Local Media Ownership and Viewpoint Diversity in Local Television News

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Executive Summary

This study proposes a theory-driven, market-based measure of viewpoint diversity in local television news. It then calculates this viewpoint diversity metric using a panel dataset of local television ratings. Finally, an econometric model is used to determine whether viewpoint diversity is associated with local media market ownership structure. The estimated elasticities of viewpoint diversity with respect to media ownership variables are very close to zero.

Introduction

This study was written for the United States Federal Communications Commission ("FCC") as part of its 2010 Quadrennial Review of Media Ownership Rules. Its purpose is two-fold.

First, it proposes a new market-based measure of viewpoint diversity in local television news programs. The market-based approach is desirable because it relies on consumers' actions to define viewpoint diversity. However, it is complicated by the fact that consumers' actions depend on consumer preferences as well as media content. The key to the approach is to use local viewing of national news programs to learn about local market preferences. This allows local media content to be distinguished from local market preferences.

Second, the analysis uses a descriptive regression to relate the proposed viewpoint diversity index to local media cross-ownership, co-ownership and ownership diversity. The associations between viewpoint diversity and ownership variables are all found to be very close to zero.

Section 1.1 gives a brief overview of the Media Ownership Rules that the FCC is currently reviewing. Section 1.2 discusses the tortured legal history of viewpoint diversity, so that the reader may understand the proposed definition in context. Section 2 defines the proposed measure of viewpoint diversity. Section 3 presents the empirical approach of relating viewpoint diversity to local media market ownership structure, controlling for time-invariant market characteristics. Section 4 contains the estimation results and section 5 concludes by relating the empirical results to the rules the FCC is reviewing.

1.1. *Media Ownership Rules*

Three media ownership rules are relevant to the present analysis. This section gives just a brief overview of the rules. FCC (2010) and [47 CFR 73.3555] are more expansive.

Newspaper/Broadcast Cross-Ownership Rule: Since 1975, the FCC has restricted the common ownership of a broadcast station and a newspaper when, roughly speaking, the station's footprint contains the newspaper's distribution area. Waivers to this rule may be granted when common ownership is judged to be aligned with the public interest. In 2007, the waiver criteria were relaxed so that common ownership would be presumed to be not inconsistent with the public interest in the 20 largest media markets, so long as the TV station is not among the four largest in the market and there would be at least eight post-merger "voices" available in the market.[1] Common ownership is still presumed to be inconsistent with the public interest in smaller media markets unless (1) one of the two media outlets were "failed" or "failing," or (2) the joint entity would significantly increase the amount of news available in the market.

Local TV Ownership Limit: One entity may own two television stations within the same market if (1) their signals do not overlap (this case is rare), or (2) one of the stations is not ranked in the top four stations in the market based on market share, and there are at least eight independently-owned stations in the market. This second provision essentially rules out dual station ownership in smaller markets, as they are typically served by fewer than eight stations.

Local Radio/TV Cross-Ownership Rule: In markets with at least 20 independently-owned voices, one entity may own one TV station and up to seven radio stations or two TV stations and up to six radio stations, subject to the Local TV Ownership Limit. In markets with 10-19 independently-owned voices, one entity may own up to two TV stations and up to four radio stations. In markets with 9 or fewer independently-owned voices, an entity that owns a TV station may not own more than one radio station.

1.2. *Viewpoint Diversity*

The FCC's policy objectives are competition, localism and diversity. The FCC's diversity policymaking objective is nuanced and sometimes controversial. It is motivated by the observation that, since the public owns the airwaves on which television and radio signals are broadcast, the media should serve all segments of the population. The need for regulation is implied by the well known result that some types of content may be underprovided by a

[1] A "voice" may be a TV station, radio station, newspaper or a cable system.

competitive market. As the US Supreme Court noted in *AP v. United States*, “[the First] Amendment rests on the assumption that the widest possible dissemination of information from diverse and antagonistic sources is essential to the welfare of the public, that a free press is a condition of a free society.” The Court justified media ownership regulations to preserve this freedom, saying “freedom to publish is guaranteed by the Constitution, but freedom to combine to keep others from publishing is not.” (326 U. S. 1)

The FCC has operationalized its diversity objective in five ways (FCC 2010):

Outlet diversity is the number of independently-owned media outlets.

Source diversity is the availability of media content from a variety of content creators.

Minority and female ownership diversity is the number of media outlets owned by minority race/ethnic groups and women.

Program diversity is the variety of program formats and content provided by the media.

Viewpoint diversity is the availability of content reflecting a variety of perspectives.

The first three definitions reflect the concept of *source* diversity, that is, increasing the number of voices available in the media market. Source diversity is fairly straightforward to define and measure. The final two definitions reflect the concept of content diversity, that is, increasing the number of types of programs and opinions that are available in the media market. Source diversity has sometimes been seen as a standalone policy objective, and it has sometimes been seen as a means to achieve content diversity.

The purpose of the present analysis is to determine whether media co-ownership, cross-ownership and ownership diversity within a market are associated with viewpoint diversity in that market’s television news. It is emphasized that the analysis seeks to examine *viewpoint diversity*, not program diversity.

Empirical analysis of viewpoint diversity requires a measure of viewpoint diversity. The “availability of content” component of the definition is fairly straightforward but a “variety of perspectives” component is not. What qualifies as a “perspective?” And what constitutes a “variety” of perspectives?

The current paper is not the first to grapple with the question of how to define viewpoint diversity. The Newspaper/Broadcast Cross-Ownership Rule was challenged shortly after its passage in 1975. The Supreme Court upheld the rule, noting that “the regulations, which are designed to promote diversity of mass media as a whole, are based on public interest goals that the FCC is authorized to pursue." The court went further to note 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; emphasis added) 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."

In 2003, the FCC relaxed its ownership rules substantially. It eliminated cross-media ownership regulations in media markets with eight or more television stations, and allowed newspaper/television/radio cross-ownership in media markets served by four to eight television stations. This action was justified by an analysis based on the "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 and combined those "market shares" for commonly owned outlets. For example, New York was served by 23 television stations, so each television station was assigned a "market share" of 4.3% (or 1/23). Finally, based on these weights and "market shares," the Diversity Index was calculated using a sum-of-squares approach similar to the HHI.

The ownership rule relaxation was challenged in court 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 proposed definition of viewpoint diversity in this paper should be understood in light of these past difficulties. When this concept was used to justify media ownership restrictions in the 1970's, it was not precisely defined. The FCC's one attempt to measure this concept in 2003 was rejected expeditiously.

Despite these difficulties, it is important to try to measure important policymaking criteria. Unmeasurable policy objectives lead to inevaluable policies. The next section undertakes this challenge.

2. A Market-Based Measure of Viewpoint Diversity

This section proposes a market-based measure of viewpoint diversity. Section 2.1 explains the use of a market-based measure. Section 2.2 explores some intuitive properties that any reasonable measure should exhibit, and it shows the difficulty of separating the viewpoint diversity expressed in the media from the preferences exhibited by the audience of the media. Section 2.3 defines the proposed measure formally, and section 2.4 shows how viewership for national news programs can be used to separate local preferences from local news program characteristics. Section 2.5 discusses the limitations of the proposed definition.

2.1. *Basis for Measurement*

In considering the question of how to measure the variety of perspectives offered among a set of media programs, one might quite naturally start by thinking about conducting a content analysis. For example, one could use computers or human coders to analyze samples of media content and encode the perspectives expressed in each sample.

While intuitive, such content-based approaches to diversity measurements face three difficulties. First, accurate content quantification is quite difficult. Human collection of content data is typically labor-intensive and subjective, and therefore may be costly, slow or inaccurate. Computer collection of content data can be performed quickly but may fail to capture aspects of the content which are important but difficult to quantify. Second, time and cost constraints force the researcher to decide which aspects of content to encode, and those decisions may be at odds with the aspects of content that actually matter to consumers. Third, measures which are based solely on media content cannot predict how different audiences would react to the same content.

Consider a thought experiment to illustrate this final point. Suppose there are two subjective issues, 1 and 2, and two markets, A and B. Suppose everyone in market A is interested in issue 1 and everyone in market B is interested in both issue 1 and issue 2. Suppose a news program in market A uses four minutes of program time to present four perspectives on issue 1. Suppose a news program in market B uses two minutes to present two perspectives on issue 1 and another two minutes to present two perspectives on issue 2. A content-based measure of viewpoint diversity might well conclude that the news program in market A exhibits greater diversity, since more perspectives about issue 1 were expressed. However, from a policy perspective, it might be argued that the two news programs served their markets equally well given market preferences and time constraints. Yet this conclusion depends on information about market preferences, and therefore would be very impossible to draw using a purely content-based measurement of viewpoint diversity.

More generally, this is why viewpoint diversity has proven so difficult to define and measure. It is subjective, depending as much on the preferences of the audience as on the contents of the media.

The market-based approach proposed below alleviates all three problems of content-based diversity measurements. It obviates a burdensome data collection task, eliminates the need to predetermine what content characteristics are important, and it relies on consumers' observed choices which embed market-specific preferences. It should be remembered, however, that the market-based approach is no panacea. It has limitations of its own, discussed in section 2.5.

By presenting these limitations of content analysis, it is not the authors' intention to diminish the validity of content-based measures of viewpoint diversity. To the contrary, content analysis is a worthwhile and informative exercise. For example, Gentzkow and Shapiro (2010) invented a brilliant means of avoiding the primary limitations of content analysis, text mining the Congressional Record to identify Democratic and Republican phrases, then counting their frequency of use in local newspaper articles. They found that media outlets' use of political language typically reflected their customer bases' preferences.

The view of the authors is that policymakers and judges should consider both content- and market-based approaches to measuring viewpoint diversity. Each type of approach should be evaluated with a rational understanding of its strengths and weaknesses and the degree to which those strengths and weaknesses affect the specific application of the method.

2.2. *Intuitive Properties*

This section presents a series of thought experiments to motivate and justify the viewpoint diversity measure.

Suppose two competing television stations, A and B, within a market each offer a local news program, and suppose that each station has a 50% share of the local news audience. The following two extreme possibilities are fundamentally different but observationally equivalent.

1) The market's television audience consists of two equally sized segments with polar 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 be consistent with 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 same preferred viewpoint. Since they offer essentially identical programs, they split the market again, with half the viewers watching station A and half watching station B. This would be consistent with low 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 local news viewing alone cannot provide a measure of viewpoint diversity, since media consumption choices are based on both viewer preferences and media content. Since the concept of viewpoint diversity is fundamentally subjective, its measurement must account for the preferences of the group receiving the viewpoints.

Another thought experiment can show 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 garners a 80% share of viewers in a particular local market, and the national news program on station B garners 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. It is clear that, relative to the national market, the local market has a strong, homogeneous 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 roughly 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 indicates 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 tell us that stations A and B are providing programs that contain very different viewpoints. This is because viewers in the local market exhibit some heterogeneity in viewpoint preferences but the local news on station B is so far away from the preferred viewpoint of the average consumer that few consumers watch it.

These examples convey the intuition underlying the market-based measure of viewpoint diversity. It 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.

2.3. *A Market-Based Viewpoint Diversity Index*

This subsection defines the proposed viewpoint diversity index. It shows how to recover this index from program audience data, and shows that it cannot be empirically separated from the dispersion in local tastes, as illustrated in the examples above.

Consider a market *m* that is served by three local news programs, indexed in order of ascending market share by $j = 1,2,3$. Assume that the programs are differentiated by a single dimension of viewpoint diversity, as in Hotelling (1929). 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.[2] Assume for simplicity that the programs are ordered such that program 1 is closest to the left side of the line and program 3 is closest to the right side of 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.[3] The

[2] Higher-order viewpoint spaces are not considered because the available data do not allow for the nonparametric identification of additional dimensions of program differentiation. The single line in the model could be thought of as the first principal component of a higher-dimensional viewpoint diversity space.
[3] Below, an assumption is made that the national distribution of preferred viewpoints is Standard Normal. Neither assumption is necessary-and-sufficient for the other to hold, but they are compatible if viewers' preferred viewpoints are imperfectly correlated with their locations and if the moments of the national distribution are compatible with the moments of the market-specific 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 market.

Normal distribution is less tractable than the typical assumption of uniform preferences but is more realistic. 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. It is assumed that each viewer watches the program whose viewpoint is closest to her preferred viewpoint. 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. This assumption is considered to be the primary limitation of the proposed approach and is discussed in depth in section 2.5.

A useful theoretical construct is the point at which a consumer is just indifferent between watching programs 1 and 2, $\hat{x}_{12}^{m}$. Setting $u_{i1}^{m} = u_{i2}^{m}$ shows that $\hat{x}_{12}^{m} = (x_1^{m} + x_2^{m})/2$. Similarly, the point of indifference between programs 2 and 3 is $\hat{x}_{23}^{m} = (x_2^{m} + x_3^{m})/2$.

The proposed Viewpoint Diversity Index D_m is defined as the difference between these two points of indifference:

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

Figure 1 provides the intuition underlying 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 less of the line. Accordingly, the diversity index $D_{m'}$ is greater than D_m.

A few remarks are made to help explain the Viewpoint Diversity Index. First, the definition in equation (2) 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 common dispersion indices, such as a standard deviation based on the three news program locations, are not advisable in this setting. Second, notice that it is based purely on station locations. Local market preferences, as represented by distributional parameters μ_m and σ_m, do not enter the index. Third, notice that if either station 1 or station 3 changes its location in viewpoint space, the diversity index will change its value. However, it will not change with small movements of station 2 (small enough that station 2 remains between stations 1 and 3), since this would result in a reallocation of market shares without altering the range of viewpoints provided by the marketplace. Fourth, the index is independent of the scale of available viewpoints. That is, the index is the same for $(x_1^m, x_2^m, x_3^m) = (1,2,3)$ as it is for $(x_1^m, x_2^m, x_3^m) = (11,12,13)$. Finally, while the Viewpoint Diversity Index will always be positive, there are no benchmark values that take on special meaning.

To calculate the viewpoint diversity index, it is necessary to determine the program locations in the viewpoint space. This may be done by relating the predicted audience shares in the model to data. The market share of program 1 is given by the probability mass of viewers 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 is 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 $\hat{x}_{23}^m$,

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

Presuming s_1^m and s_3^m are available in the data, the points of indifference can be recovered from equations (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 the empirical Viewpoint Diversity Index is

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

Equation (7) shows, formally, the indeterminacy between program dispersions and market-specific tastes. With data from a single market, it will be impossible to separate the program locations from the dispersion in market-specific tastes, σ_m. The next section shows how this problem may be resolved using local audience shares for national news programs.

2.4. *Recovering Local Preferences*

This section uses local viewership of national news programs to separate local preferences from local stations' viewpoint diversity.

It is assumed that all three national news programs are available in many local markets and are indexed with $k \in (A, B, C)$ in ascending order of national audience share. It is assumed that these news programs are differentiated on the same viewpoint scale as the local news programs. This assumption is not innocuous. If the viewpoint diversity expressed in national news programs is of a fundamentally different nature than that expressed in local news programs, then the approach proposed here will not work. The arguments in favor of this assumption are as follows. First, the national news almost always immediately follows or precedes the local news. Since the two programs' audiences mostly overlap, attributes that the audience finds important in one program may also be the attributes that the audience finds important in the other program. Second, because these are two news programs, they are likely to share many characteristics in common, such as the types of stories they cover and the possible styles or slants available in their coverage of those stories. Third, both local and national news use some of the same publicly available video footage for some of the stories they cover, so some of the main inputs to the two types of programs are the same.

For simplicity, assume national news program A is closest to the left side of the line and program C is closest to the right side of the line. Note that national news program A does not necessarily correspond to local news program 1, and that the two positions of the national and local news programs on a particular station need not be correlated.

To anchor the location and scale of preferences, it is assumed that the national distribution of consumer viewpoint preferences is Standard Normal. Under these assumptions, the locations of the indifferent viewers for national news programs in viewpoint space are given by equations (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, equations (10) and (11) relate those locations to the local market shares of the national news programs:

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

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

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

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

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

Equations (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.

2.5. *Limitations*

The primary limitation of the proposed Viewpoint Diversity Index is that it excludes the idea of "vertical differentiation" in news programming. Vertical differentiation refers to news program attributes that all consumers like. For example, it may be that spending more money on special effects, presenters or set design would lead to higher viewing among all consumers, regardless of their viewpoint preferences. This extension was considered but found to be infeasible. An outline of the reasons is given.

First, consider how the diversity 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.

In the previous paragraph, it was assumed at every step 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.

Figure 2 illustrates this. Viewers to the left of $\hat{x}_{01}^{N}$ do not watch news, and viewers to the right of $\hat{x}_{30}^{N}$ do not watch news. However, the data on the market share of the outside option do not distinguish between these two groups.

It would be possible to pin down the fourth point of indifference if an additional assumption were added to the framework. For example, if it were assumed that the national news programs have positions that leave symmetric tails of unserved viewers, then the same number of viewers would lie to the left of $\hat{x}_{01}^{N}$ as to the right of $\hat{x}_{30}^{N}$. This would reduce the number of locations to be pinned down from four to three, a feasible task given the three available degrees of freedom. Or, if it were assumed that the three national news programs were evenly spaced on the line, then there would only be three locations to pin down. However, both of these assumptions are at odds with the motivation to undertake the analysis in the first place.

The measure of Viewpoint Diversity has other more obvious limitations. It assumes that distributions of viewpoint preferences are Normal; assuming a different distribution function may alter the results. It assumes that programs are differentiated on a single dimension, which may be overly simple. It assumes that viewers know the locations of each available station.

While the proposed definition of a Viewpoint Diversity Index is far from perfect, it does seem better than what has been done before, since it may be objectively measured, it separates viewer preferences from program content, and its underlying assumptions may be clearly evaluated. The next section shows how the new index is constructed and analyzed using data.

3. Empirical Approach

This section describes the empirical model, estimation and data used to link the Viewpoint Diversity Index to media market ownership.

3.1. *Model and Estimation*

The model links the Viewpoint Diversity Index to media ownership variables. The model is designed to fit the available data, which is characterized by the "large *N*, small *T*" property common to many survey panel datasets.

The approach is to estimate a descriptive regression since viewpoint diversity and media ownership may be driven by common factors. If one adopts the assumption that media ownership drives viewpoint diversity, a position that has sometimes been taken by the courts, then the empirical results may be interpreted as causal. However, the analysis here is more cautious and does not seek to attach causal inferences to the empirical results.

D_{mt} represents the Viewpoint Diversity Index in media market *m* at time $t \in \{0,1,2\}$ (corresponding to 2005, 2007 and 2009). It is constructed from the available viewing data as presented in section 2.4. x_{mt} is the vector of ownership variables; variable selection and definitions are discussed in section 3.3. It is assumed that

$$\ln D_{mt} = \alpha_m + \alpha_t + x_{mt}\beta + \varepsilon_{mt} \ , \tag{14}$$

where α_m represents all 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. Equation (14) should be thought of as a moving-average representation that likely includes serial correlation in ε_{mt}. If the precise form of the serial correlation were known, equation (14) 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 equation (14) are likely to be correlated with the media ownership variables. The panel is too short to estimate these intercepts precisely, so two standard approaches to estimation, first differencing (FD) and fixed effects (FE), are employed so that they drop out of the estimating equations. The FD approach lags the dependent variable to transformation equation (14) into

$$(\ln D_{mt} - \ln D_{mt-1}) = (\alpha_t - \alpha_{t-1}) + (x_{mt} - x_{mt-1})\beta + (\varepsilon_{mt} - \varepsilon_{mt-1}) \ , \tag{15}$$

The FE approach drop time-invariant terms, changing equation (14) into

$$(\ln D_{mt} - \overline{\ln D_m}) = (\alpha_t - \overline{\alpha}) + (x_{mt} - \overline{x_m})\beta + (\varepsilon_{mt} - \overline{\varepsilon_m}) , \tag{16}$$

where $\overline{\ln D_m} = T^{-1}\sum_t^T \ln D_{mt}$, $\overline{\alpha} = T^{-1}\sum_t^T \alpha_t$, $\overline{x_m} = T^{-1}\sum_t^T x_{mt}$, 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. When the sample contains more than two time periods, they provide different sets of estimates and both are provided. FD is more efficient when ε_{mt} follows a random walk while FE is more efficient when ε_{mt} is serially uncorrelated (Wooldridge 2010). Given the likelihood of habit formation in media usage, FD estimates will be preferred to FE estimates. However, we present both types of estimates to facilitate comparison.

Two sets of standard errors are presented for each of equations (15) and (16). The common approach would be to apply Ordinary Least-Squares (OLS) regression to equations (15) and (16). This is commonly known as the “differences-in-differences” estimate in the case of equation (15) and the “pooled OLS” estimator in the case of equation (16).

The problem with the OLS approach is that, when serial correlation is present in the errors, the standard errors of the parameter estimates may be severely biased. This has been known since Cochrane and Orcutt (1949). Recently, Bertrand, Duflo and Mullainathan (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. This is quite strong evidence against OLS estimation of equations (15) and (16). Yet while OLS is not viewed as a desirable model in the current setting, it is presented in section 4 as a familiar benchmark.

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 second set of estimates presented below follows this advice. This allows for autocorrelation in the errors and uses an unstructured “sandwich” estimator to control for possible correlation among the error terms, as in Arellano (1987).

A word is in order about an estimation technique that is not used. The recent dynamic panel estimation literature (e.g., Arellano and Bond 1991) has advocated using lags and previous levels as instruments for endogenous variables. In our application, that would imply using

$(x_{mt} - x_{mt-1})$ as an instrument for x_{mt-1} and assuming that $(x_{mt} - x_{mt-1})$ is uncorrelated with ε_{mt}. This exogeneity assumption is problematic in the context of media stations, as it would be in most industrial organization settings. The valuation of a media outlet such as a television station or a newspaper is typically calculated as the discounted sum of the station's future earnings, and this value influences media outlet's price. 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 to viewpoint diversity, or that they disregard those shocks in their media station retention/acquisition decisions. This assumption is not testable and not considered to be credible. This is the primary reason why this paper takes a descriptive approach rather than claiming to infer causality.

3.2. *Data*

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

3.2.1. *Data Description*

The dataset contains information about 210 local media markets in each of three time periods from two sources. Media ownership variables were provided by the FCC. They correspond to three snapshots in time: December 31, 2005, December 31, 2007, and December 31, 2009.

The second dataset consists of television ratings provided by Nielsen Media Research Galaxy ProFile. The ratings correspond to the November and May "sweeps" months in the 2005-06, 2007-08 and 2009-10 television seasons. Nielsen selects participants through geographic randomization and provides financial incentives to participate. In larger media markets, Nielsen measures television viewing with PeopleMeters, which record television usage and tuning continuously and prompt viewers to indicate their presence via remote control once or twice per hour. In smaller markets, audimeters attached to televisions measure set usage and tuning continuously. Viewer presence is measured via self-reported diaries. Nonresponsive participants are removed from the sample quickly. Responsive participants are replaced at regular intervals.

The Nielsen data were inconsistently reported. Many datapoints and some entire market-month datasets were missing from the data. These issues affected the variable definitions in three ways. First, five markets (Alpena, Biloxi, Miami, New Orleans and West Palm Beach) were dropped since a balanced panel could not be constructed for these markets. Second, because the measurement technology is more reliable for households than for demographic groups, the analysis focuses on household ratings. Demographic group ratings are excluded as these are more often missing. Third, even in the household-level ratings, about 20% of the possible observations are missing. Therefore, the local news audience share analysis focuses primarily on evening news viewing, since this daypart featured the highest percentage of data availability (94%) and local news programming.

The time window analyzed was 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. Virtually every local station in the sample airs a local newscast in the first half-hour within this window, and airs its affiliated network's national newscast within the second half-hour of this window. There were a few markets, such as Spokane, in which local newscasts did not precede national news but were aired immediately afterwards; in those markets the time period analyzed started thirty minutes later.

Data on market-level demographics are used in section 4.4, including 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 were provided by the FCC in conjunction with the media ownership data. They are used to ensure consistency with other studies in the quadrennial review. It was not clear whether the demographic variables were defined consistently across the three snapshots in the sample, so 2007 and 2009 demographic data are not used in the analysis.

The study was undertaken with the understanding that the television viewing data would contain local viewing of national cable networks. Those data would have provided additional degrees of freedom and allowed for a more nonparametric diversity metric. However, contrary to the authors' repeated inquiries, the data provider did not provide local audience data for national cable networks.

3.2.2. *Media Ownership Variables*

This section defines the set of media ownership variables. Ownership variables were chosen according to their relevance to the media ownership rules, but their number was limited to prevent multicollinearity from inflating the standard errors of the estimates. 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 was only measured reliably in 2007 and 2009; see Turner (2006) for further discussion.

Unfortunately, *TV/Newspaper* does 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.

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.

To summarize the ownership variables, *TV/Newspaper* is relevant to the Newspaper/Broadcast Cross-Ownership Rule; *Co-ownedTV* is relevant to the Local TV Multiple Ownership Rule; *TV/Radio* is relevant to the Local Radio/TV Cross-Ownership Rule; and *LocalOwnerTV* and *MinorityOwnerTV* are relevant to the impact of ownership diversity on media market competition and localism.

3.2.3. *Market Selection*

Since the Viewpoint Diversity Index defined in section 2 requires at least three newscasts, and since multiple newscasts would fundamentally change the definition and implications of the measure, market selection is an important consideration. Local media markets that did not offer all three national broadcast networks' news programs (ABC, CBS, NBC) and local news programs on those network affiliates were dropped from the analysis. This narrowed the number of markets included from 205 to 132.

Further, the Viewpoint Diversity Index will be fundamentally different in a market with a larger number of local newscasts. FOX affiliates provided local newscasts in the evening daypart in some markets. To gauge the sensitivity of the empirical results to the presence of a fourth local newscast, the empirical analysis is also performed using the subsample of 99 markets in which evening news was *not* available on the local FOX affiliate. This was done to gauge the sensitivity of the results to the assumption of three local newscasts.

Third, in addition to the ABC, CBS and NBC national newscasts, Spanish-language networks Univision and Telemundo also offer national news programs. It is unlikely that these newscasts compete extensively with the English-language national news programs for viewers, as most viewers are not bilingual, so they are not incorporated into the Viewpoint Diversity Index. However, their presence in a market could potentially change the dynamics of competition among the English-language language local newscasts. Therefore, the analysis is repeated on the subsample of 103 markets in which fewer than 20% of self-identified heads of household report that English is not their native language.

4. Empirical Results

This section reports the estimation results.

4.1. *Viewpoint Diversity Index*

The Viewpoint Diversity Index was straightforward to calculate and displays substantial variation across markets. Table 1 shows the raw data for 2007-2009, so that the reader may compare the changes in the log of the Viewpoint Diversity Index to changes in the media ownership variables.

The table is sorted in ascending order of the change in log Viewpoint Diversity. Visual inspection shows that there is little in the way of a relationship between Viewpoint Diversity and the media ownership variables. Extreme changes in viewpoint diversity at the high end and low end do not coincide with unusual changes in any of the ownership variables. A similar pattern was observed in the 2005-2007 data.

4.2. *Results: Base Ownership Variables, Full Sample*

Table 2 reports estimation results for the base set of three ownership variables in the full sample. The first three columns report the FD point estimates and two sets of standard errors, one provided by OLS estimation and one provided by clustered standard error estimation. The second set of three columns report the FE point estimates, followed by two sets of standard errors.

The set of FD estimates with clustered standard errors is the preferred set of estimates, so the discussion focuses on these; the other estimates are provided as benchmarks. The final column in Table 2 displays 95% confidence intervals for the mean elasticity on each effect, based on the FD parameter estimates and clustered standard errors.

Three results merit discussion. First, media ownership variables and time dummies explain little of the variation in the Viewpoint Diversity Index. The R-squared indicates that the media ownership variables and time dummies explain approximately 2.4% of the variation in the Viewpoint Diversity Index. Second, none of the media ownership estimates is statistically distinguishable from zero. This is true when considering either FD or FE estimates with either type of standard error. Third, while the standard errors tend to be larger than the point estimates, none of the confidence intervals admits any appreciable effect of media ownership variables on viewpoint diversity. It may be safely estimated that none of the elasticities is greater than 0.03 in absolute value.

4.3. *Results: All Ownership Variables, Limited Sample*

Table 3 reports model estimation results for the set of five ownership variables based on the final two years in the sample. The data were limited to the years 2007 and 2009 because *TV/Newspaper* showed almost no variation between 2005 and 2007 and because *MinorityOwnerTV* was not available in 2005. Since FD and FE provide identical estimates when the sample contains just two time periods, only one set of estimates are presented in the table.

Model fit is slightly better in the subsample, with an R-squared of 0.036, but all estimates continue to be statistically indistinguishable from zero. Again, the confidence intervals on the elasticities exclude the possibility of large effects. All elasticities may be safely estimated to be smaller than 0.04 in absolute value.

4.4. *Robustness Check: Market Selection*

The calculation of the Viewpoint Diversity Index assumes that there are exactly three news outlets within a market. This assumption is violated in two markets where FOX affiliates offered an evening newscast or in markets where appreciable portions of the population consume Spanish-language news. To check whether these violations influenced the results, the regressions in Table 2 were re-run 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.

Table 4 offers the results. The point estimates in all three cases are similar to those in Table 2. Neither change in the market selection criteria admits the possibility of substantial effects of media ownership structure on viewpoint diversity.

4.5. *Robustness Check: Market Demographics and Year Splits*

FD and FE estimation remove time-invariant within-market variation by differencing out market-specific intercepts. However, if market-specific intercepts can be accurately characterized with demographic variables, the power reduction due to differencing out the intercepts may outweigh the benefit of doing so. If this is true, FD or FE estimation may yield imprecise parameter estimates.

As a robustness check, equation (1) was estimated using a cross-sectional 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, a dummy variable indicating whether the local FOX affiliate offered evening news, the number of TV channels per capita, and the percentages of households with pay-TV service or any TV service. The estimation is done with clustered standard errors. The effects of both the market characteristics and ownership variables are allowed to vary with time.

The results are in Table 5, broken out by year of the sample. The general conclusion is that the FD and FE estimation techniques did not cause us to fail to find statistically significant effects when those effects were actually present. Out of 33 parameter estimates, only two are statistically significant at the 95% confidence level. They indicate that television penetration was positively related to viewpoint diversity and that increased television station ownership concentration was negatively associated with viewpoint diversity. Both parameter estimates are significant in 2007 but are statistically indistinguishable from zero in 2005 and 2009. As such, they do not provide robust support for the existence of those effects.

5. Summary and Conclusions

This paper proposed a novel market-based approach to measuring Viewpoint Diversity and used data from a panel of local media markets to investigate how it is associated with local media ownership variables. These associations are statistically indistinguishable from zero, and all are estimated to have elasticities less than .04 in absolute magnitude. Still, the following results may contribute to the policy discussion on the FCC's media ownership rules.

Newspaper/Broadcast Cross-Ownership Rule: Based on the 2007-2009 subsample, the elasticity of viewpoint diversity with respect to TV/Newspaper cross-ownership is 95% likely to be less than .01 in absolute value.

Local TV Multiple Ownership Rule: The elasticity of viewpoint diversity with respect to TV station ownership concentration is 95% likely to lie in the range $[-.02,.01]$.

Local Radio/TV Cross-Ownership Rule: The elasticity of viewpoint diversity with respect to TV/radio cross-ownership is 95% likely to lie in the range $[0,.02]$.

Ownership Diversity: The full sample results indicate that the elasticity of viewpoint diversity with respect to local TV station ownership is 95% likely to lie within the range $[-.02,.01]$. The 2007-2009 subsample indicated the elasticity of viewpoint diversity with respect to minority ownership of TV stations is 95% likely to lie within the range $[-.02,.01]$.

In general, these findings show that under the proposed definition of viewpoint diversity, variation in television station co-ownership and cross-ownership is generally found to negligible effects on viewpoint diversity. However, it is important to note that the data are limited to the degree of media co-ownership and cross-ownership currently allowed under FCC rules.

The evidence provided in this report is intended to contribute to the policy debate around the media ownership rules. It does not provide any conclusive basis for policymaking. This paper describes statistical relationships without any claims of causality. Its findings are limited by the range of the available data and the reader is reminded that an absence of evidence is not evidence of absence.

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Table 1. Raw Data fo0072 2007-2009 Subsample

Television Market	Chg. in Log *Viewpoint Diversity*	Chg. in *MinorityOwnerTV*	Chg. in *LocalOwnerTV*	Chg. in *Co-OwnedTV*	Chg. in *TV/Radio*	Chg. in *TV/Newspaper*	Television Market	Chg. in Log *Viewpoint Diversity*	Chg. in *MinorityOwnerTV*	Chg. in *LocalOwnerTV*	Chg. in *Co-OwnedTV*	Chg. in *TV/Radio*	Chg. in *TV/Newspaper*	Television Market	Chg. in Log *Viewpoint Diversity*	Chg. in *MinorityOwnerTV*	Chg. in *LocalOwnerTV*	Chg. in *Co-OwnedTV*	Chg. in *TV/Radio*	Chg. in *TV/Newspaper*
Juneau, AK	-0.19	0	0	0	0	0	Waco-et al.	-0.02	0	-1	0	0	-1	Chico-Redding, CA	0.02	0	0	0	0	0
Anchorage, AK	-0.14	0	0	0	0	0	Columbus, GA	-0.02	0	0	0	0	0	Norfolk-et al.	0.02	0	1	0	0	0
Harlingen-et al.	-0.13	0	0	0	0	0	Washington, DC	-0.02	0	0	0	0	0	Atlanta, GA	0.02	0	0	0	0	0
Madison, WI	-0.13	0	0	0	0	0	Dayton, OH	-0.01	0	0	0	0	0	Detroit, MI	0.02	0	0	0	0	0
San Angelo, TX	-0.11	1	-1	0	0	0	Charleston-et al.	-0.01	0	0	0	0	0	Hartford-et al.	0.02	0	0	0	0	0
Tampa-et al.	-0.11	0	0	0	0	0	Jackson, MS	-0.01	0	0	0	0	0	Charlotte, NC	0.02	0	0	0	0	0
Denver, CO	-0.09	0	0	0	-1	0	Johnstown-et al.	-0.01	0	0	0	0	0	Sacramento-et al.	0.02	0	0	0	0	0
Spokane, WA	-0.08	0	0	0	0	0	Los Angeles, CA	-0.01	1	0	0	1	0	Albany-et al.	0.02	0	0	0	0	0
Bangor, ME	-0.08	0	0	0	0	0	Shreveport, LA	-0.01	0	0	1	0	0	Memphis, TN	0.02	0	0	0	0	0
Meridian, MS	-0.07	0	0	0	0	0	Greenville,SC-et al.	-0.01	0	0	0	0	0	Kansas City	0.02	0	0	0	0	0
Charlottesville, VA	-0.07	0	0	0	0	0	Montgomery, AL	-0.01	0	1	0	0	0	Monroe-et al.	0.02	0	-1	0	0	0
La Crosse-et al.	-0.07	0	0	0	0	0	Minneapolis - et al.	-0.01	0	0	0	0	0	Minot-et al.	0.02	0	0	0	0	0
Peoria-et al.	-0.07	0	0	0	0	0	Lexington, KY	0.00	0	-1	0	0	0	Duluth-et al.	0.02	0	0	0	0	0
Savannah, GA	-0.07	0	0	0	0	0	Oklahoma City, OK	0.00	0	1	1	0	0	Columbia-et al.	0.03	0	0	0	1	0
Las Vegas, NV	-0.06	0	0	-1	0	0	Knoxville, TN	0.00	0	0	0	-1	0	Mobile, et al.	0.03	0	0	0	0	0
Sioux Falls-et al.	-0.06	0	0	0	0	0	Baton Rouge, LA	0.00	0	0	0	0	0	Springfield-et al.	0.03	0	0	0	0	0
Paducah-et al.	-0.05	1	0	0	0	0	Youngstown, OH	0.00	0	0	2	0	0	Raleigh-et al.	0.03	0	0	0	0	0
Lansing, MI	-0.04	1	0	0	0	0	Chicago, IL	0.00	0	0	0	0	0	Springfield, MO	0.03	0	-1	1	0	0
Fresno-Visalia, CA	-0.04	0	-2	0	0	0	Tallahassee-et al.	0.00	0	0	0	0	0	Abilene-et al.	0.04	1	0	0	0	0
Birmingham, AL	-0.04	0	0	0	0	0	Joplin, et al.	0.00	0	0	0	0	0	Dallas-et al.	0.04	0	0	1	0	1
Charleston, SC	-0.04	0	0	0	0	0	Columbia, SC	0.00	0	0	0	0	0	Odessa-et al.	0.04	0	0	0	1	0
Columbus, OH	-0.04	0	-1	0	0	0	Little Rock-et al.	0.00	0	-2	1	0	0	Green Bay-et al.	0.04	0	0	0	0	0
Huntsville-et al.	-0.04	0	0	0	0	0	Augusta, GA	0.00	0	0	0	0	0	Ft. Wayne, IN	0.04	1	0	0	0	0
Houston, TX	-0.04	0	-1	0	0	0	Amarillo, TX	0.00	0	0	1	0	0	Omaha, NE	0.04	0	0	-1	0	0
Pittsburgh, PA	-0.04	0	0	0	0	0	Columbus-et al.	0.00	0	0	0	0	0	Evansville, IN	0.04	0	0	0	0	0
Louisville, KY	-0.04	0	0	0	0	0	South Bend-et al.	0.01	0	0	0	0	0	Ft. Smith-et al.	0.04	0	0	1	0	0
Idaho Falls-et al.	-0.04	0	0	0	0	0	Greenville-et al.	0.01	0	0	0	0	0	Wilkes Barre-et al.	0.05	0	0	0	0	0
Fargo, ND-et al.	-0.04	0	0	0	0	0	Syracuse, NY	0.01	0	0	0	0	0	Tulsa, OK	0.05	0	0	0	0	0
Binghamton, NY	-0.04	0	0	0	0	0	Buffalo, NY	0.01	0	0	0	0	0	New York, NY	0.05	0	1	0	0	-1
Cedar Rapids-et al.	-0.03	0	0	1	0	0	Ft. Myers-et al.	0.01	0	0	0	0	0	Tyler-Longview, TX	0.05	0	0	1	0	0
Burlington, VT-et al.	-0.03	0	0	0	0	0	Milwaukee, WI	0.01	0	0	0	0	0	Tucson, AZ	0.05	0	0	1	0	0
Corpus Christi, TX	-0.03	0	1	0	0	0	Harrisburg-et al.	0.01	0	0	0	0	0	Greensboro-et al.	0.06	1	0	0	0	0
Traverse City-et al.	-0.03	1	0	0	0	0	Flint-et al.	0.01	1	0	0	0	0	St. Louis, MO	0.06	0	0	1	-1	0
Phoenix, AZ	-0.03	1	0	0	0	0	Nashville, TN	0.01	0	0	0	0	0	Philadelphia, PA	0.06	1	-1	0	-1	0
Baltimore, MD	-0.03	0	0	0	0	0	San Francisco-et al.	0.01	-1	0	0	-1	0	Rockford, IL	0.07	0	0	0	0	0
Topeka, KS	-0.03	0	0	0	0	0	Jacksonville, FL	0.01	0	0	-1	0	0	Santa Barbara-et al.	0.08	0	0	0	0	0
Wichita - et al.	-0.03	0	0	0	0	0	Tri-Cities, TN-VA	0.01	0	0	0	0	0	Bluefield-et al.	0.08	0	0	0	0	0
Des Moines-et al.	-0.03	0	0	0	0	0	Portland-Auburn	0.01	0	0	1	0	0	Austin, TX	0.09	0	0	0	0	0
Providence-et al.	-0.02	0	0	0	0	0	Cincinnati, OH	0.01	0	0	0	0	-1	Lubbock, TX	0.09	0	0	0	0	0
Macon, GA	-0.02	0	0	0	0	0	San Antonio, TX	0.01	0	0	0	0	0	Salt Lake City, UT	0.09	0	0	0	0	0
Orlando-et al.	-0.02	0	0	0	0	0	Wichita Falls, et al.	0.01	0	0	0	0	0	Toledo, OH	0.10	0	0	0	0	0
Indianapolis, IN	-0.02	0	0	0	0	0	Davenport, IA-et al.	0.02	0	0	0	0	0	Marquette, MI	0.12	0	0	0	0	0
Rochester, NY	-0.02	0	0	0	0	0	Champaign-et al.	0.02	0	0	0	0	0	Medford-et al.	0.19	0	0	0	0	0
Grand Rapids-et al.	-0.02	1	0	0	0	0	Roanoke-et al.	0.02	0	-1	1	0	0	Boston, MA	0.27	-1	0	0	0	0

Table 2. Estimation Results: Base Ownership Variables, 2005-2009 Sample

	First Differences			Fixed Effects			Mean Elasticity
	Point	Std. Errors		Point	Std. Errors		95% Conf. Int.
	Est.	*OLS*	*Clust.*	Est.	*OLS*	*Clust.*	(FD, Clust. s.e.)
Logged Diversity Index							
LocalOwnerTV	-.006	(.008)	(.007)	-.004	(.007)	(.006)	(-.02,.01)
Co-Owned TV	.004	(.009)	(.007)	.001	(.008)	(.007)	(-.01,.02)
TV/Radio	.012	(.011)	(.009)	.011	(.010)	(.009)	(.00,.02)
Num. Obs.	264			396			
R-squared	.024			.553			

Year-specific intercept estimates excluded from table for brevity.
** Significant at the 99% confidence level. * Significant at the 95% confidence level.

Table 3. Estimation Results: All Ownership Variables, 2007-2009 Subsample

	First Differences			Mean Elasticity
	Point	Std. Errors		95% Conf. Int.
	Est.	*OLS*	*Clust.*	(FD, Clust. s.e.)
Logged Diversity Index				
LocalOwnerTV	.008	(.012)	(.007)	(-.01,.02)
Co-Owned TV	.014	(.013)	(.009)	(.00,.03)
TV/Radio	.006	(.020)	(.020)	(-.02,.03)
Minority	-.027	(.016)	(.025)	(-.02,.01)
TV/Newspaper	-.004	(.029)	(.013)	(.00,.00)
Num. Obs.	132			
R-squared	.036			

Year-specific intercept estimates excluded from table for brevity.
** Significant at the 99% confidence level. * Significant at the 95% conf. level.

Table 4. Market Selection Robustness Checks, 2005-2009 Sample

	No FOX Markets		No Spanish Markets		No FOX or Spanish Markets		Mean Elasticity 95% Conf. Int. (No FOX or Span.)
	Point Est.	Std. Err.	Point Est.	Std. Err.	Point Est.	Std. Err.	
Logged Diversity Index							
LocalOwnerTV	-.002	(.008)	-.013	(.008)	-.010	(.007)	(-.02,.00)
Co-Owned TV	.002	(.008)	.002	(.007)	-.003	(.008)	(-.01,.01)
TV/Radio	.014	(.012)	.011	(.010)	.016	(.014)	(.00,.01)
Num. Obs.	198		238		176		
R-squared	.019		.036		.035		

Year-specific intercept estimates excluded from table for brevity.
** Significant at the 99% confidence level. * Significant at the 95% confidence level.

Table 5. Estimation Robustness Check, 2005-2009 Sample

Explanatory Variable	2005 sample Point Est.	2005 sample Std. Err.	2007 sample Point Est.	2007 sample Std. Err.	2009 sample Point Est.	2009 sample Std. Err.
Median age	.000	(.003)	.000	(.002)	.003	(.002)
Median income	.000	(.000)	.000	(.000)	.000	(.000)
Spanish-speaking population	.039	(.040)	.008	(.062)	-.004	(.051)
Local evening FOX news	-.004	(.012)	.010	(.016)	.027	(.015)
TV channels per capita	-.003	(.003)	-.001	(.002)	-.001	(.002)
Pay TV penetration	-.073	(.104)	-.175	(.126)	.015	(.149)
TV penetration	.087	(.150)	.220	(.108) *	.011	(.079)
LocalOwnerTV	-.001	(.003)	-.002	(.004)	.000	(.004)
Co-Owned TV	-.004	(.005)	-.014	(.007) *	-.008	(.005)
TV/Radio	.005	(.007)	.007	(.009)	.009	(.008)
Year 2005 Intercept	-.045	(.123)				
Year 2007 Intercept			-.111	(.164)		
Year 2009 Intercept					-.188	(.131)
Num. Obs.		132		132		132
R-squared		.713		.639		.661

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

Figure 1. Diversity Index Example

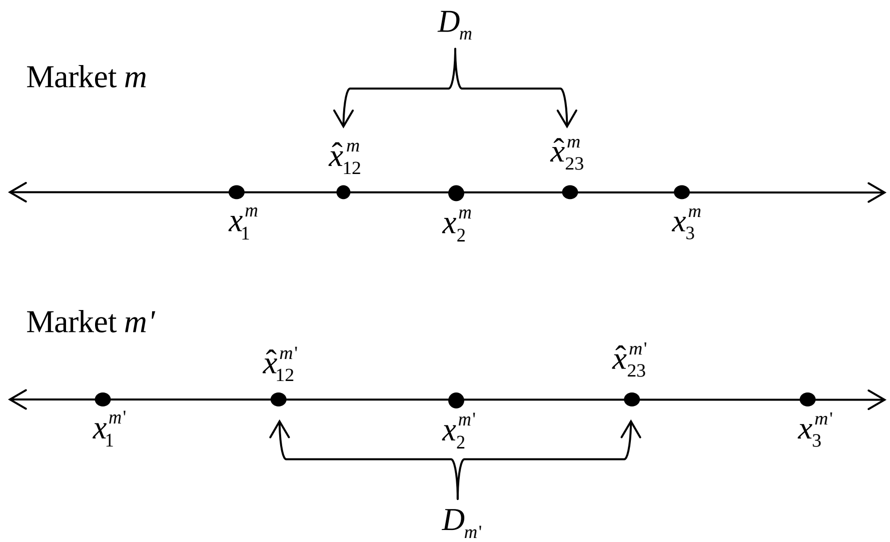

Figure 2. Uncovered Media Market