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Market-based measures of viewpoint diversity ☆

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ABSTRACT

Existing market-based measures of viewpoint diversity in the media have been criticized for lacking a theoretical foundation. This paper proposes a theoretical framework to develop market-based measures of viewpoint diversity. It then uses this framework to develop four viewpoint diversity measures using a panel dataset of local television ratings. Finally, an econometric model relates these viewpoint diversity measures to media ownership variables. It does not appear that market-based measures of viewpoint diversity are strongly related to media ownership structures.

1. Introduction

In many countries, communications regulators seek to ensure that a diverse array of viewpoints are expressed in the mass media. In the United States, the Federal Communications Commission (FCC) "has regulated media ownership as a means of enhancing viewpoint diversity based on the premise that diffuse ownership among media outlets promotes the presentation of a larger number of viewpoints in broadcast content than would be available in the case of a more concentrated ownership structure." (FCC, 2012) In the United Kingdom, Ofcom seeks to ensure that "a wide range of TV and radio services of high quality and wide appeal are available." The Canadian Television-radio Telecommunications Commission expressly prioritizes the "creation and broadcast of diverse Canadian programming."

Although regulators agree on the need to promote viewpoint diversity in the media, there is no consensus as to how it should be measured. For example, the US Supreme Court upheld the FCC's right to regulate viewpoint diversity in 1975, but it simultaneously noted that "diversity and its effects are elusive concepts, not easily defined let alone measured without making quality judgments that are objectionable on both policy and First Amendment grounds." (436 U.S. 775). As McCann (2010) put it, "In other words, the court didn't require the FCC to specifically define viewpoint diversity, [it] instead relied on the FCC's rational judgment based on experiences."

The economic literature has proposed numerous content-based measures of viewpoint diversity in various media. In the radio industry, Berry and Waldfogel (2001), Sweeting (2010) and Jeziorski (2012) used the number of formats available in a media market to measure product variety and viewpoint diversity. In the print news industry,

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George (2007, 2008) used data on reporters' and editors' job titles to measure the diversity of content provided. Ho and Quinn (2009) used newspapers' editorials on divided Supreme Court decisions to measure the papers' viewpoints. Gentzkow and Shapiro (2010) counted local newspapers' usage of partisan phrases identified within the US Congressional Record. In local television news, George and Oberholzer-Gee (2011) measured diversity in terms of issues, political coverage and local stories, in terms of both variety and differentiation, by counting keywords within local news transcripts. Across several media, Groseclose and Milyo (2005) measured viewpoint diversity by comparing national news outlets' citations of think tanks and policy groups to politicians' citations of the same think tanks and policy groups.

While content-based measures of viewpoint diversity have allowed researchers to study viewpoint diversity, they present a number of challenges for policymakers. Content-based measures may be subjective, and therefore difficult to defend in court; non-comprehensive, measuring only a fraction of the viewpoints expressed in a medium; reliant on single-purpose databases and therefore costly to construct; incomparable across media; and potentially open to manipulation by the media outlets they might be used to regulate. In fact, we do not know of any systematic attempts to use content-based measures of viewpoint diversity to regulate media industries.

An alternate approach to content-based measures of viewpoint diversity is to develop a market-based measure. If some media consumers respond to changes in viewpoint diversity by changing media consumption, then changes in market shares might serve as lagging indicators of changes in the variety of viewpoints offered. Such market-based measures might seem to offer objective, low-cost means to measure viewpoint diversity across a variety of media industries.

Just (2009) reviews several governments' attempts to construct market-based measures of viewpoint diversity. For example, in 2003, the FCC invented a new measure it called a "diversity index," which sought to measure viewpoint diversity in a manner inspired by the Herfindahl–Hirschmann index (HHI) that antitrust authorities use to gauge market competitiveness. The diversity index used consumers' average time spent with each medium to weight its importance. It then assigned equal "market shares" to each outlet within each medium. For example, New York was served by 23 television stations, so each television station was assigned a "market share" of 1/23. It then combined those "market shares" for commonly owned outlets. Finally, based on these weights and "market shares," the diversity index was calculated using a sum-of-squares approach similar to the HHI.

This diversity index was objective and straightforward to calculate, but its use to justify media ownership deregulation was challenged immediately and quickly overturned. In *Prometheus Radio Project vs. FCC*, the 3rd Circuit Court was emphatic on its view of the diversity index. It ruled that "the Commission did not justify its choice and weight of specific media outlets." Further, "the Commission did not justify its assumption of equal market shares." And, "the Commission did not rationally derive its Cross-Media Limits from the diversity index results," (373 F.3rd 372).

The current article seeks to develop a theoretical framework for devising market-based measures of viewpoint diversity. This problem is made difficult by the dependence of market shares on both consumer preferences and media content, whereas viewpoint diversity is normally defined in terms of media content alone. The key to the proposed approach is to use *local* consumption of *national* news media, whose content is uniform across local markets, to learn about local market preferences. Once those local preferences have been identified, they may be distinguished from local media content.

After developing this theoretical framework, it is applied to the local television news industry in the US and four measures of viewpoint diversity are considered. A series of descriptive regressions relate the viewpoint diversity measures to local media cross-ownership, co-ownership and ownership diversity, using several techniques to control for time-invariant market characteristics. There is little robust evidence linking changes in media ownership to changes in candidate viewpoint diversity indices.

The article proceeds in the following way. Section 1.1 uses thought experiments to illustrate the approach of separating local preferences from local media content. Section 2 proposes the theoretical framework for deriving market-based measures of viewpoint diversity. Section 3 describes four such measures, a dataset and an econometric approach to relate the measures to local media market ownership variables, controlling for persistent unobserved market characteristics. Section 4 contains the estimation results and Section 5 discusses their implications for viewpoint diversity policy makers.

1.1. Separating consumer preferences from media content

Suppose two competing news outlets, A and B, within a local market each offer a local news program, and suppose that each station has a 50% share of the local news audience. (We will refer to these outlets as television stations, but the theoretical framework may be applied more widely.) The following two extreme possibilities are observationally equivalent:

(1) The market's television audience consists of two equally sized segments with opposite viewpoint preferences. The observed 50/50 audience split suggests that each local news program is tailored to one segment's preferred viewpoint. This would indicate high viewpoint diversity among the programs provided by the media market.
(2) All viewers in the market have the same preferred viewpoint. The two stations both offer this viewpoint. The programs are identical and split the market evenly, with half the audience watching station A and half watching station B. This would indicate no viewpoint diversity among the programs provided by the media market.

The observational equivalence of these extreme possibilities illustrates the primary difficulty in measuring

viewpoint diversity. Audience data on media consumption within a single market cannot provide a market-based measure of viewpoint diversity, because media consumption choices are based on both viewer preferences and media content. The concept of viewpoint diversity is fundamentally subjective, so any market-based measure must account for the preferences of the group receiving the viewpoints.

Another thought experiment shows how this difficulty will be resolved. Suppose that each of the two television stations offers a national news program in addition to its local news program. Assume that the national news programs offer different viewpoints, that they air in each of many local media markets, and that each garners a 50% rating nationwide. Now, consider two subcases of this example.

First, suppose that the national news program on station A is watched by 80% of viewers in a particular local market, and the national news program on station B gets a 20% share of viewers in that market. Further, suppose that the two local news programs split the local audience with a 50% audience share each. These figures would suggest that, relative to the national market, the local market has a strong preference for viewpoints of the type provided in station A's national newscast. Since the two local newscasts split the local market, their content must be fairly similar, indicating a low level of viewpoint diversity.

In the second subcase, suppose the national news programs on stations A and B split the local audience, each with a 50% share of local viewers. This suggests that the variety in local consumers' preferred viewpoints roughly matches the variety in national consumers' preferred viewpoints. Further, suppose the local news program on station A is watched by 80% of the market while the local news on station B is watched by 20% of the market. This information will suggest that the viewpoint diversity in local programs on stations A and B is substantially larger than that in the national news market.

These examples convey the intuition underlying our proposed market-based measures of viewpoint diversity. They will weigh dispersion in *local* market shares for *local* news programs against dispersion in *local* market shares for *national* news programs. The latter indicates the degree to which the local market's preferences differ from the national market, and this will distinguish between the two observationally equivalent extreme cases discussed at the beginning of this subsection.

2. A theoretical framework for deriving market-based measures of viewpoint diversity

This section lays out the theoretical framework and then discusses its limitations.

2.1. Theoretical framework

Suppose a geographic market m is served by three local news programs, indexed by $j = 1, 2, 3$. Assume that the programs are differentiated by a single dimension of viewpoint diversity, as in Hotelling (1929), which might be interpreted as the first principal component of a higher-dimensional viewpoint diversity space. The range of possible viewpoints can then be represented by a single horizontal line, and the viewpoint expressed by each program j in market m may be represented by a point x_j^m on that line. Suppose that the programs are numbered according to position, such that program 1 is the farthest to the left, program 2 is in the middle and program 3 is the farthest to the right on the line.

Let x_i represent a point on the horizontal line denoting the preferred viewpoint of viewer i. These points are assumed to be distributed Normal with mean μ_m and variance σ_m^2. Consumer i gets utility u_{ij}^m from watching program j:

$$u_{ij}^m = V - |x_i - x_j^m|, \tag{1}$$

where V is the value of watching the news and x_j^m is the location of the viewpoint expressed in the local news program j. We further assume that consumers know stations' locations in viewpoint space and consumers choose programs to maximize utility. It is also assumed that V is large enough that the market is fully covered, i.e., that all consumers who want to watch local news watch one of the available local news programs.Under these assumptions, one may find the consumer who is just indifferent between consuming two neighboring programs j and $j+1$. This point of indifference is labeled $\hat{x}_{jj+1}^m = (x_j^m + x_{j+1}^m)/2$. It then can be seen that the viewpoint diversity offered by the market (referred to as the "diversity index") is the range covered by the two points of indifference among the three local news programs:

$$D_m = \hat{x}_{23}^m - \hat{x}_{12}^m. \tag{2}$$

Fig. 1 illustrates this measurement of viewpoint diversity. It shows that the news programs in market m provide less diversity than those in market m', since they cover a narrower portion of the line. Accordingly, the diversity index $D_{m'}$ is greater than D_m.

This definition of viewpoint diversity is proportional to the entire span of viewpoints available in the market, $x_3^m - x_1^m$. It is written in terms of the points of indifference because the audience shares must sum to one, so the three audience shares in the data really provide only two degrees of freedom. Writing the diversity index in terms of the two points of indifference makes this fact more salient and shows that other dispersion measures, such as a standard

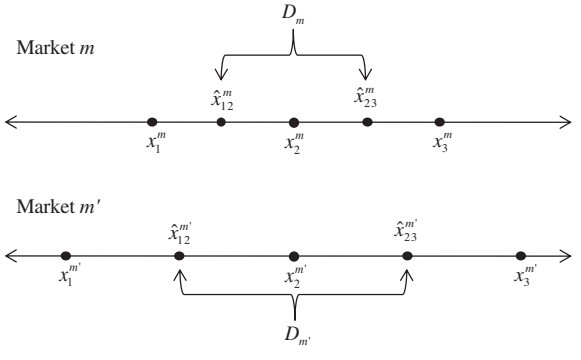

Fig. 1. Diversity index example.

deviation based on the three news program locations, would provide no further information.

This diversity index exhibits several desirable properties. First, it is defined only in terms of station locations. Local market preferences for viewpoints, represented by distributional parameters μ_m and σ_m, do not enter the index. Second, the diversity index is scale-free; it is the same for $(x_1^m, x_2^m, x_3^m) = (1,2,3)$ as it is for $(x_1^m, x_2^m, x_3^m) = (11,12,13)$. Third, this measure of viewpoint diversity is symmetric; swapping the locations of stations 1 and 3 will not change its value. Fourth, the viewpoint diversity index will change if either stations 1 or 3 move, but it is unaffected by local movements by station 2 (as long as it remains between stations 1 and 3). Any such movement by station 2 would result in a reallocation of market shares without altering the range of viewpoints provided by the marketplace.

To calculate the viewpoint diversity index, one needs to determine the program locations in the viewpoint space. This may be done by relating the model's formulas for market shares to audience data. The market share of program 1 is given by the probability mass of viewers in market m whose preferred viewpoints lie to the left of $\hat{x}_{12}^m$

$$s_1^m = \Phi((\hat{x}_{12}^m - \mu_m)/\sigma_m), \tag{3}$$

where Φ represents the standard normal cumulative distribution function. Similarly, the market share of program 3 is given by the probability mass of preferred viewpoints to the right of $\hat{x}_{23}^m$.

$$s_3^m = 1 - \Phi((\hat{x}_{23}^m - \mu_m)/\sigma_m). \tag{4}$$

The points of indifference can be recovered from Eqs. (3) and (4) as

$$\hat{x}_{12}^m = \sigma_m \Phi^{-1}(s_1^m) + \mu_m, \tag{5}$$

$$\hat{x}_{23}^m = \sigma_m \Phi^{-1}(1 - s_3^m) + \mu_m. \tag{6}$$

These can be substituted into (2) to show that

$$D_m = \sigma_m(\Phi^{-1}(1 - s_3^m) - \Phi^{-1}(s_1^m)). \tag{7}$$

Eq. (7) formalizes the indeterminacy between consumer preferences and media content within a single market. With data from a single market, it is impossible to separate the program locations from the dispersion in market-specific tastes, σ_m.

To address this indeterminacy, assume the existence of three national news programs that are available in many local markets and are indexed by $k \in (A, B, C)$. Assume national news programs are indexed such that A is closest to the left side of the line and program C is closest to the right side of the line. The positions of the national and local news programs aired by a particular station need not be related.

Suppose further that the national news programs are differentiated on the same viewpoint scale as the local news programs. This assumption is not entirely innocuous; if the viewpoints expressed in national news programs are fundamentally different than those expressed in local news programs, then the approach proposed here will not work. However, the assumption seems reasonable. First, national news programs air proximate to local news. The two programs' audiences mostly overlap so it seems likely that they would consider similar attributes important in both programs. Second, national and local news share many characteristics such as the types of stories they cover and the possible slants available in their coverage of those stories. Third, local and national news share many raw inputs such as anchors, desks and publicly available video footage.

To anchor the location and scale of preferences, it is assumed that the national distribution of consumer viewpoint preferences is Standard Normal.[2] Under these assumptions, the locations of the indifferent viewers for national news programs in viewpoint space are given by Eqs. (5) and (6) as

$$\hat{x}_{AB}^N = \Phi^{-1}(s_A^N), \tag{8}$$

$$\hat{x}_{BC}^N = \Phi^{-1}(1 - s_C^N), \tag{9}$$

where s_k^N is the fraction of all national news viewers (in all markets) tuned to the national news program on network k.

Let s_k^m be the fraction of local news viewers in market m who watch the national news program on local channel k. Since (8) and (9) pin down the points of indifference among national news programs, Eqs. (10) and (11) relate those locations to the local market shares of the national news programs:

$$\hat{x}_{AB}^N = \sigma_m \Phi^{-1}(s_A^m) + \mu_m, \tag{10}$$

$$\hat{x}_{BC}^N = \sigma_m \Phi^{-1}(1 - s_C^m) + \mu_m. \tag{11}$$

Eqs. (10) and (11) now can be solved for local preference parameters:

$$\sigma_m = \frac{\hat{x}_{BC}^N - \hat{x}_{AB}^N}{\Phi^{-1}(1 - s_C^m) - \Phi^{-1}(s_A^m)}, \tag{12}$$

$$\mu_m = \hat{x}_{AB}^N - \sigma_m \Phi^{-1}(s_A^m). \tag{13}$$

Eqs. (8) and (9) may be substituted into (12), so that local dispersion in preferences σ_m is defined in terms of local and national viewing shares of national news programs. This, in turn, may be substituted into (7) so that the viewpoint diversity index may be expressed purely in terms of data on local audience shares of local news programs, local audience shares of national news programs, and national audience shares of national news programs. Eq. (14) shows how the final diversity index in market m is constructed from the data.

$$D_m = \frac{(\Phi^{-1}(1 - s_3^m) - \Phi^{-1}(s_1^m))(\Phi^{-1}(1 - s_C^N) - \Phi^{-1}(s_A^N))}{\Phi^{-1}(1 - s_C^m) - \Phi^{-1}(s_A^m)}. \tag{14}$$

[2] The assumptions that local market preferences are Normal and national preferences are Standard Normal are compatible so long as the means of the national viewpoint preference distribution conform to the moments of the local market distributions. For example, if the weighted sum of market-specific mean viewpoint preferences is zero, where the weights represent the percentage of the national population contained within each local market.

2.2. Discussion

The advantages of the theoretical framework proposed here is that a diversity index can be quickly and easily computed from readily available market share data. This index may be compared across markets, time and media. However, the development of this index incorporated several assumptions which may only be in applicable in specific contexts. Here we discuss the primary limitations of this theoretical framework: identifying the endpoints, relaxing the full coverage assumption and the assumption about viewpoint diversity as an antecedent of market shares.

2.2.1. Identifying the endpoints

While the theoretical framework proposed above easily generalizes to any number of stations, the calculation of the diversity index is impossible without knowing which two stations are on the ends of the line. In a few settings, this information may be common knowledge; for example, in the US, most observers would say that the national cable news networks FOX News and MSNBC are both more extreme than CNN. Another possible approach would be to identify which stations are the most extreme by supplementing market share data with consumer surveys. A third possibility is to use theory or other market-specific information to identify which stations are on the endpoints or interior of the line. The validity of the viewpoint diversity metric will generally be limited by the quality of the inference about which stations are on the endpoints.

2.2.2. Full coverage assumption

The theoretical framework's assumption of full market coverage excludes the possibility of vertical differentiation in news programming (i.e. differentiation in attributes that all news consumers like). To understand the role of the full coverage assumption, consider how the statistic in equation (2) is calculated. Two degrees of freedom in national viewership of national news programs are used to pin down the two points of indifference between the three national news programs. These two points of indifference are used, in conjunction with the two degrees of freedom available in local viewership of national news programs, to pin down two moments of the distribution of local viewpoint preferences. Finally, all of these inferences are used, along with the two degrees of freedom available in local viewership data of local news programs, to pin down the two points of indifference between the three local news programs provided in each media market.

At every step it was assumed that each news viewership market was fully covered. This is why three audience datapoints can pin down two points of indifference. When the assumption of full coverage is dropped, two things happen. One change is positive from the standpoint of the analysis: an additional degree of freedom is acquired, since the market share of the "outside option" (not watching television news) may be used in the analysis. There are now three degrees of freedom, not two. The other change is negative from the standpoint of the analysis: there are now four parameters to be pinned down, not two. It is still necessary to pin down the points of indifference among the three news programs, as before. But it is also necessary to pin down the ranges of unserved viewers on each end of the market.

Fig. 2 illustrates this. Viewers to the left of $\hat{x}^N_{01}$ do not watch news, and viewers to the right of $\hat{x}^N_{30}$ do not watch news. However, the data on the market share of the outside option do not distinguish between these two groups. If the full market coverage assumption is judged to be a poor representation of a media market, the framework might be extended to use additional data about the proportion of unserved viewers on each end of the line to calculate the diversity index.

2.2.3. Viewpoint diversity as an antecedent of market shares

The theoretical framework incorporates the regular economic assumptions that agents make informed choices to maximize utility. Indeed, these assumptions are entirely standard in the economic literature and motivate the fundamental desire for a market-based measure of viewpoint diversity. However, an alternate view might hold that viewpoints served by media programs are complementary to those programs' main benefits and might not actually drive consumer choice. For example, suppose that the major component of differentiation among news programs is the physical beauty of their presenters. Then, the viewpoints expressed within the programs might not be useful for predicting market shares but might still have important consequences for public debate. Under this view—that the important effects of viewpoint diversity follow, rather than precede, media program choice—the desirability of market-based measures of viewpoint diversity is called into question. As such, this objection is not a remediable limitation of the framework; it is a reason to argue in favor of using content-based measures to evaluate viewpoint diversity policies.

Some other limitations of this model (e.g. distributional assumptions, single-dimensionality) can be relaxed rather easily to gauge the measures' sensitivity to alternate assumptions. While the theoretical framework is far from perfect, it may add a worthwhile dimension to viewpoint diversity policy evaluation, since it produces objective

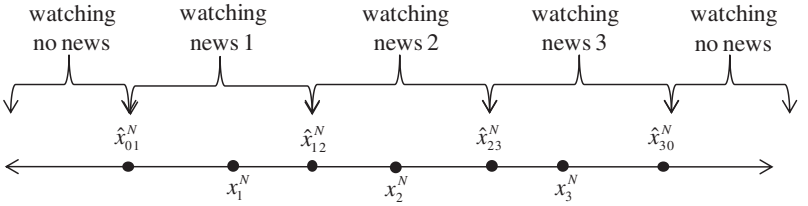

Fig. 2. Uncovered media market.

measures, separates viewer preferences from program content, and its underlying assumptions may be clearly evaluated. The next section applies it in the context of local television news markets.

3. Empirical approach

This section derives four measures of viewpoint diversity based on the theoretical framework, develops an econometric model to link them to changes in media ownership variables, and describes local television news data used to estimate these relationships.

3.1. Calculating the viewpoint diversity index

To construct a viewpoint diversity index from media market data, the first step is to establish which stations are on the endpoints of the line. We will analyze three-channel media markets, so determining the endpoints is equivalent to determining which station is in the middle. We present four diversity indices based on four alternate assumptions about station ordering.

3.1.1. Ordering based on observed market share

The simplest way to infer the ordering of media stations is to use theory. Prescott and Visscher (1977) solved for equilibrium station positions in a sequential entry game. They found that the first two movers would maximally differentiate and the third mover would enter in the middle of the line and gain the smallest market share. On this basis one might assume that the station with the smallest audience share is the one that is in the middle.

3.1.2. Ordering based on station entry dates

Prescott and Visscher (1977) also predicted that the last station into the market would be the one located in the middle, so data on stations' time of entry might be used to determine which station is in the middle.

3.1.3. Ordering based on correlations in ratings

One implication of the Hotelling framework is that viewers switch between the middle station and the stations on the ends, but viewers do not switch directly between the two stations on the ends of the line. Accordingly, the ratings of the middle station should exhibit higher correlations with its two competitors' ratings. A short time series of television ratings, described in Section 3.3 below, was used to calculate correlations between stations' ratings. The endpoints of the line were determined by the bivariate correlation between stations' ratings which is closest to zero in absolute value.

3.1.4. Ordering based on channel number

Research studies on television consumption have noted that viewing patterns appear to be influenced by inertia. This inertia is at least partially explained by switching costs associated with changing the channel (see, e.g., Esteves-Sorenson and Perretti, 2012; Shachar and Emerson, 2000, or Wilbur, 2008). On the notion that channel switching costs exist, one could order media stations channels from left to right in the same order in which they appear on the television dial, i.e., based on ascending channel numbers. In this manner, the station in the middle of the dial might be assumed to be located between its rivals on the Hotelling line.

In summary, the first candidate diversity index relies on a theoretical prediction while the final three incorporate additional data about TV stations' entry dates, audience correlations and positions on the dial. We do not hold strong priors as to which of these alternatives should be preferred to the others; our primary interest is in the application of the theoretical framework.

3.2. Model and estimation

The model is designed to estimate correlations between a viewpoint diversity index and media ownership data, controlling for time-invariant market characteristics. It is designed to fit the available data, which is characterized by the "large N, small T" property common to many panel datasets. The approach is to estimate a descriptive regression since viewpoint diversity and media ownership may be driven by common factors. If one instead assumes a one-way impact of media ownership on viewpoint diversity, a position that has sometimes been taken by the courts, then the empirical results may be interpreted as causal, but the approach here is more cautious.

D_{mt} represents a viewpoint diversity index in media market m at time $t \in \{0, 1, 2\}$ (corresponding to 2005, 2007 and 2009). x_{mt} is the vector of media ownership variables, defined in Section 3.3 below. It is assumed that

$$\ln D_{mt} = \alpha_m + \alpha_t + x_{mt}\beta + \varepsilon_{mt}, \tag{15}$$

where α_m represents time-invariant market characteristics that may influence the viewpoint diversity provided by the media market, α_t is a time fixed effect, β is a parameter vector to be estimated and the object of primary interest, and ε_{mt} captures idiosyncratic shocks that vary across markets and time periods. The log transformation is used so that parameter estimates may be interpreted as percentage changes in the viewpoint diversity index. Eq. (15) should be thought of as a moving-average representation that is likely to include serial correlation in ε_{mt}. If the precise form of the serial correlation were known, Eq. (15) could equivalently be expressed as an auto-regressive model with lags of the dependent variable appearing as regressors on the right-hand side.

The market-specific intercepts, α_m, in Eq. (15) may be correlated with the media ownership variables. The panel is too short to estimate these intercepts precisely, so we tried three approaches to controlling for time-invariant market heterogeneity. First, we used two standard approaches to estimation which drop the market effects out of the estimating equation, first differencing (FD) and fixed effects (FE). The FD approach lags the dependent variable to transform Eq. (15) into

$$(\ln D_{mt} - \ln D_{mt-1}) = (\alpha_t - \alpha_{t-1}) + (x_{mt} - x_{mt-1})\beta + (\varepsilon_{mt} - \varepsilon_{mt-1}). \tag{16}$$

The FE approach drops time-invariant terms, changing Eq. (15) into

$$(\ln D_{mt} - \overline{\ln D_m}) = (\alpha_t - \bar{\alpha}) + (x_{mt} - \overline{x_m})\beta + (\varepsilon_{mt} - \overline{\varepsilon_m}), \quad (17)$$

where $\overline{\ln D_m} = T^{-1}\sum_t^T \ln D_{mt}$, $\bar{\alpha} = T^{-1}\sum_t^T \alpha_t$, $\overline{x_m} = T^{-1}\sum_t^T x_{mt}$, and $\overline{\varepsilon_m} = T^{-1}\sum_t^T \varepsilon_{mt}$. When the sample contains exactly two time periods, FD and FE provide identical parameter estimates; our sample contains three time periods, so they differ. FD is more efficient when ε_{mt} is auto correlated while FE is more efficient when ε_{mt} is serially uncorrelated (Wooldridge, 2010). Consumers' media habits are known to be persistent, so we expect autocorrelation in the errors. Thus FD estimates will be preferred to FE estimates. Third, as a robustness check, we use market demographics in place of market-specific intercepts and estimate cross-sectional models.

A common approach would be to apply Ordinary Least-Squares (OLS) regression to Eqs. (16) and (17), known as the "difference-in-differences" estimator in the case of Eq. (16) and the "pooled OLS" estimator in the case of Eq. (17). The problem with the OLS approach is that, when serial correlation is present, the standard errors of the parameter estimates may be severely biased (Cochrane and Orcutt, 1949). Recently, Bertrand et al. (2004) explored the extent to which this issue affects policy-oriented econometric research. They generated random treatments in their data and estimated the effects of these "placebo laws" on female wages. They found that 45% of the placebo treatments' parameter estimates were statistically significant at the 95% confidence level, strong evidence against OLS estimation of Eqs. (16) and (17). Bertrand, Duflo, and Mullainathan (2004, §IV.E) advocate using clustered standard errors, showing that this alternative to OLS performs about as well as nonparametric estimation in Monte Carlo simulations. The estimates presented below follow this advice. This allows for autocorrelation in the errors by using an unstructured "sandwich" estimator to control for possible correlation among the error terms, as in Arellano (1987).[3]

3.3. Data

This section describes the data sources, variables, and market selection.

3.3.1. Data sources

Recent empirical work on media economics follows the industrial organization literature (e.g., Bresnahan and Reiss, 1990) in taking the intersection of a geographic media market and year as the basic unit of analysis. The dataset is comprehensive, containing all television stations in 205 local media markets in each of three time periods. Media ownership variables were collected and provided by the FCC.[4] They correspond to three snapshots in time: December 31 on 2005, 2007 and 2009.

The second dataset consists of television ratings from Nielsen Media Research's Galaxy ProFile database. The ratings correspond to the November and May "sweeps" months in the 2005–06, 2007–08 and 2009–10 television seasons. The sample focuses on periods when Nielsen's measurement errors are minimized: household ratings of evening news programs (6:00–7:00 p.m. EST, 5:00–6:00 p.m. CST, 5:00–6:00 p.m. MST and 6:00–7:00 p.m. PST).

Television station entry dates and channel numbers were obtained from R.R. Bowker's Broadcast & Cable Yearbook. Data on market-level demographics include median household income, median age, the proportion of Spanish-speaking households, the number of television stations per capita, the percentages of households with televisions and pay-television service. These data were collected by the American Community Survey and provided by the FCC.

3.3.2. Media ownership variables

The media ownership variables were identified by economists working at the FCC and have been used in numerous empirical studies of media markets.[5] Three ownership variables were reliably measured and varied extensively, and therefore are included in the base set of ownership variables x_{mt}:

Co-ownedTV: The number of television station parents that controlled more than one television station in the same media market.
TV/Radio: The number of television stations whose parent controlled at least one radio station in the same market.
LocalOwnerTV: The number of television stations in the market controlled by entities located within the market.

Two additional ownership variables are available:

TV/Newspaper: The number of television stations whose parent controlled at least one newspaper in the same market. This ownership variable exhibits the least variation. It changed in only one market in 2005–2007, and changed in five markets in 2007–2009.
MinorityOwnerTV: The number of television stations in the market with an identifiable controller who was a member of a minority race/ethnicity. This variable

[3] We considered using dynamic panel estimators (Arellano and Bond 1991) but decided against it. This literature advocates using lags and previous levels as instruments for endogenous variables. However, media outlets, like other businesses, are valued according to discounted streams of future profits; therefore, expected future shocks influence current media station valuations and their owners' acquisition/divestiture decisions. The exogeneity assumption required by the Arellano/Bond approach would imply that media station owners and potential buyers are either unable to foresee future market-specific shocks or that they disregard those shocks in their media station retention/acquisition decisions. This assumption is not testable and is considered unlikely.

[4] We considered using owner fixed effects but decided against it. Because the unit of observation is a market/year, we will normally see more owners within a media market than observations of that market in the sample.

[5] All ownership variables are defined as count data. Percentage definitions were found to be misleading, as they are influenced by changes in the base number of television stations in the market. Small independent TV stations sometimes start or stop broadcasting, which then changes all cross-ownership and co-ownership percentage variables in the market. However, because these changes typically occur on the fringe of the TV market, they seldom indicate meaningful changes in station ownership concentration.

was only measured reliably in 2007 and 2009; see Turner (2006) for further discussion.

Unfortunately, *TV/Newspaper* did not show meaningful variation in 2005–2007, and *MinorityOwnerTV* data are not available for 2005. Therefore, these two variables must be excluded from the base set of ownership variables. However, both can be included in a regression based on 2007–2009 data alone. Therefore, these two variables are included in an augmented set of ownership variables below.

3.3.3. Market selection

It is impossible to calculate the diversity index with fewer than three local media stations. Therefore, small local markets that did not offer at least three local news programs were dropped, narrowing the number of markets included from 205 to 132.

4. Findings

This section describes the four candidate viewpoint diversity indices, presents the estimation results, and then offers robustness checks in the form of cross-sectional regressions and re-estimation based on subsets of markets.

4.1. Viewpoint diversity measures and correlations

The four candidate viewpoint diversity indices display substantial variation across markets. The index based on market shares is bimodal with a strong central tendency, while the other three indices appear to be approximately normal. The indices based on channel number and ascending shares are larger in smaller markets, while the indices based on ratings correlations and station entry dates do not vary much by market size.

Table 1 offers raw correlations between the four candidate viewpoint diversity indices and the media ownership variables. Of six possible correlations among the four candidate indices, only two correlations are statistically significant, and those two correlations have opposite signs. The viewpoint diversity index constructed by assuming the lowest-rated station is in the middle is positively correlated with the index that assumes the latest entrant is in the middle. Meanwhile, the index based on entry date is negatively correlated with the viewpoint diversity index constructed based on channel number. This lack of correlation among the candidate indices underscores the importance of the theoretical underpinnings of any market-based measure of viewpoint diversity.

While the media ownership variables are all highly positively correlated with each other, only one of 12 correlations between media ownership variables and viewpoint diversity indices is statistically significant: TV station co-ownership is negatively correlated with viewpoint diversity when measured using the channel number assumption.

4.2. Panel estimates

Table 2 presents FD estimates using the full sample (2005–09) and base set of ownership variables, for each of the four viewpoint diversity indices using clustered standard errors. After controlling for market-level heterogeneity, none of the media ownership variables have a statistically significant relationship with any of the measures of viewpoint diversity. There also is no common sign shared by any set of point estimates. The FE estimates reproduce this pattern exactly and are therefore omitted.

Table 3 offers the FD estimates based on the limited sample (2007–2009) and augmented set of ownership variables. This time, one of twenty possible coefficients is significant at the 90% confidence level: TV/Newspaper co-ownership is positively correlated with the diversity index based on ratings correlation. The number of statistically significant effects is not different from what one might expect based on Type I error alone, so we hesitate to attach strong meaning to this finding.

4.3. Robustness check: cross-sectional estimation

The purpose of FD and FE estimation is to eliminate time-invariant market characteristics by differencing out market-specific intercepts. However, if market-specific intercepts can be accurately characterized using demographic variables, the power reduction due to differencing out the intercepts may outweigh the benefit of doing so. In that case, FD or FE estimation may yield inefficient parameter estimates compared to cross-sectional regression. Therefore, Eq. (15) was estimated using a cross-sectional

Table 1
Correlations among diversity indices and media ownership variables.

	View. Div. (Mkt. Shares)	View. Div. (Chan. Age)	View. Div. (Rating Co it.)	View. Div. (Chan. Num.)	Local OwnerTV	Co-Owned TV	TV/Radio
View. Div. (Mkt. Shares)	1						
View. Div. (Channel Age)	.34**	1					
View Div. (Rating Co it.)	−.07	−.06	1				
View Div. (Channel Num.)	−.04	−.17**	−.05	1			
LocalOwnerTV	.02	.07	−.01	.09	1		
Co-Owned TV	−.01	.03	−.09	−.16*	.38**	1	
TV/Radio	−.07	.02	.07	−.05	.58**	.55**	1

** Significant at the 99% confidence level.
* Significant at the 95% confidence level.

Table 2
Panel estimates, 2005–2009 sample, limited media ownership variables.

	View. Div. (Mkt. Shares) PointEst. (Std. Err.)	View. Div. (Station Age) Point Est. (Std. Err.)	View Div. (Rating Corr.) Point Est. (Std. Err.)	View Div. (Channel Num.) Point Est. (Std. Err.)
Media ownership				
LocalOwnerTV	0.023	0.014	−0.042	−0.001
	(0.033)	(0.027)	(0.031)	(0.015)
Co-Owned TV	0.032	−0.012	−0.013	0.013
	(0.023)	(0.021)	(0.032)	(0.014)
TV/Radio	−0.1	−0.009	0.07	−0.012
	(0.035)	(0.026)	(0.044)	(0.016)
Num. Obs.	264	264	264	264
R-squared	0.004	0.018	0.067	0.037

Table 3
Panel estimates, 2007–2009 subsample, all media ownership variables.

	View. Div. (Mkt. Shares) Point Est. (Std. Err.)	View. Div. (Station Age) Point Est. (Std. Err.)	View Div. (Rating Corr.) Point Est. (Std. Err.)	View Div. (Channel Num.) Point Est. (Std. Err.)
Media ownership				
LocalOwnerTV	0.013	0.000	−0.060	0.002
	(0.036)	(0.02)	(0.057)	(0.02)
Co-Owned TV	0.024	−0.036	−0.047	0.017
	(0.039)	(0.023)	(0.057)	(0.02)
TV/Radio	−0.014	0.060	0.087	−0.018
	(0.075)	(0.055)	(0.097)	(0.023)
MinorityOwnerTV	0.080	0.047	0.003	0.027
	(0.07)	(0.043)	(0.059)	(0.037)
TV/Newspaper	−0.056	−0.036	0.134*	0.038
	(0.091)	(0.033)	(0.072)	(0.034)
Num. Obs.	132	132	132	132
R-squared	0.008	0.027	0.089	0.066

* Significant at the 90% confidence level.

Table 4
Cross-sectional estimates, 2005–2009 sample, limited media ownership var.

	View. Div. (Mkt. Shares) Point Est. (Std. Err.)	View. Div. (Station Age) Point Est. (Std. Err.)	View Div. (Rating Corr.) Point Est. (Std. Err.)	View Div. (Channel Num.) Point Est. (Std. Err.)
Media ownership variables				
LocalOwnerTV	0.029	0.014	−0.008*	0.020***
	(0.029)	(0.009)	(0.005)	(0.006)
Co-Owned TV	0.109**	0.005	−0.034***	−0.025**
	(0.043)	(0.017)	(0.013)	(0.011)
TV/Radio	−0.066	−0.023	0.043*	−0.005
	(0.071)	(0.018)	(0.022)	(0.014)
Demographics and media demand predictors				
Median age	−0.012	−0.011	0.013***	0.003
	(0.030)	(0.009)	(0.005)	(0.004)
Median income	0.000	0.000	1.5E−06	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Minority population (%)	−0.796*	−0.075	0.06	0.046
	(0.456)	(0.158)	(0.109)	(0.088)
TV channels per capita	0.021	−0.004	0.001	0.000
	(0.011)	(0.004)	(0.006)	(0.003)
Pay TV penetration	0.773	−0.045	−0.085	0.001
	(1.374)	(0.406)	(0.279)	(0.223)
TV penetration	−1.625**	0.221***	0.057	−0.126
	(0.629)	(0.027)	(0.428)	(0.222)
Num. Obs.	396	396	396	396
R-squared	0.628	0.701	0.688	0.113

*** Significant at the 99% confidence level.
** 95%.
* 90%.

Table 5
Cross-Sectional Estimates, 2007–2009 Subsample, All Media Ownership Var.

	View. Div. (Mkt. Shares) Point Est. (Std Err.)	View. Div. (Station Age) Point Est. (Std. Err.)	View Div. (Rating Co it.) Point Est. (Std. Err.)	View Div. (Channel Num. Point Est. (Std. Err.)
Media ownership variables				
LocalOwnerTV	0.048	0.024**	−0.011**	0.015**
	(0.047)	(0.011)	(0.005)	(0.007)
Co-Owned TV	0.109**	0.012	−0.032	−0.033**
	(0.042)	(0.017)	(0.024)	(0.010)
TV/Radio	0.006	−0.026	0.060***	−0.016
	(0.058)	(0.020)	(0.013)	(0.015)
Minori tyOwnerTV	−0.087	−0.021	−0.004	0.033***
	(0.095)	(0.022)	(0.028)	(0.008)
TV/Newspaper	−0.070	−0.033	0.010	0.002
	(0.097)	(0.042)	(0.047)	(0.018)
Demographics and media demand predictors				
Median age	−0.032	−0.018**	0.013**	0.006
	(0.028)	(0.009)	(0.005)	(0.004)
Median income	0.000	0.000	0.000 **	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Minority population (%)	−0.986	−0.167	0.013	0.102*
	(0.448)	(0.170)	(0.135)	(0.060)
TV channels per capita	0.024**	−0.004	0.006***	0.000
	(0.011)	(0.005)	(0.002)	(0.004)
Pay TV penetration	1.505	−0.121	−0.203	−0.089
	(1.520)	(0.539)	(0.364)	(0.240)
TV penetration	−1.529**	0.251	−0.370**	−0.124
	(0.695)	(0.155)	(0.150)	(0.306)
Num. Obs.	264	264	264	264
R-squared	0.625	0.669	0.722	0.158

*** Significant at the 99% confidence level.
** 95%.
* 90%.

approach wherein the market intercepts α_m were replaced with the product of a vector of market characteristics and a parameter vector to be estimated, $z_m\phi_t$. The market characteristics included the median age, median income, percentage of the population whose native language was Spanish, the number of TV channels per capita, and the percentages of households with pay-TV service or any TV service. The estimation uses clustered standard errors.

Table 4 displays the cross-sectional estimates using the full sample (2005–09) and base set of ownership variables. Table 5 reports the cross-sectional estimates using the limited sample (2007–09) and augmented set of ownership variables. The discussion focuses on effects that are consistent across the two tables.

Unlike the FD and FE estimates, the cross-sectional regressions show several strong correlations between ownership variables and diversity indices, but there is substantial conflict among the findings. Local TV ownership increases with the diversity index based on channel number, but falls with the index based on ratings correlations. TV ownership consolidation increases with the diversity index based on market shares but falls with the index based on TV station number. TV/Radio cross-ownership rises with the diversity index based on ratings correlation but is unrelated to any other index. Minority station ownership is positively related to the diversity index based on channel number but none of the other three diversity indices. TV/newspaper cross-ownership shows no significant correlations with any of the candidate viewpoint diversity indices.

In terms of the cross-sectional market characteristics used to proxy for market fixed effects, only two parameter estimates are significant and have the same sign in both regressions. Television penetration is negatively related to the viewpoint diversity index based on market shares, and the median age within the market is positively related to the index based on ratings correlations.

4.4. Robustness check: market selection

To gauge the sensitivity of the results to the assumption of three news outlets in the market, the regressions in Table 3 were re-estimated using three subsamples of data: all markets without any FOX affiliate news; all markets in which less than 20% of the viewing population speaks Spanish as a native language; and the intersection of these two subsamples. The results did not change from the pattern described above, so they are excluded for brevity.

5. Discussion

Numerous governments have enacted policies to promote viewpoint diversity in the media. Regulators seem to prefer market-based measures of viewpoint diversity but have never proposed such a measure that is based on an internally consistent theory.

This paper proposes a theoretical framework to develop market-based measures of viewpoint diversity. Employing a standard economic assumption that stations' market shares are determined by the viewpoints they espouse,

local preferences may be distinguished from local media content using data on local consumption of national media. Four candidate diversity indices were developed and an econometric model was used to estimate correlations between the proposed viewpoint diversity indices and media ownership variables using local television news audience shares.

The results of these regressions could be interpreted in three different ways. First, one might develop a theory about the right way to identify the stations on the ends of the line. Such a theory might lead to one of the diversity indices proposed in this paper, in which case the reader should choose the set of correlations that correspond to the theory. Or, it might lead to a new candidate viewpoint diversity index, in which case the regressions could be re-run using this new index.

Second, those who wish to avoid attaching too much significance to any particular assumption about identifying which stations are on the ends of the line might instead interpret these findings more broadly as a null result. The panel estimates did not indicate any robust evidence of correlations between viewpoint diversity indices and media ownership variables.

Third, one might interpret these non-findings as consistent with prior literature on viewpoint diversity. Studies that employ content-based measures generally find that media ownership influences viewpoint diversity, while evidence on the link between media ownership and media stations' market shares is more mixed and more tenuous (George and Oberholzer-Gee, 2011). In fact, this third interpretation might even call into question the desirability of a market-based measure of viewpoint diversity without strong theory or data about which outlets offer the most extreme viewpoints.

In summary, we believe that market-based measures of viewpoint diversity are promising when good information is available about which stations offer the most extreme viewpoints. In the absence of such information, we would encourage regulators to use content-based measures to evaluate viewpoint diversity policies.

References

Arellano, M., 1987. Computing robust standard-errors for within-group estimators. Oxford Bulletin of Economics and Statistics 49 (4), 431–434.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58 (2), 277–297.

Berry, S., Waldfogel, J., 2001. Do mergers increase product variety: evidence from radio broadcasting. Quarterly Journal of Economics 116 (3), 969–1007.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Quarterly Journal of Economics 119 (1), 249–275.

Bresnahan, T.F., Reiss, P.C., 1990. Entry in monopoly markets. Review of Economic Studies 57 (4), 531–553.

Broadcasting & Cable Yearbook, 2008. New Providence, NJ, R.R. Bowker.

Cochrane, D., Orcutt, G.H., 1949. Application of least-squares regression to relationships containing auto-correlated error terms. Journal of the American Statistical Association 44 (245), 32–61.

Esteves-Sorenson, C., Perretti, F., 2012. Micro-costs: inertia in television viewing. Economic Journal 122 (563), 867–902.

Gentzkow, M., Shapiro, J.M., 2010. What drives media slant? Evidence from U.S. daily newspapers. Econometrica 78 (1), 35–71.

George, L.M., 2007. What's fit to print: the effect of ownership concentration on product variety in daily newspaper markets. Information Economics and Policy 19 (3–4), 285–303.

George, L.M., 2008. The Internet and the Market for Daily Newspapers. The B.E. Journal of Economic Analysis & Policy, 8, 1 (article 26).

George, L.M., Oberholzer-Gee, F., 2011. Diversity in Local Television News. FCC Quadrennial Review Media Ownership Study 8b. <http://hraunfoss.fcc.gov/edocs_public/attachmatch /DOC-308602A1.pdf>.

Groseclose, T., Milyo, J., 2005. A measure of media bias. Quarterly Journal of Economics 120 (4), 1192–1237.

Ho, D.E., Quinn, K.M., 2009. Viewpoint diversity and media consolidation: an empirical study. Stanford Law Review 60, 781–866.

Hotelling, H., 1929. Stability in competition. Economic Journal 39, 41–57.

Jeziorski, P. 2012. Effects of Mergers in Two-Sided Markets: Examination of the U.S. Radio Industry. Working paper, University of California, Berkeley.

Just, N., 2009. Measuring media concentration and diversity: new approaches and instruments in Europe and the US. Media Culture Society 31 (1), 97–117.

McCann, K., 2010. A diversity policy model & assessment: debates and challenges of [Media] diversity. Fordham University, Working paper.

Prescott, E.C., Visscher, M., 1977. Sequential location among firms with foresight. Bell Journal of Economics 8 (2), 378–393.

Shachar, R., Emerson, J., 2000. Cast demographics, unobserved segments and heterogeneous switching costs in a TV viewing choice model. Journal of Marketing Research 37 (2), 173–186.

Sweeting, A., 2010. The effects of mergers on product positioning: evidence from the music radio industry. RAND Journal of Economics 41 (2), 372–397.

Turner, S.D., 2006. Out of the Picture: Minority & Female TV Station Ownership in the United States. <http://www.freepress.net/files/out_of_the_picture.pdf>, (accessed March 2011).

US Federal Communications Commission, 2012. 2010 Quadrennial Regulatory Review. https://www.federalregister.gov/articles/2012/01/19/2012-148/2010-quadrennial-regulatory-review (accessed September 2013).

Wilbur, K.C., 2008. A two-sided, empirical model of television advertising and viewing markets. Marketing Science 27 (3), 356–378.

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data, second edition. MIT Press, Cambridge, MA.