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

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Abstract

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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 that 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 the degree of facts versus opinion in the program. 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. For each show, we observe whether or not the respondent watched it at least once in the last week

[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.

(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 broadcasting schedule of 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.

In addition to the viewing data for CNN and FOX News shows, for each hour from 4pm to 10.59pm we observe whether or not the TV was on at least once in the last 5 weekdays, and

[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), separately for weekdays and weekend. Among *Larry King* viewers, 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.

[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 or later, depending on the network and season). 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, 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*.

[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*, so we cannot estimate its location in the attribute space.

whether or not it was tuned to one of the broadcast networks (ABC, CBS, FOX, NBC, PBS, etc – but we don't observe which network). Like the data for the news shows, we do not observe the number of times over the last 5 weekdays, just two binary variables for each hour. In some cases (but not always), these data allow us to determine whether or not the respondent watched any other TV channel (besides CNN and FOX News) at a given hour at least once in the last 5 weekdays. Specifically, if at a given hour, the TV was on, and the respondent did not choose CNN or FOX News at this hour, then we know for sure that she watched some other channel. Same thing if the respondent chose one of the broadcast networks at this hour. However, if at this hour, the TV is on, and the respondent also chose CNN or FOX News, and did not choose any of the broadcast networks, then we cannot determine whether the respondent also watched some other cable channels at this hour (she might have watched CNN or FOX News one day, and some other cable channel another day, or maybe she only watched CNN or FOX at this hour – both situations are consistent with the data). We explicitly deal with both situations in estimation.

In our analysis, we restrict attention to the subsample of the respondents who are at least 18 years old, live in the Eastern time zone[11], and have cable or satellite TV subscription[12]. This subsample is 10,329 observations.

Tables 2a-5c present some descriptive statistics for this subsample. The most popular shows are *The O'Reilly Factor* on FOX News, watched by 11.7% of the respondents in the past week, and *Larry King Live* on CNN, watched by 11.1% (table 2a). The rest of the shows have much lower shares, ranging from 1.3% for *Anderson Cooper 360⁰* to 6.7% for *Hannity and Colmes*. Most of the respondents (73.7%) did not watch any of the CNN or FOX News shows in the sample in the past week (Table 2b). However, some respondents watch a lot of cable news: 3.7% report watching at least 3 different shows on CNN in the past week, and 5.5% report watching at least 3

[11] The cable news networks broadcast the same lineup of shows simultaneously everywhere in the US, so a show that airs at 5pm on the East Coast is at 2pm on the West Coast. Accounting for the time zone differences would unnecessarily complicate the model.

[12] One potential complication in the data is that we do not observe the specific packages or tiers they subscribe to on cable or satellite TV. On cable systems, CNN and FOX News are typically offered on the expanded-basic tier, so most of the respondents who only subscribe to basic cable do not have access to them at home. However, according to the FCC's *2005 Report on Cable Prices*, 84% of all cable subscribers purchased the expanded-basic tier, and another 4% had a basic service that included most of the cable networks typically offered on the expanded-basic tier (their cable systems did not offer a separate expanded-basic tier). Thus, the proportion of cable subscribers who do not have access to CNN or FOX News at home is quite minor. The same issue applies to the entry-level packages offered by the main satellite TV providers (DirecTV and DISH Network). We do not know what proportion of satellite subscribers purchase the entry-level packages. 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 that include CNN and FOX News.

different shows on FOX News (notice that this refers to the number of different shows watched once or more during the week, and not the total number of times all the shows were watched). Such respondents are important for our identification scheme, because the distances between the shows in the attribute space are identified by the joint audiences for different shows (see the identification section for details).

While the total audience of the FOX News shows is lower than that of CNN shows (15.7% of the respondents watched at least one FOX News show last week, vs 17.8% for CNN), FOX News viewers appear to be more loyal than CNN viewers (an average FOX News viewer watched 2.37 different shows on FOX News, vs 1.84 CNN shows for an average CNN viewer[13]). 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 17% 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 natural 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 84% (just 3.5% of the viewers of *The O'Reilly Factor* also watched *Anderson Cooper 360⁰*, while 84% of the viewers of *Hannity and Colmes* also watched *The O'Reilly Factor*[14]). Despite the much-

[13] 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.

[14] Notice that this is driven in part by the low total audience of *Anderson Cooper 360⁰* and the high total audience

discussed differences between CNN and FOX News, a surprisingly high percentage of CNN viewers also watched FOX News, and vice versa. For example, 30% 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* viewers, 17% also watched *Wolf Blitzer Reports* (often perceived to be one of the most left-leaning CNN shows), and 29% 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[15]. 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, working full-time, slightly less educated, slightly more religiously conservative, and more politically conservative. These differences are consistent with the conventional wisdom about CNN and FOX News viewers. Comparing between "heavy" CNN and FOX News viewers (at least 3 different shows 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 (2.96 and 2.16 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. A lot of respondents watch both CNN and FOX News. For most demographics, they look like an average between CNN and FOX News viewers[16].

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

of *The O'Reilly Factor*.

[15] Unlike the 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 we treat missing political outlook as a useful demographic variable.

[16] 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.

and competition between shows, the viewer demographics for each show depend not only on its 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 bias" question 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* has 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 average viewer. 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 should not be taken too seriously).

There is surprising heterogeneity in average demographics across shows. For example, the proportion of male viewers ranges from 43% for *Paula Zahn Now* to 62% for *Wolf Blitzer Reports* (figure 1b). The proportion of college graduates and above ranges from 27% for *Big Story with John Gibson* to 45% for *Lou Dobbs Tonight (*figure 1c). On average, the viewers of *Hannity and Colmes* earn the most, about $9000 a year more than the viewers of *Paula Zahn Now* (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 9% of CNN viewers (vs 11% in the population), while "very liberal" respondents account for 3% of FOX News viewers (vs 5% in the population). Tables 5b and 5c present the distribution of political outlook for each show on FOX News and CNN. 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 for FOX is higher for more conservative respondents, and the reverse 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 targets a more conservative audience. An interesting pattern is that the profile of viewing shares across political outlook categories is not monotone. Specifically, for both CNN and FOX, the viewing share is lower among those who report 3 than among those who report 2 or 4 (on the political outlook scale from 1-5). This might mean that those with stronger opinions in either direction are more interested in 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-watching, and latent-attribute structure of utility from the shows.

There are 5 weekdays, indexed by d. There are T one-hour periods each day (from 4pm to 10pm), indexed by t. 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

$$U^d_{i,j,t} = \eta_{j,t} + Z_{j,t}(\Gamma X_i + \upsilon^Z_i) + \delta I\{c^d_{i,t-1} = j\} + \varepsilon^d_{i,j,t}$$

where $(\Gamma X_i + \upsilon^Z_i)$ 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 $\upsilon^Z_i \sim N(0, \Sigma^Z_\upsilon)$ are her unobservable characteristics, $\delta I\{c^d_{i,t-1} = j\}$ represents the switching costs ($c^d_{i,t-1}$ denotes her choice in the previous period of the same day), and $\varepsilon^d_{i,j,t}$ 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-watching (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 ($\Gamma, \Sigma_\upsilon^Z$)[17]. 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 the important product attributes are not obvious.

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

$$U_{i,0,t}^d = 0 + \delta^{out} I\{c_{i,t-1}^d = 0\} + \varepsilon_{i,0,t}^d$$

where the coefficients on X_i are normalized to zero, $\delta^{out} I\{c_{i,t-1}^d = 0\}$ represents the switching costs, and $\varepsilon_{i,0,t}^d$ is a logit error.

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

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

where $\beta_t X_i$ captures the effect of the demographics X_i, the period-specific coefficients η_t^{other}, β_t allow us to control for the shows offered on other channels in each period, $\upsilon_i^{other} \sim N(0, \sigma_{other}^2)$ captures the unobservable characteristics of the individual[18], $\delta^{other} I\{c_{i,t-1}^d = J+1\}$ captures the

[17] 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.

[18] 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.

switching costs[19], 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. We use it as a reduced-form control for the competing 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 in income and education, but less strongly. 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 (and normalize the effect of demographics on the outside alternative to zero), our estimates will indicate that the utility from *Larry King* decreases in income and education. In contrast, when we model "other-TV" separately, our estimates will correctly capture the effect of competition, with the *American Idol* stealing the rich and educated viewers from *Larry King*[20].

3.1. Scale and Rotation Invariance, Normalizations

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,

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

[19] 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 from that for CNN and FOX News.

[20] This still relies on the (arbitrary) normalization that the coefficients on demographics in the outside alternative (TV-off) are zero. However, this normalization looks more plausible than setting to zero the coefficients in a mixture of the *American Idol* and TV-off (where the proportion of the *American Idol* vis-a-vis TV-off also depends on the same demographics).

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 $cov(\Gamma X_i + \upsilon_i^Z) = I$ (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[21].

4. The Likelihood

Compared to standard discrete-choice models for panel data, the main complication in computing the likelihood for our model is that instead of panel data for 5 days, we only observe a weekly summary of the data (whether or not each show was watched at least once over the last 5 weekdays). So, in computing the likelihood, we have to integrate out the unobserved choices over 5 days consistent with the weekly summary we observe in the data. Directly integrating out all possible 5-day choice sequences is computationally infeasible (there are too many possible combinations), however the likelihood can be computed recursively at a much lower computational cost, as we show below.

We're going to use the following notation in the derivations below:

$c_{i,t}^d$ is the choice of individual i in period t of day d,

$c_{i,t} = (c_{i,t}^1, c_{i,t}^2, ..., c_{i,t}^5)$ is the vector of choices for period t for each day from Monday to Friday,

$Y_{i,t} = \{Y_{i,0,t}, ..., Y_{i,J+1,t}\}$ is the weekly summary of the choices for period t,

where $Y_{i,j,t} = \begin{cases} 1, \text{ if } c_{i,t}^d = j \text{ for at least one of the } d\text{-s} \\ 0 \text{ otherwise} \end{cases}$

and $C(Y_{i,t})$ is the set of all possible $c_{i,t}$-s that yield the weekly summary $Y_{i,t}$.

In the data, we observe $Y_{i,t}$-s, but not $c_{i,t}$-s.

The likelihood for individual i can be written as

$$\Pr(Y_{i,1}...Y_{i,T}|X_i) = \int \Pr(Y_{i,1}...Y_{i,T}|X_i, \upsilon_i) dF_\upsilon(\upsilon_i|X_i)$$

where $F_\upsilon(\upsilon_i|X_i)$ is the cdf of the unobserved characteristics of the individual $\upsilon_i = (\upsilon_i^Z, \upsilon_i^{other})$. In estimation, we compute this integral using standard simulation methods. The main complication is

[21] 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.

computing the conditional likelihood $\Pr(Y_{i,1}...Y_{i,T}|X_i, \upsilon_i)$ at a reasonable computational cost (doing it by brute force is computationally infeasible – for some observations, there are too many possible 5-day choice sequences consistent with the data). We compute it recursively in the following way.

First, the conditional likelihood can be rewritten as[22]

$$\Pr(Y_{i,1}...Y_{i,T}|X_i, \upsilon_i) = \prod_{t=1}^{T} \Pr(Y_{i,t}|Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i)$$

Next, we compute $\Pr(Y_{i,t}|Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i)$ in the following way. For period $t = 1, ..., T$, we can decompose

$$\Pr(Y_{i,t}|Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i) = \sum_{c_{i,t} \in C(Y_{i,t})} \Pr(c_{i,t}|Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i)$$

where

$$\Pr(c_{i,t}|Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i) = \sum_{c_{i,t-1} \in C(Y_{i,t-1})} \Pr(c_{i,t}|c_{i,t-1}, Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i) \Pr(c_{i,t-1}|Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i) \tag{4.1}$$

We can rewrite the first term in equation (4.1) as

$$\Pr(c_{i,t}|c_{i,t-1}, Y_{i,1}...Y_{i,t-1}, X_i, \upsilon_i) = \Pr(c_{i,t}|c_{i,t-1}, X_i, \upsilon_i) = \prod_{d=1}^{5} \Pr(c^d_{i,t}|c^d_{i,t-1}, X_i, \upsilon_i),$$

where $\Pr(c^d_{i,t}|c^d_{i,t-1}, X_i, \upsilon_i)$ is a standard logit probability. (Notice that after conditioning on $c_{i,t-1}$ (and X_i, υ_i), $Y_{i,1}...Y_{i,t-1}$ do not provide any additional information on the distribution of $c_{i,t}$, so we do not have to condition on them[23]).

[22] Conditional on υ_i, the distribution of the choice in period t of day d ($c^d_{i,t}$) only depends on the choice in the previous period of the same day ($c^d_{i,t-1}$), via the switching costs. However, the distribution of the 5-day summary for period t ($Y_{i,t}$) depends on all of $Y_{i,1}...Y_{i,t-1}$ (not just $Y_{i,t-1}$), since the Y-s from the earlier periods provide additional information on the distribution of $c^d_{i,t-1}$.

[23] The reason is that only one lag of choices enters the switching costs, so conditioning on $c_{i,t-1}$ accounts for the entire effect of all the lagged choices on $c_{i,t}$. Notice, however, that we cannot use the same logic and reduce $\Pr(c_{i,t}|Y_{i,1}...Y_{i,t-1})$ to $\Pr(c_{i,t}|Y_{i,t-1})$, as explained in the previous footnote.

We can rewrite the second term in equation (4.1) as

$$\begin{aligned}
\Pr(c_{i,t-1}|Y_{i,1}...Y_{i,t-1},X_i,\upsilon_i) &= \frac{\Pr(c_{i,t-1},Y_{i,t-1}|Y_{i,1}...Y_{i,t-2},X_i,\upsilon_i)}{\Pr(Y_{i,t-1}|Y_{i,1}...Y_{i,t-2},X_i,\upsilon_i)} = \\
&= I\{c_{i,t-1}\in C(Y_{i,t-1})\}\frac{\Pr(c_{i,t-1}|Y_{i,1}...Y_{i,t-2},X_i,\upsilon_i)}{\Pr(Y_{i,t-1}|Y_{i,1}...Y_{i,t-2},X_i,\upsilon_i)}
\end{aligned}$$

Notice that in $\frac{\Pr(c_{i,t-1}|Y_{i,1}...Y_{i,t-2},X_i,\upsilon_i)}{\Pr(Y_{i,t-1}|Y_{i,1}...Y_{i,t-2},X_i,\upsilon_i)}$, both the numerator and the denominator follow the formulas we have already derived above, but for $t-1$. For $t=1$, these probabilities simplify to:

$$\begin{aligned}
\Pr(Y_{i,1}|X_i,\upsilon_i) &= \sum_{c_{i,1}\in C(Y_{i,1})}\Pr(c_{i,1}|X_i,\upsilon_i) \\
\Pr(c_{i,1}|X_i,\upsilon_i) &= \prod_{d=1}^{5}\Pr(c_{i,1}^{d}|X_i,\upsilon_i) \\
\Pr(c_{i,1}|Y_{i,1},X_i,\upsilon_i) &= I\{c_{i,1}\in C(Y_{i,1})\}\frac{\Pr(c_{i,1}|X_i,\upsilon_i)}{\Pr(Y_{i,1}|X_i,\upsilon_i)}
\end{aligned}$$

which are easy to compute. So, first we compute the probabilities for $t=1$, after that we can use the above formulas to compute the probabilities for $t=2$ (using the results for $t=1$), and so on, when the computations for period t rely on the probabilities we have already computed for $t-1$.

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[24]). 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 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". Technically, we use the Bayes Information Criterion (BIC) to choose the rank of the attribute space (this follows the approach in the literature, e.g. Goettler and Shachar 2001 in industrial organization, or Chintagunta 1994 in marketing).

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[25]. If this is the case in the data, two shows that cover a similar set of topics will have a disproportionately small joint

[24]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.

[25]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.

audience, and the model will overestimate the "distance" between them in the attribute space[26]. 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[27]. 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[28]. Notice that the show locations in the attribute space are pinned down by their "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

[26] 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.

[27] 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).

[28] 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 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).

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 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".

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[29], 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 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

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

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[30]. 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 (Eastern time). 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[31]) and *Crossfire* (4.30–4.59pm) on CNN. In estimation, we treat both shows as a single 1-hour show, from 4pm to 4.59pm[32]. The broadcasting schedule changed during the sample: on September 8 2003 (about 1/3 of the sample period), 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 the schedule change, however we know the aggregate distribution of the sampling dates. In estimation, we integrate out the unobserved sampling date for each respondent.

For the "other-TV" alternative, we estimate 2 separate sets of coefficients on demographics, one for daytime and another for primetime. The objective is to give a reasonably accurate reduced-form approximation for "other-TV" viewing, while keeping the number of parameters low.

We estimate the model by simulated maximum likelihood. We choose the number of latent attributes using the Bayes Information Criterion (BIC). The optimal number of dimensions of the attribute space is $M = 2$. The original estimates for $M = 2$ are presented in Table 6 (however, the

[30] 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.

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

[32] 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.

normalizations in Table 6 are convenient for estimation, but not for interpretation of the estimates of show locations, 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 $\delta = 1.40$ (0.08), for other TV channels $\delta^{other} = 1.11$ (0.07), and for the outside alternative $\delta^{out} = 0.99$ (0.07)). 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 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 $cov(\Gamma X_i + v_i)$ becomes an identity matrix. The re-normalized estimates are presented in Table 8, and the estimated show locations are plotted in Figure 2.

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 all the shows, the nearest show in the attribute space is offered by the same network[33]. In fact, the location of any CNN show is significantly different from the location of any FOX News network, 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 71% 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.

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

[33] Notice that after the re-normalization, the preferences for the attributes are uncorrelated across the dimensions and their variance is the same for all the dimensions, so Euclidean distance in the attribute space is a meaningful measure of distance between the shows.

before the beginning of our sample, so this likely reflects the fundamental characteristics of their shows rather than viewer loyalty[34]. For the rest of the shows in our data, none of the anchors ever worked for the other cable news network (CNN or Fox News).

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 to capture 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 show on CNN is *Paula Zahn Now* (formerly a Fox News anchor). The most left-wing show on Fox News is *On the Record with Greta van Susteren* (formerly a CNN anchor). The most right-wing shows on Fox News are *Your World with Neil Cavuto*[35] and *Special Report with Brit Hume*.

The most natural interpretation of attribute 2 (the Y axis) is the proportion of "facts" vs "opinions" in a show. Specifically, the show lowest on attribute 2 on CNN is *Wolf Blitzer Reports*, which is widely considered to present intense opinions**.** The CNN shows highest on attribute 2 are *Anderson Cooper 360*[0] and *Larry King Live*, which are widely considered to focus more on "facts" than "opinions". The Fox News show highest on attribute 2 is *Fox Report with Shepard Smith*, and the Fox News show lowest on attribute 2 is *Your World with Neil Cavuto*[36]. Interestingly, the two signature FOX News shows, *The O'Reilly Factor* and *Hannity and Colmes*, are slightly above average in terms of "facts vs opinion".

[34] 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. However, more than a year after the move, the residual effect of such viewer loyalty or habit should be negligible.

[35] *Your World with Neil Cavuto* focuses primarily on business news, so it might not be directly comparable ideologically with the rest of the shows. Furthermore, its estimated location can change a lot after we control for the initial conditions (it airs at 4pm, at the beginning of our sample).

[36] As discussed in the previous footnote, *Your World with Neil Cavuto* might not be directly comparable to the other shows.

We verify the interpretation of attribute 2 ("facts vs opinions"), 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 (heavy on opinions relative to facts), as well as the "general news" section (hopefully, heavier on "facts" than "opinions"). 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, and explanatory variables are demographics X_i and the posterior means of the unobserved preferences for the attributes[37]. 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 negative and highly significant (Table 9). This supports our interpretation of attribute 2 as "facts vs opinions".

Counterfactuals xxx.

[37] The sample is restricted to the respondents who report reading the "general news" section in the last daily newspaper read. Otherwise, our estimates might be picking up general preferences for news.

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. The market shares of the shows (% of respondents who watched each show at least once in the last 5 weekdays)

	CNN	FOX News
4pm	5.3%	3.5%
5pm	5.1%	2.0%
6pm	2.3%*	4.6%
7pm	1.3%*	4.7%
8pm	4.6%	11.7%
9pm	11.1%	6.7%
10pm	3.2%	4.1%

The sample (here and in all the descriptive statistics below): cable and satellite subscribers, at least 18 years old, in the Eastern time zone (10,329 obs.).

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

	CNN	FOX News	both
0	82.2%	84.3%	73.7%
1	9.3%	6.9%	9.8%
2	4.8%	3.3%	5.6%
3	2.3%	2.3%	4.3%
4	0.8%	1.1%	2.8%
5	0.3%	0.8%	1.6%
6	0.1%	0.6%	0.9%
7	0.3%	0.7%	0.5%
8+	---	---	0.8%
average number of shows	0.33	0.37	0.70
average number of shows among those who watched at least one show	1.84	2.37	2.67

Note: Only refers to weekday shows from 4pm to 10.59pm. If the respondent watched the same show on several days, 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	–	37%	17%	10%	25%	**46%**	24%	12%	7%	15%	12%	36%	18%	13%
Wolf Blitzer Reports	38%	–	26%	12%	28%	**54%**	26%	14%	9%	17%	14%	38%	22%	22%
Lou Dobbs Tonight	39%	**57%**	–	18%	30%	48%	39%	21%	15%	26%	23%	42%	29%	27%
Anderson Cooper 360°	43%	47%	33%	–	44%	**63%**	39%	18%	15%	21%	18%	32%	21%	21%
Paula Zahn Now	29%	31%	15%	12%	–	**59%**	21%	10%	5%	14%	9%	35%	18%	16%
Larry King Live	22%	25%	10%	7%	24%	–	16%	8%	4%	10%	9%	**30%**	17%	13%
Newsnight with Aaron Brown	39%	42%	28%	16%	30%	**55%**	–	15%	10%	18%	21%	30%	20%	20%
Your World with Neil Cavuto	18%	21%	14%	7%	13%	24%	13%	–	37%	64%	53%	**77%**	61%	44%
Big Story with John Gibson	19%	22%	17%	9%	12%	21%	16%	64%	–	71%	65%	**76%**	64%	50%
Special Report with Brit Hume	18%	20%	13%	6%	14%	24%	12%	49%	31%	–	51%	**73%**	57%	43%
Fox Report with Shepard Smith	14%	15%	11%	5%	9%	21%	15%	39%	28%	50%	–	**75%**	57%	40%
The O'Relly Factor	16%	17%	8%	4%	14%	29%	8%	23%	13%	29%	30%	–	**48%**	28%
Hannity & Colmes	14%	16%	10%	4%	12%	27%	10%	32%	19%	39%	40%	**84%**	–	41%
On the record with Greta van Susteren	17%	28%	15%	7%	17%	35%	16%	37%	25%	48%	46%	**81%**	67%	–

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	--	**0.34**	0.23	0.19	0.23	0.27	0.27	0.10	0.09	0.12	0.08	0.18	0.11	0.11
Wolf Blitzer Reports	0.34	--	**0.36**	0.21	0.26	0.32	0.30	0.13	0.11	0.14	0.10	0.19	0.14	0.21
Lou Dobbs Tonight	0.23	**0.36**	--	0.23	0.19	0.18	0.31	0.15	0.14	0.16	0.13	0.15	0.14	0.18
Anderson Cooper 360°	0.19	0.21	0.23	--	0.22	0.19	**0.23**	0.09	0.10	0.09	0.07	0.07	0.06	0.10
Paula Zahn Now	0.23	0.26	0.19	0.22	--	**0.33**	0.22	0.08	0.05	0.10	0.05	0.16	0.10	0.13
Larry King Live	0.27	0.32	0.18	0.19	**0.33**	--	0.26	0.08	0.04	0.09	0.07	0.20	0.14	0.16
Newsnight with Aaron Brown	0.27	0.30	**0.31**	0.23	0.22	0.26	--	0.11	0.10	0.11	0.14	0.10	0.10	0.15
Your World with Neil Cavuto	0.10	0.13	0.15	0.09	0.08	0.08	0.11	--	0.47	**0.54**	0.43	0.38	0.41	0.38
Big Story with John Gibson	0.09	0.11	0.14	0.10	0.05	0.04	0.10	**0.47**	--	0.45	0.41	0.29	0.33	0.34
Special Report with Brit Hume	0.12	0.14	0.16	0.09	0.10	0.09	0.11	**0.54**	0.45	--	0.48	0.42	0.44	0.43
Fox Report with Shepard Smith	0.08	0.10	0.13	0.07	0.05	0.07	0.14	0.43	0.41	**0.48**	--	0.43	0.44	0.40
The O'Relly Factor	0.18	0.19	0.15	0.07	0.16	0.20	0.10	0.38	0.29	0.42	0.43	--	**0.61**	0.45
Hannity & Colmes	0.11	0.14	0.14	0.06	0.10	0.14	0.10	0.41	0.33	0.44	0.44	**0.61**	--	0.50
On the record with Greta van Susteren	0.11	0.21	0.18	0.10	0.13	0.16	0.15	0.38	0.34	0.43	0.40	0.45	**0.50**	--

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%	56%	58%
age	0.58	0.73	0.74	0.73	0.76	0.77	0.79
white	80%	86%	85%	86%	84%	79%	87%
black	14%	10%	11%	10%	12%	17%	11%
other race	6%	4%	4%	4%	4%	4%	3%
Hispanic household	8%	5%	5%	4%	4%	2%	4%
high-school dropout	13%	10%	9%	10%	8%	7%	11%
high-school graduate	35%	36%	37%	37%	41%	37%	35%
some college	20%	17%	17%	17%	15%	17%	18%
college graduate and above	32%	37%	38%	36%	36%	39%	36%
student	7%	4%	4%	2%	1%	2%	2%
working full-time	55%	45%	43%	46%	42%	36%	42%
working part-time	11%	10%	10%	10%	10%	8%	5%
not working	35%	45%	47%	44%	48%	56%	52%
respondent income***	0.91	0.99	0.98	0.99	0.97	0.95	1.10
household income	1.21	1.20	1.17	1.21	1.14	1.09	1.24
top-100 DMA	80%	79%	78%	80%	77%	68%	79%
religious conservative (1-5)	2.96	3.10	3.03	3.16	3.04	2.91	3.31
family-centered (1-5)	3.03	3.12	3.14	3.08	3.07	3.13	3.09
work-centered (1-5)	2.95	2.89	2.90	2.95	3.03	2.88	2.95
political outlook (1 – very conservative, 5 -very liberal)	2.75	2.59	2.79	2.40	2.65	2.94	2.16
political outlook missing	16%	10%	10%	9%	8%	9%	9%

* watched at least one show on CNN or FOX News between 4-10.59pm in the last 5 weekdays.
** watched at least one CNN show and one FOX News show between 4-10.59pm in the last 5 weekdays.
*** only for those who work full-time or part-time.

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	54%	62%	61%	43%	43%	46%	49%
age	0.73	0.77	0.74	0.69	0.76	0.77	0.70
white	83%	85%	77%	79%	84%	86%	78%
black	12%	12%	17%	17%	12%	11%	15%
other race	5%	3%	6%	4%	5%	3%	6%
Hispanic household	4%	4%	6%	3%	2%	4%	6%
high-school dropout	11%	8%	3%	10%	8%	9%	9%
high-school graduate	39%	36%	29%	41%	40%	38%	37%
some college	18%	20%	23%	10%	18%	16%	13%
college graduate and above	33%	36%	45%	39%	34%	38%	41%
student	4%	4%	7%	2%	4%	3%	2%
working full-time	36%	39%	38%	40%	41%	43%	30%
working part-time	10%	7%	11%	11%	10%	11%	11%
not working	54%	53%	51%	49%	49%	47%	59%
respondent income	0.92	1.00	1.04	1.03	0.91	1.01	0.94
household income	1.08	1.14	1.21	1.13	1.07	1.19	1.04
top-100 DMA	71%	72%	80%	84%	72%	80%	66%
religious conservative (1-5)	3.03	2.85	2.94	2.79	2.92	3.09	2.94
family-centered (1-5)	3.24	3.17	3.15	3.02	3.25	3.12	2.96
work-centered (1-5)	3.00	2.78	2.98	2.95	2.73	2.85	3.01
political outlook (1 – very conservative, 5 -very liberal)	2.84	2.85	3.10	3.12	2.89	2.82	2.97
political outlook missing	10%	8%	13%	15%	7%	9%	12%

Table 4c. Average viewer demographics for FOX News shows

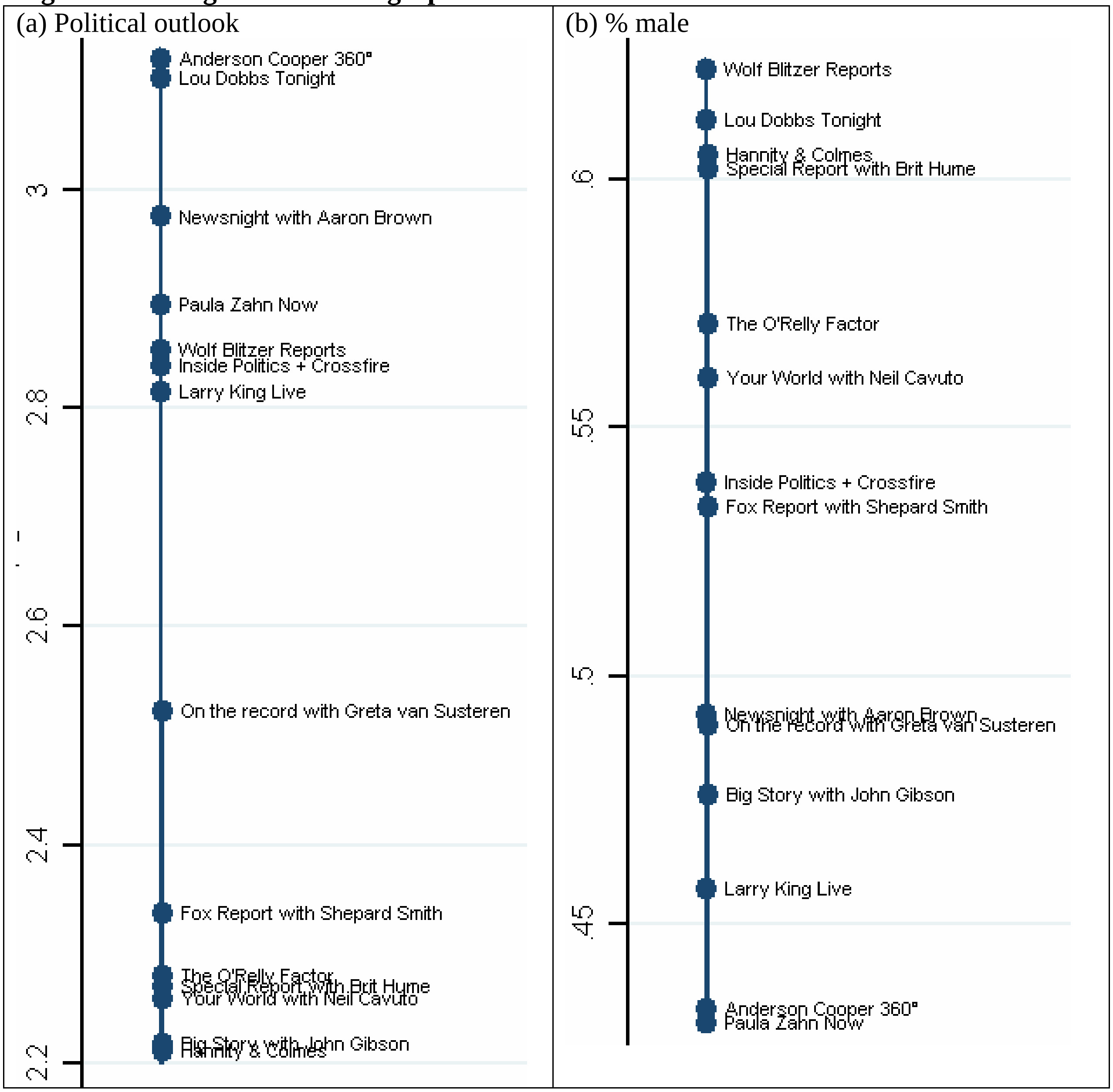
	Your World with Neil Cavuto	Big Story with John Gibson	Special Report with Brit Hume	Fox Report with Shepard Smith	The O'Relly Factor	Hannity & Colmes	On the record with Greta van Susteren
male	56%	48%	60%	53%	57%	60%	49%
age	0.79	0.82	0.79	0.75	0.75	0.73	0.77
white	79%	82%	86%	86%	86%	87%	83%
black	18%	15%	12%	11%	11%	9%	14%
other race	4%	2%	2%	3%	3%	4%	4%
Hispanic household	4%	5%	3%	5%	4%	4%	2%
high-school dropout	13%	23%	11%	7%	10%	8%	10%
high-school graduate	38%	34%	34%	41%	37%	33%	37%
some college	14%	16%	18%	18%	17%	18%	21%
college graduate and above	35%	27%	37%	34%	36%	41%	33%
student	2%	4%	2%	2%	2%	2%	2%
working full-time	35%	27%	44%	43%	47%	50%	37%
working part-time	9%	6%	8%	7%	9%	6%	8%
not working	56%	67%	48%	50%	44%	44%	55%
respondent income	1.02	0.99	1.09	1.03	1.00	1.09	1.04
household income	1.21	1.07	1.21	1.18	1.23	1.27	1.19
top-100 DMA	84%	75%	80%	74%	80%	80%	80%
religious conservative (1-5)	3.18	3.35	3.23	3.20	3.21	3.28	3.22
family-centered (1-5)	3.09	2.91	3.01	3.25	3.10	3.06	3.02
work-centered (1-5)	3.11	3.01	3.01	2.87	2.91	2.98	2.88
political outlook (1 – very conservative, 5 -very liberal)	2.26	2.22	2.27	2.34	2.28	2.21	2.52
political outlook missing	15%	12%	9%	10%	9%	9%	12%

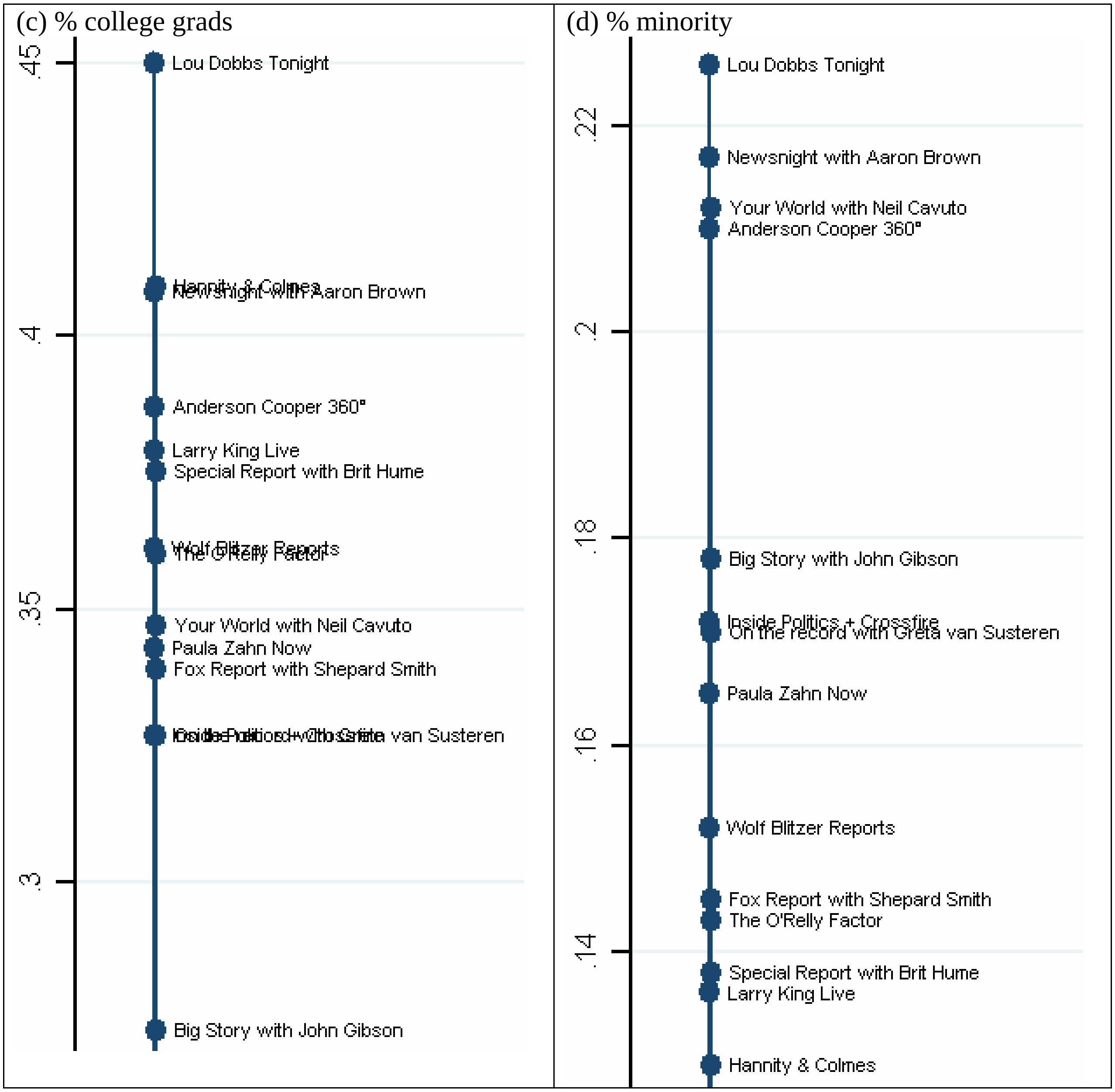
Table 4d. Normalized distance between average viewer demographics for different shows. = sqrt[(avgX[i]-avgX[j])'*inv(covX)*(avgX[i]-avgX[j])]

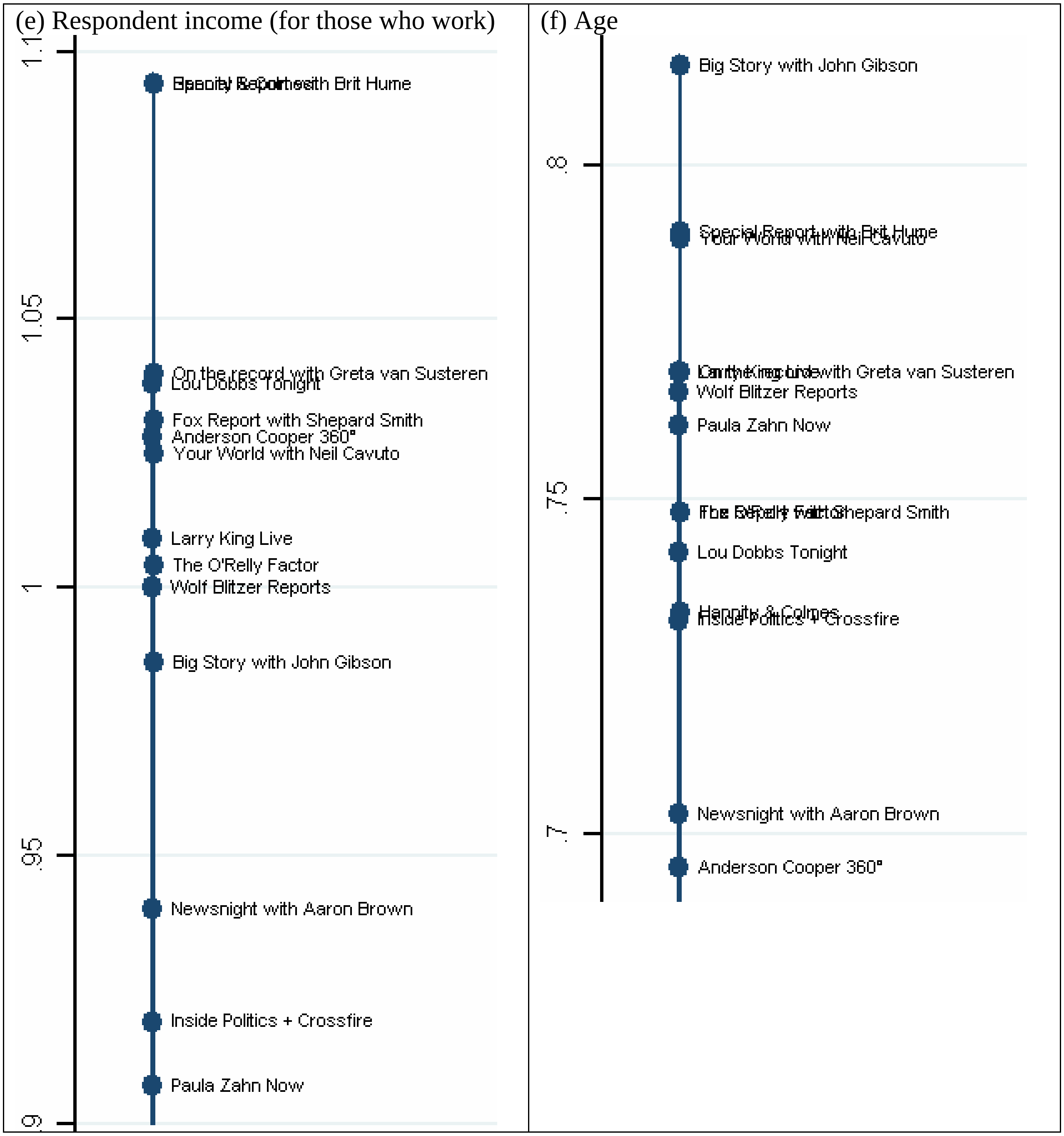
	Inside Politics + Crossfire	Wolf Blitzer Reports	Lou Dobbs Tonight	Anderson Cooper 360°	Paula Zahn Now	Larry King Live	Newsnight with Aaron Brown	Your World with Neil Cavuto	Big Story with John Gibson	Special Report with Brit Hume	Fox Report with Shepard Smith	The O'Relly Factor	Hannity & Colmes	On the record with Greta van Susteren
Inside Politics + Crossfire		0.52	0.80	**0.41**	0.55	0.64	0.62	0.68	1.54	0.68	0.75	0.77	0.83	0.65
Wolf Blitzer Reports	0.52		0.66	0.54	**0.51**	0.61	0.93	0.68	1.62	0.63	0.80	0.62	0.72	0.62
Lou Dobbs Tonight	0.80	**0.66**		0.69	0.94	0.92	0.85	1.16	1.89	1.27	1.38	1.34	1.43	1.06
Anderson Cooper 360°	**0.41**	0.54	0.69		0.67	0.63	0.48	0.87	1.58	1.09	1.19	1.18	1.32	0.70
Paula Zahn Now	0.55	0.51	0.94	0.67		**0.51**	0.99	0.98	1.86	0.93	0.92	0.77	1.02	0.78
Larry King Live	0.64	0.61	0.92	0.63	**0.51**		1.03	0.84	1.85	0.81	0.84	0.62	0.88	0.66
Newsnight with Aaron Brown	0.62	0.93	0.85	**0.48**	0.99	1.03		1.05	1.62	1.17	1.22	1.34	1.36	1.04
Your World with Neil Cavuto	0.68	0.68	1.16	0.87	0.98	0.84	1.05		1.16	0.46	0.61	0.75	0.61	**0.34**
Big Story with John Gibson	1.54	1.62	1.89	1.58	1.86	1.85	1.62	**1.16**		1.22	1.45	1.70	1.37	1.30
Special Report with Brit Hume	0.68	0.63	1.27	1.09	0.93	0.81	1.17	0.46	1.22		0.40	0.55	0.34	**0.24**
Fox Report with Shepard Smith	0.75	0.80	1.38	1.19	0.92	0.84	1.22	0.61	1.45	0.40		0.44	**0.35**	0.47
The O'Relly Factor	0.77	0.62	1.34	1.18	0.77	0.62	1.34	0.75	1.70	0.55	0.44		**0.41**	0.49
Hannity & Colmes	0.83	0.72	1.43	1.32	1.02	0.88	1.36	0.61	1.37	0.34	0.35	0.41		**0.32**
On the record with Greta van Susteren	0.65	0.62	1.06	0.70	0.78	0.66	1.04	0.34	1.30	**0.24**	0.47	0.49	0.32	

Bold – lowest distance in the row

Figure 1. Average viewer demographics for the shows




(c) % college grads
.45
.4
.35
.3
Lou Dobbs Tonight
Hannity & Colmes
Newsnight with Aaron Brown
Anderson Cooper 360°
Larry King Live
Special Report with Brit Hume
Wolf Blitzer Reports
The O'Reilly Factor
Your World with Neil Cavuto
Paula Zahn Now
Fox Report with Shepard Smith
Big Story with John Gibson
(d) % minority
.22
.2
.18
.16
.14
Lou Dobbs Tonight
Newsnight with Aaron Brown
Your World with Neil Cavuto
Anderson Cooper 360°
Big Story with John Gibson
Inside Politics + Crossfire
On the record with Greta van Susteren
Paula Zahn Now
Wolf Blitzer Reports
Fox Report with Shepard Smith
The O'Relly Factor
Special Report with Brit Hume
Larry King Live
Hannity & Colmes


(e) Respondent income (for those who work)
1.1
1.05
1
.95
.9
On the record with Greta van Susteren
Lou Dobbs Tonight
Fox Report with Shepard Smith
Anderson Cooper 360°
Your World with Neil Cavuto
Larry King Live
The O'Relly Factor
Wolf Blitzer Reports
Big Story with John Gibson
Newsnight with Aaron Brown
Inside Politics + Crossfire
Paula Zahn Now
(f) Age
.8
.75
.7
Big Story with John Gibson
Wolf Blitzer Reports
Paula Zahn Now
Lou Dobbs Tonight
Newsnight with Aaron Brown
Anderson Cooper 360°

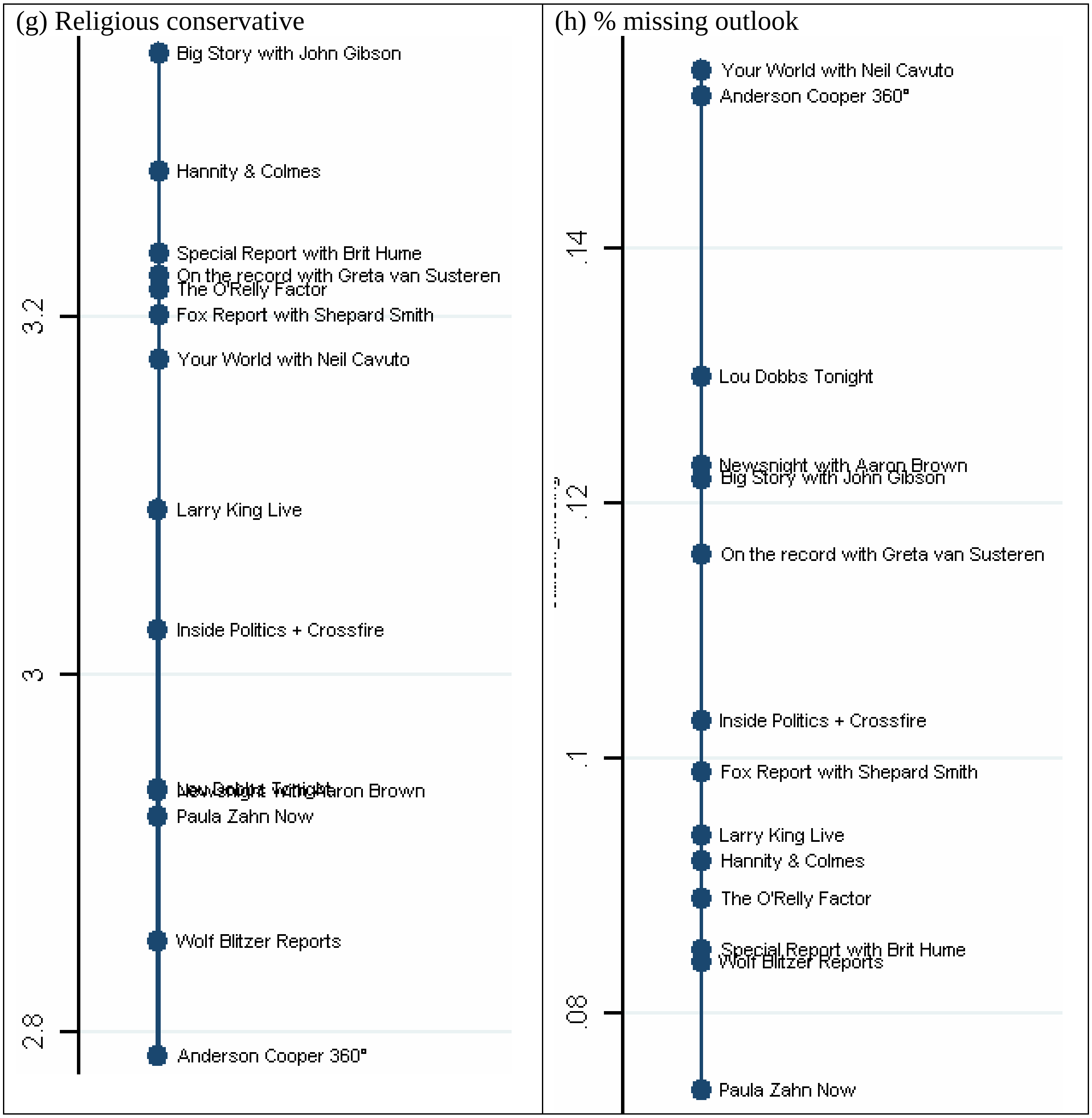

(g) Religious conservative
Big Story with John Gibson
Hannity & Colmes
Special Report with Brit Hume
On the record with Greta van Susteren
The O'Relly Factor
Fox Report with Shepard Smith
Your World with Neil Cavuto
Larry King Live
Inside Politics + Crossfire
Lou Dobbs Tonight
Newsnight with Aaron Brown
Paula Zahn Now
Wolf Blitzer Reports
Anderson Cooper 360°
3.2
3
2.8
(h) % missing outlook
Your World with Neil Cavuto
Anderson Cooper 360°
Lou Dobbs Tonight
Newsnight with Aaron Brown
Big Story with John Gibson
On the record with Greta van Susteren
Inside Politics + Crossfire
Fox Report with Shepard Smith
Larry King Live
Hannity & Colmes
The O'Relly Factor
Special Report with Brit Hume
Wolf Blitzer Reports
Paula Zahn Now
.14
.12
.1
.08

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%	11%	26%	9%	6%	19%	26%
2	27%	29%	35%	41%	31%	28%	38%	43%
3	43%	37%	37%	25%	37%	40%	31%	21%
4	14%	17%	14%	6%	16%	17%	10%	5%
5 - very liberal	5%	8%	3%	2%	6%	9%	3%	4%

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	8%	8%	5%	8%	7%	9%	8%
2	34%	31%	29%	25%	29%	29%	27%
3	33%	37%	28%	28%	40%	39%	38%
4	16%	17%	26%	23%	16%	17%	15%
5 - very liberal	9%	8%	12%	15%	8%	6%	12%

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	24%	34%	23%	21%	22%	28%	16%
2	43%	34%	43%	41%	39%	38%	38%
3	23%	19%	22%	28%	29%	22%	28%
4	5%	4%	7%	6%	7%	8%	12%
5 - very liberal	6%	9%	5%	5%	2%	4%	5%

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	15.6%	22.3%	16.3%	22.0%	23.5%
FOX	28.4%	24.2%	12.1%	12.2%	8.5%
CNN or FOX	36.5%	36.2%	21.6%	26.0%	27.1%
CNN&FOX	7.5%	10.3%	6.8%	8.1%	4.9%

Table 6. The structural estimates for M=2.

	est	s.e.
switching costs		
delta	1.40	0.08
deltaOther	1.11	0.07
deltaOut	0.99	0.07
“other-TV parameters”		
eta400	-3.69	0.15
eta500	-2.22	0.16
eta600	-2.03	0.16
eta700	-2.15	0.16
eta800	-1.62	0.17
eta900	-1.75	0.17
eta1000	-2.08	0.16
DAYTIMEmale	-0.13	0.03
age	0.13	0.15
age^2	0.17	0.12
white	0.00	.
black	-0.04	0.05
other race	-0.05	0.04
Hisp_HH	-0.06	0.03
HS dropout	-0.09	0.04
HS grad	0.00	.
some college	0.05	0.04
college grad and above	0.01	0.03
student	0.00	0.06
full-time	0.00	.
part-time	0.00	0.04
not working (retired/unemployed/other)	0.19	0.07
resp_income	0.00	0.14
resp_income^2	-0.03	0.08
hh_income	0.43	0.15
hh_income^2	-0.22	0.07
top-100 DMA	0.02	0.03
religious conservativeness (5 max)	-0.03	0.01
family-centered	0.04	0.01
work-centered	-0.04	0.01
pol_outlook(5-very liberal)	0.25	0.06
outlook^2	-0.04	0.01
outlook_missing	0.14	0.09
PRIMETIMEmale	-0.12	0.03
age	0.42	0.16
age^2	-0.41	0.12
white	0.00	.
black	-0.29	0.05
other race	-0.22	0.05
Hisp_HH	-0.12	0.04
HS dropout	-0.07	0.04
HS grad	0.00	.
some college	0.22	0.04
college grad and above	0.28	0.03

	est	s.e.
student	-0.05	0.06
full-time	0.00	.
part-time	0.07	0.04
not working (retired/unemployed/other)	0.06	0.07
resp_income	-0.31	0.14
resp_income^2	0.23	0.08
hh_income	0.28	0.17
hh_income^2	-0.12	0.08
top-100 DMA	0.05	0.03
religious conservativeness (5 max)	-0.03	0.01
family-centered	0.01	0.01
work-centered	-0.06	0.01
pol_outlook(5-very liberal)	0.29	0.06
outlook^2	-0.05	0.01
outlook_missing	0.13	0.09
sdW_other	0.72	0.02
vertical characteristics of the shows		
etaCNN1	-7.40	0.38
etaCNN2	-7.84	0.54
etaCNN3	-7.68	0.50
etaCNN4	-7.69	0.51
etaCNN5	-6.68	0.43
etaCNN6	-4.93	0.30
etaCNN7	-7.80	0.47
etaFOX1	-8.12	0.65
etaFOX2	-6.23	0.48
etaFOX3	-5.88	0.52
etaFOX4	-4.84	0.43
etaFOX5	-4.18	0.40
etaFOX6	-5.44	0.47
etaFOX7	-6.80	0.45
attribute 1 - preferences		
male	0.34	0.06
age	1.42	0.36
age^2	0.19	0.27
white	0.00	.
black	0.13	0.09
other race	0.13	0.10
Hisp_HH	-0.76	0.08
HS dropout	-0.66	0.09
HS grad	0.00	.
some college	0.14	0.08
college grad and above	0.35	0.07
student	-0.09	0.13
full-time	0.00	.
part-time	0.44	0.10
not working (retired/unemployed/other)	0.49	0.16
resp_income	-0.43	0.33
resp_income^2	0.43	0.18
hh_income	0.03	0.34

	est	**s.e.**
hh_income^2	0.11	0.16
top-100 DMA	0.09	0.07
religious conservativeness (5 max)	0.03	0.02
family-centered	-0.01	0.02
work-centered	0.04	0.02
pol_outlook(5-very liberal)	-0.33	0.13
outlook^2	0.08	0.02
outlook_missing	-0.36	0.19
attribute 1 – show locations		
z1_CNN1	1.00	.
z1_CNN2	1.09	0.08
z1_CNN3	1.01	0.09
z1_CNN4	0.76	0.09
z1_CNN5	1.02	0.07
z1_CNN6	0.76	0.05
z1_CNN7	0.93	0.08
z1_FOX1	1.56	0.11
z1_FOX2	1.00	0.10
z1_FOX3	1.28	0.09
z1_FOX4	0.87	0.07
z1_FOX5	1.11	0.07
z1_FOX6	1.14	0.09
z1_FOX7	1.20	0.09
sd_w1	1.82	0.09
attribute 2 - preferences		
male	0.35	0.10
age	0.08	0.69
age^2	-0.48	0.49
white	0.00	.
black	-0.27	0.18
other race	0.11	0.19
Hisp_HH	0.05	0.15
HS dropout	0.07	0.18
HS grad	0.00	.
some college	-0.01	0.13
college grad and above	-0.37	0.12
student	0.10	0.26
full-time	0.00	.
part-time	-0.05	0.18
not working (retired/unemployed/other)	-0.20	0.29
resp_income	0.26	0.58
resp_income^2	-0.27	0.31
hh_income	-0.26	0.69
hh_income^2	0.16	0.30
top-100 DMA	0.27	0.13
religious conservativeness (5 max)	0.05	0.03
family-centered	0.03	0.03
work-centered	-0.03	0.03
pol_outlook(5-very liberal)	-1.50	0.23
outlook^2	0.10	0.04

	est	**s.e.**
outlook_missing	-3.54	0.40
attribute 2 – show locations		
z2_CNN1	0.00	.
z2_CNN2	-0.20	0.05
z2_CNN3	-0.01	0.05
z2_CNN4	-0.11	0.07
z2_CNN5	0.02	0.04
z2_CNN6	-0.07	0.03
z2_CNN7	-0.14	0.05
z2_FOX1	1.00	.
z2_FOX2	0.71	0.08
z2_FOX3	0.83	0.08
z2_FOX4	0.71	0.07
z2_FOX5	0.66	0.06
z2_FOX6	0.78	0.08
z2_FOX7	0.47	0.05
sd_w2	1.81	0.13

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.

	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	--	18.0	0.0	9.1	0.4	30.5	8.4	--*	72.0	112.2	116.1	133.4	106.4	74.3
Wolf Blitzer Reports	18.0	--	8.6	11.9	14.2	25.1	3.9	747.6	78.5	108.2	104.2	112.3	102.2	77.0
Lou Dobbs Tonight	0.0	8.6	--	6.7	0.2	11.4	3.9	372.6	50.7	83.6	68.4	73.5	69.9	39.3
Anderson Cooper 360°	9.1	11.9	6.7	--	8.3	0.3	3.1	312.4	55.4	88.4	64.5	79.2	73.1	50.7
Paula Zahn Now	0.4	14.2	0.2	8.3	--	18.9	7.6	506.4	53.2	85.5	80.2	88.2	76.4	43.7
Larry King Live	30.5	25.1	11.4	0.3	18.9	--	7.2	1336.8	74.0	126.8	94.6	135.7	107.9	84.3
Newsnight with Aaron Brown	8.4	3.9	3.9	3.1	7.6	7.2	--	604.5	66.5	98.8	87.1	99.9	88.7	67.0
Your World with Neil Cavuto	--*	747.6	372.6	312.4	506.4	1336.8	604.5	--	22.5	6.4	37.9	35.8	13.7	100.4
Big Story with John Gibson	72.0	78.5	50.7	55.4	53.2	74.0	66.5	22.5	--	7.8	1.8	2.2	1.8	14.8
Special Report with Brit Hume	112.2	108.2	83.6	88.4	85.5	126.8	98.8	6.4	7.8	--	20.8	7.7	2.2	25.5
Fox Report with Shepard Smith	116.1	104.2	68.4	64.5	80.2	94.6	87.1	37.9	1.8	20.8	--	18.4	9.9	37.4
The O'Relly Factor	133.4	112.3	73.5	79.2	88.2	135.7	99.9	35.8	2.2	7.7	18.4	--	3.4	17.4
Hannity & Colmes	106.4	102.2	69.9	73.1	76.4	107.9	88.7	13.7	1.8	2.2	9.9	3.4	--	25.8
On the record with Greta van Susteren	74.3	77.0	39.3	50.7	43.7	84.3	67.0	100.4	14.8	25.5	37.4	17.4	25.8	--

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.

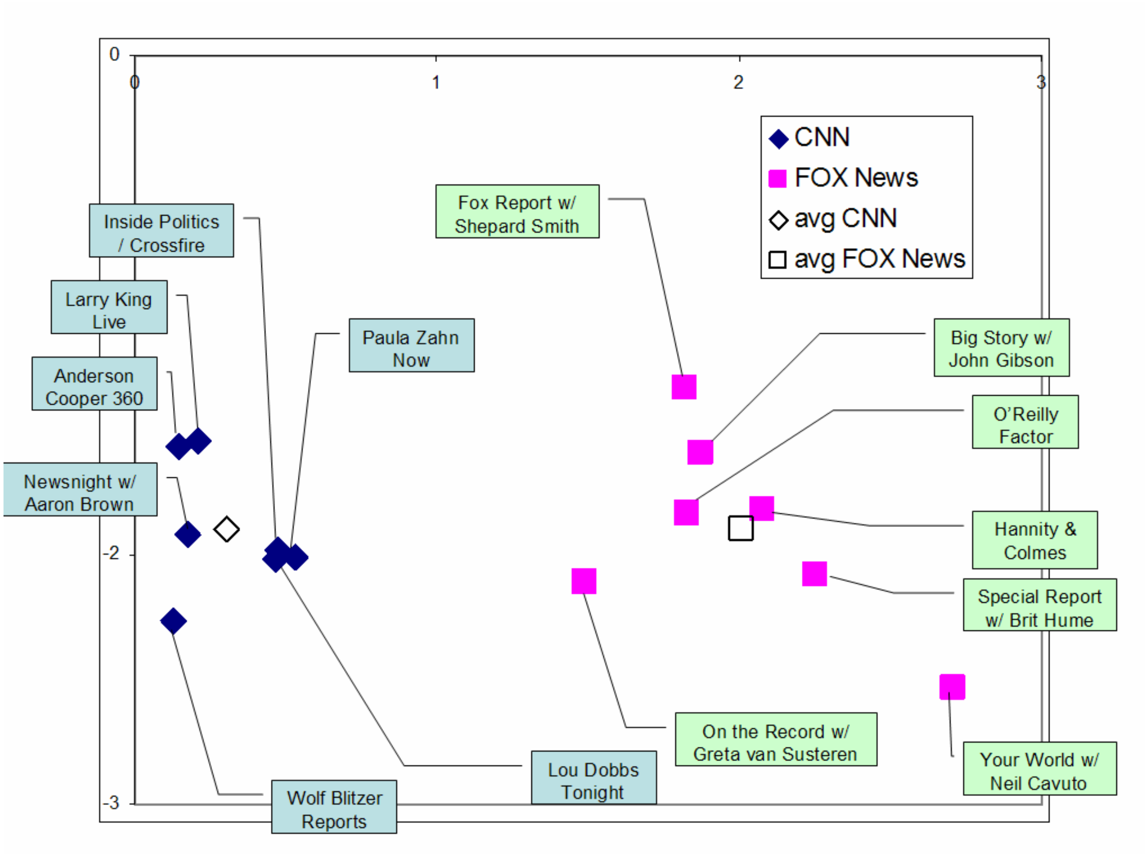


Figure 2. The show locations (after the re-normalization of preferences and rotation)

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

	attribute 1	attribute 2
Inside Politics/Crossfire	0.47	-1.98
Wolf Blitzer	0.13	-2.27
Lou Dobbs	0.47	-2.01
Cooper	0.14	-1.56
Paula Zahn	0.53	-2.01
Larry King	0.21	-1.54
Newsnight	0.17	-1.92
Cavuto	2.71	-2.53
Big Story - Gibson	1.87	-1.59
Special Report - Brit Hume	2.25	-2.08
Fox Report - Shepard Smith	1.82	-1.33
O'Reilly	1.83	-1.83
Hannity and Colmes	2.08	-1.82
Greta Van Susteren	1.49	-2.11

preferences for the attributes

	attr1	attr2
male	0.21	-0.12
age	0.23	-0.66
age^2	-0.20	-0.14
white	0.00	0.00
black	-0.11	-0.09
other race	0.07	-0.05
Hisp_HH	-0.08	0.36
HS dropout	-0.05	0.32
HS grad	0.00	0.00
some college	0.01	-0.07
college grad and above	-0.13	-0.21
student	0.04	0.05
full-time	0.00	0.00
part-time	0.03	-0.21
not working (retired/unemployed/other)	-0.03	-0.25
resp_income	0.07	0.23
resp_income^2	-0.07	-0.24
hh_income	-0.12	-0.04
hh_income^2	0.09	-0.03
top-100 DMA	0.14	-0.01
religious conservativeness (5 max)	0.03	-0.01
family-centered	0.01	0.01
work-centered	-0.01	-0.02
pol_outlook(5-very liberal)	-0.76	-0.02
outlook^2	0.06	-0.03
outlook_missing	-1.73	-0.23
sdW	.86	.89

Table 9. "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.