimension, z, on which (i) A and B are similar, (ii) C and D are similar, and (iii) the two groups of shows are different from each other.[5]

This approach both complements and departs from content analysis. First, if ideological

[3] Gentzkow and Shapiro use the term "ideological slant" rather than bias, as a reference to "any differences in news content that, ceteris paribus, tends to increase a reader's support for one side of the political spectrum over the other" (p.3).

[4] http://www.media-awareness.ca/english/resources/educational/handouts/broadcast_news.html

It is also often noted that the color of the picture, or the facial expressions of the reporter or anchor can convey strong impressions on television. Lee and Solomon (1992) describe how "manipulative photo journalism can assume various (other) guises. Photographs may have erroneous captions, or two photos might be juxtaposed in such a way as to create a misleading picture. The selection of photos is significant, for a picture sends a cue about how to perceive an article before we actually read it." In his book *Who Killed CBS?* Peter Boyer tells how network executive Van Gordon Sauter let correspondent Lesley Stahl file critical reports on the Reagan administration while CBS producers illustrated her words with pictures that contradicted the message. A story focusing on the adverse impact of Reagonomics on the elderly, for example, would be accompanied by a picture of President Reagan opening a new nursing home. Much to her surprise, Stahl at one point got a phone call from a Reagan aide who thanked her for a story that she thought was critical of the President" (pgs 46-47).

[5] An alternative explanation is variety-seeking. Section 5 discusses this in the context of our identification strategy in more detail.

"slant" really mattered in the data, it would be captured as one of the latent dimensions. Second, the identification logic is different: if two shows have the same textual content but their audiences never overlap, our approach would treat them as different. Conversely, two shows that have different content but whose audiences are very similar will be estimated to be similar shows. Third, our approach reveals other empirically relevant product attributes in the market for news rather than restricting attention a priori to the dimension of slant.

In contrast to prior focus on (mostly) newspapers, our focus is on the cable television news market, specifically programs on Fox News and CNN. These channels are invariably at the center of the debate around media bias. Our empirical analysis exploits an individual-level dataset that contains, among other things, detailed viewing data for the shows on the cable news networks. The individual level data allows us to observe the overlap in audiences between different programs, which is the main source of identification for show locations.

Our metholodogy draws on a growing empirical literature on latent attribute estimation. Prior work includes studies in marketing (Elrod 1988, Erdem 1996, Chintagunta 1994 and 1999), political economy (Heckman and Snyder 1999), and industrial organization (Goettler and Shachar 2002). Our basic estimation and identification approach builds on these papers. Section 4 describes how particular features of our data require us to modify and extend this line of work.

Our results reveal the existence of two attributes: one that corresponds to (right-left) ideological slant, and a second that corresponds to "light" vs "heavy" shows. xxx Counterfactuals: xxx.

2. The Data

We use data from the Simmons National Consumer Survey, collected between May 2003 – May 2004. It is an individual-level dataset that contains, among other things, detailed viewing data for the shows on the cable news networks. The full dataset is 28,724 observations, representing the entire US population except Hawaii and Alaska.

We focus on the weekday shows that air between 4pm–10.59pm (Eastern time) on the two major cable news networks, CNN and FOX News[6]. The schedule of the shows is presented in Table 1. We focus on Eastern and Central time zones (unless explicitly stated otherwise, all the

[6] We do not include MSNBC, because it had much lower viewership than CNN and FOX News in our data. The national and local news on the broadcast networks (ABC, CBS, FOX, NBC, PBS, etc) and news programs on specialized channels like CNBC or C-SPAN are not directly comparable to the shows on CNN and FOX News, and therefore we do not include them as well.

times are for the Eastern time zone). Notice that the cable news networks do not time-shift their programming for different time zones, i.e. a show that airs at 8pm in the Eastern time zone will air at 7pm local time in the Central time zone (we exploit this fact in estimation). For each show, we observe whether or not the respondent watched it at least once in the last week (notice that we don't observe the number of times each show was watched during the week, just a binary variable for each show). The shows air 5 days a week[7], at the same time every weekday[8]. Most of the shows are one hour long, except for *Crossfire* (30 minutes) and *Inside Politics* (typically 30 minutes, but sometimes it starts earlier and lasts longer) on CNN. In the analysis below, we merge *Inside Politics* and *Crossfire*, and treat them like a single one-hour show[9]. We do not have data on the weekend shows and the weekday shows that air before 4pm, therefore we do not include them in the analysis.

Our dataset spans a year from May 2003 to May 2004 (the data for each respondent refer to the last 7 days, but different respondents were sampled on different dates). During that year, there was a change in the schedule of shows for CNN. Specifically, on September 8 2003 CNN introduced two new shows, *Anderson Cooper* 360^0 (7pm-7.59pm) and *Paula Zahn Now* (8pm-8.59pm), replacing *Live from the Headlines* (7pm-8.59pm)[10]. The schedule of Fox News was stable throughout the year, except for several one-time changes related to the 2004 election campaign. (Source: *TV Guide* for different dates, 2003-2004). We do not observe when exactly each respondent in the dataset was sampled, however we know the aggregate distribution of dates. We use this distribution in the empirical analysis to account for the schedule change on CNN.

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[7] The only exception is *Larry King Live* on CNN, which airs original shows (not re-runs) 7 days a week. Since the two weekend shows are outside the timeframe of our model, that can be a problem if many respondents watch *Larry King* on the weekends only. We do not observe the proportion of such weekend-only *Larry King* viewers in the viewing choices data, however we can infer its magnitude from additional variables. Specifically, we observe whether the respondents watched CNN between 9-11pm last week (*Larry King* airs between 9-10pm ET), separately for weekdays and weekend. Among *Larry King* viewers in the Eastern time zone, only 10% watched CNN between 9-11pm on the weekend but not on weekdays, and 90% watched it on weekdays. This number is not entirely accurate, because many respondents have missing data for watching CNN between 9-11pm, and they might be watching another show between 10-11pm rather than *Larry King*. However, it suggests that the proportion of weekend-only *Larry King* viewers is quite low. Therefore, we treat *Larry King* like a weekday-only show in estimation. xxx Central time zone

[8] In addition to the original airing of each show, the news networks also air re-runs of their shows at night. We do not observe whether the respondent watched the original airing of the show or a late-night re-run. We assume it is always the former, which is quite accurate for the Eastern time zone (the re-runs start at 11pm ET or later, depending on the network and season), possibly less accurate for the Central time zone. Specifically, our main concern would be the 11pm re-run of the most popular FOX News show *The O'Relly Factor*. Among the *O'Reilly Factor* viewers in the Eastern time zone, only 7% report watching FOX News between 11pm-1am but not between 8-9pm (the original airing of the show), and 93% report watching FOX News between 8-9pm last week. Although not entirely accurate due to a large proportion of missing data on FOX News viewing between 8-9pm and 11pm-1am, this suggests that the 11pm re-run accounts for a small share of the total audience of *The O'Reilly Factor*. xxx check Central time zone

[9] This substantially simplifies the estimation of the structural model, since the rest of the data is in terms of one-hour periods.

[10] We do not have viewing data for *Live from the Headlines*.

In addition to the viewing data for CNN and FOX News shows, for each hour we observe whether or not the respondent watched TV at least once in the last 5 weekdays (a binary variable for each hour). This gives us some information about other TV-viewing (broadcast networks and other cable networks besides CNN and FOX News).

In our analysis, we restrict attention to the subsample of the respondents who are at least 18 years old, live in the Eastern and Central time zones[11], and have cable or satellite TV subscription[12]. In addition, we drop the respondents who do not report watching any cable shows (on any cable channel, not just CNN and FOX News)[13]. The final subsample is 14,109 observations (8815 in the Eastern time zone and 5294 in the Central time zone).

Tables 2a-5c present descriptive statistics for this subsample. The time frame is 4pm-10.59pm local time for the respondents in the Eastern time zone, and 3pm-9.59pm local time in the Central time zone. The most popular shows are *The O'Reilly Factor* on FOX News, watched by 12.3% of the respondents in the past week, and *Larry King Live* on CNN, watched by 11.9% (table 2a). The rest of the shows have much lower shares, ranging from 2.2% for *Anderson Cooper 360*^{0} or *Big Story with John Gibson* to 7.4% for *Paula Zahn Now*. Most of the respondents (71.7%) did not watch any of the CNN or FOX News shows in the past week (Table 2b). However, some respondents watch a lot of cable news: 4.1% report watching at least 3 different shows on CNN in the past week, and 5.9% report watching at least 3 different shows on FOX News (notice that this refers to the number of distinct show titles watched once or more during the week, and not the total number of episodes watched for all the shows). Such respondents are important for our identification scheme, because the distances between the shows in the attribute space are identified by the joint audiences

[11] The only location variable we have is respondent's state. A few states span two time zones, in which case we assign the entire state to the time zone with the majority of the state's population. Also, we drop observations for Indiana, because many counties in Indiana do not observe daylight saving time.

[12] One issue in the data is that we do not observe specific packages or tiers they subscribe to on cable or satellite TV. For cable, CNN and FOX News are typically carried on the expanded-basic tier (as opposed to the basic tier), so most of the basic-only cable subscribers do not have access to them at home. However, basic-only subscribers are just 12% of all cable subscribers (*FCC Report on Cable Prices*, 2005), thus at least 88% of cable subscribers have access to CNN and FOX News at home. For satellite television (DirecTV and Dish Network), all packages offered in 2003-2004 include CNN, and all packages but one (Dish Network's entry-level *America's Top-60* package [AT60]) include FOX News. We do not know the share of the AT60 package. However, Goolsbee and Petrin (2004) find that the closest substitute to satellite is premium cable, thus a large majority of satellite subscriber likely purchase the higher-end packages.

[13] This might be because: (a) the respondent did not fill out the cable viewership part of the questionnaire, (b) she subscribes to a basic cable package that contains broadcast channels but not the major cable channels, (c) she does not watch cable networks even though she has access to them. Ideally, we would want to drop (a) and (b) while keeping (c) in the sample, however we do not have enough data to identify which respondents are (a), (b) or (c). We prefer to drop them all rather than keep them, because (c) is probably much less common in our data than (a) and (b). We drop 13% of our subsample on this criterion.

for different shows (see the identification section for details).

While FOX News has lower total audience than CNN (16.6% of the respondents watched at least one FOX News show last week, vs 19.6% for CNN), FOX News viewers appear to be more loyal than CNN viewers (an average FOX News viewer watched 2.4 different show titles on FOX News last week, vs 1.8 CNN show titles for an average CNN viewer[14]). This might be because FOX News is offering a more homogeneous line-up of shows than CNN, or because most of other media is "liberal media", located closer to CNN than to FOX News in the attribute space. Alternatively, it might reflect a different product positioning approach by the two networks: it might be that CNN is choosing a relatively mainstream location in the attribute space, which no one dislikes a lot but no one likes a lot among the potential viewers, while FOX News is choosing a more extreme location, which more potential viewers dislike but the viewers who are targeted like a lot.

Table 3a reports the joint audience of the shows in row r and column c, as a percentage of the audience of the row-r show. On average, the joint audience for two shows on the same network is 40% (32% for CNN and 49% for FOX News), vs 18% for two shows on different networks. This might be due to two reasons: (a) the line-up of shows on each network is relatively homogeneous, compared to the differences between the networks, or (b) there are strong switching costs in TV-viewing. Previous research (e.g. Emerson and Shachar 2000) found that the switching costs are very substantial for TV-viewing, and because of them the viewers are more likely to keep watching consecutive shows on the same network, and less likely to switch to another network. There is no easy way to neutralize the effect of the switching costs at the level of the descriptive statistics, so we cannot infer which shows are closest to each other in the attribute space based on the descriptive statistics alone (the structural model allows us to fully control for the effect of the switching costs, as well as competition from other shows). The joint audiences of the shows range from 3.5% to 86% (just 3.5% of the viewers of *The O'Reilly Factor* also watched *Anderson Cooper 360^0*, while 86% of the viewers of *Hannity and Colmes* also watched *The O'Reilly Factor*[15]). Despite the much-discussed differences between CNN and FOX News, a surprisingly high percentage of CNN viewers also watched FOX News, and vice versa. For example, 31% of the *Larry King* viewers on CNN also watched *The O'Reilly Factor* on FOX News, and 17% watched *Hannity and Colmes* (these two shows are widely perceived to be the signature FOX News shows). Among the *O'Reilly Factor*

[14] A FOX News (CNN) viewer is a respondent who watched at least one FOX News (CNN) show last week, among the 4pm-10pm weekday shows we focus on.

[15] Notice that this is driven in part by the low total audience of *Anderson Cooper 360^0* and the high total audience of *The O'Reilly Factor*.

viewers, 17% also watched *Wolf Blitzer Reports* (often perceived to be one of the most left-leaning CNN shows), and 30% watched *Larry King Live*.

Table 4a presents the demographics for CNN and FOX News viewers. Compared to the entire sample, the cable news viewers are more likely to be male, older (especially retired), white, college-educated, with higher employment income (among those who work), slightly more conservative (both politically and religiously), and they are more likely to report their political outlook[16]. This demographic profile for the cable news viewers is quite intuitive. Comparing between CNN and FOX News viewers, FOX News viewers are more likely to be male, slightly more religiously conservative, and more politically conservative. These differences are consistent with the conventional wisdom about CNN and FOX News. Comparing between "heavy" CNN and FOX News viewers (at least 3 different show titles on the respective network in the past week), the difference in religious conservativeness and political outlook is larger than for casual viewers. Interestingly, even for "heavy" CNN and FOX News viewers, the average political outlook is quite moderate (2.87 and 2.10 respectively, on a scale from 1 to 5). In terms of average political outlook, CNN viewers are closer to the entire population than are the FOX News viewers (this holds for both casual and "heavy" viewers). This might suggest that CNN shows occupy a more mainstream area of the attribute space, compared to the FOX News shows. In addition, "heavy" FOX News viewers earn more (if they work) than "heavy" CNN viewers. In addition to respondent's self-reported political outlook, we also look at the average political outlook in the respondent's state (measured as the percentage of vote for the Democratic candidate in the 2000 and 2004 presidential elections). There are two reasons for that. First, self-reported political outlook measures are probably relative, e.g. a self-reported "moderate conservative" probably has a different meaning in Massachusetts than in Texas. Second, there might be important differences in viewership between "blue" and "red" states. Surprisingly, there are essentially no differences in the "blue-red state" measures between CNN and FOX News viewers. In other words, CNN viewers are not concentrated in the "blue states", and FOX News viewers are not concentrated in the "red states". Also, many respondents watch both CNN and FOX News. For most demographics, they look like an average between CNN and FOX News viewers[17].

[16] Unlike other variables, the respondents had an option to not report their political outlook, and a substantial fraction do not report it. Those respondents probably have less intense opinions about politics, or care less about it, therefore missing political outlook is a useful demographic variable.

[17] Alternatively, we could expect this group (which presumably samples different points of view from different news channels, perhaps to get an unbiased perspective – the conscientious viewers) to be quite different from other respondents.

Tables 4b-4c present the average viewer demographics for each show. Our identification scheme implies that similar shows should attract similar demographic groups (after controlling for the switching costs and competition from other shows). Notice that because of the switching costs and competition between shows, the viewer demographics for each show depend not only on its own location in the attribute space, but also on the locations of all the other shows aired before it or at the same time with it, so the descriptive statistics do not give a fully reliable measure of similarity between the shows.

In Figure 1, we plot some of the key average viewer demographics for each show (the original numbers are presented in tables 4b-4c). The demographic variable most relevant to the "media slant" issue is the self-reported political outlook (it ranges from 1 for "very conservative" to 5 for "very liberal"). In terms of political outlook, the average viewers of CNN shows are quite different from the average viewers of FOX News shows (figure 1a). The average viewer of any CNN show is more liberal than the average viewer of any FOX News show. On CNN, the show with the most liberal average viewer is *Anderson Cooper 360^0*, while *Larry King Live* and *Inside Politics/Crossfire* have the most conservative viewers on average. On FOX News, *On the Record with Greta van Susteren* has the most liberal viewers on average, while *Hannity and Colmes* attracts the most conservative viewers. This ranking is consistent with a common perception of those shows. (Notice that these descriptive statistics do not control for switching costs and competition from other shows, so they do not necessarily indicate the actual "ideological slant" ranking of the shows).

There is surprising heterogeneity in average demographics across shows. For example, the proportion of male viewers ranges from 42% for *Paula Zahn Now* to 63% for *Wolf Blitzer Reports* (figure 1b). The proportion of college graduates and above ranges from 29% for *Big Story with John Gibson* to 44% for *Hannity and Colmes (*figure 1c). On average, the viewers of *Hannity and Colmes* earn the most, about $7500 a year more than the viewers of *Big Story with John Gibson* (figure 1e). For most variables, there is a lot of overlap in average viewer demographics between CNN and FOX News shows. The exceptions are political outlook (figure 1a), as discussed above, and religious conservativeness (figure 1g), consistent with the conventional-wisdom view of the two networks.

Table 5a presents the distribution of self-reported political outlook for CNN and FOX News viewers. The differences between CNN and FOX News are quite intuitive. The main surprise is that quite a lot of people with extreme political outlook watch the network closer to the opposite position. For example, "very conservative" respondents account for 10% of CNN viewers (vs

11% in the population), while "very liberal" respondents account for 2% of FOX News viewers (vs 5% in the population). Tables 5b and 5c present the distribution of political outlook for each show on CNN and FOX News. Again, the main surprise is that CNN shows attract quite a lot of "very conservative" respondents, while FOX News shows attract quite a lot of "very liberal" respondents. Table 5d presents the fraction of CNN or Fox viewers for each category of political outlook. As expected, the viewing share of FOX is higher for more conservative respondents, and the reverse is true for CNN. However, for CNN the profile of viewing shares among different political outlook categories is relatively flat, whereas for FOX there are large differences between "very conservative" and "very liberal" respondents. This again might suggest that CNN is more mainstream whereas FOX specifically targets a more conservative audience. An interesting pattern is that the profile of viewing shares is not monotone with respect to the political outlook. Specifically, CNN viewership and overall news viewership both drop in the middle of the political outlook scale (outlook=3), with higher viewership for both moderately liberal and moderately conservative respondents (outlook=2,4). This might mean that those with stronger opinions in either direction are more interested in the news than those in the middle.

3. The Empirical Model

Our model is an individual-level discrete-choice model for panel data, with switching costs to account for the dynamics of TV-viewing, and latent-attribute structure of utility for the shows.

There are 5 weekdays, indexed by d. Each day there are T one-hour periods, indexed by t ($t = 1...T$ represents 4pm to 10pm local time in the Eastern time zone, and 3pm to 9pm local time in the Central time zone). In each period t of each day d, individual i chooses alternative j among the following alternatives: $j = 0$ outside alternative (not watching TV), $j \in \{1, ..., J\}$ cable news networks ($j = 1$ CNN, $j = 2$ FOX News), $j = J + 1$ "other-TV" alternative (watching any other TV channel).

The show aired by network j in period t of each day (show j, t) has a vertical characteristic $\eta_{j,t}$ and horizontal characteristics $Z_{j,t}$. For each show, $Z_{j,t}$ is an M-dimensional vector of latent attributes, which are free parameters in estimation. The $Z_{j,t}$-s represent the show locations in the M-dimensional latent attribute space. Notice that each show is aired at the same time each day, and its characteristics are assumed to be the same throughout the sample period.

The utility from watching show j, t on day d is

$$U_{i,j,t}^d = \eta_{j,t} + Z_{j,t}(\Gamma X_i + \upsilon_i^Z) + \delta I\{c_{i,t-1}^d = j\} + \varepsilon_{i,j,t}^d$$

where $(\Gamma X_i + \upsilon_i^Z)$ is an M-dimensional vector that represents the preferences for the show attributes $Z_{j,t}$, X_i are the observable demographics of individual i and $\upsilon_i^Z \sim N(0, \Sigma_\upsilon^Z)$ are her unobservable characteristics, $\delta I\{c_{i,t-1}^d = j\}$ represents the switching costs ($c_{i,t-1}^d$ denotes her choice in the previous period of the same day), and $\varepsilon_{i,j,t}^d$ is an i.i.d. logit error. In each d, t, the individual chooses the alternative that yields the highest utility, and her choice is $c_{i,t}^d \in \{0, ..., J+1\}$.

We include the switching costs because previous reseach has found strong switching costs in TV-viewing (e.g. Shachar and Emerson 2000), and because properly controlling for state-dependence is important for the identification of the latent show attributes (see the identification subsection for details).

The latent-attribute structure of the utility allows us to estimate (up to the normalizations we discuss later) both the show locations in the attribute space ($Z_{j,t}$) and the parameters of preferences for those attributes $(\Gamma, \Sigma_\upsilon^Z)$[18]. There are several advantages to using this approach. First, instead of imposing an *a priori* list of relevant product attributes, we let the data identify the relevant dimensions of differentiation. Thus, if "media bias" or "ideological slant" is important in the data, it will be identified as one of the latent dimensions, along with other dimensions of differentiation that turn out to be important in the data. Second, we do not have to impose any *a priori* interpretation on those attributes. This is particularly useful for products like news shows, for which it is not clear *a priori* even how to define (let alone measure) the most important product attributes.

The utility from the "other-TV" alternative $j = J + 1$ (watching any other channel) is

$$U_{i,J+1,t}^d = \eta_t^{other} + \eta_t^{ET} ET_i + \beta_t X_i + \sigma_t \upsilon_i^{other} + \delta^{other} I\{c_{i,t-1}^d = J+1\} + \varepsilon_{i,J+1,t}^d$$

where $ET_i = 1$ for the respondents in the Eastern time zone, $\beta_t X_i$ captures the effect of the

[18] We use a linear specification of utility from the latent attributes. Alternatively, we could use an ideal-point specification (*a priori*, it would seem to be more appropriate for attributes like ideological slant). However, in preliminary estimation with an ideal-point structure, we found that the ideal points of all the respondents are located outside the area where all the shows are located. This implies that the utility is monotone with respect to the show attributes, and therefore the linear structure is more appropriate for our data. Notice that in the empirical specification, we allow a non-monotone effect of demographics (age, income, self-reported political outlook, etc) on the preferences for the attributes, thus the linear specification is less restrictive than it might seem.

demographics X_i, $\upsilon_i^{other} \sim N(0, \sigma^2_{other})$ captures the unobserved characteristics of the individual[19], $\delta^{other} I\{c^d_{i,t-1} = J+1\}$ captures the switching costs[20], and $\varepsilon^d_{i,J+1,t}$ is a logit error. The "other-TV" alternative includes multiple channels, which we do not model individually because we do not have sufficiently detailed data. The period-specific coefficients η_t^{other}, η_t^{ET}, β_t, σ_t allow us to control (in reduced form) for the characteristics of the shows offered on other channels (cable channels and local broadcast channels). Notice that the same t refers to different hours (local time) in the two time zones (e.g. $t = 1$ is 4pm local time in the Eastern time zone, and 3pm local time in the Central time zone), and part of the television programming for the same t is different between the two time zones (although most of the programming is identical). Specifically, the programming on the cable networks and the national prime-time programming (8-10pm ET) on the broadcast networks is identical between the Eastern and Central time zones, and it is not time-shifted (thus, cable programming for all t-s and broadcast programming for $t = 5...7$ [8-10pm ET / 7-9pm CT] is absolutely identical between the two time zones). However, the local programming block (before 8pm ET / 7pm CT) on the broadcast channels varies by city (it is filled by the local affiliates), and there are substantial differences between the two time zones with respect to the late-afternoon viewership of broadcast networks[21]. To control for the differences in broadcast programming between the time zones, we introduce timezone-specific constants η_t^{ET} for $t = 1...4$ (we set $\eta_t^{ET} = 0$ for $t = 5...7$, because prime-time programming is the same in both time zones)[22]. Our main goal in choosing the specification for "other-TV" utility is to have a reasonably accurate but parsimonious reduced-form control for the viewership of other channels (primarily entertainment, but also some news shows, especially local and national news on the broadcast networks).

The main reason we explicitly model the "other-TV" alternative, instead of merging it into the outside alternative, is that it gives us a somewhat cleaner interpretation of the audience attracted by the cable news shows, and competition with other shows. Suppose, for example, that the main "other-TV" competitor to *Larry King Live* is the *American Idol*, and the utility from the *American Idol* strongly increases in income and education, while the utility from *Larry King* also increases

[19] We allow υ_i^{other} to be correlated with υ_i^Z, so that $(\upsilon_i^Z, \upsilon_i^{other})' \sim N(0, \Sigma_\upsilon)$ for a general Σ_υ.

[20] If the respondent switches between two channels which are both included in the "other-TV" alternative, it will not count as a switch in this reduced-form specification. Therefore, the switching-cost parameter here is different than that for CNN and FOX News.

[21] The viewership of broadcast networks between 4-6pm local time is substantially lower in the Central time zone than in the Eastern time zone, however this gap disappears during prime time (8pm ET/ 7pm CT and later).

[22] In addition, we could allow the coefficients on demographics (β_t) to vary by time zone, for $t = 1...4$. However, since all cable programming is identical between the time zones, and most of daytime broadcast programming is quite similar, the improvement in fit would likely be moderate, not enough to justify adding a lot of additional parameters.

in income and education, but less strongly, and the utility from the outside alternative does not depend on them. As a result, the richest most educated demographics will be less likely to watch *Larry King* (not because they do not like it, but because they like the *American Idol* even more). Then, if we pool "other-TV" with the outside alternative, our estimates will indicate that the utility from *Larry King* decreases in income and education. In contrast, when we model "other-TV" separately (with an appropriate normalization for the outside alternative), our estimates will correctly capture the effect of competition, with the *American Idol* stealing the rich and educated viewers from *Larry King*.

The utility from the outside alternative $j = 0$ (not watching TV) is

$$U^d_{i,0,t} = \eta^{out}_{t-CT_i} + \lambda_{t-CT_i} X_i + \delta^{out} I\{c^d_{i,t-1} = 0\} + \varepsilon^d_{i,0,t}$$

where $CT_i = 1$ for the respondents in the Central time zone (0 otherwise), the coefficients $\eta^{out}_{t-CT_i}, \lambda_{t-CT_i}$ are indexed by local time $\tau = t - CT_i$[23], $\delta^{out} I\{c^d_{i,t-1} = 0\}$ represents the switching costs, and $\varepsilon^d_{i,0,t}$ is a logit error. Like in all discrete-choice models, we have to normalize the utility for one alternative (we normalize $\eta^{out}_{\tau} = 0$, $\lambda_{\tau} = 0$ for $\tau = 8pm$ local time). However, notice that conditional on this normalization, $\eta^{out}_{\tau}, \lambda_{\tau}$ for the other periods are fully identified (which is not typically the case in standard panel models). The reason for this is that we are using data for two time zones, and cable news programming is identical and not time-shifted between them. For example, *Larry King Live* airs at 9pm ET / 8pm CT. Consider two identical individuals (identical X_i and υ_i), one in each time zone. One of them can watch *Larry King* at 9pm local time (Eastern), while the other can watch it at 8pm local time (Central). Notice that the utility from Larry King is the same for both individuals, and their utility from the competing FOX News show and "other-TV" is also identical (since the TV programming in the Central time zone at 8pm Central is the same as in the Eastern time zone at 9pm Eastern). The only difference between the two individuals is that one of them is facing outside utility for 8pm local time, while the other one is facing outside utility for 9pm. Thus, the difference in choice probabilities between Eastern and Central time zones will identify $\eta^{out}_{9pm} - \eta^{out}_{8pm}$ and $\lambda_{9pm} - \lambda_{8pm}$ (thus, we only have to normalize one period, e.g. 8pm)[24].

[23] Thus, $\eta^{out}_0 ... \eta^{out}_T$, $\lambda_0 ... \lambda_T$ are the coefficients for 3pm-10pm local time, with 3pm being relevant only for the Central time zone respondents, and 10pm being relevant only for the Eastern time zone.

[24] The identification before 8pm ET is slightly more complicated, because "other-TV" programming can be different between the two time zones. However, the utility from each CNN or FOX News show is still the same for both individuals, thus the difference in their choice probabilities for CNN and FOX News shows, combined with the difference in their choice probabilities for "other-TV" is enough to identify the outside utility and the "other-TV"

3.1. Scale and Rotation Invariance, Normalizations for the Latent-Attribute Structure

In the latent-attribute model, we estimate both the show attributes and the preferences for those attributes as free parameters. This requires imposing several normalizations (in addition to the standard normalizations for random-utility models). The latent-attribute component of utility has the following structure

$$U^d_{i,j,t} = ... + Z_{j,t}(\Gamma X_i + \upsilon^Z_i) + ...$$

where $Z_{j,t}, \Gamma$ and $\Sigma^Z_\upsilon \equiv cov(\upsilon^Z)$ are free parameters in estimation.

For any invertible matrix A of the appropriate size,

$$(Z_{j,t}A)((A^{-1}\Gamma)X_i + A^{-1}\upsilon_i) = Z_{j,t}(\Gamma X_i + \upsilon_i) \text{ for any } X_i, \upsilon_i$$

Thus, for any given values of the $Z_{j,t}$-s, Γ and Σ_υ, the likelihood is invariant to transformations using any invertible matrix A. We use the standard normalization from the latent-attribute literature $cov(\Gamma X_i + \upsilon^Z_i) = I$ (e.g. Elrod 1988). After this normalization, the $Z_{j,t}$-s and Γ are identified up to a rotation (a transformation using any matrix A of the appropriate size that satisfies $A'A = I$ will give the same likelihood, and will preserve $cov(\Gamma X_i + \upsilon_i) = I$). Therefore, we add additional normalizations to pin down a specific rotation[25].

4. Estimation

We estimate the model by simulated GMM. The moments are simulated in an unbiased way for each individual, therefore the estimates are consistent for a finite number of simulated draws.

For each individual, we have the following data: demographics X_i, time zone dummies ET_i, CT_i, show choices $Y_{i,j,t}$ for $j = 1, 2$ and $t = 1...T$ ($Y_{i,j,t} = 1$ if the individual watched show j, t at least once in the last 5 weekdays), and overall TV viewership $TVon_{i,t}$ for $t = 1...T$ ($TVon_{i,t} = 1$ if the respondent watched TV at hour t at least once in the last 5 weekdays).

In estimation, we match predicted moments from the model to the actual moments in the data, for the following sets of moments:

(1) viewing shares for each show on CNN and FOX News

utility for each period (subject to the normalization for 8pm).

[25] For the first show, only the first element of $Z_{j,t}$ is non-zero, and the rest are set to zero. For the second show, only the first two elements of $Z_{j,t}$ are non-zero, and so on.

(2) overall TV viewership for each hour

(3) covariances between show choices and demographics X_i, for each show

(4) covariances between overall TV-viewership choices and demographics X_i, for each hour

(5) joint audience between each pair of shows on CNN and FOX News

(6) joint audience between each show and overall TV-viewership for each hour

Moments (1)-(4) are matched separately for each time zone, since many coefficients on demographics are timezone-specific. Moments (5), (6) are matched for the entire sample, in order to keep the total number of moments manageable.

The predicted probabilities are computed in the following way. xxx. Simulation xxx.

Due to the presence of switching costs, it is important to control for the initial conditions in estimation. One possibility would be to model the distribution of the unobserved lagged choice ($t = 0$, which corresponds to 3pm ET / 2pm CT), and to integrate it out of the probabilities for the first period in the data ($t = 1$, which is 4pm ET / 3pm CT). However, since we do not have detailed data for $t = 0$, the identification would have to rely heavily on the functional forms. Therefore, we use a less structural but more reliable alternative. We approximate the distribution of the choices for $t = 1$ (conditional on the draw of the unobserved heterogeneity but not the lagged choice), using a flexible specification of utilities for the shows at $t = 1$. Specifically, for each of the shows at $t = 1$, we estimate an unconstrained show-specific vector of coefficients on demographics and unobservables, without imposing the constraints implied by the latent-attribute structure[26]. This allows us to get more reliable estimates than the fully-structural approach (explicitly modeling the unobserved choice for $t = 0$). The drawback of our approach is that we cannot estimate the locations of the shows aired at $t = 1$. However, the shows aired at $t = 1$ are quite different from the rest of the shows (CNN airs two 30-minute shows, while FOX News airs a business show), so a reduced-form treatment for $t = 1$ would probably be a good idea even if we had enough data for $t = 0$[27].

The total number of moments in estimation is large (1218 moments in the full model with 2 latent dimensions), therefore it would be dangerous to use the (estimated) optimal GMM weighting matrix (see xxx for details). We use an identity weighting matrix (after rescaling the moments so

[26] Notice that we do not have to add a more flexible specification for the outside utility and "other-TV" utility at $t = 1$, because they are sufficiently flexible for each t as they are.

[27] If the shows aired at $t = 0$ are in fact very different from the rest of the shows, and we attempt to estimate their locations in the latent attribute space, then additional latent dimensions might be required to accurately capture the difference between $t = 0$ and the rest of the shows. This would complicate the interpretation of the estimates.

that all of them are roughly the same order of magnitude). As a result, the estimates are consistent but not efficient. However, given the size of our dataset, the estimates are still reasonably precise.

5. Identification

5.1. Identification of Latent Attributes - General Intuition for Panel Data

First, we discuss the general intuition behind the identification of the latent attributes, on regular panel data. After that, in the next subsection, we discuss the additional identification issues in our case, where we have 5-day summary data rather than a panel.

The show locations in the attribute space are identified by the joint audiences for different shows (after controlling for the switching costs and competition faced by each show, which also affect their joint audiences). Specifically, if two shows are close to each other in the attribute space (have similar $Z_{j,t}$-s), it implies two things. First, the effect of the demographics on utility $Z_{j,t}\Gamma X_i$ is similar for the two shows, so they will attract the same demographic groups. Second, the effect of the unobservables $Z_{j,t}\upsilon_i$ is similar for the two shows, so conditional on the demographics X_i, the choices for the two shows will be positively correlated (in other words, among people with the same demographics, the audiences of the two shows will overlap a lot[28]). Thus, the "distance" between two shows in the attribute space is identified from two sources: how similar are the demographic groups attracted by the shows, and how much their audiences overlap within each demographic group (for both sources, it is after controlling for the switching costs and competing shows). The first source is measured by comparing the shows' profiles of utility with respect to the demographics, while the second is measured by computing the covariance of utilities from the shows conditional on the demographics.

Next, once we have the "distances" for each pair of shows, those distances identify the number of dimensions of the attribute space and the shows' relative locations in this space, up to a rotation. Suppose, for example, that we have 3 shows, A, B and C, and suppose that the "distances" between A-B, B-C and A-C are the same. If we use only one latent dimension, we cannot place the shows in a way that will summarize the distances accurately. For 2 dimensions, the distances can be summarized accurately by placing the shows in a triangle (and any rotation of this triangle will preserve the distances). Using more than 2 dimensions will not improve the fit. The same logic

[28] Notice that we could have a situation where two shows attract the same demographics, but half of them only watch show A, and the other half only watch show B, with zero overlap between them. In this case, they would not be estimated as being similar.

applies when we have more than 3 shows: the show locations in the attribute space try to fit the "distances" between each pair of shows, and the number of dimensions of the attribute space is the minimum number of dimensions required to accurately fit all the "distances".

One concern about this identification scheme is related to possible variety-seeking in TV-viewing. In particular, the topics covered by different news shows on the same day overlap a lot. As a result, if the viewers prefer variety in the news topics, then after watching one news show they will be less likely to watch another show that covers the same topics[29]. If this is the case in the data, two shows that cover a similar set of topics will have a disproportionately small joint audience, and the model will overestimate the "distance" between them in the attribute space[30]. A number of studies in marketing (for example, Erdem 1996 and Chintagunta 1999) point out this problem, and propose practical reduced-form ways of dealing with it. Specifically, they allow the consumer preferences for product attributes to depend on the attributes of the product chosen on the previous purchase occasion. This reduced-form specification of variety-seeking is probably accurate enough in the context of those studies (they focus on consumer goods like margarine or liquid detergent), however it is too restrictive in the context of the news shows[31]. Our dataset is not detailed enough to allow reliable identification of a more realistic specification of variety-seeking (even in reduced form). However, we argue that even if variety-seeking behavior is strong in the data, the bias in our estimates is likely to be quite small.

As an extreme case, suppose that there are two absolutely identical shows on the same day. Due to variety-seeking, their joint audience will be very low (or zero, if the variety-seeking is sufficiently strong), and the model will estimate a non-zero "distance" between them. However, we would expect the bias in the estimated show *locations* to be quite moderate even in this extreme case. The reason is that since the two shows are identical, their "distances" to any other show will also be identical[32]. Notice that the show locations in the attribute space are pinned down by their

[29] In addition, other forms of variety-seeking might be present in the data. For example, the viewers might seek variety of TV genres, or variety of activities (besides watching TV) more generally. Notice that unlike preference for variety of news topics within a day, other forms of variety-seeking would apply equally to news and entertainment shows. Using a detailed panel of TV-viewing choices on broadcast networks (primarily entertainment), Goettler and Shachar (2001) found no evidence of variety-seeking. Therefore, our primary concern is about possible preference for variety of news topics (the form of variety-seeking relevant for the news but not entertainment), as opposed to other forms of variety-seeking.

[30] Notice that the effect of the overlap in topics might depend on other characteristics, e.g. it might be weaker for two shows offering different perspectives on the same topic.

[31] At least, we would have to allow the preferences for show attributes to depend on the attributes of all the other news shows chosen on the same day (as opposed to just the previous period, like in the studies cited above).

[32] Since the shows are identical, we would expect the total audience to split equally between them (after controlling for the switching costs and the competition each of them is facing). If there is some strong systematic preference for

"distances" to *all* the other shows. Thus, one "distance" will indicate that the locations of those two shows are somewhat different, while 12 other "distances" will indicate that their locations are identical. As a result, although there might be some bias in the estimated show locations, it will be quite moderate. Therefore, we do not control for variety-seeking in our data.

Notice that it is important to control for the switching costs in estimation, otherwise the estimates of show locations can be strongly biased for the following reason. Two shows can attract a large joint audience for one of two reasons (a) they are located close to each other in the attribute space, so they attract the same viewers, or (b) one of them follows the other on the same channel and the viewers have strong switching costs, so most of the viewers of the first show stick around for the second show. Thus, if we do not control for the switching costs, consecutive shows on the same channel would appear closer to each other in the attribute space than they actually are. The switching costs are identified separately from the show locations from the following sources. First, the show locations are identified by the variation in demographics X_i across the individuals. Thus, if two consecutive shows have a large joint audience, but their utility profiles with respect to the demographics are different, then they will not be identified to be close to each other in the attribute space, and the disproportionately large joint audience will be attributed to the switching costs. Second, conditional on the demographics, correlation between choices of two consecutive shows can be due to either the switching costs or the unobserved heterogeneity $Z_{j,t}\upsilon_i^Z$. The distinction between the two follows the standard intuition of separate identification of unobserved heterogeneity (UH) and state-dependence in panel data. Specifically, the UH affects the entire history of choices, so the choices from any other period help predict the choice in period t (after controlling for the choice in $t-1$). In contrast, the switching costs only apply to two consecutive periods, thus if we control for the choice in period $t-1$, choices in the other periods do not help us predict the choice in period t.

In addition to the switching costs, it is important to control for the competition with other shows aired at the same time. Otherwise, the estimates of show locations will be biased. Suppose, for example, that CNN airs two shows with similar "ideological slant" at 8pm and 9pm (for simplicity, suppose there are no switching costs, and the "ideological slant" is the only attribute), while FOX News airs its most conservative show at 8pm and its most liberal show at 9pm. Thus, the 8pm show on FOX News is too conservative to attract any of the CNN viewers, while the 9pm

one of the two shows, it would mean they are not really identical (for example, one is a re-run of the other, and the consumers value up-to-date news).

show attracts the more conservative part of the CNN viewers. Because of the competition from FOX News, the audience of the 9pm CNN show will be more liberal than that of the 8pm CNN show, even though they have identical “ideological slant”. For similar reasons, it is also important to control for the outside utility for each hour.

After choosing the number of dimensions of the attribute space and estimating the show locations in this space, the next step is interpreting those dimensions. In doing this, we rely on prior knowledge we have about the shows, and we verify our interpretation of the dimensions using additional data (see the estimation results section for details).

5.2. Identification without a Panel - Additional Issues

We use 5-day summary data rather than a panel, which introduces several additional issues for the identification. First, we discuss the identification of the show locations in the simpler case without the switching costs. After that, we show how the switching costs can be identified separately from the unobserved heterogeneity even though we do not have panel data.

If there are no switching costs, then conditional on the realization of the unobserved heterogeneity υ_i, the choices are independent across days, and the probability of choosing show j, t is the same for each of the 5 days. Thus, we have a one-to-one mapping from the probabilities for the 5-day summary (which we identify directly from the data) to the choice probabilities for each day[33], which in turn identify the parameters of the structural model as described in the previous section. The unobserved heterogeneity υ_i is identified by the covariance matrix of choices conditional on the demographics X_i.

The complication for identifying the switching costs separately from the UH is that we do not observe the choices for each day. So, if we observe that the individual watched both the 8pm show and the 9pm show on the same network, we are not sure whether or not she watched them on the same day (thus, we are not sure whether or not the switching costs apply between them). However, there is some probability (which can be computed given the structure of the model) that they were watched on the same day, in which case the switching costs apply. Thus, if we find that after controlling for the UH, the 8pm choice still affects the 9pm choice, it indicates the presence of switching costs. (Notice that the number of dimensions of the UH, equal to the number of dimensions of the latent attribute space, is much lower than the number of shows, thus the UH

[33] Specifically, $Pr(Y_{i,j,t} = 0|X_i, \upsilon_i) = \Pr(c_{i,t}^d \neq j|X_i, \upsilon_i)^5$, where $Y_{i,j,t}$ is the 5-day summary of choices, $c_{i,t}^d$ is the choice for day d, and the 1-day probability is the same for each day.

would not be flexible enough to replicate the covariance structure implied by the switching costs).

5.3. Additional Identification Issues

As we have mentioned above, the show locations are identified up to a rotation. Thus, in interpreting the show locations, we can pick the rotation that yields the most convenient interpretation (we discuss the choice of the rotation in the empirical results section).

Also, since we estimate a separate vertical characteristic for each show, the constant term in the preferences for the latent attributes cannot be identified separately from the vertical characteristics, unless we impose additional orthogonality conditions. Specifically, we can always rewrite

$$U^d_{i,j,t} = \eta_{j,t} + Z_{j,t}(\Gamma X_i + \upsilon_i) + ... = \widetilde{\eta}_{j,t} + Z_{j,t}(\Gamma_0 + \Gamma X_i + \upsilon_i) + ...$$

for any value of Γ_0 (with an appropriate choice of $\widetilde{\eta}_{j,t}$). This situation is similar to that in micro-BLP (Berry, Levinsohn, Pakes 2004), where a separate vertical characteristic is estimated for each product. As a result, the constant terms in the coefficients on price and observable product characteristics (equivalent to Γ_0 in our specification) are not identified from the individual-level data. Micro-BLP identifies them in the second stage, after imposing orthogonality conditions on the η-s (e.g. $\eta_{j,t} \perp Z_{j,t}$), and the precision of those estimates is determined not by the number of observations in the individual-level data, but by the number of products. In our empirical example, the number of products (14 shows) is likely too small to get accurate estimates of Γ_0 in the second stage[34]. On the other hand, our main focus is on identifying the show attributes $Z_{j,t}$ rather than Γ_0, and the show attributes are identified from the individual-level data without imposing any orthogonality conditions on the η-s.

6. Empirical Results

In estimation, we focus on the weekday shows on CNN and Fox News from 4pm to 10.59pm ET. The schedule of the shows is presented in Table 1. All the shows are one hour long, except for *Inside Politics* (4.00-4.30pm[35]) and *Crossfire* (4.30–4.59pm) on CNN. In estimation, we treat both

[34] The second stage would be a least-squares regression or an IV regression with 14 observations. In micro-BLP, the second-stage estimates were very imprecise, even though the number of products is much larger, so micro-BLP had to add a structural pricing equation to get reasonably accurate estimates of the price coefficients.

[35] Sometimes *Inside Politics* starts before 4pm, but it always ends at the same time.

shows as a single 1-hour show, from 4pm to 4.59pm[36]. The schedule of shows on CNN changed during the sample period: on September 8 2003, CNN replaced *Live from the Headlines* with 2 new shows, *Anderson Cooper 360*^{0} and *Paula Zahn Now*. We do not have viewing data for *Live from the Headlines,* so we cannot estimate its attributes. Also, we do not observe which respondents were sampled before or after the schedule change, however we know the aggregate distribution of the sampling dates (approximately 1/3 are before the schedule change). In estimation, we integrate out the unobserved sampling date for each respondent[37]. In addition, the data on overall TV viewership for each hour is not entirely reliable[38], so we modify the model to allow for a simple measurement error process in overall TV viewership[39].

We estimate the model by simulated GMM. To choose the number of latent dimensions M, we estimate the model with 1, 2 and 3 dimensions. Going from 1 to 2 dimensions substantially improves the fit of the model (we compare predicted and actual joint audiences of the shows). Increasing the number of dimensions from 2 to 3 has a negligible effect on the fit of the model, therefore we conclude that the optimal number of dimensions is $M = 2$. The original estimates for $M = 2$ are presented in Table 6 (however, the normalizations in Table 6 are convenient for estimation but not for interpretation of the estimates, therefore we re-normalize before discussing the show locations below).

Fit xxx.

The switching costs are large in magnitude and highly significant (for the news networks $\delta = 0.82$ (0.17), for "other-TV" $\delta^{other} = 0.82$ (0.42), and for the outside alternative $\delta^{out} = 1.89$ (0.53)). A priori, it could be more plausible to expect $\delta^{other} > \delta$. The reason is that the "other-TV" alternative aggregates all the other TV channels, so when viewers switch between two channels

[36] Treating them as two separate 30-minute shows (while the rest of the data is in terms of one-hour periods) would substantially complicate the empirical model.

[37] For simplicity, we assume that the attributes of *Live from the Headlines* are the same as *Anderson Cooper 360*^{0} (the first hour) and *Paula Zahn Now* (the second hour). This allows us to treat *Anderson Cooper 360*^{0} and *Paula Zahn Now* as if they were available throughout the sample period, but their choices were not always recorded in the data (i.e. with probability 2/3, we observe the actual choices for those shows, and with probability 1/3 we observe zeros in the data regardless of the actual choices). This approach simplifies the estimation.

[38] For example, many respondents who report watching a CNN or FOX News show at hour t do not report watching TV at hour t. Our data contains self-reported viewership, reported retroactively for the last 5 weekdays. We expect the self-reported data to be much more reliable for specific shows than for overall TV viewership, because it is much easier to remember the titles of the shows you watched rather than the exact hours when you watched TV.

[39] Specifically, we assume that with probability ρ, the respondent remembers her actual TV viewership for hour t of day d. With probability $1-\rho$, she remembers not watching TV, regardless of her actual viewership. The measurement error draws are assumed to be i.i.d. across days and hours, and ρ is a free parameter in estimation. Notice that the measurement error only refers to overall TV-viewership for hour t, while we assume perfect recall in the reported choices of CNN and FOX News shows (identified by show title, not by hour, which makes them easier to remember).

included in the "other-TV" alternative, it does not count as a switch in terms of the model. However, it is also quite likely that the switching costs really are higher for news shows than for entertainment (a majority of "other-TV" channels), since the cable news shows require more viewer involvement and attention than most entertainment.

For more convenient interpretation of the estimates of show locations and preferences for the latent attributes, we re-normalize the estimates so that the covariance matrix of the preferences for show attributes $cov(\Gamma X_i + \upsilon_i)$ becomes an identity matrix. The re-normalized estimates are presented in Table 8, and the estimated show locations are plotted in Figure 2 (we do not report the locations of the 4pm shows, because their estimated "locations" include a reduced-form correction for the initial conditions, and therefore they are not meaningful as actual show locations).

The shows on CNN and FOX News occupy two distinct areas of the attribute space, without any overlap between the networks (Figure 2). Furthermore, for almost all the shows, the nearest show in the attribute space is offered by the same network (the only exception is *On the Record with Greta van Susteren* on FOX News)[40]. In fact, the location of any CNN show is significantly different from the location of any FOX News show, at any reasonable significance level (Table 7). Thus, the line-up of shows offered by each network is relatively homogeneous, compared to the differences between the networks. At the same time, there is quite a lot of variation within each network. For 83% of all pairs of shows on the same network, the show locations are significantly different from each other at the 5% significance level (Table 7). The exceptions are several shows located close to each other in Figure 2.

Two measures of distance in Figure 2 have a meaningful interpretation. One is the distance from the show location to the origin (0,0). This distance is equal to the standard deviation of the "attribute utility" $Z_{j,t}(\Gamma X_i + \upsilon_i^Z)$ across all the potential viewers, with variation due to both observed demographics X_i and unobserved preferences υ_i^Z.[41] This distance can be interpreted as a measure of how mainstream or targeted a show is. Specifically, if a show is located close to (0,0), its utility is almost the same for consumers with very diverse X_i, υ_i^Z, i.e. it is a mainstream show. On the other hand, a show located far from (0,0) yields much higher utility for some values of X_i, υ_i^Z than for others, i.e. it is a show that targets a very specific group of viewers. The other meaningful measure is distance between two shows j_1, t_1 and j_2, t_2. It is equal to the standard deviation of

[40] Notice that after the re-normalization, the scaling of the two dimensions is similar, so Euclidean distances between shows in Figure 2 are meaningful.

[41] Since $var(\Gamma X_i + \upsilon_i^Z) = I$, $\sqrt{var(Z_{j,t}(\Gamma X_i + \upsilon_i^Z))} = \sqrt{Z_{j,t}Z'_{j,t}}$, which is exactly the Euclidean distance from $Z_{j,t}$ to (0,0).

$Z_{j_1,t_1}(\Gamma X_i + v_i^Z) - Z_{j_2,t_2}(\Gamma X_i + v_i^Z)$ (the difference in "attribute utility" between the two shows). Thus, if two shows are located in the same point of the attribute space, all viewers derive the same "attribute utility" from show j_1, t_1 as from show j_2, t_2, i.e. those two shows appeal to the same group of viewers[42]. On the other hand, if two shows are located far from each other, the difference in "attribute utility" between them is highly sensitive to the individual characteristics X_i, v_i^Z, i.e. those two shows appeal to two very different groups of viewers.

As a brief sanity check on the estimates, the CNN show that is located closest to the Fox News shows is *Paula Zahn Now*, and the Fox News show closest to CNN is *On the Record with Greta van Susteren*. In fact, Paula Zahn is the only CNN anchor who had been a Fox News anchor before moving to CNN. Thus, it is quite intuitive that her show is the most Fox-like show on CNN. Likewise, Greta van Susteren is the only Fox News anchor who had been a CNN anchor before moving to Fox News. Notice that both anchors moved from the rival network more than a year before the beginning of our sample, so this likely reflects the fundamental characteristics of their shows rather than viewer loyalty[43]. For the rest of the shows in our data, none of the anchors had ever moved from CNN to Fox News or vice versa.

Next, we interpret the dimensions of the attribute space. Because of the rotation invariance, we can choose the rotation that gives the most convenient interpretation. We choose the rotation in Figure 2 and Table 8 in the following way. Axis 1 (attribute 1) captures the average difference between the networks, and its direction is pinned down by the average show locations for each network. Axis 2 captures the within-network differences orthogonal to the average between-network differences. In interpreting the dimensions of the attribute space, we rely on prior knowledge we have about CNN and Fox News and about their individual shows, and we verify the interpretation using additional evidence.

Attribute 1 (the X axis) was defined as the difference between the networks' average locations. Using prior knowledge about CNN and FOX News, the most natural interpretation for this dimension is "ideological slant". Fox News is high on attribute 1, CNN is low, so using this interpretation, a show higher on attribute 1 is more to the right ideologically. Using this measure, the most left-wing shows on CNN is *Wolf Blitzer Reports*. The most right-wing shows on CNN

[42] Notice that the total utility from the two shows will still be different, due to the vertical constants, switching costs and logit shocks.

[43] Quite likely, in the first few weeks after the move, both anchors retained a large share of their original audience (from the network they left), simply due to viewer loyalty or habit (even if their new show is quite different). However, more than a year after the move, the residual effect of such viewer loyalty or habit should be negligible.

are *Paula Zahn Now* (formerly a Fox News anchor) and *Lou Dobbs Tonight*. The most left-wing show on Fox News is *On the Record with Greta van Susteren* (formerly a CNN anchor). The most right-wing show on Fox News is *Hannity and Colmes*.

The most natural interpretation of attribute 2 (the Y axis) is whether the show is "light" or "heavy" (higher values indicate a "heavier" show). While it is easy to spot a "light" or "heavy" show while watching it, it is harder to give a rigorous formal definition of what exactly "light" or "heavy" means for news shows. A "heavy" show is probably one or several of the following: (a) it requires more attention or processing, (b) there is no humor in the show, or (c) the anchors and reporters take themselves too seriously. For example, the "lightest" shows on CNN are *Larry King Live* (relatively light interviews) and *Anderson Cooper 360* (closer to straight news), which are quite different from the shows focusing on heavy political analysis. The *O'Reilly Factor* on FOX News is in the middle of the "light"-"heavy" scale, which is reasonable since O'Reilly combines relatively heavy analysis with entertainment. The "heaviest" shows are *Lou Dobbs Tonight* on CNN and *Special Report with Brit Hume* on FOX News, which focus more on opinions and analysis, and appear to take themselves more seriously as well.

(xxx update for GMM estimates) We verify the interpretation of attribute 2 ("light vs heavy") in the following way. In our data, for each individual we also observe which sections she read in the last daily newspaper read. Among other things, we observe the "editorial" section, as well as the "general news" section. Presumably, most editorials are "heavier" than general news. Thus, we do the following. For each individual, we compute the posterior mean of the unobserved preferences for attributes 1,2, using the estimates of the structural model and their actual choices of CNN and Fox News shows (notice that choices of "editorial" or "general news" do not enter the structural model in any way, so the posterior means are not affected by them at all). After that, we run a logit regression where the dependent variable is whether the respondent read the editorial in the last daily newspaper read (among those who report reading the "general news" section in the same newspaper[44]), and explanatory variables are demographics X_i and the posterior means of the unobserved preferences for the attributes. The coefficient on the posterior preferences for attribute 1 is close to 0 and insignificant at 5%, while the coefficient on the posterior preferences for attribute 2 is positive and highly significant (Table 9). This supports our interpretation of attribute 2 as "light vs heavy".

[44]We restrict the sample to those who read "general news", because otherwise our estimates might be picking up general preferences for news, as opposed to specifically editorials.

Counterfactuals xxx.

Appendix

Table 1. The schedule of CNN and Fox News shows, weekdays 4pm-10.59pm (ET), May 2003 – May 2004.

	CNN	Fox News
4:00	Inside politics*	Your World with Neil Cavuto
4:30	Crossfire	
5:00	Wolf Blitzer Reports	Big Story with John Gibson
5:30		
6:00	Lou Dobbs Tonight	Special Report with Brit Hume
6:30		
7:00	Anderson Cooper 360°**	Fox Report with Shepard Smith
7:30		
8:00	Paula Zahn Now**	The O'Relly Factor
8:30		
9:00	Larry King Live	Hannity & Colmes
9:30		
10:00	Newsnight with Aaron Brown	On the record with Greta van Susteren
10:30		

* sometimes it starts at 3pm or 3.30pm, instead of 4pm (but ends at 4.30pm in either case).
** starting from Spt 8, 2003. Before that, 7-8.59pm was *Live from the Headlines*.

Table 2a. Average weekly audiences of the shows (% of respondents who watched the show at least once in the last 5 weekdays)

	CNN	FOX News
4pm	5.5%	3.8%
5pm	5.6%	2.2%
6pm	2.7%	5.1%
7pm	2.2%	5.3%
8pm	7.4%	12.3%
9pm	11.9%	6.8%
10pm	3.7%	4.7%

The sample (here and in all the descriptive statistics below): cable and satellite subscribers, at least 18 years old, report watching at least one show on any cable channel (not just news), Eastern and Central time zones (excluding Indiana), 14109 observations.

Table 2b. The distribution of the number of different shows on CNN and FOX News watched during the week

	CNN	FOX News	both
0	80.4%	83.4%	71.7%
1	10.6%	7.2%	10.7%
2	4.8%	3.4%	6.0%
3	2.4%	2.4%	4.2%
4	1.0%	1.2%	3.0%
5	0.3%	1.0%	1.9%
6	0.1%	0.7%	1.0%
7	0.3%	0.6%	0.6%
8+	---	---	0.9%
average number of shows	0.36	0.40	0.76
average number of shows among those who watched at least one show	1.83	2.41	2.69

Note: Only refers to weekday shows from 4pm to 10.59pm ET. If the respondent watched the same show several times during the week, it counts as one show.

Table 3a. Joint audiences of the shows, as percentage of the audience of the row show

	Inside Politics + Crossfire	Wolf Blitzer Reports	Lou Dobbs Tonight	Anderson Cooper 360°	Paula Zahn Now	Larry King Live	Newsnight with Aaron Brown	Your World with Neil Cavuto	Big Story with John Gibson	Special Report with Brit Hume	Fox Report with Shepard Smith	The O'Relly Factor	Hannity & Colmes	On the record with Greta van Susteren
Inside Politics + Crossfire	---	39%	20%	12%	24%	**49%**	24%	12%	8%	18%	12%	37%	18%	16%
Wolf Blitzer Reports	39%	---	28%	13%	26%	**55%**	26%	16%	10%	20%	15%	38%	21%	23%
Lou Dobbs Tonight	40%	**57%**	---	21%	30%	53%	37%	22%	14%	27%	21%	43%	27%	25%
Anderson Cooper 360°	45%	51%	40%	---	48%	**60%**	41%	17%	14%	20%	17%	31%	18%	22%
Paula Zahn Now	27%	29%	16%	14%	---	**54%**	20%	11%	6%	15%	10%	35%	20%	19%
Larry King Live	23%	26%	12%	7%	22%	---	17%	8%	5%	11%	11%	**31%**	17%	15%
Newsnight with Aaron Brown	35%	39%	27%	16%	26%	**52%**	---	15%	9%	20%	20%	33%	20%	21%
Your World with Neil Cavuto	18%	23%	16%	7%	15%	26%	15%	---	38%	65%	56%	**81%**	61%	44%
Big Story with John Gibson	20%	25%	18%	10%	14%	25%	16%	66%	---	68%	66%	**77%**	59%	47%
Special Report with Brit Hume	19%	22%	14%	6%	15%	27%	15%	49%	29%	---	51%	**75%**	56%	42%
Fox Report with Shepard Smith	13%	16%	11%	5%	10%	24%	14%	41%	27%	50%	---	**73%**	54%	40%
The O'Relly Factor	16%	17%	10%	4%	14%	30%	10%	25%	14%	31%	31%	---	**48%**	30%
Hannity & Colmes	14%	17%	11%	4%	14%	29%	11%	34%	19%	42%	41%	**86%**	---	44%
On the record with Greta van Susteren	18%	28%	15%	7%	20%	39%	17%	36%	22%	45%	45%	**78%**	64%	---

Bold – maximum value in the row.

Table 3b. Correlation matrix of choices for different shows

	Inside Politics + Crossfire	Wolf Blitzer Reports	Lou Dobbs Tonight	Anderson Cooper 360°	Paula Zahn Now	Larry King Live	Newsnight with Aaron Brown	Your World with Neil Cavuto	Big Story with John Gibson	Special Report with Brit Hume	Fox Report with Shepard Smith	The O'Relly Factor	Hannity & Colmes	On the record with Greta van Susteren
Inside Politics + Crossfire	---	**0.38**	0.28	0.17	0.19	0.28	0.25	0.14	0.11	0.16	0.09	0.17	0.14	0.15
Wolf Blitzer Reports	**0.38**	---	0.35	0.20	0.25	0.30	0.32	0.14	0.11	0.17	0.11	0.18	0.15	0.19
Lou Dobbs Tonight	0.28	**0.35**	---	0.22	0.20	0.21	0.31	0.17	0.13	0.17	0.12	0.14	0.13	0.15
Anderson Cooper 360°	0.17	0.20	**0.22**	---	0.21	0.16	0.20	0.08	0.10	0.08	0.07	0.08	0.07	0.11
Paula Zahn Now	0.19	0.25	0.20	0.21	---	**0.28**	0.20	0.11	0.07	0.11	0.08	0.15	0.13	0.16
Larry King Live	0.28	**0.30**	0.21	0.16	0.28	---	0.28	0.09	0.06	0.12	0.09	0.20	0.14	0.19
Newsnight with Aaron Brown	0.25	**0.32**	0.31	0.20	0.20	0.28	---	0.12	0.11	0.15	0.11	0.13	0.13	0.17
Your World with Neil Cavuto	0.14	0.14	0.17	0.08	0.11	0.09	0.12	---	0.47	**0.53**	0.46	0.41	0.43	0.36
Big Story with John Gibson	0.11	0.11	0.13	0.10	0.07	0.06	0.11	**0.47**	---	0.40	0.42	0.30	0.31	0.28
Special Report with Brit Hume	0.16	0.17	0.17	0.08	0.11	0.12	0.15	**0.53**	0.40	---	0.47	0.45	0.46	0.41
Fox Report with Shepard Smith	0.09	0.11	0.12	0.07	0.08	0.09	0.11	0.46	0.42	**0.47**	---	0.44	0.44	0.39
The O'Relly Factor	0.17	0.18	0.14	0.08	0.15	0.20	0.13	0.41	0.30	0.45	0.44	---	**0.59**	0.43
Hannity & Colmes	0.14	0.15	0.13	0.07	0.13	0.14	0.13	0.43	0.31	0.46	0.44	**0.59**	---	0.48
On the record with Greta van Susteren	0.15	0.19	0.15	0.11	0.16	0.19	0.17	0.36	0.28	0.41	0.39	0.43	**0.48**	---

Bold – maximum value in the row.

Table 4a. Viewer demographics

	entire sample	news viewers*	CNN viewers	FOX viewers	CNN& FOX viewers **	heavy CNN viewers (3+ shows)	heavy FOX viewers (3+ shows)
male	48%	53%	50%	56%	54%	57%	58%
age	0.58	0.72	0.73	0.72	0.75	0.75	0.76
white	81%	85%	83%	87%	82%	79%	89%
black	13%	10%	12%	8%	12%	15%	7%
other race	6%	5%	5%	5%	6%	6%	4%
Hispanic	7%	6%	6%	6%	6%	5%	6%
high-school dropout	13%	10%	10%	9%	9%	8%	11%
high-school graduate	36%	34%	35%	34%	38%	35%	30%
some college	20%	18%	17%	18%	16%	19%	20%
college grad and above	32%	38%	37%	38%	37%	38%	40%
not working	35%	44%	46%	44%	46%	52%	50%
respondent's income***	0.90	0.99	0.98	0.99	0.96	0.93	1.05
religious conservative (1-5)	3.05	3.22	3.16	3.28	3.18	3.08	3.43
political outlook (1 – very conservative, 5 – very liberal)	2.71	2.55	2.75	2.35	2.60	2.87	2.10
political outlook missing	15%	10%	10%	9%	9%	8%	10%
"blue-red" state****	48.2%	47.9%	48.0%	47.6%	47.6%	48.0%	47.0%

* watched at least one show on CNN or FOX News between 4-10.59pm ET in the last 5 weekdays.
** watched at least one CNN show and one FOX News show between 4-10.59pm ET in the last 5 weekdays.
*** only for those who work full-time or part-time.
**** in the respondent's state, vote for the Democratic presidential candidate as a fraction of the total for the Democratic and Republican candidates (i.e. excluding invalid votes and votes for independent candidates), average for 2000 and 2004 presidential elections.

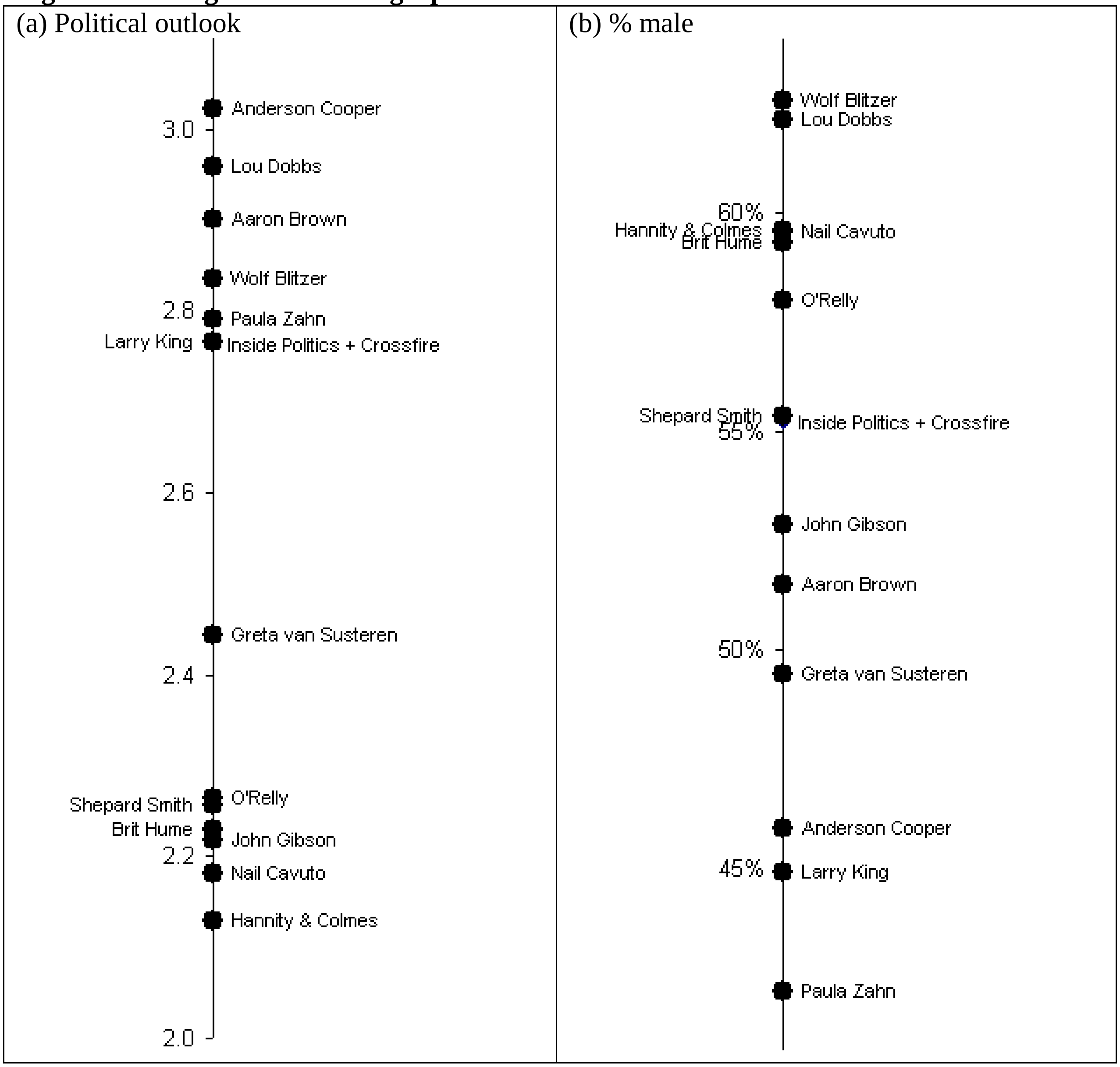
Table 4b. Average viewer demographics for CNN shows.

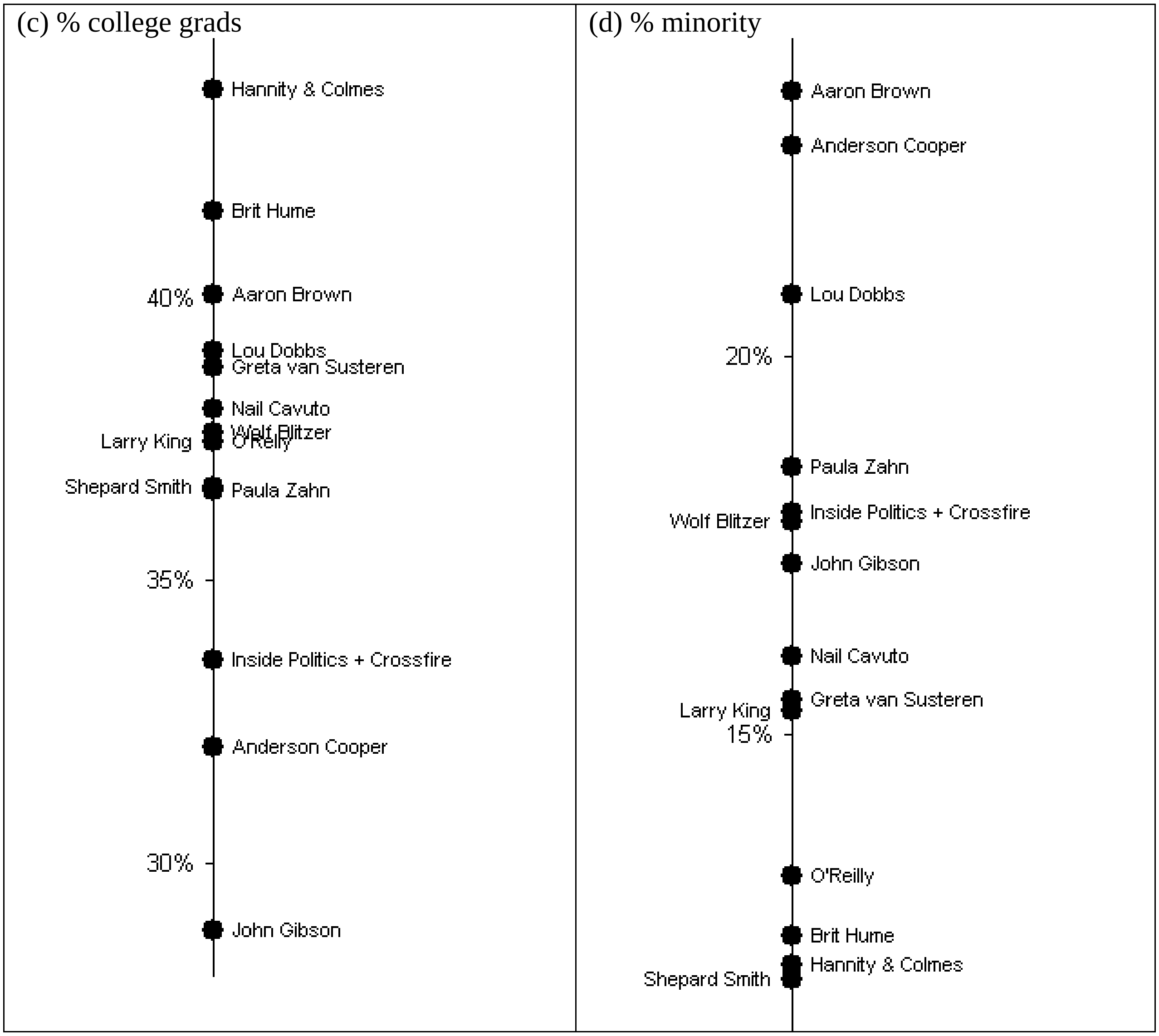
	Inside Politics + Crossfire	Wolf Blitzer Reports	Lou Dobbs Tonight	Anderson Cooper 360°	Paula Zahn Now	Larry King Live	Newsnight with Aaron Brown
male	55%	63%	62%	46%	42%	45%	52%
age	0.72	0.75	0.75	0.66	0.76	0.76	0.69
white	82%	82%	79%	77%	81%	85%	76%
black	12%	12%	14%	14%	13%	11%	16%
other race	6%	5%	7%	8%	6%	4%	8%
Hispanic	6%	6%	8%	7%	3%	5%	7%
high-school dropout	13%	9%	5%	10%	8%	9%	13%
high-school graduate	35%	35%	34%	40%	36%	37%	33%
some college	18%	19%	22%	18%	20%	17%	14%
college grad and above	34%	38%	39%	32%	37%	37%	40%
not working	50%	48%	49%	47%	50%	46%	55%
respondent's income	0.92	1.00	1.00	0.95	0.95	0.97	0.92
religious conservative (1-5)	3.17	2.88	3.06	2.96	3.16	3.23	3.04
political outlook (1 – very conservative, 5 – very liberal)	2.76	2.83	2.96	3.02	2.79	2.77	2.90
political outlook missing	10%	7%	11%	15%	8%	9%	13%
"blue-red" state	48%	48%	48%	49%	47%	48%	48%

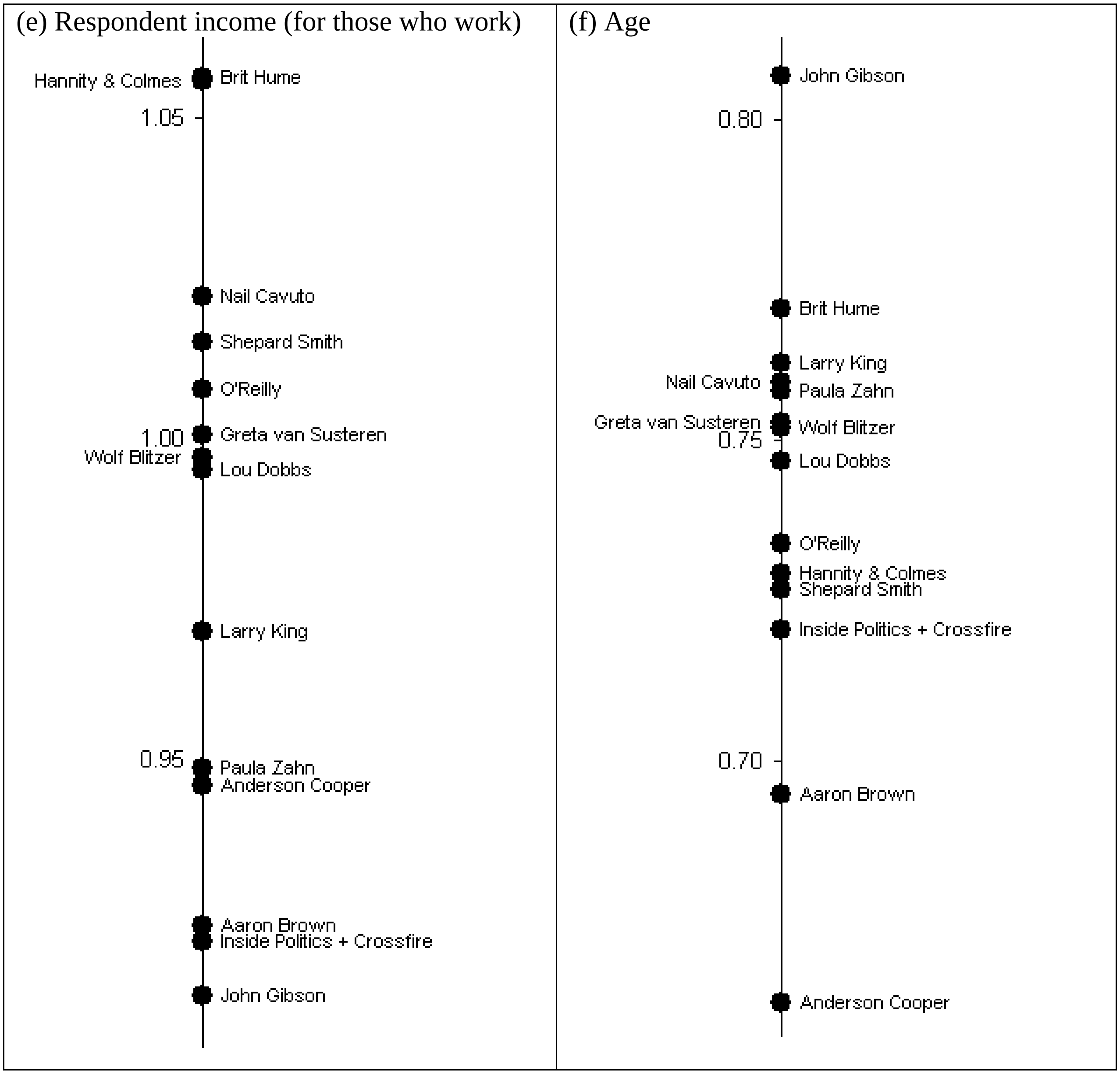
Table 4c. Average viewer demographics for FOX News shows

	Your World with Neil Cavuto	Big Story with John Gibson	Special Report with Brit Hume	Fox Report with Shepard Smith	The O'Relly Factor	Hannity & Colmes	On the record with Greta van Susteren
male	60%	53%	59%	55%	58%	60%	49%
age	0.76	0.81	0.77	0.73	0.73	0.73	0.75
white	84%	83%	88%	88%	87%	88%	85%
black	11%	12%	9%	7%	9%	7%	12%
other race	5%	5%	4%	4%	5%	5%	4%
Hispanic	7%	7%	6%	7%	6%	6%	4%
high-school dropout	14%	23%	12%	9%	9%	7%	8%
high-school graduate	30%	32%	29%	33%	35%	30%	33%
some college	18%	16%	18%	21%	18%	19%	20%
college grad and above	38%	29%	42%	37%	37%	44%	39%
not working	53%	66%	48%	47%	45%	43%	50%
respondent's income	1.02	0.91	1.06	1.02	1.01	1.06	1.00
religious conservative (1-5)	3.33	3.40	3.36	3.28	3.34	3.41	3.31
political outlook (1 – very conservative, 5 – very liberal)	2.18	2.22	2.23	2.26	2.26	2.13	2.44
political outlook missing	14%	12%	8%	9%	9%	10%	10%
"blue-red" state	47%	48%	47%	47%	48%	47%	47%

Figure 1. Average viewer demographics for the shows




(c) % college grads
Hannity & Colmes
Brit Hume
40%
Aaron Brown
Lou Dobbs
Greta van Susteren
Nail Cavuto
Wolf Blitzer
Larry King
O'Reilly
Shepard Smith
Paula Zahn
35%
Inside Politics + Crossfire
Anderson Cooper
30%
John Gibson
(d) % minority
Aaron Brown
Anderson Cooper
Lou Dobbs
20%
Paula Zahn
Inside Politics + Crossfire
Wolf Blitzer
John Gibson
Nail Cavuto
Greta van Susteren
Larry King
15%
O'Reilly
Brit Hume
Hannity & Colmes
Shepard Smith


(e) Respondent income (for those who work)
Hannity & Colmes
Brit Hume
1.05
Nail Cavuto
Shepard Smith
O'Reilly
1.00
Greta van Susteren
Wolf Blitzer
Lou Dobbs
Larry King
0.95
Paula Zahn
Anderson Cooper
Aaron Brown
Inside Politics + Crossfire
John Gibson
(f) Age
John Gibson
0.80
Brit Hume
Larry King
Nail Cavuto
Paula Zahn
Greta van Susteren
Wolf Blitzer
0.75
Lou Dobbs
O'Reilly
Hannity & Colmes
Shepard Smith
Inside Politics + Crossfire
0.70
Aaron Brown
Anderson Cooper

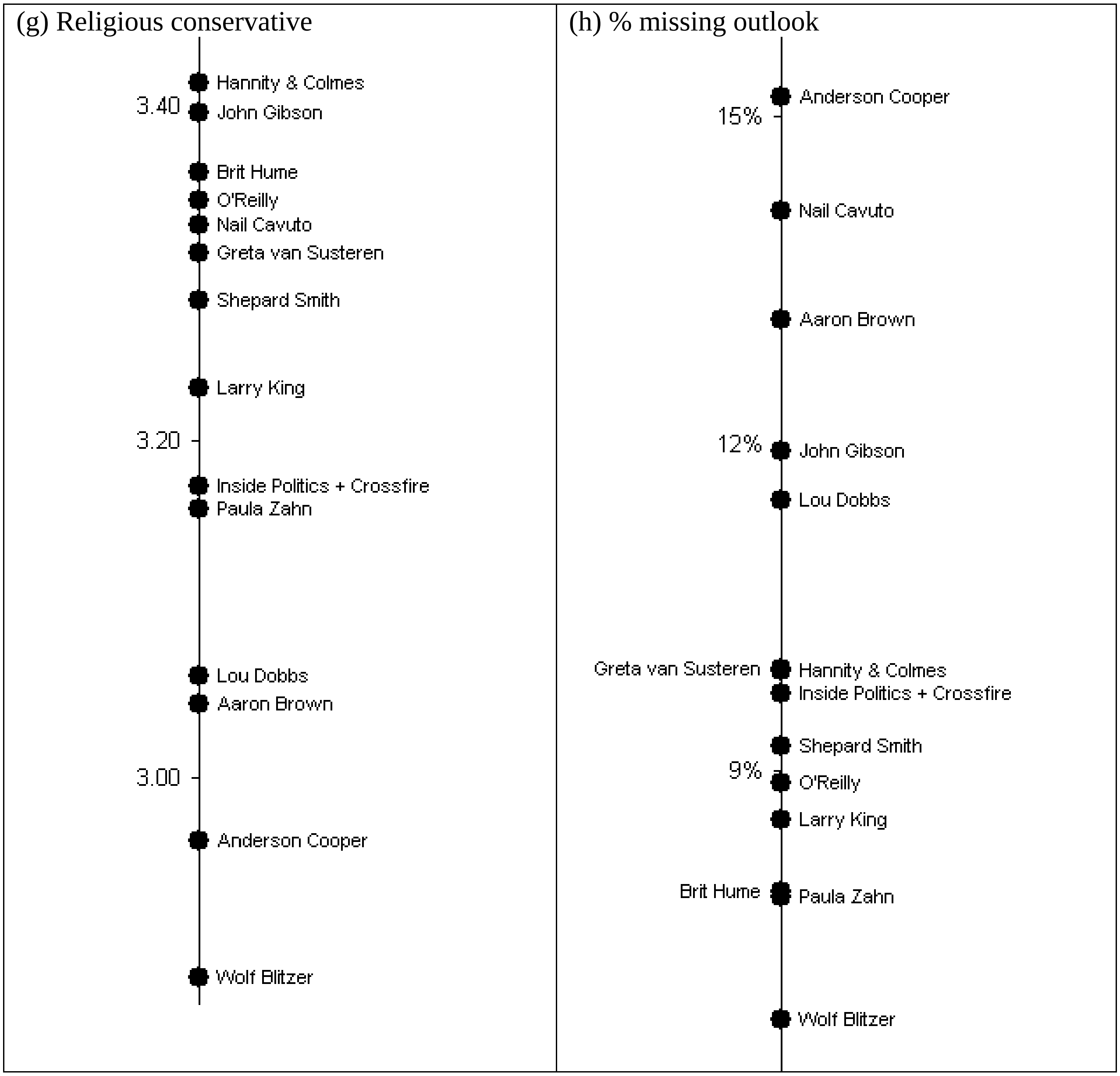

(g) Religious conservative
3.40
3.20
3.00
Hannity & Colmes
John Gibson
Brit Hume
O'Reilly
Nail Cavuto
Greta van Susteren
Shepard Smith
Larry King
Inside Politics + Crossfire
Paula Zahn
Lou Dobbs
Aaron Brown
Anderson Cooper
Wolf Blitzer
(h) % missing outlook
15%
12%
9%
Anderson Cooper
Nail Cavuto
Aaron Brown
John Gibson
Lou Dobbs
Greta van Susteren
Hannity & Colmes
Inside Politics + Crossfire
Shepard Smith
O'Reilly
Larry King
Brit Hume
Paula Zahn
Wolf Blitzer

Table 5a. The distribution of political outlook

	entire sample	CNN only	CNN & FOX News viewers (at least one on each)	FOX News only	CNN viewers	heavy CNN viewers (3+ shows)	FOX News viewers	heavy FOX viewers (3+ shows)
1 - very conservative	11%	8%	12%	25%	10%	7%	19%	26%
2	29%	31%	35%	44%	32%	31%	40%	48%
3	42%	38%	37%	25%	37%	38%	30%	19%
4	13%	17%	13%	4%	15%	15%	8%	3%
5 - very liberal	5%	7%	3%	1%	6%	8%	2%	3%

Table 5b. The distribution of political outlook – CNN shows

	Inside Politics + Crossfire	Wolf Blitzer Reports	Lou Dobbs Tonight	Anderson Cooper 360°	Paula Zahn Now	Larry King Live	Newsnight with Aaron Brown
1 – very conservative	10%	8%	7%	9%	8%	10%	8%
2	35%	32%	31%	27%	33%	31%	28%
3	33%	36%	33%	31%	38%	38%	39%
4	14%	17%	21%	19%	15%	16%	15%
5 - very liberal	8%	7%	9%	14%	6%	6%	10%

Table 5c. The distribution of political outlook – FOX News shows

	Your World with Neil Cavuto	Big Story with John Gibson	Special Report with Brit Hume	Fox Report with Shepard Smith	The O'Relly Factor	Hannity & Colmes	On the record with Greta van Susteren
1 – very conservative	23%	30%	22%	20%	22%	28%	16%
2	49%	40%	46%	47%	42%	43%	42%
3	19%	19%	23%	25%	28%	20%	28%
4	4%	3%	5%	4%	7%	7%	10%
5 - very liberal	5%	9%	4%	4%	2%	3%	4%

Table 5d. The proportion of CNN and FOX News viewers among each category of political outlook

	1 - very conservative	2	3	4	5 - very liberal
CNN	18%	23%	18%	24%	23%
FOX	30%	24%	13%	11%	9%
CNN or FOX	38%	37%	24%	27%	26%
CNN&FOX	9%	10%	7%	8%	6%

Table 6. The structural estimates for M=2.

		est	s.e.
sw costs	delta	0.82	0.17
	deltaOther	0.82	0.42
	deltaOut	1.89	0.53
other-TV	eta1	-1.97	4.33
	eta2	-1.05	2.57
	eta3	-2.08	2.51
	eta4	0.05	1.78
	eta5	0.19	1.92
	eta6	0.31	1.72
	eta7	-0.25	2.31
4pm - otherTV	male	-1.62	0.33
	age	-0.04	5.75
	age^2	-0.23	4.40
	black	0.01	0.52
	other race	-0.71	0.47
	Hisp_HH	-0.87	0.36
	HS dropout	-0.50	0.46
	some college	0.36	0.36
	college grad and above	-0.06	0.37
	not working (retired/unemployed/other)	0.42	2.22
	resp_income	-0.16	6.64
	resp_income^2	-0.26	3.77
	religious conservativeness (5 max)	-0.24	0.12
	pol_outlook(5-very liberal)	0.94	2.63
	outlook^2	-0.69	2.24
	outlook_missing	0.71	3.47
	%D	1.37	2.19
	%D^2	0.00	.
	otherUHmult	2.51	0.55
5pm - otherTV	male	-1.00	0.19
	age	0.44	3.66
	age^2	-0.12	2.74
	black	-0.45	0.33
	other race	-0.80	0.29
	Hisp_HH	-0.94	0.25
	HS dropout	-0.36	0.29
	some college	0.45	0.25
	college grad and above	0.38	0.24
	not working (retired/unemployed/other)	0.24	1.52
	resp_income	0.35	4.28
	resp_income^2	0.05	2.31
	religious conservativeness (5 max)	0.00	0.07
	pol_outlook(5-very liberal)	0.79	1.46
	outlook^2	-0.57	1.26
	outlook_missing	0.81	1.90
	%D	1.66	1.46
	%D^2	0.00	.
	otherUHmult	1.31	0.26
6pm - otherTV	male	-0.81	0.18
	age	-0.51	3.37
	age^2	0.44	2.61
	black	-1.52	0.36
	other race	-0.47	0.28
	Hisp_HH	-0.09	0.22
	HS dropout	0.04	0.28
	some college	0.56	0.24
	college grad and above	0.57	0.24
	not working (retired/unemployed/other)	0.12	1.50
	resp_income	-0.01	4.22
	resp_income^2	0.38	2.28
	religious conservativeness (5 max)	-0.12	0.07
	pol_outlook(5-very liberal)	0.86	1.51
	outlook^2	-0.61	1.32
	outlook_missing	0.47	1.94
	%D	1.90	1.42
	%D^2	0.00	.
	otherUHmult	1.12	0.22

		est	s.e.
7pm - otherTV	male	-0.46	0.14
	age	0.36	2.81
	age^2	-0.03	2.12
	black	-1.26	0.29
	other race	-0.45	0.25
	Hisp_HH	-0.21	0.19
	HS dropout	-0.01	0.24
	some college	0.38	0.19
	college grad and above	0.44	0.19
	not working (retired/unemployed/other)	0.37	1.29
	resp_income	-0.14	3.61
	resp_income^2	0.34	1.93
	religious conservativeness (5 max)	-0.01	0.05
	pol_outlook(5-very liberal)	1.26	0.99
	outlook^2	-0.80	0.88
	outlook_missing	1.18	1.27
	%D	-1.27	1.21
	%D^2	0.00	.
	otherUHmult	1.49	0.28
8pm - otherTV	male	-0.42	0.12
	age	1.16	2.49
	age^2	-1.17	2.00
	black	-1.16	0.23
	other race	-0.64	0.20
	Hisp_HH	-0.48	0.16
	HS dropout	-0.02	0.18
	some college	0.38	0.17
	college grad and above	0.59	0.17
	not working (retired/unemployed/other)	0.53	1.11
	resp_income	0.77	3.20
	resp_income^2	-0.15	1.75
	religious conservativeness (5 max)	-0.11	0.05
	pol_outlook(5-very liberal)	1.05	1.24
	outlook^2	-0.79	1.05
	outlook_missing	0.89	1.63
	%D	-0.96	1.00
	%D^2	0.00	.
	otherUHmult	1.00	.
9pm - otherTV	male	-0.41	0.13
	age	1.06	2.16
	age^2	-1.16	1.68
	black	-1.24	0.24
	other race	-0.04	0.20
	Hisp_HH	-0.84	0.18
	HS dropout	-0.17	0.19
	some college	0.68	0.18
	college grad and above	0.68	0.17
	not working (retired/unemployed/other)	0.21	0.89
	resp_income	0.28	2.49
	resp_income^2	0.06	1.36
	religious conservativeness (5 max)	-0.16	0.05
	pol_outlook(5-very liberal)	0.51	1.13
	outlook^2	-0.27	0.97
	outlook_missing	0.34	1.48
	%D	-0.39	0.99
	%D^2	0.00	.
	otherUHmult	1.34	0.22
10pm - otherTV	male	-0.37	0.15
	age	0.13	3.46
	age^2	0.47	2.63
	black	-1.03	0.28
	other race	-0.22	0.25
	Hisp_HH	-0.65	0.20
	HS dropout	-0.63	0.24
	some college	0.50	0.20
	college grad and above	0.55	0.19
	not working (retired/unemployed/other)	0.28	1.21
	resp_income	-0.03	3.40

		est	s.e.
	resp_income^2	0.56	1.84
	religious conservativeness (5 max)	0.05	0.06
	pol_outlook(5-very liberal)	1.00	1.42
	outlook^2	-0.74	1.23
	outlook_missing	0.63	1.85
	%D	-1.46	1.17
	%D^2	0.00	.
	otherUHmult	1.52	0.31
	sdW_other	1.10	0.20
	aux_pr_obs	-0.99	0.06
outside alt	eta3	1.09	4.71
	eta4	1.10	3.43
	eta5	0.46	2.38
	eta6	0.69	2.02
	eta7	0.13	2.12
	eta8	0.00	.
	eta9	0.12	2.04
	eta10	0.25	2.59
out 3pm	male	-0.67	0.33
	age	0.64	6.98
	age^2	0.11	5.38
	black	-0.18	0.59
	other race	-0.40	0.52
	Hisp_HH	-0.99	0.40
	HS dropout	-0.60	0.50
	some college	0.37	0.41
	college grad and above	0.08	0.41
	not working (retired/unemployed/other)	-0.29	2.37
	resp_income	0.89	7.07
	resp_income^2	0.10	3.98
	religious conservativeness (5 max)	-0.19	0.13
	pol_outlook(5-very liberal)	0.56	2.84
	outlook^2	-0.44	2.41
	outlook_missing	0.83	3.74
	%D	0.04	2.31
	%D^2	0.00	.
out 4pm	male	-0.64	0.23
	age	0.14	5.19
	age^2	-0.05	3.95
	black	-0.24	0.45
	other race	-0.60	0.35
	Hisp_HH	-0.75	0.29
	HS dropout	-0.07	0.35
	some college	0.50	0.30
	college grad and above	0.48	0.31
	not working (retired/unemployed/other)	-0.20	1.99
	resp_income	0.65	5.93
	resp_income^2	0.30	3.32
	religious conservativeness (5 max)	-0.15	0.09
	pol_outlook(5-very liberal)	0.39	2.07
	outlook^2	-0.27	1.78
	outlook_missing	0.50	2.70
	%D	0.16	1.62
	%D^2	0.00	.
out 5pm	male	-1.01	0.18
	age	-0.46	3.55
	age^2	-0.24	2.68
	black	-0.87	0.33
	other race	-0.55	0.26
	Hisp_HH	-0.75	0.23
	HS dropout	-0.34	0.26
	some college	0.45	0.24
	college grad and above	0.48	0.23
	not working (retired/unemployed/other)	0.08	1.46
	resp_income	0.41	4.10
	resp_income^2	0.23	2.21
	religious conservativeness (5 max)	-0.05	0.06
	pol_outlook(5-very liberal)	0.48	1.40

		est	s.e.
	outlook^2	-0.28	1.22
	outlook_missing	0.63	1.83
	%D	0.35	1.40
	%D^2	0.00	.
out 6pm	male	-0.67	0.16
	age	-1.99	3.17
	age^2	0.48	2.43
	black	-0.72	0.29
	other race	-0.30	0.25
	Hisp_HH	-0.27	0.20
	HS dropout	0.23	0.25
	some college	0.24	0.20
	college grad and above	0.38	0.20
	not working (retired/unemployed/other)	0.09	1.44
	resp_income	0.83	4.07
	resp_income^2	-0.21	2.20
	religious conservativeness (5 max)	-0.04	0.06
	pol_outlook(5-very liberal)	0.27	1.24
	outlook^2	-0.13	1.09
	outlook_missing	-0.03	1.57
	%D	-0.11	1.19
	%D^2	0.00	.
out 7pm	male	0.08	0.16
	age	-0.55	3.24
	age^2	0.85	2.56
	black	-0.23	0.26
	other race	-0.17	0.25
	Hisp_HH	-0.04	0.19
	HS dropout	0.08	0.24
	some college	0.03	0.21
	college grad and above	0.16	0.20
	not working (retired/unemployed/other)	0.03	1.28
	resp_income	0.46	3.58
	resp_income^2	0.00	1.92
	religious conservativeness (5 max)	0.02	0.06
	pol_outlook(5-very liberal)	-0.10	1.35
	outlook^2	0.23	1.18
	outlook_missing	-0.29	1.71
	%D	-0.11	1.24
	%D^2	0.00	.
out 8pm	male	0.00	.
	age	0.00	.
	age^2	0.00	.
	black	0.00	.
	other race	0.00	.
	Hisp_HH	0.00	.
	HS dropout	0.00	.
	some college	0.00	.
	college grad and above	0.00	.
	not working (retired/unemployed/other)	0.00	.
	resp_income	0.00	.
	resp_income^2	0.00	.
	religious conservativeness (5 max)	0.00	.
	pol_outlook(5-very liberal)	0.00	.
	outlook^2	0.00	.
	outlook_missing	0.00	.
	%D	0.00	.
	%D^2	0.00	.
out 9pm	male	0.10	0.15
	age	0.18	3.18
	age^2	0.14	2.52
	black	0.07	0.22
	other race	0.26	0.23
	Hisp_HH	-0.22	0.19
	HS dropout	-0.16	0.22
	some college	-0.06	0.20
	college grad and above	-0.21	0.19
	not working (retired/unemployed/other)	-0.22	1.14

		est	s.e.
	resp_income	0.47	3.34
	resp_income^2	-0.29	1.84
	religious conservativeness (5 max)	-0.06	0.06
	pol_outlook(5-very liberal)	-0.47	1.31
	outlook^2	0.51	1.12
	outlook_missing	-0.54	1.70
	%D	0.35	1.30
	%D^2	0.00	.
out 10pm	male	-0.28	0.17
	age	-0.01	3.53
	age^2	0.79	2.70
	black	-1.11	0.33
	other race	0.07	0.29
	Hisp_HH	-0.61	0.23
	HS dropout	-0.44	0.26
	some college	-0.01	0.22
	college grad and above	-0.19	0.21
	not working (retired/unemployed/other)	-0.07	1.21
	resp_income	0.31	3.42
	resp_income^2	0.36	1.86
	religious conservativeness (5 max)	-0.04	0.06
	pol_outlook(5-very liberal)	0.27	1.69
	outlook^2	-0.21	1.44
	outlook_missing	0.23	2.20
	%D	-0.32	1.39
	%D^2	0.00	.
CNN-ini cond	male	0.02	0.23
	age	0.01	5.08
	age^2	-0.12	3.78
	black	0.64	0.42
	other race	-0.12	0.37
	Hisp_HH	-0.48	0.29
	HS dropout	0.18	0.37
	some college	0.15	0.28
	college grad and above	-0.09	0.29
	not working (retired/unemployed/other)	-0.22	1.67
	resp_income	0.07	5.06
	resp_income^2	0.10	2.88
	religious conservativeness (5 max)	-0.14	0.09
	pol_outlook(5-very liberal)	0.12	2.03
	outlook^2	-0.07	1.70
	outlook_missing	0.38	2.71
	%D	1.58	1.66
	%D^2	0.00	.
FOX-ini conditions	male	-0.13	0.26
	age	0.29	7.28
	age^2	0.00	5.21
	black	1.34	0.50
	other race	0.38	0.43
	Hisp_HH	-0.38	0.33
	HS dropout	0.11	0.40
	some college	0.06	0.33
	college grad and above	-0.14	0.32
	not working (retired/unemployed/other)	0.33	2.24
	resp_income	0.12	6.42
	resp_income^2	0.14	3.53
	religious conservativeness (5 max)	-0.29	0.10
	pol_outlook(5-very liberal)	-0.23	3.19
	outlook^2	0.15	3.00
	outlook_missing	0.44	3.85
	%D	-0.47	1.96
	%D^2	0.00	.
	etaCNN1	-6.73	3.78
	etaCNN2	-7.35	2.37
	etaCNN3	-10.07	2.55
	etaCNN4	-6.29	1.58
	etaCNN5	-5.95	1.81
	etaCNN6	-4.23	1.32

		est	s.e.
	etaCNN7	-6.93	1.77
	etaFOX1	-8.15	5.29
	etaFOX2	-7.72	1.82
	etaFOX3	-8.69	2.15
	etaFOX4	-5.20	1.27
	etaFOX5	-4.69	1.56
	etaFOX6	-8.05	2.01
	etaFOX7	-5.89	1.41
	otherET4pm	0.42	0.22
	otherET5pm	0.57	0.22
	otherET6pm	1.31	0.27
	otherET7pm	-0.56	0.25
	---	0.00	.
attr1	male	-0.14	0.10
	age	4.67	1.87
	age^2	-2.22	1.41
	black	-0.45	0.17
	other race	0.04	0.15
	Hisp_HH	-0.73	0.14
	HS dropout	-0.58	0.15
	some college	0.39	0.13
	college grad and above	0.62	0.13
	not working (retired/unemployed/other)	0.30	0.80
	resp_income	-0.06	2.25
	resp_income^2	0.23	1.21
	religious conservativeness (5 max)	-0.05	0.04
	pol_outlook(5-very liberal)	0.30	0.77
	outlook^2	-0.03	0.66
	outlook_missing	0.35	1.01
	%D	-1.35	0.77
	%D^2	0.00	.
	---	0.00	.
	z1_CNN1	1.22	0.10
	z1_CNN2	1.69	0.18
	z1_CNN3	1.88	0.24
	z1_CNN4	1.07	0.11
	z1_CNN5	1.40	0.13
	z1_CNN6	1.00	.
	z1_CNN7	1.31	0.11
	z1_FOX1	1.47	0.20
	z1_FOX2	1.28	0.20
	z1_FOX3	1.56	0.23
	z1_FOX4	0.85	0.13
	z1_FOX5	1.18	0.14
	z1_FOX6	1.36	0.24
	z1_FOX7	1.13	0.11
	sd_w1	-1.49	0.13
	c_w1_other	-0.38	0.18
attr2	male	0.51	0.10
	age	1.07	2.17
	age^2	-0.97	1.51
	black	-0.55	0.19
	other race	-0.20	0.14
	Hisp_HH	-0.04	0.13
	HS dropout	-0.03	0.16
	some college	0.11	0.12
	college grad and above	0.14	0.12
	not working (retired/unemployed/other)	0.41	0.90
	resp_income	0.69	2.45
	resp_income^2	-0.36	1.29
	religious conservativeness (5 max)	0.10	0.03
	pol_outlook(5-very liberal)	0.49	0.60
	outlook^2	-1.26	0.61
	outlook_missing	-0.96	0.72
	%D	-1.69	0.74
	%D^2	0.00	.
	---	0.00	.
	z2_CNN1	0.04	0.08

		est	s.e.
	z2_CNN2	-0.15	0.12
	z2_CNN3	0.26	0.12
	z2_CNN4	-0.16	0.11
	z2_CNN5	0.18	0.08
	z2_CNN6	0.00	.
	z2_CNN7	-0.04	0.09
	z2_FOX1	1.38	0.13
	z2_FOX2	0.95	0.14
	z2_FOX3	1.46	0.17
	z2_FOX4	0.92	0.09
	z2_FOX5	1.00	.
	z2_FOX6	1.56	0.26
	z2_FOX7	0.49	0.07
	sd_w2	1.70	0.18
	c_w2_other	-0.25	0.08

Table 7. Wald tests for the equality of show locations – entry i,j is the result of the Wald test of the null hypothesis that the locations of shows i,j in the attribute space are the same.

	Wolf Blitzer Reports	Lou Dobbs Tonight	Anderson Cooper 360°	Paula Zahn Now	Larry King Live	Newsnight with Aaron Brown	Big Story with John Gibson	Special Report with Brit Hume	Fox Report with Shepard Smith	The O'Relly Factor	Hannity & Colmes	On the record with Greta van Susteren
Wolf Blitzer Reports	---	21.6	15.0	18.4	15.1	5.6	86.8	87.6	92.8	132.9	71.8	49.6
Lou Dobbs Tonight	21.6	---	23.6	4.7	17.7	16.5	34.6	79.9	50.7	64.8	47.0	18.0
Anderson Cooper 360°	15.0	23.6	---	24.6	2.4	7.1	44.0	63.9	71.9	121.9	43.8	34.3
Paula Zahn Now	18.4	4.7	24.6	---	17.3	12.6	31.8	56.4	68.6	156.4	51.6	21.1
Larry King Live	15.1	17.7	2.4	17.3	---	7.5	48.8	77.7	111.4	--*	49.2	52.9
Newsnight with Aaron Brown	5.6	16.5	7.1	12.6	7.5	---	48.4	77.0	90.0	168.9	57.4	60.5
Big Story with John Gibson	86.8	34.6	44.0	31.8	48.8	48.4	---	8.8	9.0	0.9	8.4	14.2
Special Report with Brit Hume	87.6	79.9	63.9	56.4	77.7	77.0	8.8	---	19.9	8.7	5.1	38.1
Fox Report with Shepard Smith	92.8	50.7	71.9	68.6	111.4	90.0	9.0	19.9	---	14.0	8.8	42.6
The O'Relly Factor	132.9	64.8	121.9	156.4	--*	168.9	0.9	8.7	14.0	---	6.7	60.8
Hannity & Colmes	71.8	47.0	43.8	51.6	49.2	57.4	8.4	5.1	8.8	6.7	---	23.9
On the record with Greta van Susteren	49.6	18.0	34.3	21.1	52.9	60.5	14.2	38.1	42.6	60.8	23.9	---

The critical value is 5.99 at 5% significance level, 9.21 at 1%, 13.82 at 0.1% (Chi2 with 2 degrees of freedom).

* cannot be tested formally due to the normalizations.

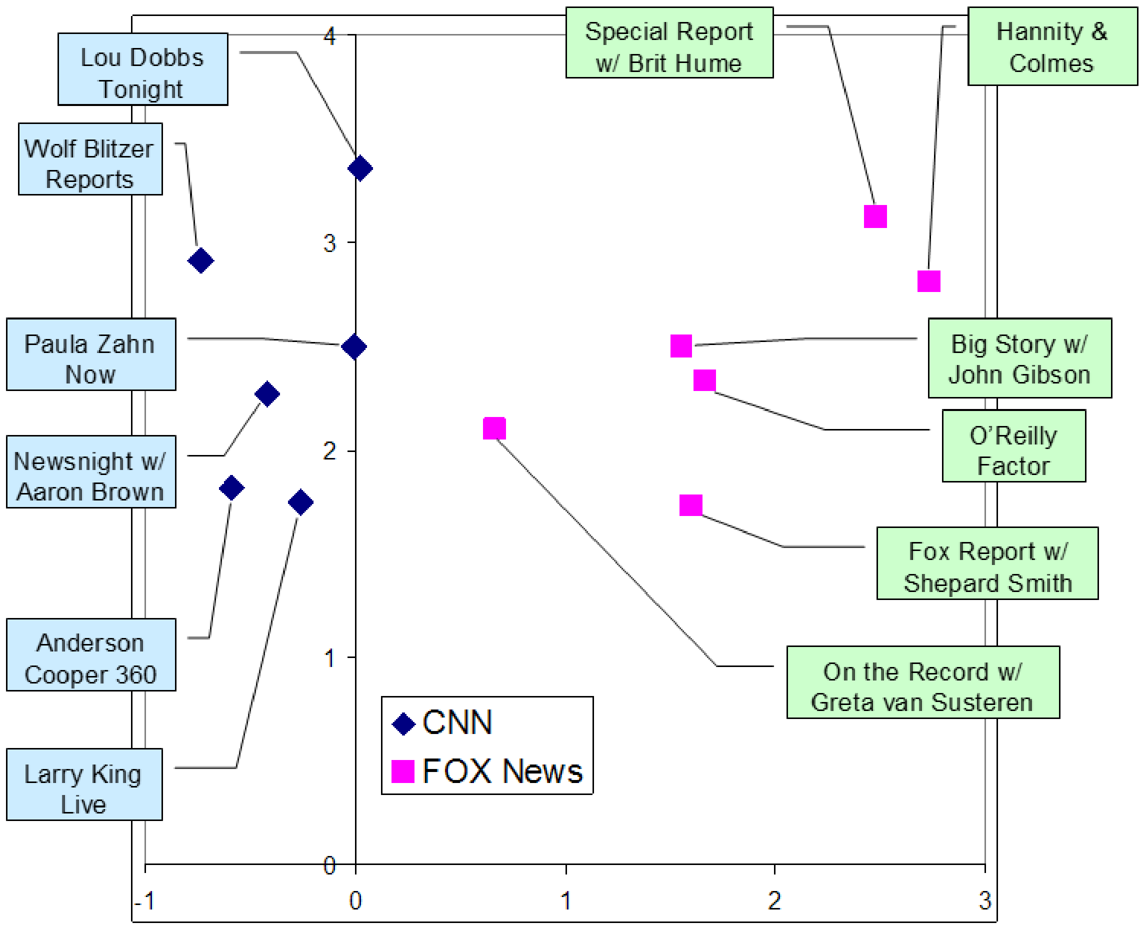


Figure 2. The show locations (after the re-normalization of preferences and rotation)

Table 8. Show attributes and preferences for those attributes
Show locations

	attribute 1		attribute 2	
	est.	s.e.	est.	s.e.
Wolf Blitzer	-0.73	0.24	2.91	0.29
Lou Dobbs	0.03	0.27	3.36	0.42
Cooper	-0.59	0.22	1.82	0.20
Paula Zahn	0.00	0.20	2.50	0.18
Larry King	-0.26	0.19	1.75	0.15
Newsnight	-0.42	0.19	2.27	0.20
Big Story - Gibson	1.55	0.30	2.50	0.31
Special Report - Brit Hume	2.48	0.31	3.12	0.31
Fox Report - Shepard Smith	1.60	0.20	1.73	0.18
O'Reilly	1.67	0.20	2.34	0.18
Hannity and Colmes	2.74	0.46	2.81	0.29
Greta Van Susteren	0.67	0.18	2.10	0.18

preferences for the attributes

	attr 1		attr 2	
	est.	s.e.	est.	s.e.
male	0.26	0.04	-0.04	0.05
age	0.17	1.02	2.70	0.93
age^2	-0.31	0.72	-1.32	0.73
black	-0.24	0.09	-0.29	0.09
other race	-0.10	0.08	0.01	0.08
Hisp_HH	0.04	0.06	-0.41	0.07
HS dropout	0.03	0.08	-0.33	0.08
some college	0.02	0.06	0.23	0.07
college grad and above	0.02	0.05	0.36	0.06
not working (retired/unemployed/other)	0.18	0.49	0.20	0.41
resp_income	0.35	1.32	0.02	1.15
resp_income^2	-0.20	0.69	0.10	0.62
religious conservativeness (5 max)	0.05	0.02	-0.02	0.02
pol_outlook(5-very liberal)	0.22	0.32	0.20	0.39
(outlook^2)/5	-0.62	0.31	-0.11	0.34
outlook_missing	-0.50	0.39	0.13	0.51
“blue-red” state (% D vote)	-0.73	0.35	-0.88	0.41

Table 9 (xxx). "Editorial" in the last daily newspaper read

	est	s.e.
male	0.30	0.06
age	1.18	0.43
age^2	0.21	0.32
white	-0.85	0.36
black	-0.97	0.38
other race	-0.65	0.38
Hisp_HH	-0.23	0.09
HS dropout	-0.39	0.11
HS grad	0	.
some college	0.09	0.09
college grad and above	0.18	0.08
student	-0.52	0.16
full-time	0	.
part-time	0.15	0.11
not working (retired/unemployed/other)	0.24	0.16
resp_income	-0.16	0.33
resp_income^2	0.01	0.18
hh_income	0.52	0.40
hh_income^2	-0.18	0.18
top-100 DMA	-0.16	0.08
religious conservativeness (5 max)	0.04	0.02
family-centered	0.02	0.02
work-centered	0.00	0.02
pol_outlook(5-very liberal)	-0.29	0.15
outlook^2	0.08	0.03
outlook_missing	-0.18	0.21
attr1 – posterior mean of w	0.14	0.08
attr2 – posterior mean of w	0.32	0.06

Dependent variable: whether or not the respondent read the editorial section in the last daily newspaper read.
The sample: the same criteria as in the structural model, plus restricted only to the respondents who reported reading the "general news" section in the last daily newspaper read.