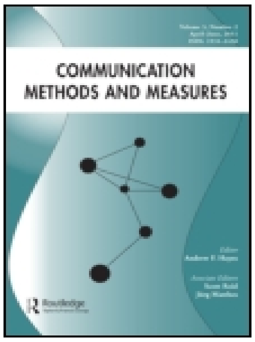

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ABSTRACT
As media options continue to expand in both quantity and variety and move to new media platforms, consumers' media diets are becoming increasingly varied and complex. This complexity calls for a more nuanced method of quantifying media consumption that goes beyond the binary like-minded or cross-cutting categories currently used in studies of selective exposure. We develop a measure that captures the full diversity of content in an individual's media diet, the media diet imbalance score, by adapting Brader, Tucker, and Therriault's (2014) measure of sociodemographic cross-pressures. Our method allows for research on important aspects of the current media environment that are impossible with existing measures, and it is less labor intensive than previous strategies for measuring selective exposure.

The recent proliferation of media sources provides individuals with more programming choice than ever before. While some individuals consume media of a single type, others select a more diverse programming diet. Though scholars of selective exposure evaluate each type of media independently, the net causes and effects of media consumption may depend on the combination of programs consumed. We developed a novel methodology for measuring the balance of content in an individual's overall media diet. Our measure allows for research on important aspects of the current media environment that cannot be done with existing measures and our approach is less labor intensive than previous strategies for measuring selective exposure.

In the next section, we explain the methodology for constructing this holistic measure, termed the media diet imbalance (MDI) score, using exposure to partisan-media programming as an example. We use public opinion data from the 2008 National Annenberg Election Survey (NAES) to develop a single measure of the balance of the content of each respondent's media consumption based on audience composition for 73 television and political talk radio shows. Next, we describe several tests we conducted to check the validity and reliability of the measure and establish appropriate bounds for its use. We then discuss the benefits of our approach for explorations of the effect of media consumption on audience behavior. The article concludes with a discussion of strategies for theory testing using MDI scores.

Methodology for measuring media diet imbalance

Our measurement strategy can be applied to a variety of dimensions of selective exposure such as exposure to entertainment versus news programming, exposure to violence, and exposure to scientific or medical information. For illustrative purposes, we focus this article on partisan-media

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exposure. For this example, we use Wave 2 of the 2008 NAES Internet panel (N = 5,251) that surveyed exposure to numerous television and radio programs from different networks and across genres: hard news, satirical news, soft news, and entertainment.[1] Participants were shown lists of approximately 15 shows at a time, and asked to indicate shows that they consumed "regularly" or "at least once a month."[2]

We employ the responses to develop a measure of Partisan Media Diet Imbalance (PMDI) for each respondent. Our approach adapts a method for measuring sociodemographic cross-pressures developed (and validated) by Brader, Tucker, and Therriault (2014). The measure is constructed using a four-step process:

(1) We use our 73 measures of media exposure to predict preference for McCain[3] using logistic regression. This first step generates coefficient estimates describing the direction and intensity of each media program's partisanship based on the composition of their audiences.[4] Estimated coefficients for a subsection of the shows are shown in Figure 1, with a complete listing of estimated coefficients in Supplemental Appendix 2.
(2) We use the coefficient estimates generated in Step 1 to calculate each respondent's predicted probability to prefer McCain based solely on media consumption, suppressing the constant term generated in Step 1.[5]
(3) We calculate the predicted probability of preferring Obama as 1 minus the probability of preferring McCain.
(4) We calculate the *absolute value* of the difference between these two probabilities.

The four-step process results in the PMDI, a measure bounded between 0 and 1. For example, the estimated coefficients (Step 1) were large in magnitude but opposite in direction for *Countdown with Keith Olbermann* (β = -.77) and *The Rush Limbaugh Show* (β = .90), the most extreme programs on the left and right, respectively. If we calculate PMDI for a hypothetical individual who consumed only Limbaugh's show, his/her predicted probability of voting for McCain during the primaries was 0.71[6] (Step 2), yielding a predicted probability of voting for Obama of 0.29 (Step 3), and a PMDI of 0.42 (Step 4). An individual who consumed both shows (but only these shows) would have a predicted probability of voting for McCain of 0.53[7] (Step 2), a probability of supporting Obama of 0.47 (Step 3) and a PMDI of 0.06 (Step 4).

Importantly, PMDI measures the partisan imbalance of media content and not the diversity of programs per se. Individuals with a PMDI score close to 1 were thus individuals whose media diet strongly favors one candidate, indicating that the content of their media diet was strongly partisan

[1]Forty of the shows were classified as news, including 24 cable and 16 network shows. Eighteen programs were classified as non-news content, including dramas and talk shows. Finally, questions regarding 15 talk-radio shows were asked of a random subsample of respondents (n = 5,251). Most radio programs were hosted by prominent conservatives with the exception of NPR's "All Things Considered." Programs were selected based on their Nielson ratings (Dilliplane, Goldman, & Mutz, 2013). This technique of measuring media exposure was found to be a very reliable and valid in tests using the 2008 NAES survey (Dilliplane et al., 2013).

[2]Respondents could check off any number of programs, with the average respondent reporting that they consumed almost 11 programs (M = 10.608; SD = 7.064). A complete list of programs is included in Supplemental Appendix 1.

[3]To code preference for candidates, we first used vote intention to identify McCain and Obama supporters. If a respondent reported no preference, we used party membership (e.g., a Democrat was coded as favoring Obama) or the party they leaned toward (e.g., someone who leaned Republican was coded as favoring McCain).

[4]In this step, we do not make causal claims in either direction. Instead, we generate estimates of the extent to which watching a program is associated with partisan preferences.

[5]We suppressed the constant because we are interested in calculating the predicted bias of a given *media diet*, not the bias of a given *respondent*. Our reasons for including the constant in Step 1 but suppressing it in Step 2 are as follows: suppressing the constant in Step 2 prevents bias in our initial estimates for the effects of media due to general preference for Obama in the dataset, but including the constant in Step 1 avoids forcing our media variables to soak up the variation caused by this preference. In suppressing the constant in Step 2, we deviate from the methodology used by Brader et al. (2014).

[6]Probability of voting for McCain = 0.71 = $1 / (1 + e^{-0.9})$

[7]Probability of voting for McCain = 0.53 = $1 / (1 + e^{-(.9-.71)})$

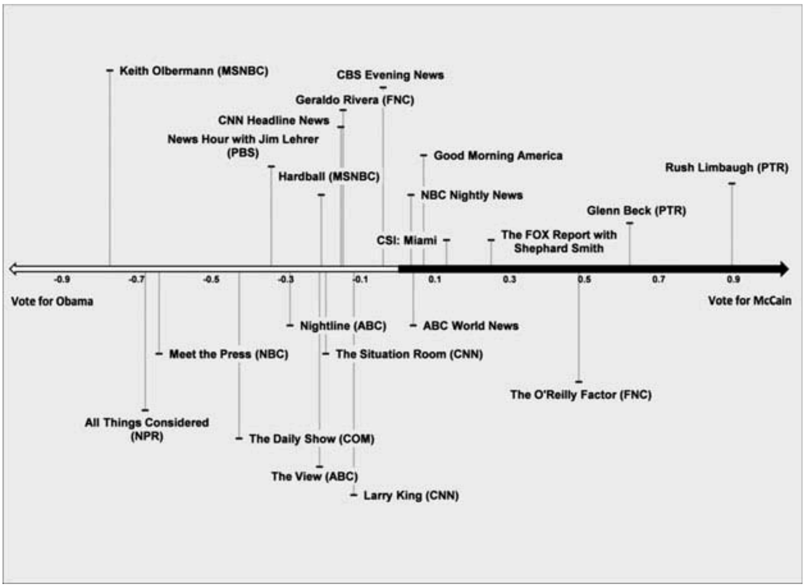

Figure 1. Calculated coefficients for select shows.

from one side of the ideological spectrum without any exposure to counter-attitudinal arguments. In contrast, people with values close to 0 were exposed to balanced content in their media diets because they consumed neutral media and/or equal amounts of partisan media from each side.[8] A respondent might have a low PMDI score because he or she watches internally diverse shows (neutral programs which present views from both sides of the ideological spectrum) or externally diverse shows (equal amounts of partisan media associated Republicans and Democrats). A low PMDI thus indicates a media diet with balanced content, while a high PMDI indicates a partisan-media diet with homogeneous and extreme content. Figure 2 shows the distribution of PMDI scores among NAES respondents.

Validity, reliability and bounds of measure

For the PMDI to be a useful representation of an individual's media consumption choices, we must establish it as a valid and reliable measure of the makeup of a person's media diet. It is impossible to directly measure cross-pressuring, so we lack an absolute standard against which to compare our method (Brader et al., 2014). However, we can increase our confidence in its validity and reliability by establishing that PMDI scores conform to basic expectations, correlate with existing measures, and are not subject to significant variation based on researcher assumptions or the size of our dataset. These checks also help to establish the appropriate bounds for use of the method.

We begin our investigation of construct validity by checking whether our measure accurately reflects basic expectations about respondents who watch different media programs. Our approach is similar to one used by Brader et al. (2014, pp. 36–39). We first calculate the PMDI scores for the actual respondents in our data set. We then compared the average PMDI scores for purposive subsamples we expect to be different; we consider whether differences are significant, large, and in the expected direction. We compared the average PMDI scores for respondents whose consumption included *both*

[8]Brader et al. (2014) rescale their measure so that higher values represent sociodemographic "cross-pressures" rather than certainty. We do not include this final inversion step.

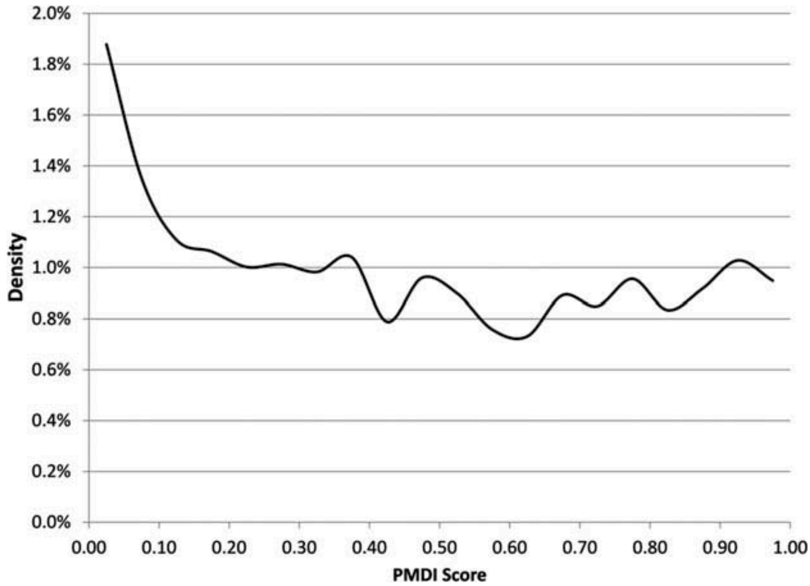

Figure 2. Distribution of PMDI scores calculated from 2008 NAES data.
Notes: Grouped in 0.05 width bins.

"Countdown with Keith Olbermann" (MSNBC) and "The O'Reilly Report" (FNC) against those who watched *either* "Countdown" *or* "The O'Reilly Report" *but not the other*. We include in these sub-samples all respondents who watched these shows regardless of what else they watched. We expect respondents that watched both programs to have a lower PMDI (i.e. consume a more balanced news diet) on average than those who consumed only one of the programs. This expectation is confirmed, as respondents who indicated that they watched both shows had an average PMDI of 0.49, significantly less than the average (0.72) among those who watched either show ($p < .001$).

Next, the validity of PMDI depends on the appropriateness of our measure of partisan media slant. To construct PMDI we use audience partisanship as a proxy for relative partisan slant of each program. Research suggests that programs favoring one party or viewpoint are likely to attract audiences skewed toward the same position. Additionally, media professionals respond to demand-side cues from consumers when developing content (Gentzkow & Shapiro, 2006; Mullainathan & Shleifer, 2005). Thus, we expect patterns of media use to indicate partisan favoritism in programming.[9] Available evidence suggests that our proxy for program slant is sound. The percent of the audience preferring McCain (included in Supplemental Appendix 2) is strongly related to other measures of partisan slant created with different criteria, data sources and coding procedures. It is highly correlated with Dilliplane's (2011) measure based on survey respondents' perceived bias of programs ($r = .83$, $n = 42$), and with two human-coded content analyses conducted by Pew (2008): the relative tone of candidate coverage ($r = .63$, $n = 16$); and relative amount of candidate coverage (−.76, $n = 19$).

Finally, we establish the robustness of the PMDI by examining the effect of varying the media programs from which the measure was generated. These tests are prompted by two concerns: (1) that inclusion of programs consumed by few respondents may exert undue influence on the PMDI and (2) that the programs included in future surveys may differ from those included in the NAES in a manner that affects the calculation of the PMDI score.

[9]We measure relative favoritism (slant) rather than accuracy of coverage relative to an objective standard (bias) (Groseclose & Milyo, 2005).

To examine the sensitivity of PMDI to outlier programs, we ranked the 73 programs included in the NAES from "most watched" to "least watched" based on responses. We then recalculated PMDI with subsets of the most popular media programs, testing the effect of including between 5 and 50 media programs (increments of five) in the calculation of our measure. We correlate this restricted PMDI with the unrestricted PMDI, calculated using all 73 media programs. Figure 3 shows the results of this test, indicating that including over half of the available media programs (n = 40) results in a strong correlation (ρ = 0.90) between the scores. The sizeable increase in correlation between the scores calculated using 35 media programs and that calculated using 40, however, suggests that researchers should be wary of using datasets that do not include an extensive battery of media programs.

We also examined the sensitivity of PMDI to changes in the dataset to determine whether the scores calculated using a subset of respondents would vary significantly from those using the full pool of respondents. We randomly sampled subsets from the data (varying from 1,000 to 5,000 respondents, increments of 1,000), calculated a restricted PMDI based on this subset, and calculated the correlation between this restricted PMDI and the PMDI calculated using the full sample. We repeated this 1000 times for each increment, calculating the mean correlation and a 95% confidence interval. Figure 4 shows that PMDI scores calculated based on subsets as small as 1,000 respondents result in high correlations (ρ = 0.83 ± 0.05), increasing above 0.9 for sample sizes of 2,000 respondents or more. Similarly high correlations (ρ = 0.94 ± 0.02) were obtained when the dataset was split, using coefficients (as calculated in step 1, above) estimated with one half of the respondents to calculate PMDI scores for the remaining respondents. The robustness with respect to changes in media programs and sample is an encouraging sign for the reliability of the PMDI.

Our validity and reliability checks show that PMDI (1) confirms basic expectations about direction of differences among sample populations; (2) is based on evidence of partisan slant that is highly correlated with other measures of slant; (3) is not sensitive to the choice of media programs used in its calculation (above a certain baseline); and (4) does not vary significantly when calculated using smaller samples of respondents. These characteristics of PMDI suggest

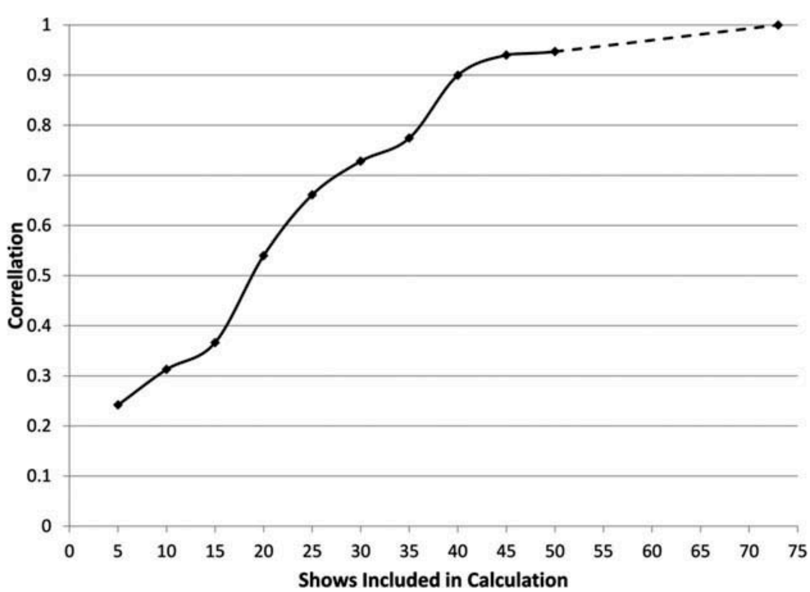

Figure 3. Correlation between PMDI score calculated with restricted sets of shows and PMDI score calculated with all 73 shows.

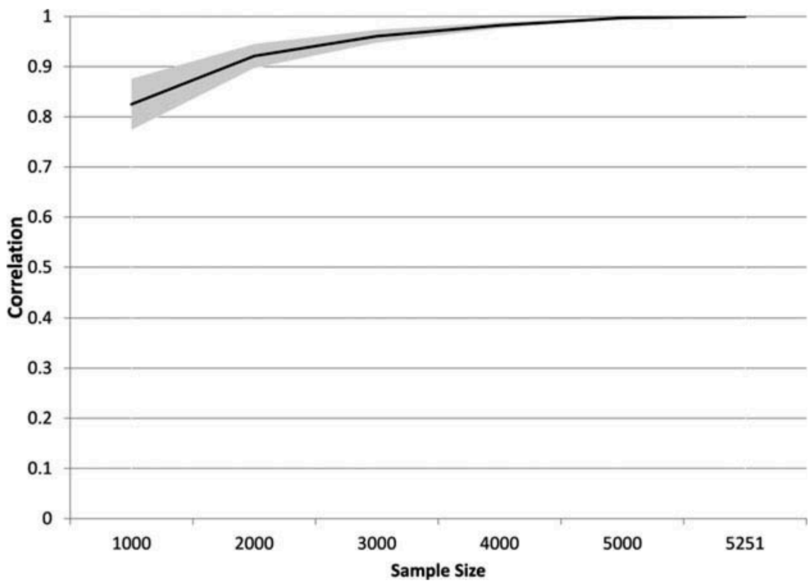

Figure 4. Correlations between PMDI scores calculated with restricted samples of respondents and PMDI score calculated with all 5,251 respondents.
Notes: The black line represents correlations between PMDI scores calculated with a restricted sample size and the PMDI score calculated with all 5,251 respondents included. The grey shaded area represents the 95% confidence interval calculated with 1000 iterations. Horizontal axis is not to scale.

that it can serve as a valid and reliable measure of the balance of someone's media diet, especially when the number of programs exceeds 40 and the sample of respondents exceeds 1,000.

Benefits of MDI methodology for measuring media diet imbalance

Our novel measurement strategy for measuring MDI scores generally, and PMDI scores specifically, reflects important features of the changing media environment not captured with existing measures. First, it allows us to evaluate the complex interactive effects of different programs by recording the balance of content in a survey respondent's total reported media diet. Researchers of partisan media can go beyond the study of exposure to likeminded, neutral, or cross-cutting media in isolation and test the causes and effects of various combinations of content. Second, MDI is based on a continuous scale indicating the degree of content. For example, PMDI reflects each program's partisan slant (from extreme left to extreme right), while other measures rely on a discrete categorization each program's type (liberal/conservative).

Third, our strategy can be applied to diverse sources including newspapers, television and radio, as well as blogs, websites, and social networking platforms. It can also incorporate programs spanning different genres into a single metric. Analyses of partisan media are typically limited to hard news programs where researchers can obtain outside evidence on partisan slant. PMDI also includes entertainment media. Fourth, PMDI is equally valid for independents and partisans. Existing measures of likeminded and crosscutting media exclude independents because they cannot be assigned to the partisan categories. In sum, the MDI method is able to capture the complexity, extremity, and diversity of media influences in our rapidly changing media environment.

Our measurement strategy also has important methodological benefits. The method is transparent and replicable. Alternative measures rely on audience perception or secondary data sources to code the partisanship of media programs. As partisan slant lies in the eye of the beholder (as argued by the hostile media thesis), individual attitudes shape the coding of partisan slant (Vallone, Ross, & Lepper, 1985). Furthermore, secondary sources on program slant are often incomplete or unavailable for a given time period, country, genre, or media technology.

The methodology described in this article is more efficient than alternative approaches. The MDI methodology requires only survey questions about media exposure. Other measures require additional evidence to measure media content that are hard to obtain. For example other measures of partisan exposure require additional survey questions about perceived slant, expert surveys, or labor-intensive content analyses. The efficiency gains of PMDI are especially attractive given the strong correlation between slant as indicated by audience preferences and the other more costly approaches we reviewed. Furthermore, the MDI method is easy to implement in commonly used programs such as R and STATA.

Importantly, the measurement strategy can be used to study dimensions of selective exposure beyond partisan-media diets. For example, scholars could use the method to study the effects of differing proportions of entertainment and news programming in a viewer's media diet on knowledge and engagement. Researchers could replace candidate preference with preference for news over entertainment in the construction of the measure, and calculate the extent to which a given person's aggregate diet is composed of shows watched by entertainment seekers or those watched by news seekers. Alternately, scholars interested in the effect of violent content on childhood development could construct a measure of violent media diet imbalance. The benefits described above with respect to the PMDI would also apply to a similarly-constructed measures of other concepts.

Suggestions for employing MDI for theory testing

Scholars should be attentive to the concept that MDI captures, the attributes of the measure, and the appropriateness of it to the theories being tested. We offer suggestions for 1) when to use—or not use—MDI, 2) conducting analyses using the measure, and 3) adapting the measure to suit research questions under investigation.

First, the MDI methodology, as described in this article, is well suited to testing some theories, but not others. The methodology combines exposure to different types of content into a single measure, which is one of the strengths of the measure. But MDI might not be useful when causal processes vary according to the type of content. For instance, scholars interested in the causes of partisan media choice might prefer separate measures for like-minded exposure and cross-cutting exposure given the causal processes generating selective avoidance and selective approach are distinct (Garrett, 2009).

In addition, MDI is best suited to testing theories where the outcomes of interest are different from the variables used to construct the measure. For example, PMDI can be used to estimate how exposure to slanted media content affects participation, knowledge, expectations of electoral outcomes, trust in the political system, trust in media, issue attitudes, cynicism, evaluations of the economy, and consumer behavior. However, there are potential endogeneity concerns to testing theories where the outcome is the same as the trait used to calculate the MDI score in the first place. For example, we used candidate preference to construct our PMDI score, so we have reservations about using that score to predict candidate preference. If scholars were to do so, candidate preference would be used to measure both the cause and the effect.

Second, MDI is the most appropriate measure for many theories of interest, but analyses must account for features of the measure. Our MDI methodology does not include controls for respondent traits. We do so for several reasons. First, there is great value in maintaining simplicity and clarity in the construction of the measure. A simple measure is easier to interpret. It also avoids the need for subjective judgment calls about what controls to include. Replication is also easier since measures of the control variables may not be available or comparable across studies. Second, we want to measure exposure to media content that is independent of audience characteristics. It is important to maintain the distinction between our measure of media exposure, on the one hand, and tests of cause and effect, on the other hand. In many cases, scholars will want to add controls to analyses using MDI so as to isolate the effects of exposure from individual traits that are correlated with exposure. Scholars may also want to include interaction terms between MDI scores and other variables to evaluate whether the effects of exposure are conditional on certain characteristics.

Furthermore, our measure records exposure to a certain type of content rather than exposure to a certain type of program. For example, a low PMDI score proxies exposure to balanced content; it includes respondents exposed to neutral programs along with those exposed to partisan programs from both sides. Researchers interested in the effects of just partisan media consumption could control for neutral media consumption in their analyses or drop neutral programs when constructing the measure.

A potential advantage of the MDI procedure is that it may be easier to replicate across surveys than existing methods. To improve measurement and facilitate comparison, estimates of program bias in the first step can be used to construct MDI scores for other studies, though this analysis strategy only works when media content is expected to be similar across studies. In such cases, we recommend using the best possible sample to estimate program bias. For example, if an experiment with an unrepresentative or small sample is run concurrently with a large-scale representative survey, one can use the estimates of program slant from the representative survey to construct the MDI scores for individuals in the experiment. Similarly, a scholar interested in a subpopulation may want to use the full sample to construct MDI, even if the subsequent analysis is limited to the population of interest. Furthermore, using the same estimates of program bias across surveys can facilitate comparison since differences in estimated effects would then reflect only differences in consumption and not differences in proxies for program bias. For example a panel analysis about the effects of changing media diets could use the estimates of media slant from the first wave to estimate MDI in both the first and subsequent waves.

Third, scholars can adapt the measure in the following ways to suit some theories of interest. Skipping the fourth step (i.e., not taking the absolute value) generates a measure ranging from only one type of media to only another type of programs. For example, skipping the fourth step for PMDI yields a measure ranging from a media diet that strongly favors the Democrats (−1) to one that strongly favors the Republicans (1), with balanced media diets at the midpoint (0). This adaptation would be useful for studying the persuasive effects of exposure to left versus right arguments. Similar formulations could be used for other MDI measures; a scholar who wants to test the effects of exposure to news versus entertainment media on knowledge could construct a measure ranging from exclusively entertainment content to exclusively news content.

Measures of media consumption should ideally reflect the amount of media consumption rather than just the type of consumption. Unfortunately, we are not aware of publicly available data on exposure to a large number of programs that also asks respondents about the frequency of their exposure to each program. If such data become available, the dummy variables measuring exposure or nonexposure to each program could be replaced with ordered variables measuring frequency of exposure to each program when constructing MDI scores. When measures of amount of exposure to each program are unavailable, scholars may be able to improve causal inference by using general measures of amount of media consumption, such as a question about how often respondents watch television. Scholars may also want to control for a measure of the total number of programs consumed.

The MDI approach can also be replicated in other countries, though adaptation would likely be needed to reflect differences in context. For example, we hope future scholarship will adapt the PMDI methodology to multi-party systems. It would be easy to apply the method by creating binary combinations of parties, such as parties in and out of ruling coalitions. However, innovative adaptations that reflect multiple axes would be most useful.

In sum, the MDI methodology is a valuable contribution to research on media exposure for the reasons outlined above. Our suggestions for analyses using MDI measures can improve causal inference and adaptations of the basic methodology can broaden its applicability. Ultimately, we envision that MDI be used as a compliment to (rather than a replacement for) extant measures of media exposure, because the methodology captures a distinct concept. Our approach is best suited to answering theoretical questions about the interactive effects of different media content, while extant measures are better suited to isolating the independent effects of a given program type.

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