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The Importance of Attention Diversity and How to Measure It

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Studies of political attention often focus on attention to a single issue, such as front-page coverage of the economy. However, examining attention to a single issue without accounting for the agenda as a whole can lead to faulty assumptions. One solution is to consider the diversity *of attention; that is, how narrowly or widely attention is distributed across items (e.g., issues on an agenda or, at a lower level, frames in an issue debate). Attention diversity is an important variable in its own right, offering insight into how agendas vary in their accessibility to policy problems and perspectives. Yet despite the importance of attention diversity, we lack a standard for how best to measure it. This paper focuses on the four most commonly used measures: the inverse Herfindahl Index, Shannon's H, and their normalized versions. We discuss the purposes of these measures and compare them through simulations and using three real-world datasets. We conclude that both Shannon's H and its normalized form are better measures, minimizing the danger of spurious findings that could result from the less sensitive Herfindahl measures. The choice between the Shannon's H measures should be made based on whether variance in the total number of possible items (e.g., issues) is meaningful.*

KEY WORDS: attention diversity, agenda setting, issue framing, measurement, Herfindahl, Shannon's H

Introduction

Political attention matters. While important debates can occur when no one is looking, most key political decisions are made under the watchful gaze of those involved. Indeed, attention is often a necessary (if insufficient) condition for political change. At the same time, attention is perhaps the scarcest of all political resources in a world faced with information overabundance (Jones, 2001). The level of attention to single issues has driven much of what we know about politics, from looking at the range of political conflict (Schattschneider, 1960), to the notion of gridlock (Binder, 2003; Richardson & Jordan, 1979; Rose & Davies, 1994), to the growing literature on punctuated equilibrium (Baumgartner & Jones, 1993; Jones & Baumgartner, 2005). Yet, while the mechanisms that drive attention to a single issue have been looked at in many different ways, existing work too often overlooks its own best lesson: since agenda space is finite, attention to one issue affects not just that issue, but all other issues and the agenda as a whole.

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Understanding political attention to a given policy on a given agenda requires an understanding of attention *diversity*—that is, the degree to which attention on an agenda is distributed across items,[1] from complete concentration (a single item receiving all attention) to complete diversity (all items receiving an equal level of attention). The diversity of attention holds particular importance in public policy research. Past work suggests that the diversity of attention across policy issues on a given institutional agenda—and across institutions—can affect issue access to the agenda, how the agenda changes over time, policymaker and citizen perceptions of the issues, and the legislative outcome of policy debates (e.g., Annesley & Gains, 2013; Baumgartner & Jones, 1993; Gamson & Wolfsfeld, 1993; Jennings et al., 2011; Sheingate, 2006; Snow, Soule, & Kriesi, 2004; Wolfe, 2010). Additionally, the notion of attention diversity applies to more than the spread or concentration of issues on an agenda. For example, we might care about the degree to which political attention is spread across parties (Hobolt & Klemmenson, 2008). And just as we can think of an agenda space in terms of how it is divided among items in the form of issues (or parties, etc.), we can think of each issue space in terms of how it is divided among items in the form of frames (Schattschneider, 1960). Capital punishment, for example, can be framed in terms of whether or not it deters crime, whether or not it costs more money than alternative forms of punishment, whether or not it is fairly applied, and so on (Baumgartner, De Boef, & Boydstun, 2008). Although we can learn much from tracking the level of attention given to a single frame of interest, it is also important to be able to measure how concentrated or diversified an issue debate is across frames (Boydstun, 2013). In short, to the extent that attention matters in politics—and it does—attention diversity matters too.

Yet, to date, scholars lack an *agreed-upon measure* that best captures our theoretical understanding of attention diversity. We want to be able to observe how concentrated or diffuse a political agenda space is using an established, systematic metric that also allows for empirical comparisons. For instance, we want to be able to differentiate between an executive speech (e.g. State of the Union, Speech from the Throne) concentrated on the environment, a speech touching equally on a plethora of issues, and everything in between. This paper examines how best to measure attention diversity quantitatively for use in political science and the social sciences more broadly, yielding best-practices advice for scholars.

Importantly, the concept of attention diversity is only useful if it is precisely defined and properly bounded. We define attention diversity as the degree of spread (vs. concentration) of a given "space" across possible "items." Here, we operationalize a space as an agenda, measuring that space through counts of attention (e.g., news stories, speeches). We operationalize items as topics or issues, but other applications would work, too. Again, for example, we could consider the attention diversity of a given agenda not across topics but across parties. Or we could consider attention diversity across frames of a given issue space, operationalizing frames as second-level agenda setting dimensions (McCombs, Llamas, Lopez-Escobar, & Rey, 1997; e.g., related to the death penalty: deterrence, economic cost, fairness) or along other dimensions such as loss and gain (Kahneman & Tversky, 1979) or episodic and thematic frames (Iyengar, 1991).

As for bounding, the space and item definitions—and their operationalizations—must be held consistent within a given study. For instance, comparing the diversity of two unrelated speeches may not be very informative or interesting (or appropriate), but comparing the diversity of an executive speech from one president or prime minister to the next is key to understanding their different agendas. Similarly, it would be problematic to compare the diversity of attention in coverage across policy topics in front page news with the diversity of attention across frames used in news coverage of gay marriage. However, it would be appropriate and interesting to compare the diversity of frames used in news coverage of gay marriage vs. Congressional discussion of gay marriage (using the same frame coding scheme for both media and Congressional attention, of course).

We begin by discussing the theoretical underpinnings of attention diversity. Then we examine four "best candidate" measures of diversity in the particular context of attention—these are the measures that have been most often used in past studies of attention diversity, and for good theoretical reasons. Yet the measures have significant differences and it is important to determine how they match existing theory.

Drawn from information theory and economics, the measures are Shannon's H, the inverse Herfindahl Index, and the normalized versions of both. We compare these four measures using simulation data as well as demonstrations using a series of different political agenda datasets. Through these analyses and the related discussion of the mechanics underlying each measure, we conclude that while all measures capture the concept of diversity in some form, Shannon's H and its normalized form better match our conceptual understanding of attention diversity across its entire range, from attention concentration (low diversity) to attention diffusion (high diversity). The choice between the two versions of Shannon's H should be based on the importance of variance in the total number of items in the study at hand.

Toward our aim of establishing a best-practices measure of attention diversity, we flesh out a conceptual understanding of attention diversity that accounts for the entire range of diffusion, from the most concentrated to the most diverse; we identify a key criterion of (relative) measurement sensitivity that an established measure of attention diversity should have; we compare four alternative ways of measuring attention diversity empirically; and we identify one measure—Shannon's H information entropy—as the most appropriate operationalization due to properties that match our conceptual understanding.

Attention Diversity: Agendas, Debates, Parties, and Policymaking

Across disciplines and within the social sciences we often care about diversity. In studies of economic inequality, we may be concerned about the equity of the distribution of income or wealth. In public policy, we may want to evaluate the success of policies like affirmative action, a program that is fundamentally about demographic diversity in areas such as the workplace, education, and Congress. In political behavior, we may be interested in how the diversity of social network interactions influence issue attitudes and vote choice.

In this paper, we discuss the concept and the measurement of one important form of diversity: attention diversity. Generally speaking, diversity is the distribution across different items in a group. In application to policy agendas, we use the term attention diversity to describe the degree of diversity—from total concentration to total diffusion—in the attention distributed across the policy items used by a given source, measured as a function of the number of items used and how much attention (e.g., in story counts) each item received.

The concept of attention diversity is particularly relevant for examining the spread of representation of ideas at two levels: (i) the diversity of policy issues receiving attention on a given agenda as a whole (e.g., is newspaper coverage focused narrowly on one hot issue or spread more evenly across multiple issues?), and (ii) the diversity of frames receiving attention in that agenda's treatment of a single issue (e.g., is immigration news coverage focused narrowly on the economic costs of immigration or spread more evenly across multiple perspectives?).

Attention Diversity in Political Agendas

At the level of political agendas, attention is divided between issues that "compete" for finite space (Jochen & De Vreese, 2003; McCombs & Jian-Hua, 1995), and this competition provides the context for policymaking, representation, and political processes more generally. An agenda with a high level of diversity is highly diffuse, with attention spread across a broad range of issues; an agenda with low diversity is highly concentrated, with attention focused on only a few issues (Jennings et al., 2011). Attention diversity is not simply the number of issues included on an agenda, but also how evenly (or unevenly) attention is distributed across these issues.

The diversity of attention on an agenda is important for several reasons. First, in the case of most agendas, each bit of attention paid to an issue is one bit less attention for everything else; agenda-setting is a zero-sum game (Zhu, 1992). Thus, if we are interested in the level of attention given to any single issue, we need to account for the behavior of the agenda as a whole, including the attention consumption of all other issues (i.e., the "congestion" of the agenda).

Second, the diversity of attention influences the overall workings of—and reaction to—a given agenda. For example, consider the agendas of public laws, speeches, and political party systems. On each of these agendas, the share of attention dedicated to particular issues or ideologies affects how they function. A speech primarily focused on the environment is not likely to change discourse on civil rights, but neither is a broad speech covering the agenda for the year ahead that includes a passing mention of civil rights. Through varying degrees of attention diversity, each political agenda serves to define contemporary political discourse by dictating *how many* issues to address and *how much* attention to give each issue. Broadly speaking, an issue is more likely to receive attention on a more diverse agenda, but the few issues picked up by a more narrowly focused agenda will garner much more attention.

Third, the diversity of attention across related specific issues (or subissues) within a larger policy area can influence the amount of attention the issue as a whole receives—and vice versa. In Boydstun's (2013) analysis of the *New York Times* front page, she finds that an increase in the diversity of media attention across subissues within a single, broad policy area in one time period has a significant positive influence on the proportion of the total front-page agenda space that the issue as a whole receives in the following time period. Thus, political agendas are shaped not only by the diversity of attention across aggregated policy areas (e.g., environment) on the agenda as a whole, but also by the diversity of attention given to individual subissues within those areas (e.g., climate change or drinking water safety). Shifts in attention diversity, then, are meaningful both across and within broadly defined issues.

Of course, the relationship between levels of attention and attention diversity runs in the other direction too. The concentration of a political agenda on a key topical issue, due to an economic crisis or a war for instance, has been shown to contract the diversity of that agenda almost uniformly across a range of political systems and over time (Jennings et al., 2011). The diversity of attention can have real political consequences through affecting policymaking reform. For example, the narrowing of an agenda during periods of concentration around a core issue has been shown to have a particular influence on the pursuit of women's rights throughout Europe, with concerns over women's rights all but disappearing during times of economic hardship (Annesley & Gains, 2013).

Attention Diversity in Policy Debates

At the level of policy debates, the significance of attention diversity has long been documented by political scientists. When Schattschneider wrote that "the outcome of all conflict is determined by the *scope* of its contagion" (1960, p. 2, emphasis in original), he was referring to the amount of public attention paid to a debate (i.e., the number of people involved). Yet Schattschenider's work suggests that the scope of a debate's contagion hinges not only on the number of people involved but on the spread of the debate across perspectives and interests. As the diversity of a debate expands, the influx of new perspectives (or frames, and those people drawn in by those frames) disrupts the status quo line of debate. With a wide enough expansion the line of debate can be displaced entirely, such that the previous losing side of the debate becomes the new majority (Riker, 1986; Schattschneider, 1960).

This early work serves as a theoretical foundation for examining the relationship between the diversity of a given issue debate and the amount of attention it receives. Supporting this notion, Baumgartner and colleagues find suggestive evidence in the case of capital punishment that the expansion of the debate in the late 1990s helped propel a cascade of attention to the issue as a whole (Baumgartner et al., 2008). Investigating both capital punishment and the war on terror, Boydstun (2013) finds evidence that an increase in the diversity of attention across different frames of a single issue has a significant positive influence on the amount of attention the issue receives in the following time period.

As an example of this link between attention diversity and the amount of attention the issue as a whole receives, consider that in the 1950s American discussion about nuclear power was dominated by talk of scientific advancement: the "atoms for peace" frame. But in the late 1960s the discussion in the United States shifted and widened, with nuclear power framed in terms of environmental danger, health risk, and military arms proliferation. This shift in emphasis had an immediate and enormous impact on public perception of and policy response to the debate (Baumgartner & Jones, 1993). What was important about the shift in definition was not merely a swap of one set of frames for another. The new frames realigned the debate not only through their substance, but also through their sheer number; the diversity of the debate had expanded.

Why Attention Diversity Matters for Politics and Society

Within and across these two levels of consideration (issues on an agenda and frames in an issue debate), the degree of attention diversity has meaningful political consequences. Theory and evidence suggest that low attention diversity tends to restrict policy change, whereas high diversity promotes change. Wolfe (2010) shows that the diversity of the information available in the political environment has a significant effect on policymaking. This is because the concentration or diffusion of the information environment directly influences government responsiveness and because the diversity of the information environment can attenuate the signal strength of public opinion and, thus, the impact of public opinion on public policy. In the realm of policymaking, Sheingate (2006) finds that the diversity of a Congressional committee's jurisdiction can, under the right conditions, have a significant effect on how active the committee will be in a given policy issue. Likewise, Jennings et al. (2011) examines executive agendas from six different countries and finds a strong positive relationship between the diversity of an agenda and its size. In particular, an expansion in the diversity of a political agenda allows newcomers to push their policy concerns to the forefront.

The importance of diversity has also been examined in the context of policy debates more generally. Snow et al. (2004) find that the diversity of a debate strongly shapes public response to that debate. And Gamson and Wolfsfeld (1993) offer compelling evidence that the diversity of a debate directly affects the likelihood that the balance of power in the debate will shift. Research in the policy area of capital punishment suggests that the specific items used in a policy debate (i.e., frames) can piggyback, or resonate, off of one another. As the diversity of a policy debate expands to include additional frames, it makes it easier for even more frames to gain traction on the agenda. An expanding debate is an exciting debate, and so as the diversity of discussion widens, attention increases. Here again, the expanding diversity of a debate is a strong contributing factor in attention cascades (Baumgartner et al., 2008).

Diversity plays an important role beyond debates and policymaking. Political party systems have often been considered in relation to diversity. The work of Stigler (1972) introduced a measure of market concentration to voting and parties, theorizing that as concentration through voting behavior increases, competition decreases. Further cross-national work on parties has offered diversity as one explanation of the fact that more political parties in a country does not necessarily mean higher turnover, as the "effective number of parties" varies based on the number of parties as well as their voting base (see Greene & Bevan, 2013; Laakso & Taagepera, 1979). Recent work has expanded the discussion of diversity and parties to consider the effects that the diversity of a party platform can have on the diversity of public debate, as well as the party platforms of opposition parties (Hobolt & Klemmenson, 2008). Clearly in relation to ideologies, the diversity of party competition (and voting) plays an important role in many fundamental democratic processes. Even more generally, Page (2007)—in line with Surowiecki (2004)—shows how groups with a diversity of perspectives can outperform groups concentrated with homogenous experts.

In short, research focused on the diversity of political attention, and politics in general, represents a promising research direction with wide-ranging and important political implications. Yet there is no consensus on how best to measure attention diversity. In the sections that follow, we examine our four candidate measures of attention diversity against our conceptual understanding of how it operates—while maintaining a particular awareness of the range of applications and degrees of concentration/diffusion that exist in attention diversity research.

Attention Diversity: Matching Measure to Concept

An ideal measure of our concept of attention diversity would capture the range of an agenda in a linear and consistent fashion across the different points on that range. For example, with a linear measure, the distance between 5 and 10 units of x is the same as the distance between 10 and 15 units of x. In the case of attention diversity then, equally sized increases and decreases in diversity should have equally sized effects on our measure of the diversity; for example, a 5% increase in attention to item x at the expense of item y should yield the same change in our measure of attention diversity as a 5% increase in attention to item y at the expense of item x.

Yet the importance of measurement consistency is at odds with the fact that the best candidate measures of diversity—the four we investigate here—are not linear. Rather, the upper and lower limits of these measures yield differences in scale across the range of the measures, making them curvilinear. The bounding of diversity measures is directly related to the concept they measure. By summarizing the share of attention each output receives, measures of diversity can never go below a bottom limit where one output receives all attention and an upper limit where attention is split equally amongst all outputs. If our measure of diversity cannot be linear, it must at least be sensitive to changes in diversity across its entire range, including at both high and low levels of diversity. This sensitivity is particularly important not only for the study of public policy, where it is common for a single issue to often dominate the political agenda due to policy punctuations, but also for other fields of research, such as the study of political parties, which focuses on political manifestos that are often quite diverse and require a measure that is sensitive to changes at the other extreme. Identifying a measure that is sufficiently sensitive to variance is crucial because of the danger that less sensitive measures pose to hypothesis testing, increasing the likelihood of spurious results.

Thus, in searching for a best measure of attention diversity, we want to give particular emphasis to one key criterion: a measure that offers the highest degree of sensitivity across the range of attention diversity, such that equal increases and decreases in diversity have relatively equally sized effects on the diversity measure, regardless of where on the range of diversity they occur. In other words, our best measure of diversity must differentiate between changes in the system regardless of the level of diversity. Our approach for determining the best measure not only matches with the definition of diversity we use, but closely matches the ecological definition of diversity and is the optimal means for assessing measures of diversity (see Jost, 2007).

Power vs. Information: The Inverse Herfindahl Index and Shannon's H

To measure attention diversity, this paper considers in detail two measures as well as their normalized forms that can be applied to a multitude of agendas.[2] The first measure is the Herfindahl (or Herfindahl–Hirschman) Index (HHI), a measure of market concentration stemming from economics and intended to capture the amount of power or monopolization in a particular business sector. The second measure is Shannon's H, a measure of information entropy born out of information theory and borrowing heavily from the second law of thermodynamics.[3] These measures are similar both conceptually and in terms of their calculations, as we discuss in detail in the next section. However, the two are separated by the subtle but key difference that one (HHI) focuses on the concentration of power (i.e., the degree of agenda monopolization), while the other (Shannon's H) focuses on the degree of information. This section discusses these two measures and their normalized forms, describing how the measures are calculated, their respective ranges, and how well they map on to the definition of attention diversity presented above, particularly as it relates to our key criterion of measurement sensitivity.

Herfindahl–Hirschman Index: Power

The HHI is a measure used by economists and the government alike to determine the degree of concentration in an industry. For example, it has often been used to assess the degree of monopolization in an industry by comparing the market share of various competitors in a similar space. As it is generally used as a threshold measure of power, where values above a certain point are considered a clear monopoly, it is not designed to handle nuance at high levels. The measure is also constructed in such a way that HHI moves quickly towards its maximum or minimum values once the power threshold is reached. This measure has been modified and used effectively in political science to consider the level of competition in elections (Stigler, 1972), the effective number of parties in multiparty systems (Laakso & Taagepera, 1979), and the diversity of interest organization populations (Gray & Lowery, 2000). Notably, none of these applications require a high degree of precision near their maximum or minimum values. Thus, despite its popularity in the field, the insensitivity of HHI to high and low levels of concentration/diffusion makes it potentially problematic as a measure of diversity across varied applications.

HHI is calculated by taking the square of the proportion of the variable in question (for our purposes, attention) captured by each item and summing these squares. Again, for the purposes of this paper we treat issues as items, but our discussion also applies to the treatment of parties, frames, or other units as items. The formula is scaled such that values range from 1/N to 1, with 1/N representing complete diffusion (e.g., each industry has an equal share of the market) and 1 representing complete concentration (e.g., in terms of industrial economics, that one firm controls an absolute monopoly).[4] As a measure of market concentration, HHI increases as diversity decreases. Thus, in order to arrive at a measure of diversity, the HHI measure should be subtracted from 1 to produce the inverse version in Formula 1 below:

Formula 1. Inverse Herfindahl–Hirschman Index

$$Inverse\ HHI = 1 - \sum_{i=1}^{n} (p(x_i))^2 \tag{1}$$

where:
x_i represents an item
$p(x_i)$ is the proportion of total attention the item receives

The inverse HHI takes into account how attention is allotted across items. For instance, if 20 items each receive an equal amount of attention in a speech, diversity as measured by inverse HHI will be very different than if one issue received the majority of attention. Specifically, as attention to a single issue *decreases* and total attention spreads more evenly across all items, inverse HHI *increases*, signaling greater dispersion.

Normalized Inverse Herfindahl–Hirschman Index: Power

One concern with using the inverse HHI is the fact that the measure does not control for the number of available items. Thus, its range from 1/N to 1 will vary as, say, smaller items disappear and then reappear on an agenda over time. However, the formula can be adjusted to account for the number of items, producing a measure that ranges from 0 to 1. Formula 2 below shows how to adjust the inverse HHI to inverse HHI*, its normalized form.

Formula 2. Normalized Inverse Herfindahl–Hirschman Index

$$Inverse\ HHI^* = \frac{1-\sum_{i=1}^{n}(p(x_i))^2 - \frac{1}{N}}{1-\frac{1}{N}} \tag{2}$$

where:
x_i represents an item
$p(x_i)$ is the proportion of total attention the item receives
N is the number of items

The inverse HHI* takes into account how attention is allotted across items while allowing the measure to move across a normalized range from 0 to 1. The inverse HHI* range is therefore uniform no matter the number of items, and the measure increases consistently at high levels of diversity, allowing researchers to use this measure in comparing different datasets.

Shannon's H Information Entropy: Information

Shannon's H Information Entropy formula is a measure of information entropy that was created by applying natural laws of physics to studying communication, specifically language and computer programs. It is a variant of the generic entropy formula, originally developed in the field of thermodynamics to measure the diffusion of heat. Shannon (1948; Shannon & Weaver, 1949) proposed that human communication can be understood in terms of the concentration and diffusion of the categorical information it contains, and developed the information variant of the entropy formula from this approach. In the field of political science, Shannon's H has been used to study such topics as institutional agenda-setting (Baumgartner, Jones, & MacLeod, 2000), comparative policy attention (Jennings et al., 2011), policy engagement by organized interests (Halpin & Thomas, 2012), shifts in agenda volatility (Talbert & Potoski, 2002), Congressional committee jurisdiction (Sheingate, 2006), and information complexity (Wolfe, 2010). Designed to capture how much information (or bits) are needed in order to classify a signal, Shannon's H is better suited than the inverse HHI to precision at high and low levels. Both conceptually and operationally, Shannon's H better meets our key criterion of sensitivity.

We can view this higher sensitivity in Formula 3 below, which shows how Shannon's H is calculated by multiplying the proportion of the agenda that each issue (or other item) receives by the natural log of that proportion, then taking the negative sum of those products.[5]

Formula 3. Shannon's H Information Entropy

$$Shannon's\ H = -\sum_{i=1}^{n}(p(x_i)) * \ln p(x_i) \tag{3}$$

where:
x_i represents an item
$p(x_i)$ is the proportion of total attention the item receives
$\ln(x_i)$ is the natural log of the proportion of attention the item receives

As with the inverse HHI and HHI*, Shannon's H entropy increases as the spread of attention across all items becomes more equal, or diffuse. Unlike the inverse HHI, however, Shannon's H directly accounts for the number of items at play; as the number of items increases, its maximum value also increases via the ln(N), where N is the number of items. In this way, the measure can appropriately differentiate between the use of nine items in a speech where only ten items might have been used and the use of nine items where hundreds are available. As the natural log of 0 is undefined, it is common to replace 0 either with a very small proportion (e.g., 0.0000001) or with the proportion the issue would receive with a single observation.[6] This paper applies the former approach, treating each 0 as a very small proportion, but the results and general shape of all figures do not noticeably change using the other technique.

Normalized Shannon's H Information Entropy: Information

Shannon's H can further be normalized to resemble the inverse HHI* such that it ranges from 0 to 1 regardless of the number of items. This measure discounts the effect that more items can have on raising Shannon's H and, thus, is potentially useful for comparing across different issue coding systems used on the same data. Formula 4 below transforms the calculation of Shannon's H by dividing it by its maximum value.

Formula 4. Normalized Shannon's H Information Entropy

$$\textit{Shannon's } H^* = \frac{-\sum_{i=1}^{n}(p(x_i))^* \ln p(x_i)}{\ln(N)} \tag{4}$$

where:
x_i represents an item
$p(x_i)$ is the proportion of total attention the item receives
$\ln(x_i)$ is the natural log of the proportion of attention the item receives
N is the total number of items

Like all three earlier measures discussed, Shannon's H* increases as the spread of attention across all items evens out. By restricting the measure between 0 and 1, the upper limit is less informative than Shannon's H, but datasets with varying numbers of items can be compared uniformly.

A Hypothetical Distribution of Attention

To demonstrate how each measure of diversity works, consider the examples presented in Table 1, which presents a snapshot of a hypothetical agenda (e.g., a month's worth of Congressional speeches) in which seven items are potentially at play. Example 1 shows the agenda where a single item receives 100% of the attention. For all four measures of diversity investigated in this paper, this agenda receives the lowest values possible (zero). On the opposite end of the spectrum is Example 6, showing an agenda where all items receive an equal share of attention (≈14.3%). In this case, each measure obtains its maximum value, and it is here that we see the greatest variation between the measures. Both of the normalized measures (inverse HHI* and Shannon's H*) take on a value of 1 due to their construction and subsequent constraints. The inverse HHI, on the other hand, takes on a lower value of 0.857 due to the small number of items at play. Shannon's H takes a value of 1.95, since in this case its formula is reduced to the natural log of 7.

The other examples in Table 1 provide further insights into how these measures of diversity behave. For instance, Examples 3 and 4 illustrate how a reversal in attention between Topic A and Topic B, with no other changes in attention to Topics C, D, E, F, and G, does not change the value for any of the measures. Examples 3 and 4 thus demonstrate the fact that none of these measures account for substantive differences in how the agenda space is spread amongst items (i.e., *which* items are receiving attention), but instead are designed to account only for the distribution of proportions. In contrast, Example 2 demonstrates that when full attention to a single item (as in Example 1) shifts to a division of attention between two items, all four measures of diversity increase. Of particular note is the quick increase in both HHI measures with this relatively minor shift in attention (from Example 1 to Example 2), indicating that these measures are not particularly sensitive to variance at low levels of diversity. This same pattern is found when comparing Example 5 to Example 6, where the divide between high diversity and complete diversity is much smaller for both HHI measures; again, comparing Examples 5 and 6 shows that the Shannon's H measures are more sensitive. Finally, Example 5 demonstrates what occurs if the attention paid to the top attended-to item in Examples 3 and 4 is split across the 5 least attended-to items. While each of the measures demonstrates an increase in diversity in this case, both of the HHI measures are again nearer to their maximum values than the two Shannon's H measures, indicating that the HHI measures are likewise not as sensitive to variance at high levels of diversity.

Simulated Distributions

While the previous section helps us get a basic handle on the inverse HHI, Shannon's H, and the normalized versions of both, a more detailed investigation is needed to understand the appropriateness of each measure as a representation of attention diversity. This section investigates all four measures through a series of simulated datasets comparing the performance of each measure in relation

Table 1. Hypothetical Seven-Item Agenda

Example	Item								Inverse HHI	Inverse HHI*	Shannon's H	Shannon's H*
	A (%)	B (%)	C (%)	D (%)	E (%)	F (%)	G (%)	Total (%)				
1	100	0	0	0	0	0	0	100	0.000	0.000	0.000	0.000
2	75	25	0	0	0	0	0	100	.375	.438	.562	.289
3	50	25	5	5	5	5	5	100	.675	.788	1.440	.741
4	25	50	5	5	5	5	5	100	.675	.788	1.440	.741
5	25	25	10	10	10	10	10	100	.825	.963	1.840	.948
6	14.3	14.3	14.3	14.3	14.3	14.3	14.3	100	.857	1.000	1.950	1.000

Source: Modified from Jennings et al. (2011).

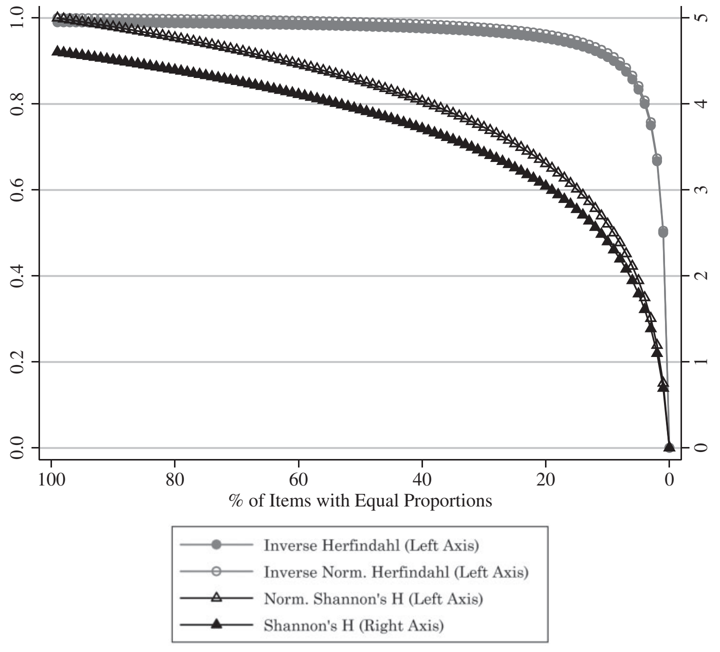

Figure 1. Simulation Results: Decreasing Diversity.
Note: Simulated data across 100 observation points and 100 items. For each observation, the number of items with equal proportions decreases by one. At 100% all items have equal proportion, while at 1% only one item has all possible agenda space. This series represents decreasing diversity with no random error.

to change, high and low levels of diversity, and other factors. The use of simulated data allows us complete control over the level of diversity, how it changes through seasonality and trends, and the degree of random error introduced at each time point. By comparing the measures in the context of known data-generating processes we can have greater confidence in our conclusions. Specifically, our goal here is to isolate the performance of each measure with regard to measurement sensitivity across the entire range of values that political attention could possibly take.

Figure 1 provides an overview of how each measure responds to continually decreasing diversity in a hypothetical 100-item space over 100 points on a continuum of diversity. Each of the 100 observation points on the continuum represents a different allocation of attention across the 100 items. In the first set of observations (represented by the first data point at the upper left-hand corner of Figure 1), all 100 items share the agenda equally, with each item receiving 1% of attention ($p_i = 0.01$). The second point represents a slight drop in diversity where a single item out of 100 no longer receives any attention, and so on with each successive point. The final observation seen in the far lower right-hand corner of Figure 1 shows the case where one item controls 100% of the agenda ($p_i = 1.00$). In other words, this graph shows how each of our four measures respond to incremental shifts in the distribution of attention, from complete diffusion (diversity) to complete concentration.

Figure 1 shows the similarities between the inverse HHI and Shannon's H in relation to their normalized parts when moving from the most diverse to the most concentrated. This result is expected, as the normalized versions are produced by re-scaling each measure based on the number of items. However, larger differences between each measure and its normalized form exist when moving between smaller and larger agenda spaces, as seen in Table 1 when comparing the maximum values of the inverse HHI and the normalized version. The scale of these measures can be important, particularly in relation to Shannon's H, where the maximum value of the measure increases with the number of items (ln[N]). Therefore, the use of the non-normalized Shannon's H may better fit those research questions where the number of items is free to vary over time and/or across observations.[7]

Most importantly, Figure 1 reveals a key difference between the inverse HHI and Shannon's H, both in their standard and normalized forms. Both measures are obviously nonlinear and resemble a second-order polynomial, having maximum and minimum values determined by the nature of the measures and/or the number of items. Beyond these similarities, the inverse HHI and Shannon's H are in fact quite different, especially at high and low levels of attention diversity. Due to how the inverse HHI is constructed, it is slow to respond to changes in the level of attention diversity at high levels of diversity. The inverse HHI is a measure of power and monopolization. Thus, sensitivity to subtle changes in competition at high levels of diversity is not the primary function of the measure. The same is true at the lowest levels of diversity, where it is clear the market competition is low and that a monopoly exists. However, in reality we know that many political agendas are either highly diverse or highly concentrated, and the lack of sensitivity and variation in the inverse HHI for such agendas makes the measure less than ideal. This limitation makes the HHI less sensitive, at least when it comes to high and low levels of diversity.

As a measure of information, Shannon's H is more sensitive at both high and low levels of diversity and behaves more consistently in differentiating between values moving from the highest to the lowest level of diversity. Unlike the inverse HHI, Shannon's H demonstrates better measurement sensitivity across the entire range of the measure and therefore better captures differences in attention diversity. Moreover, Shannon's H is not only a better and more sensitive measure of diversity as a concept, but it also better allows for statistical analyses, particularly when levels of diversity change only slightly within a high or low range. Both Shannon's H and its normalized form demonstrate these properties, and the choice between the two should be made based on how meaningful the variance in the number of items is for the research question at hand.

The behavior and appropriateness of these measures is perhaps better understood when considering data that mimics observed agendas. A series of four simulated datasets approximating the behavior of different political agendas is presented in Figure 2. Since we control the data-generation processes behind these simulated agendas, we can evaluate the performance of each measure with confidence. Figure 2 demonstrates that the Shannon's H measures are consistently more sensitive to latent variance in attention diversity than the HHI measures. Part A in the top left part of

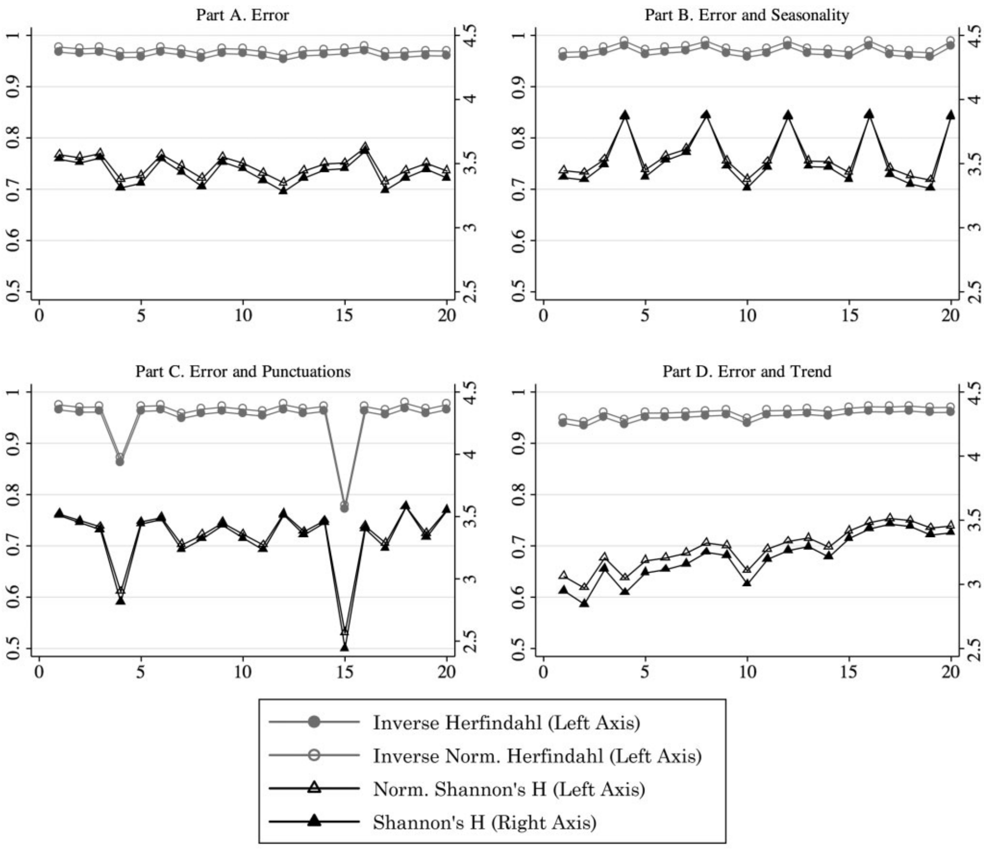

Figure 2. Simulation Results: Moderate Diversity Across Conditions.
Note: Simulated data across 20 observation points and 100 items. To simulate moderate levels of diversity with sufficient variation, base data are generated by the product of two random numbers (with bounds 0–5 and 0–100) drawn from a uniform distribution. Calculations presented are generated from corresponding relative proportions. The *x*-axis in each graph is the percentage of items with equal proportions. Part A represents a stable series with random error; Part B represents a stable series with random error and seasonality (fixed increases in diversity at every 4th observation); Part C represents a stable series with random error and two punctuations (fixed, large decreases in diversity at the 4th and 15th observation); Part D represents a series with increasing diversity (constant increases in the spread of attention across available items) and error.

Figure 2 represents a fairly diverse agenda with random error in the level of diversity over time. All four measures perform similarly, showing increases and decreases in the level of diversity at the same observation point. However, as the simulated dataset is significantly diverse, both versions of the inverse HHI remain relatively high and have far less variation than both versions of Shannon's H. The size of changes in each measure of diversity is further affected by the upper limit of the inverse HHI, while both changes in Shannon's H are approximately the same size highlighting the consistent sensitivity of the measure. This difference further underscores the higher level of sensitivity in the inverse Shannon's H across the range of the measure.

The other simulated datasets presented in Figure 2 further underscore the benefit of the Shannon's H measures over the inverse HHI measures in terms of capturing diversity across the entire range of diffusion. In particular, comparing the large seasonal increases in Part B to the punctuated decreases in Part C makes the problem of sensitivity with the inverse HHI even clearer. Comparing these two simulated agendas demonstrates that, at higher levels of diversity, increases in the HHI measures are muted compared to similarly sized decreases. Shannon's H, on the other hand, is far more sensitive. The opposing conclusions for both measures also hold true at lower levels of diversity, where decreases are muted and increases are more prevalent in the HHI measures. Part D represents a simulated dataset with both error and an upward trend in diversity, further highlighting the better sensitivity of Shannon's H with this increase appearing more linear. Overall, the results for Shannon's H in Figure 2 better fit the known data-generating process than the inverse HHI. This conclusion is true regardless of how the figures are rescaled. While both the inverse HHI and Shannon's H measure diversity in some form, Shannon's H does so in a way that better fits the actual underlying changes in diversity over the entire range of the measure, making the use of either version of Shannon's H far more appropriate.

Measuring Attention Diversity with Political Data

The use of simulated datasets to investigate the differences between these measures has many advantages, but further evidence in support of the conclusions above can be gained when considering real political data. This section further applies the four measures of attention diversity to three dynamic political agendas: the focus of U.S. voluntary associations, the content of U.S. news media, and the acts of the UK Parliament. While each of these three datasets are time series datasets used in and gathered for our other work, the same inferences would stand if they were instead associations in each state, cross-sectional comparisons of different newspapers, or laws in several different nations. The use of these particular datasets allows us to discuss the patterns of attention diversity present in each of the figures, assessing whether these patterns match our understanding of the underlying data. All three datasets include observations coded according to the U.S. or UK Policy Agendas Projects' major topic coding schemes, which contain 19 or more mutually exclusive categories of broad policy issues (e.g. Health, Macroeconomics, and Foreign Trade).[8] For the sake of consistency we selected these three datasets, each of which tracks attention across issues on a given agenda. Again, the same illustration could be performed using datasets that track frames used in attention given to a single issue.

Figure 3 plots the attention diversity of U.S. national-level voluntary associations, 1971–2001, classified into 31 issue categories according to the Encyclopedia of Associations version of the U.S. Policy Agendas Project topic scheme. The distribution of groups across issues remains highly stable in this dataset over time and, as such, the attention diversity should also be much more stable than the other two

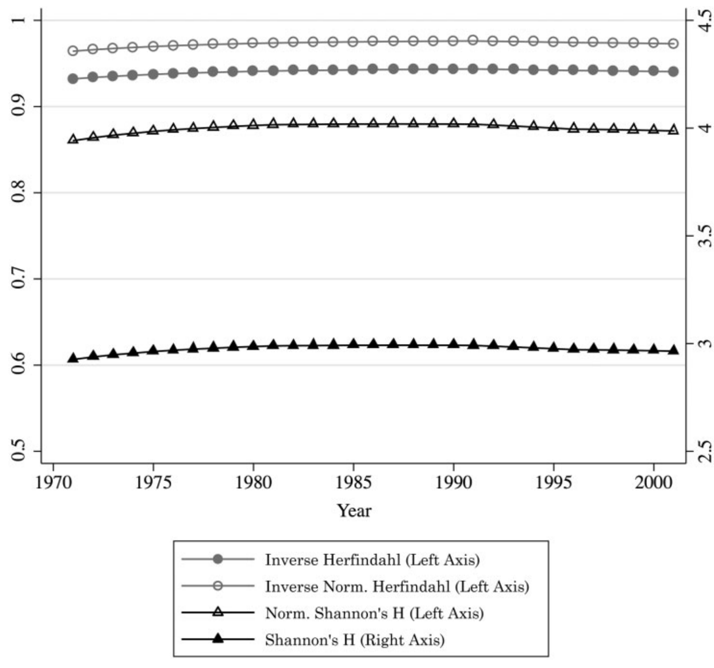

Figure 3. Diversity of U.S. National Level Voluntary Associations, 1971–2001.

datasets examined in this paper. We see this expected stability play out in Figure 3 across all four measures. While the diversity of voluntary associations over time may indeed be less fluid than the diversity of other more dynamic datasets, Figure 3 demonstrates that all four measures remain quite stable when differences in diversity from year to year are small. In this way, Figure 3 shows a baseline confirmation that the two Shannon's H measures perform well with this particular type of stable data, allowing us to turn now to evaluating the measures when applied to data series that exhibit greater variance over time.

Figure 4 plots the attention diversity of the U.S. news media, as depicted in front-page articles in the *New York Times,* 1996–2006, aggregated monthly and classified into 27 issue categories according to the *New York Times* version of the U.S. Policy Agendas Project topic scheme. Unlike the simulated data, there is no clear pattern in the level of diversity in front-page media attention, and there is also a great deal more change (as is to be expected with a largely event-driven dataset). For example, we can observe three major dips in diversity coinciding with major events: November 2000 (the 2000 presidential election), October 2011 (the deployment of troops to Afghanistan following 9/11), and April 2003 (the first full month of U.S. military operations in Iraq). Indeed, these punctuations in attention are registered by all four measures, but again both HHI measures appear to be less sensitive to the relative degree of changes at the ends of the diversity spectrum. Specifically, the HHI measures appear to overestimate the diversity in those months relative to the Shannon's H measures. The amount of change in front-page media attention produces a

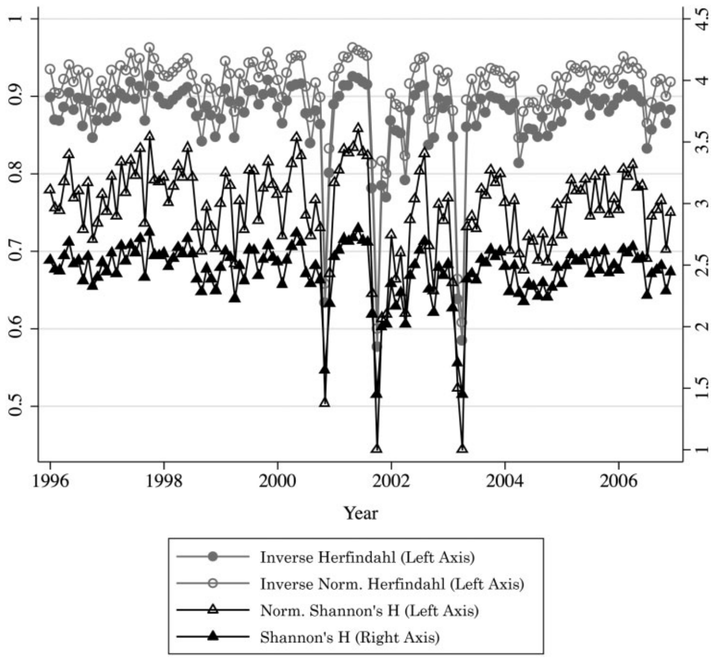

Figure 4. Diversity of Front Page *New York Times* Articles (Monthly), 1996–2006.

high degree of volatility in each measure, but two main conclusions can be drawn from Figure 4. First, the inverse HHI is again generally quite high, leading to problems distinguishing changes in diversity using this measure. Second, due to the lower level of variation and sensitivity in the HHI measures, the inverse HHI appears smoothed when compared to the two Shannon's H measures. While all four measures capture the diversity of front-page media attention, the increased variation in the Shannon's H measures and better sensitivity at higher levels of diversity makes Shannon's H more appropriate, especially for the purposes of subsequent statistical analyses.

The same conclusions can be drawn looking at Figure 5, showing the attention diversity of UK Acts of Parliament, 1911–2008, over 19 topics coded according to the UK Policy Agendas Project topic scheme. Again here, we see no clear pattern of attention diversity, but all four measures clearly match known changes in Acts of Parliament. For example, we see sharp decreases in diversity coinciding with the special short session in 1922 concerning the Irish Free State (that led to only a limited number of acts, as it was not a complete parliamentary session) as well as at the start of both world wars. With these data, the inverse HHI is also generally quite high and has a lower level of variation and sensitivity, leading to smoother measures compared to the two Shannon's H measures. Again, the two Shannon's H measures appear the most appropriate for statistical analyses given their greater levels of variation and sensitivity.

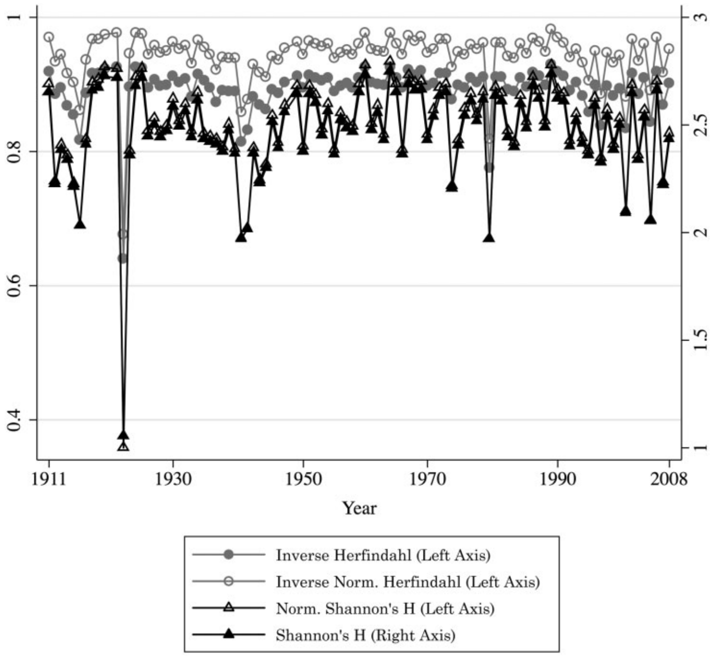

Figure 5. Diversity of UK Acts of Parliament, 1911–2008.

Conclusion

In this paper we make a case for diversity as an important conceptual variable for understanding attention, whether it comes in the form of issues, frames, ideologies, or any other type of political discussion. For example, the level of diversity in a legislative agenda affects which issues are addressed, helping to explain that most elusive of all political questions: why government pays attention to the issues it does. And the level of diversity in media attention to a specific issue affects how much attention a broad policy area as a whole receives, helping to explain the likelihood that citizens will be primed to think about that issue on a given day. While attention diversity is not a silver bullet of political understanding, it is an important variable that can shed further light on our understanding of political systems. By taking the agenda-setting literature's own best lesson about attention to heart—that attention to any given issue is indelibly linked to attention paid to other issues—we can view the picture of political agendas more clearly.

Toward the aim of accounting for the importance of attention diversity, we have sought to identify how best to measure this important variable. We have compared the four most accepted measures of attention diversity used in the social sciences: the inverse HHI, Shannon's H, and the normalized versions of both. Through a discussion of each measure, various simulations, and the application of these measures to real political agendas, we have examined and compared the behavior and appropriateness of these measures for capturing the latent attention diversity of theoretical interest. All four measures represent the concept of diversity in some form, both when it comes to known data-generating processes and real-world data with observed events. However, Shannon's H and its normalized version have properties that make them more appropriate, both conceptually and for the purposes of statistical analyses. Specifically, Shannon's H more consistently captures changes in attention diversity through its various levels due to its higher sensitivity, particularly when diversity is either high or low. Shannon's H also has a higher degree of variance, again particularly at high or low levels of diversity, whereas both HHI measures are less sensitive (see Figure 1).

Interestingly, both Shannon's H and normalized Shannon's H perform equally well in demonstrating good measurement sensitivity across the entire range of diversity. The difference between the two is strictly in the scale (or rescaling) of the measure. While the normalized version of the measure is restricted between 0 and 1, Shannon's H is restricted between 0 and ln(N), where N is the number of potential items on the agenda space in question. Therefore, determining which measure is more appropriate should be based on whether or not variance in the number of items across observations or over time is meaningful to the study at hand. For example, if two different legislative agendas exist, one with 10 issues and one with 100 issues, and researchers want to compare the diversity of the two, they could normalize the measure such that the difference in the issues did not matter; or, they could investigate both agendas using Shannon's H, thereby capturing differences in the issue space in the measure. Both approaches are valid, but they imply different conceptualizations of attention diversity, namely within issue spaces (normalized Shannon's H) or absolutely (Shannon's H).

Attention diversity is an important and growing concept in political science. Yet the use of this concept requires the use of a proper and properly understood measure. While the choice of any particular measure should be informed by the specific requirements of a given research question, we conclude that the best measure of attention diversity is Shannon's H or its normalized form. Relative to inverse HHI (and other generalizations of both core measures), they are more appropriate as a match for our conceptual understanding of diversity as applied to attention, more suitable for statistical analyses, and finally more practical from a calculation standpoint. This conclusion is not ours alone. The sensitivity of Shannon's H is clearly a better match to the concept of ecological diversity, with other measures, including the inverse HHI, too quick to converge at high and low levels of diversity (Jost, 2007). Shannon's H also provides a much improved means for assessing numerical diversity in an alternative effective number of parties measure (Greene & Bevan, 2013) that addresses the creator's own biggest concern, the lack of sensitivity in concentrated political systems (Taagepera, 1999). These concerns from other studies are based on variation in the number of items, but as we have shown the lack of sensitivity in the inverse HHI is a problem even when the number of items remains static. All of this evidence points to a clear best measure of diversity: Shannon's H. Our study additionally demonstrates that the value of using Shannon's H or normalized Shannon's H should also be based on the importance that different numbers of possible items have on the research question at hand.

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Notes

1. We refer to attention here as the count of observations associated with each item. For the purposes of our discussion, we treat items as issues. However, items could also be defined as frames, political parties, or any other classifications that separate an agenda into theoretically meaningful parts.
2. While often called by other names, Shannon's H and the Herfindahl Index have been used in numerous disciplines outside political science including, but not limited to economics, computer science, sociology, and biology. The vast assortment of data that these measures have been used on supports their candidacy as a general measure of attention diversity.
3. Entropy concerns the degree of uncertainty associated with a random variable. It can also be thought of as the distribution of possible outcomes. For an accessible introduction to the concept see Ben-Naim (2007).
4. The non-normalized Herfindahl Index's lower range of 1/N is due to the fact that its minimum value cannot be lower than the sum of the squares of 1/N, which thus equals 1/N in the case of a market with equal attention across all items.
5. Other logs besides the natural log can and are used in some applications, with the most common being base 2 for binary data. When comparing across units with varying numbers of items, the common natural log is generally the most appropriate. However, the use of other bases has little effect on the resulting measure.
6. Overall, the effect of this mathematical shortcut on the output is minimal, but this approach does produce a slight bias towards diversity that remains insignificant as long as it is applied uniformly across datasets.
7. For example, social media (e.g., Twitter) and new media (e.g., blogs) are relatively new agendas that have expanded greatly during their short lives in comparison to many of the agendas we commonly consider, such as the old media agenda. In these cases non-normalized Shannon's H as a measure based off proportions (as are our other measures) is not only equipped to handle the millions of individual items due to the transformation of the data, but is able to capture the expansion of the agenda space into large numbers of new items with its variable maximum value.
8. For complete information regarding the U.S. and UK coding schemes see http://www.policyagendas.org and http://policyagendas.org.uk/.

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