

# Does Interpersonal Discussion Increase Political Knowledge? A Meta-Analysis

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## Abstract

Theorists have long argued that discussing public affairs with others increases citizens' knowledge of politics. Yet, empirical tests of this claim reach contradictory results, with some studies reporting large effects of discussion on knowledge while others report small effects or fail to confirm the hypothesis. To account for this inconsistency, the current study meta-analyzes this literature. The results, based on 163 research findings from 134 independent studies ( $N = 412,933$ ), indicate positive and significant mean effect sizes of  $r = .15$  for discussion frequency,  $r = .1$  for discussion heterogeneity, and  $r = .18$  for discussion network size. While all three effects are statistically significant, a meta-analytic relative weights analysis reveals that discussion heterogeneity explains little variance in political knowledge once discussion frequency and network size have been accounted for. In other words, how much citizens talk about politics matters much more than whom they talk to.

## Keywords

interpersonal communication, political discussion, political knowledge, meta-analysis, deliberation

Interpersonal communication is a mainstay of democracy. While direct interaction among citizens can benefit democracy in various ways, theorists have placed special emphasis on the potential of political conversations to contribute to an informed citizenry by increasing people's knowledge of public affairs (Gastil & Dillard, 1999; Kim, Wyatt, & Katz, 1999). Talking to others about politics exposes discussants to information they have not been aware of before, thereby increasing their set of available

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arguments for and against an issue (Mutz, 2006). It also leads participants to question their own and their peers' views, thus contributing to the formation of more accurate and manipulation-resistant attitudes (Druckman, 2001). At the societal level, increased citizen knowledge promotes arrival at informed solutions for collective problems and increases civic engagement in politics (Fishkin, 1997).

In the past two decades, researchers have accumulated a large body of evidence putting the theoretical claim that interpersonal discussion increases political knowledge to an empirical test. These studies, however, yield contradictory results, with some documenting moderate to large effects of discussion on knowledge (e.g., Eveland, McLeod, & Horowitz, 1998), while others report very small effects (e.g., Nisbet & Scheufele, 2004), null results (e.g., de Boer & Velthuisen, 2001) or, in a few instances, even weak *negative* effects (e.g., Gil de Zúñiga, Weeks, & Ardevol-Abreu, 2017). Another source of inconsistency in the literature relates to the impact of the composition of one's discussion network. Specifically, some scholars argue that knowledge gains are more likely when people discuss politics across lines of disagreement (e.g., Mutz, 2006), while others find that disagreement (or heterogeneity) in political discussions has a deleterious effect on people's political knowledge (e.g., Feldman & Price, 2008).

The goal of the current study is threefold. First, we seek to reveal whether, despite the contradictory results reported in the literature, the overall effects of different aspects of political discussion—namely, frequency, heterogeneity, and network size—are significantly different from zero when examined across contexts. Second, we estimate how large each average effect is. Third, we assess which dimension of political discussion contributes more than the others to citizens' political knowledge. While no single study can provide a definitive answer to these questions, a meta-analysis can get close, as it considers the entire available empirical evidence on a given theoretical relationship. Our goal here, therefore, is to quantitatively assess what the literature exploring this theoretical relationship has accomplished so far.

We believe a meta-analytic investigation of this literature is called for not only because of the importance of interpersonal communication and political knowledge for democratic citizenship but also due to the especially large number of empirical studies investigating their relationship that have been conducted in the past two decades. To the best of our knowledge, research findings on this effect have yet to be systematically integrated and substantively interpreted. In addition, as we elaborate below, a thorough search of the literature finds that studies on the effect of discussion on political knowledge have been conducted in different political contexts and relied on different operationalizations of the variables of interest. In the moderator analyses section below, we test whether differences in study context and design can explain why an effect is present in some studies but absent in others, or larger in some studies than in others.

Our results indicate that in our pool of data, which encompasses 134 studies conducted among 412,933 citizens, talking about politics with others has a positive and significant overall effect on political knowledge. This conclusion remains robust even

after subjecting the data to a comprehensive battery of sensitivity analyses (Kepes, Bushman, & Anderson, 2017). This result, which confirms a major premise of deliberative democracy theory, signals that studies reporting null or negative effects are likely, in many cases, to be false negatives stemming from low statistical power or from unique sample and model specifications. In addition, our systematic assessment of the relative importance of different dimensions of political discussion points to discussion frequency and network size as much more important determinants of political knowledge than discussion heterogeneity. In other words, how much citizens talk about politics and with how many people matters more for their knowledge levels than whom they talk to.

## Conceptualizing Political Knowledge

Political knowledge is a core construct in studies of political communication and behavior that affects diverse fields of research, from public opinion and media effects to voting behavior (Mondak, 2001). Since being informed about political matters is considered a desirable democratic outcome, citizens' knowledge levels have been studied extensively. Research finds that knowledgeable citizens hold political views that are more consistent across time and issues (Galston, 2001), process new political information more efficiently (Miller & Krosnick, 2000), and are much more likely to participate in politics (Althaus, 2003).

The most prominent conceptualization of political knowledge defines it as "a citizen's ability to provide correct answers to a specific set of fact-based questions" (Boudreau & Lupia, 2011, p. 171; Delli Carpini & Keeter, 1996). While the tendency to generalize about citizens' competence from their responses to factual questions has been criticized (e.g., Lupia, 2006), the use of factual questions remains, by far, the most prominent way of measuring knowledge levels. The questions scholars use to tap political knowledge ask respondents about the structure and functioning of political institutions; officeholders and political parties; specific laws and policies; issues related to national and international affairs, and more (Barabas, Jerit, Pollock, & Rainey, 2014; Delli Carpini & Keeter, 1996; Mondak, 2001). Typically, a knowledge index summing the number (or calculating the proportion) of correct answers respondents could provide to a battery of factual questions is constructed and used for statistical analysis.

It should be noted that other conceptualizations of political knowledge exist in the literature as well. One such conceptualization is structural political knowledge, which taps "the extent to which individuals see connections or relationships among various concepts within the political domain" (Eveland & Hively, 2009, p. 212). Another conceptualization is subjective political knowledge, where respondents are asked to evaluate their own knowledge levels or the knowledge levels of the people they interact with (e.g., Huckfeldt, Beck, Dalton, & Levine, 1995). As we show below, however, the literature on interpersonal discussion and political knowledge has almost uniformly adopted factual political knowledge measures.

## The Effect of Discussion on Political Knowledge

A growing empirical literature investigates the impact of citizens' face-to-face discussions on their acquisition of political knowledge. In this literature, the prevalent theoretical view is that the effect of discussions on political knowledge should be positive (e.g., Eveland & Hively, 2009). Several mechanisms have been proposed as explanations for this association, with two prominent mechanisms being exposure and cognitive elaboration. *Exposure* posits that discussing politics with others is an opportunity for citizens to access information they would have never been exposed to otherwise. The second explanation posits that discussions elicit *cognitive elaboration*, which is "the process of connecting new information to other information stored in memory . . . or the connection of two new bits of information together in new ways" (Eveland, 2001, p. 573). According to Eveland (2004), the process of elaboration can take place either before a conversation, as part of participants' internal deliberations when preparing themselves for discussion, or during the act of discussion, when novel inferences are made. Other mechanisms of influence are the correction of inaccurate information by more knowledgeable discussion partners (Mill, 1861/1972) and the crystallization of existing knowledge resulting from the act of retrieving information from memory and repeating it verbally (Hirst & Echterhoff, 2012).

Recognizing the multidimensional nature of political discussion, researchers have studied the impact of different aspects of this construct on political knowledge, with the three most commonly studied and theoretically developed aspects being (a) discussion frequency, (b) discussion heterogeneity, and (c) discussion network size. *Discussion frequency* measures how often (typically operationalized as the number of days per week) people talk about politics with others, such as family members, friends, and co-workers. Based on the theoretical mechanisms described above, the assumption in this line of research is that the more conversations on politics people have, the more likely they are to get exposed to new information, elaborate on their existing knowledge, and correct inaccurate information they possess (Kim et al., 1999).

The second aspect, *discussion heterogeneity*, taps the extent to which people are exposed to different views in their political conversations (Scheufele, Nisbet, Brossard, & Nisbet, 2004). Studies focusing on this dimension ask whether discussions with people with divergent political viewpoints increase one's political knowledge levels more or less than do discussions with like-minded others. Even though discussion heterogeneity has been studied much less than discussion frequency, meta-analyzing the evidence on the effects of this dimension of discussion on knowledge seems especially important given the conflicting theoretical arguments in the literature. While some work argues that exposure to disagreement enhances political knowledge because conflicting viewpoints stimulate cognitive elaboration (Hively & Eveland, 2009), other research posits that disagreement confuses voters and dampens knowledge gained from other sources, such as the news media (Feldman & Price, 2008).

The third aspect of political discussion examined in relation to political knowledge is *network size*, defined as the number of people with whom an individual discusses politics. Discussing politics with more people is consistently theorized to have a

positive effect on political knowledge because talking to more people exposes one to a broader range of information and increases the likelihood of encountering politically knowledgeable discussion partners (e.g., Eveland & Hively, 2009). This aspect of discussion is typically measured using “name generator” techniques asking respondents to list their discussion partners (Huckfeldt et al., 1995) or by asking respondents to report how many people they discuss politics with on a regular basis (Moy & Gastil, 2006).

While survey-based measures of political discussion, such as the three just depicted, are widely used, experimental studies testing the influence of interpersonal discussion on political knowledge are extremely rare (Eveland & Schmitt, 2015). One related body of *quasi*-experimental literature, however, assesses the effects of *deliberative events* on political knowledge (Luskin, Fishkin, & Jowell, 2002).<sup>1</sup> In these studies, citizens participate in an intensive period of group deliberations, usually on a single policy issue. Prior to the deliberative event, participants are sent briefing materials to engage with for a few days. The deliberation then takes place in a single site, where participants spend between a few hours and several days discussing the selected issue in groups and interacting with experts.

Even though deliberative events offer strong data in terms of assessing causality, these studies are not included in our meta-analysis for two reasons. The first is their fundamentally different research design. While survey-based self-reports ask people how they *usually* discuss politics with the people closest to them, in deliberative events discussions take place in a single event among a selected group of individuals who did not know each other prior to the discussion. In addition, participants in deliberative events receive an extensive information packet prior to group discussions, participate in plenary question and answer sessions with experts, and their discussions are often facilitated by a professional moderator (Mutz, 2006). This makes these studies too different to be included in the same meta-analysis. The second reason for the exclusion of these studies is that a diverse set of deliberative designs have been adopted over the years (e.g., in terms of event length, type of discussion, with or without a moderator, etc.). This suggests that this literature is worthy of a detailed and comprehensive meta-analysis of its own, a goal that is beyond the scope of the current study.

## The Current Meta-Analysis

Even though most theoretical accounts predict a positive relationship between interpersonal discussion and political knowledge, empirical studies on the issue reach contradictory conclusions, with some confirming the hypothesis that discussion increases knowledge (e.g., Eveland, 2004) while others fail to do so (e.g., de Boer & Velthuisen, 2001). In the absence of a meta-analysis that systematically synthesizes the existing evidence on this relationship, we can neither conclude that political discussion increases knowledge beyond the context of a single study nor estimate the overall magnitude of the effect. Moreover, studies exploring this relationship vary substantially in terms of precision, with some utilizing relatively small samples while others are huge *N* studies. Under such conditions, a simple “vote counting” of the number of

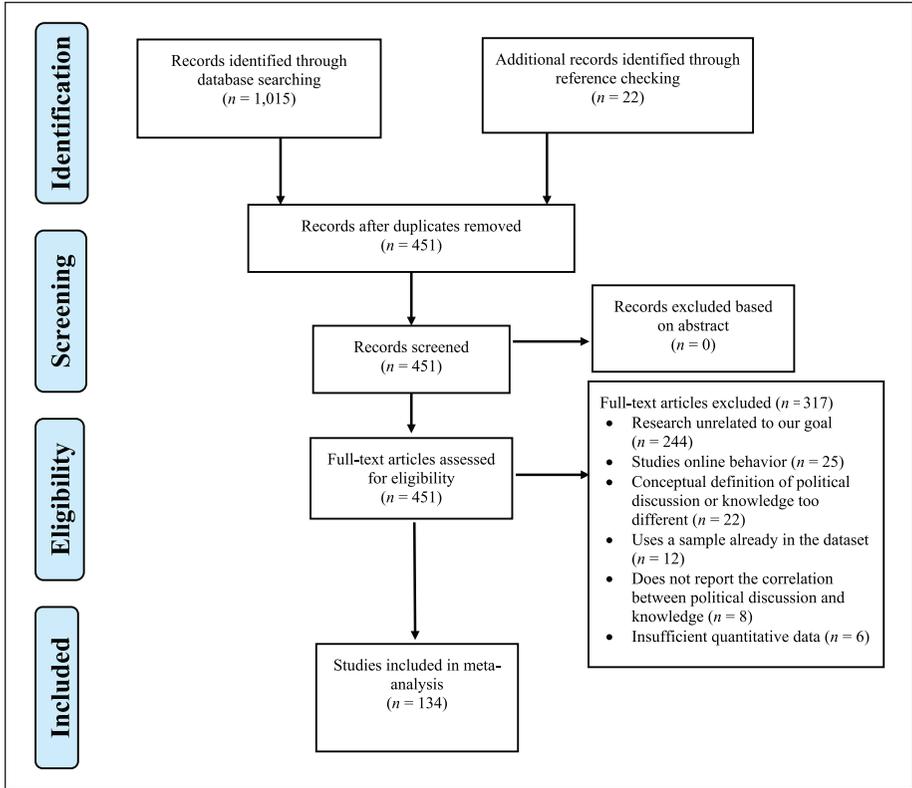
significant effects in the literature can yield extremely biased results, since “while a nonsignificant finding could be due to the fact that the true effect is nil, it can also be due simply to low statistical power” (Borenstein, Hedges, Higgins, & Rothstein, 2009, p. 252). In other words, a study’s statistical power, which is most easily approximated by its sample size, must be taken into consideration when synthesizing results from multiple studies.

## Method

To gather studies on the effect of discussion on political knowledge, we searched, through March 2019, for relevant studies in the following databases: Communication and Mass Media Complete, Google Scholar, ProQuest, PsycINFO, ScienceDirect, and Web of Science. After an initial pool of studies was gathered, we complemented it by thoroughly searching the databases on the websites of major publishers in the fields of communication and political science (Cambridge, University of Chicago Press, Elsevier, Sage, Springer, Taylor & Francis, and Wiley) and the websites of prominent scholars working on these topics. In addition, we visually inspected the reference lists of all studies included in the dataset and the lists of studies citing them as they appear in Google Scholar.

The keywords we searched for were terms used in the literature to denote political discussion and political knowledge.<sup>2</sup> Studies relying on fundamentally different theoretical assumptions to measure knowledge have been excluded. This includes variables such as subjective evaluation of one’s own knowledge (e.g., Klofstad, 2011) and knowledge structure density (e.g., Hively & Eveland, 2009). These studies were excluded not only because they are theoretically distinct but also because research has shown repeatedly that they yield fundamentally different results. For example, subjective (self-reported) measures yield different effects than objective measures (factual knowledge) because people tend to overestimate their own knowledge levels (Ran, Yamamoto, & Xu, 2016), and structural knowledge is affected differently from factual knowledge because identifying the relationships between political concepts is theoretically distinct from merely remembering the concepts (Eveland & Schmitt, 2015).

Figure 1 visualizes the different stages of our systematic literature search according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, Altman & The PRISMA Group, 2009). After being screened for initial relevance, each study was examined in depth to ensure (a) that it measures political discussion and political knowledge as they were conceptualized above<sup>3</sup> and (b) that it reports an effect size or statistics that can be converted into an effect size. In addition, since an important assumption in a meta-analysis is that the studies analyzed are independent, in cases where multiple studies using the same dataset were located, we only included the study with the largest sample (i.e., the more precise estimation). When one study reported multiple independent effects of discussion on knowledge (e.g., an article reporting two studies, each utilizing a different sample), each independent effect was treated as a separate study. Finally, when a study reported several relevant effect sizes obtained from the same sample, we computed the mean of the outcomes for that study and used this score as the unit of analysis



**Figure 1.** Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram.

(Borenstein et al., 2009). The resulting dataset consists of 134 independent studies conducted among 412,933 citizens. Online Appendix A presents the full list of studies included in the meta-analysis, and Online Appendix B displays the characteristics of each study.

We should note here that although we made significant efforts to conduct a thorough literature search, additional studies on this relationship may exist that were not available to us for various reasons (e.g., studies not indexed in popular search engines). This is an inevitable limitation of any literature search. Yet, thanks to the large sample of studies we did locate, a large number of studies reporting opposite results to those reported here would be needed to change our conclusions. We consider the existence of such a pool of studies highly unlikely.

### Effect Size Computation

For the studies in a meta-analysis to be comparable, the statistics they report must be converted to a common, standardized metric. In our dataset, the effect size metrics

reported varied, with studies reporting bivariate correlations (Pearson's  $r$ ), regression coefficients ( $b$  or  $\beta$ ), mean differences,  $t$ -tests,  $F$ -tests, and proportion tests. To render the studies comparable, we converted all statistics to a standard and widely used effect size measure with a straightforward interpretation—Pearson's correlation coefficient ( $r$ ). This effect size measure is appropriate because the studies in our dataset employ a correlational design. Effect size conversions were based on the formulas and recommendations of Borenstein et al. (2009) and conducted using the R package *compute.es*.

For studies reporting regression models, we relied on Peterson and Brown's (2005) formula for converting standardized regression coefficients (betas) to correlation coefficients.<sup>4</sup> Analyzing more than 1,700 corresponding regression and correlation coefficients published across the behavioral sciences, Peterson and Brown (2005) demonstrate that beta values can be transformed to  $r$  values regardless of the number of predictors included in the regression. Their approach was adopted in many subsequent meta-analyses, including in communication (e.g., Matthes, Knoll, & von Sikorski, 2018).<sup>5</sup> Yet, in light of recent criticism of this approach (Roth, Oh, Le, Iddekinge, & Bobko, 2018), we present in the results section a moderator analysis comparing the results of studies reporting regression models with the results of studies reporting bivariate correlations.

## Moderators

To test whether study-level factors predict the effect size a study reports, each study in our dataset was coded for multiple variables. First, we coded for research design, as some studies in the literature are cross-sectional surveys while others are panel studies. Second, studies differ in the type of knowledge they examine, with some focusing on general political knowledge while others examine knowledge of a specific issue. Third, a more fine-grained version of the previous variable was constructed to tap the knowledge domain a study examines. This moderator distinguishes between questions about (a) political figures and institutions, (b) current events, and (c) the issue positions of candidates. Fourth, based on the political discussion questions asked in each primary study, we coded for the identity of the discussion partner (a general frequency question, discussions with friends or family members, or youth discussions with their parents).<sup>6</sup> Fifth, studies differ in their sample composition, with most studies sampling voting-age citizens but some relying on youth samples (typically, high-school students).

Sixth, although a large majority of the studies were conducted in the United States, studies have also been conducted in multiple other countries. Since most non-U.S. countries had only one or two studies, however, a test comparing all existing subgroups would have very low statistical power. Therefore, we treated country as a binary variable differentiating between studies conducted in the United States and studies conducted elsewhere. Seventh, to test whether temporal context has an impact on the average effect size, we measured whether a study was conducted during an election campaign or in a nonelection period. Eighth, as mentioned above, we compared studies reporting multivariate regressions and studies reporting bivariate correlations.

Finally, we also measured two continuous moderators. The first is the number of items used to tap political knowledge, as some primary studies use as few as two or three knowledge questions while others use more than 10. Since studies using fewer items produce higher measurement error, they may underestimate the effect size. The second continuous moderator measured the number of covariates used in a model, as some studies in our dataset include no controls while others control for as many as 10 or even 15 alternative explanations.

## Results

### *Characteristics of Studies*

The 134 studies included in the meta-analysis were published in the period between 1973 and 2018, with the median year of publication being 2007. In total, 104 studies were conducted in the United States and 30 in other countries. The studies' sample sizes ranged from 53 to 69,125, with a median sample size of 935. Of the 117 publications included in the meta-analysis,<sup>7</sup> 87 are journal articles, four are books or chapters from edited books, and 26 are unpublished papers (e.g., conference papers, dissertations). As for disciplinary orientation, among the 87 journal articles, 35 were published in communication journals, 24 in political science journals, 16 in journals at the intersection of both disciplines (e.g., *Political Communication*), and 12 in journals from other disciplines (e.g., education).

### *The Effect of Interpersonal Discussion on Political Knowledge*

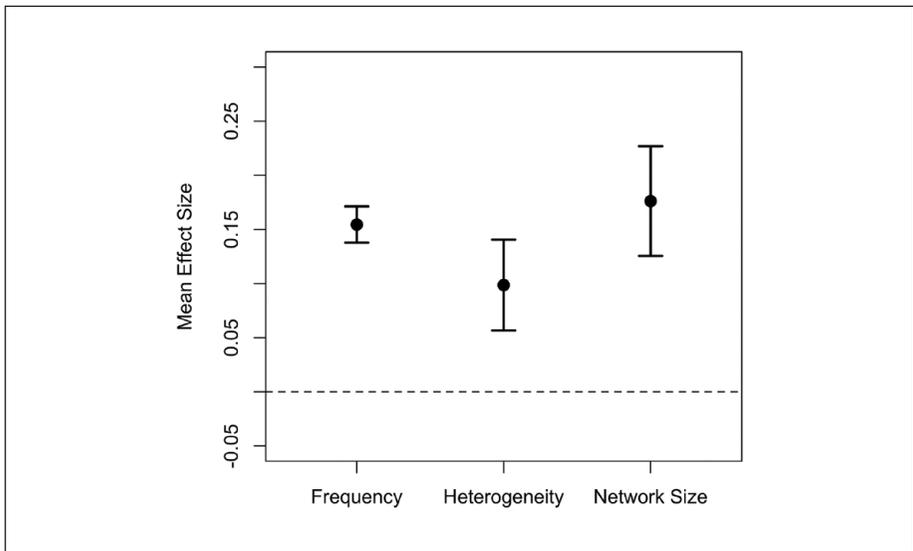
To test the studies' main research questions, we conducted a random-effects meta-analysis using the R package *meta*. Since we explore three distinct aspects of political discussion, we conduct three meta-analyses, one for each aspect. We begin by analyzing the relationship between *discussion frequency* and political knowledge. We find an average effect of  $r = .15$  in the 113 studies examining this relationship. This result is highly significant (95% CI = [.14, .17],  $z = 17.73$ ,  $p < .001$ ), which allows us to confirm the hypothesis that the more frequently citizens discuss politics, the more politically knowledgeable they are. Our second meta-analysis focuses on the effect of *discussion heterogeneity* on political knowledge. We find an average effect of  $r = .1$  for this aspect of discussion (95% CI = [.06, .14],  $z = 4.57$ ,  $p < .001$ ,  $k = 37$ ), which indicates that talking to people with divergent political views increases political knowledge. Finally, we find an average effect of  $r = .18$  for *discussion network size* (95% CI = [.13, .23],  $z = 6.67$ ,  $p < .001$ ,  $k = 13$ ), indicating that the larger the number of people one talks to about politics, the more knowledgeable one is. The full results of our three meta-analyses, along with heterogeneity statistics, are presented in Table 1.

Figure 2 illustrates our main results by plotting the mean effect size and 95% confidence interval for each dimension of political discussion. The figure shows that the correlation between political discussion and political knowledge is positive and

**Table 1.** A Meta-Analysis of the Correlation Between Interpersonal Discussion and Political Knowledge.

Predictor	<i>k</i>	<i>N</i>	$\bar{r}$	95% CI	<i>Z</i>	<i>p</i>	<i>Q</i>	$\tau$	<i>I</i> <sup>2</sup>
Discussion frequency	113	394,046	.15	[.14, .17]	17.73	<.001	2,771.03	.09	96%
Discussion heterogeneity	37	29,911	.1	[.06, .14]	4.57	<.001	478.9	.12	92.5%
Discussion network size	13	11,756	.18	[.13, .23]	6.67	<.001	92.68	.09	87.1%

Note. *k* = number of effect sizes; *N* = number of individual respondents;  $\bar{r}$  = mean observed correlation; 95% CI = 95% confidence interval; *Q* = weighted squared deviations from the mean;  $\tau$  = between-sample standard deviation; *I*<sup>2</sup> = proportion of unexplained variance: the percentage of variation across studies that is due to heterogeneity rather than chance.



**Figure 2.** The average effects of interpersonal discussion on political knowledge. Note. Point estimates are mean correlations, error bars are 95% confidence intervals.

significant for all three aspects of discussion. Furthermore, it shows that the average effect size is noticeably smaller for discussion heterogeneity than it is for the two other aspects. To formally evaluate this variation, we have conducted both a meta-analytic relative weights analysis (Tonidandel & LeBreton, 2011) and assessed the incremental validity (Banks, McCauley, Gardner, & Guler, 2016) of discussion heterogeneity and discussion network size over and above discussion frequency. The relative weights analysis shows that when modeling the three independent variables together and taking into account their intercorrelations, discussion heterogeneity

explains only 10% of the variance in political knowledge, compared with 38% and 52% for discussion frequency and discussion network size, respectively. Furthermore, an incremental validity analysis indicates that while discussion network size almost doubles the variance in political knowledge attributed to discussion frequency (from  $R^2 = .026$  to  $R^2 = .045$ ), discussion heterogeneity explains practically zero additional variance after discussion frequency has been accounted for (from  $R^2 = .026$  to  $R^2 = .029$ ). More details on these analyses, which indicate that network heterogeneity has little practical relevance once discussion frequency and network size have been accounted for, are presented in Online Appendix F.

### *Moderator Analyses*

In this section, we test whether the characteristics of a study are predictive of the effect size it reports. Our tests focus on the factors moderating the effect of discussion frequency because this aspect of interpersonal discussion is the only one for which we have a large enough sample of studies that allows powerful moderator analyses (Hedges & Pigott, 2004).<sup>8</sup> A test for the heterogeneity of the mean effect size of discussion frequency is statistically significant,  $Q(112) = 2,771.03$ ,  $p < .001$ , and the  $I^2$  statistic in this meta-analysis is 96% (see Table 1), indicating that 96% of the observed variance in effect sizes can be attributed to real differences between studies rather than to chance. According to the conventions introduced by Higgins, Thompson, Deeks, and Altman (2003),  $I^2$  values above 75% denote high degrees of heterogeneity. To try and account for this heterogeneity, we conduct multiple moderator analyses, which are summarized in Table 2. As the table shows, the mean correlation of discussion and political knowledge is of a similar magnitude for different research designs, for general and issue-specific knowledge, for different knowledge domains, for adult and youth samples, and for U.S. and non-U.S. samples.

On the other hand, three moderators were found to have a statistically significant effect. First, as the “discussion partner” moderator shows, youth discussing politics with their parents yields a slightly larger average effect size than other types of discussion. This result can be attributed to the greater chances for knowledge gains prior to fully entering adulthood (Jennings, 1996). Second, studies reporting bivariate correlations yield, on average, slightly larger effect sizes than studies reporting regression coefficients. We attribute this to the multidimensional nature of political knowledge, which is known to be correlated with multiple other factors, including mass media use, political interest, gender, and education (Delli Carpini & Keeter, 1996). Since studies reporting regression coefficients typically control for most of the abovementioned alternative explanations, the average effect size they observe tends to be slightly smaller. Third, studies conducted during election campaigns yield, on average, slightly larger effect sizes than studies conducted at nonelection times. This result is in line with prior research finding that interpersonal political discussions are an especially important source of political learning for citizens during election campaigns (e.g., Andersen & Hopmann, 2018).

**Table 2.** Moderator Tests for Discussion Frequency Meta-Analysis.

	<i>k</i>	$\bar{r}$	95% CI	<i>Q</i>	<i>I</i> <sup>2</sup>	Test	<i>p</i>	Res. <i>I</i> <sup>2</sup>
Design						<i>Q</i> (1) = 0.94	.33	95.9%
Cross-section	83	.16	[.14, .18]	2,392.08	96.6%			
Panel	30	.14	[.11, .17]	337.27	91.4%			
Type of knowledge						<i>Q</i> (1) = 0.78	.38	95.5%
General	88	.16	[.14, .18]	2,365.54	96.3%			
Issue-specific	25	.14	[.12, .16]	115.05	79.1%			
Knowledge domain						<i>Q</i> (3) = 0.6	.9	95%
Figures and institutions	42	.16	[.14, .18]	422.65	90.3%			
Candidate/party positions	27	.16	[.13, .19]	311.06	91.6%			
Issues	18	.14	[.1, .19]	125.43	86.4%			
Other	26	.15	[.1, .2]	1,301.22	98.1%			
Discussion partner						<i>Q</i> (3) = 10.01	.02	95.5%
General	19	.14	[.11, .16]	217.25	91.7%			
Family or friends	64	.16	[.13, .18]	1,975.22	96.8%			
Parents	7	.21	[.17, .24]	18.29	67.2%			
Other	23	.15	[.11, .18]	200.43	89%			
Sample composition						<i>Q</i> (1) = 1.83	.18	95.9%
Adult	91	.15	[.13, .17]	2,526.33	96.4%			
Youth	22	.18	[.14, .21]	182.09	88.5%			
Country						<i>Q</i> (1) = 0.69	.4	95.7%
U.S.	86	.16	[.14, .18]	966.39	91.2%			
Non-U.S.	27	.14	[.1, .18]	1,606.4	98.4%			
Type of effect size						<i>Q</i> (1) = 6.3	.01	96.1%
Correlation coefficient	19	.21	[.16, .27]	260.21	93.1%			
Regression coefficient	91	.14	[.12, .16]	2,488.19	96.4%			
Context						<i>Q</i> (1) = 4.56	.03	95.9%
Election	64	.17	[.15, .19]	882.29	92.9%			
Nonelection	46	.13	[.1, .16]	1,783.72	97.5%			

Note. *k* = number of studies;  $\bar{r}$  = mean correlation; 95% CI = 95% confidence interval; *Q* = weighted squared deviations from the mean; *I*<sup>2</sup> = proportion of unexplained variance; Res. *I*<sup>2</sup> = residual *I*<sup>2</sup> after adjusting for moderator.

Finally, to test for the effects of our two continuous moderators, we estimated two meta-regressions using the R package *metafor*. We find that both the number of items used to measure political knowledge ( $b = -0.0002$ , 95% CI =  $[-0.0028, 0.0025]$ ,  $z = -0.12$ ,  $p = .91$ ) and the number of covariates controlled for in a model ( $b = -0.0022$ , 95% CI =  $[-0.0058, 0.0013]$ ,  $z = -1.23$ ,  $p = .22$ ) have no influence on the magnitude of the effect.

In summary, seven of 10 moderators we have examined have no impact on the effect size. In addition, for the three moderators that did yield a statistically significant effect, the subgroup analyses presented in Table 2 clearly show that meta-analyzing each subgroup separately yields an average effect size that is positive, significant, and of a very similar magnitude as the pooled analysis in all cases. This, in addition to the high residual  $I^2$  values presented in Table 2, indicates that in all cases tested here, the differences between subgroups of studies are of little practical and theoretical importance.

### Sensitivity Analyses

To examine whether our meta-analytic results remain stable when the conditions of the data or the analysis change, we have conducted a series of sensitivity analyses. We rely on the comprehensive battery of sensitivity analyses recently recommended by Kepes et al. (2017), which includes a series of publication bias analyses (trim-and-fill, cumulative meta-analysis, and selection models), a one-sample removed analysis, and a battery of influence diagnostics. The results of all sensitivity analyses, conducted using the *meta* and *metafor* R packages, are displayed in Table 3 and in Online Appendices C, D, and E. In addition, in Online Appendix G, we conduct these sensitivity analyses at the subgroup level as well.<sup>9</sup>

**Trim-and-fill.** The fact that significant results and large- $N$  studies are more likely to get published than studies with nonsignificant results and small samples raises serious concerns that the published literature overestimates effect sizes (Dickersin, 2005). To test and correct for potential such bias, we conducted a trim-and-fill analysis (Duval & Tweedie, 2000), which is a frequently used technique that estimates the number of studies missing due to publication bias and then re-evaluates the mean effect size after “filling in” the missing effect sizes. We applied both a fixed-effects and a random-effects trim-and-fill model, both using the  $L_0$  estimator (Kepes, Banks, McDaniel, & Whetzel, 2012). The results, displayed in Table 3, show no evidence of publication bias in the discussion frequency and discussion network size literatures. However, they do indicate potential bias in the discussion heterogeneity literature, where the average effect size decreases from  $r = .1$  to  $r = .05$  in the fixed-effects model and to  $r = .06$  in the random-effects model. Additional details on our trim-and-fill analyses, as well as graphs plotting their results, are available in Online Appendix C.

**Cumulative meta-analysis.** A cumulative meta-analysis examines how the meta-analytic effect size shifts as a function of some factor of interest. The procedure entails first

**Table 3.** Sensitivity Analyses.

Predictor	FE trim-and-fill		RE trim-and-fill		Selection models			osr $\bar{r}$	
	<i>ik</i>		$t\&f_{FE} \bar{r}$	<i>ik</i>	$t\&f_{RE} \bar{r}$	$sm_{om} \bar{r}$	$sm_{os} \bar{r}$	$sm_{tm} \bar{r}$	$sm_{ts} \bar{r}$
Discussion frequency	44	.22	0	.15	.14	.14	.15	.14	.15, .16
Discussion heterogeneity	8	.05	7	.06	.07	-.26	.09	.08	.09, .11
Discussion network size	2	.19	3	.2	.17	.16	.17	.16	.16, .18

Note. FE trim-and-fill = fixed-effects trim-and-fill; RE trim-and-fill = random-effects trim-and-fill; *ik* = number of imputed effect sizes from trim-and-fill procedure;  $t\&f_{FE} \bar{r}$  = fixed-effects trim-and-fill-adjusted mean correlation;  $t\&f_{RE} \bar{r}$  = random-effects trim-and-fill-adjusted mean correlation;  $sm_{om} \bar{r}$  = one-tailed moderate selection model-adjusted mean correlation;  $sm_{os} \bar{r}$  = one-tailed severe selection model-adjusted mean correlation;  $sm_{tm} \bar{r}$  = two-tailed moderate selection model-adjusted mean correlation;  $sm_{ts} \bar{r}$  = two-tailed severe selection model-adjusted mean correlation; osr  $\bar{r}$  = minimum and maximum mean correlations from one-sample removed analysis.

performing a meta-analysis with one study, then with two studies, and so on, until all relevant studies have been included in the analysis (Borenstein et al., 2009). In Online Appendix D, we display three cumulative meta-analyses, in which we sort the studies from the most to the least precise; if studies at the bottom of the graph (small ones) report larger effects, this is evidence of publication bias. We find no evidence that smaller studies increase the overall effect size of discussion frequency and discussion network size. However, we do find evidence of publication bias for discussion heterogeneity, where smaller studies tend to report larger effects.

*Selection models.* We estimated a series of selection models, which use weights to assess the likelihood of a study being published based on a given a priori  $p$ -value (Vevea & Woods, 2005). This method of assessing publication bias is advantageous because it performs well under realistic scenarios of heterogeneous effect sizes, can be applied to both large and small samples of studies, and allows to explore different conditions of publication bias (McShane, Böckenholt, & Hansen, 2016). Specifically, if the magnitude of the mean effect size is reduced under any of the selection models, this suggests that publication bias may be driving the estimates and that the true average effect size is smaller than reported. As shown in Table 3, we find that our estimates are, by and large, highly stable across different selection models.<sup>10</sup>

*One-sample removed analysis.* To assess the influence of each individual study on our results, we repeated each meta-analysis  $k$  times, each time leaving one sample (i.e., one primary study) out (Borenstein et al., 2009). The results, presented in the final column of Table 3, illustrate the range of possible effect sizes if any one sample is removed from the analysis. As the table shows, our results are virtually identical for all three meta-analytic estimates, indicating that our conclusions are robust to the removal of any single primary study.

*Influence diagnostics.* Finally, to ensure that our conclusions are not driven by extreme observations, we ran the influence diagnostics battery recommended by Viechtbauer and Cheung (2010). This battery calculates a variety of outlier and influential case diagnostics for each primary study, including Cook's distance and a covariance ratio. We find that two studies have rather large residuals and may be considered outliers. First, in the discussion frequency meta-analysis, Gil de Zúñiga, Valenzuela, and Weeks (2016) report an effect size of  $r = -.1$ . Second, in the discussion network size meta-analysis, Diehl, Weeks, & Gil de Zúñiga (2016) report an effect size of  $r = .4$ . The removal of each study from the respective meta-analysis, however, leaves our estimates practically identical. In Online Appendix E, we present all influence diagnostics as well as the relevant meta-analyses after removal of these two influential cases.

## Discussion

Even though a considerable body of literature exploring the relationship between interpersonal discussion and political knowledge has accumulated over the past two

decades, to date, the existing evidence on this effect has not been systematically combined nor substantively interpreted. Synthesizing results from 134 independent studies conducted among more than 400,000 subjects, we find that, consistent with the prevalent theoretical perspective in the literature, the average effect of different dimensions of interpersonal discussion on political knowledge is positive and significant.

While our results are generally consistent in terms of the direction, magnitude, and significance of the summary effect, our relative weights and incremental validity analyses have allowed us to isolate the unique contribution of each dimension of political discussion, while controlling for the influence of the two other dimensions. We find that, in contrast to the claim that heterogeneous political discussion increases the range of information citizens are exposed to and thus enhances their political knowledge (e.g., Huckfeldt et al., 1995; Mutz, 2006), discussion heterogeneity contributes little to political knowledge once discussion frequency and network size have been accounted for. This conclusion, which is based on an especially number of studies ( $k = 134$ ), is further supported by the smaller effect size we observe for discussion heterogeneity ( $r = .1$ , compared with  $r = .15$  and  $r = .18$ ) and by evidence we present suggesting that this effect (but not the two others) is driven by publication bias (see Table 3). Our conclusion is that, considering the literature as a whole, disagreement in discussion contributes much less to political knowledge than discussing politics (a) often and (b) with many people.

An important question regarding the relationship we are studying is what the direction of causality is. On the one hand, both our data and previous research support the view that causality runs from discussion to knowledge. For example, we find that panel studies, in which discussion at Time 1 is correlated with knowledge at Time 2, report substantial and significant knowledge gains. This result is in line with Eveland, Hayes, Shah, and Kwak's (2005) systematic account of the direction of causality between these two variables. Using panel data, they compare different structural models and demonstrate that causality indeed runs from discussion to knowledge. Yet, in our case, since most of the data we rely on is cross-sectional, we cannot rule out the possibility for reverse causality or reciprocal effects. It is possible, for instance, that those who discuss politics frequently gain political knowledge, which in turn makes them better equipped or more motivated to engage in further discussions.

As for the size of the effect, while correlations in the range between .1 and .2 are considered small by some standards, we believe an effect size of this magnitude is substantively important in the context we are studying. Two reasons lead us to this conclusion. The first is that both classic (Abelson, 1985) and more recent accounts (Anderson et al., 2010) show that correlations of this size can have important practical implications. Since political knowledge is determined by multiple processes (Delli Carpini & Keeter, 1996), a single variable is not likely to account for a large proportion of the variance, especially when other relevant variables are controlled for. In addition, interpersonal discussion effects are likely to be cumulative, as a single or only a few discussions probably contribute little to political knowledge but repeated discussions over time become substantial knowledge gains. Our argument is that under such conditions, a relatively small effect size can translate into meaningful influence

given repeated interactions. To illustrate this point, according to Rosenthal's (1986) notion of a "binomial effect-size display" (BESD), a correlation of  $r = .15$  for discussion frequency suggests that, on average, 42% of the citizens who seldom discuss politics are expected to be politically knowledgeable, compared with 58% of the citizens who discuss politics frequently. We see this difference as nontrivial when considering the population as a whole.

The second fact that makes this effect size nontrivial is that it is comparable to the effect sizes obtained in other meta-analyses on political communication effects. Research syntheses of studies on media priming (Roskos-Ewoldsen, Klinger, & Roskos-Ewoldsen, 2007), the spiral of silence (Matthes et al., 2018), and other influences consistently yield effect sizes that fall within the range of .1 and .3. In fact, previous studies focusing specifically on communication effects on political knowledge have yielded summary effect sizes almost identical to ours (e.g., Benoit, Leshner, & Chattopadhyay, 2007; Zoizner, 2018).

Future studies are encouraged to broaden the scope of this investigation in several ways. One rather surprising finding emerging from our literature search is the severe scarcity of experimental research on the impact of discussion on political knowledge.<sup>11</sup> While experiments are often limited in terms of external validity, studies manipulating political discussion in a controlled setting and testing its effect on knowledge have the potential to complement survey research in important ways such as assessing causality and investigating the mechanisms of influence. We, therefore, believe that a crucial focus for future studies should be experimental designs varying discussion while holding all else constant. A second important way forward would be conducting cross-country comparisons of this effect. Our data show that the literature on political discussion and knowledge has a strong U.S. focus, with 78% of the studies in our dataset originating from the United States. While we find no evidence of differential effect sizes or measurement techniques across countries, we see this U.S. focus as a limitation of existing knowledge. We thus urge scholars to study this relationship in additional contexts and to examine it comparatively, for example, by collecting data in several countries simultaneously and exploring the system-level moderators of the effect.

Third, we encourage scholars to conduct additional meta-analyses on the effects of interpersonal political discussion. Particularly important in this context is a synthesis of studies on the effect of online political discussion on political knowledge. We did not include online discussion in this meta-analysis because past research suggests that online and offline talks differ fundamentally. Specifically, online participants are younger, more educated, and differ in their motivations for talking, their deliberation experience, and the perceived consequences of their actions (Baek, Wojcieszak, & Delli Carpini, 2012). A final direction for future research would be aggregating the results of group deliberation studies (Luskin et al., 2002). While these studies are insightful in their empirical tests of deliberative principles, they are too different in terms of research design, empirical strategy, and theoretical assumptions to be included in the same analysis as political discussion studies. Yet, this literature is both voluminous and diverse, which justifies an independent meta-analysis assessing its effects comprehensively.

In conclusion, we wish to propose a gold standard for reporting effect sizes in future studies. We believe the following set of recommendations is relevant not only to studies on the relationship explored here but to quantitative studies in the discipline in general. First, we strongly recommend including a correlation matrix of all study variables at the end of each quantitative study (e.g., in an online appendix). This will facilitate future meta-analyses and enable readers to better interpret study results, and it is especially important given the potential problems with regression coefficients (e.g., Roth et al., 2018). We thus believe that correlation coefficients—or statistics that can be converted into correlations without loss of information, such as Cohen's  $d$ —should *always* be reported. Second, we recommend reporting standardized statistics whenever possible. This includes correlation coefficients, standardized regression coefficients (betas), or standardized mean differences (Cohen's  $d$ ) in addition to unstandardized statistics, which have no substantive interpretation outside the context of a given study. Third, we urge scholars to properly assess and report the reliability of their measures. Only 68 of 134 studies in our dataset report *any* reliability score for their political knowledge measure, even though virtually all studies sum or average multiple factual items. Moreover, since political knowledge is an index and not a scale, coefficient alpha may be an inappropriate statistic for assessing its reliability (Streiner, 2003). While our field has advanced substantially with regard to properly reporting quantitative results, we believe that following stricter guidelines will facilitate the accumulation and interpretation of high-quality scientific knowledge.

### Authors' Note

The data and code required to replicate all analyses in this article are available on the publisher's website.

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### Supplemental Material

Supplemental material for this article is available online.

### Notes

1. Deliberative events are considered quasi-experiments rather than fully controlled experiments because they typically have no random assignment to groups and no control group.

2. Our search words and Boolean operators for all databases were as follows: (“political discussion” OR “interpersonal discussion” OR “interpersonal communication” OR “political talk” OR “political conversation” OR “discussion frequency” OR “frequency of discussion” OR “heterogeneous discussion” OR “heterogeneous political discussion” OR “discussion heterogeneity” OR “network heterogeneity” OR “network disagreement” OR “network diversity” OR “discussion diversity” OR “discussion disagreement” OR “disagreement in discussion” OR “diversity of discussion” OR “network size” OR “size of discussion network” OR “size of network”) AND (“political knowledge” OR “knowledge of politics” OR “knowledge about politics” OR “political information” OR “political learning” OR “political sophistication” OR “civic knowledge” OR “issue knowledge”).
3. Some studies in our dataset do not focus theoretically on the relationship between interpersonal discussion and political knowledge but use one of the variables as a covariate. These studies are included because they report reliable data on the relationship under investigation.
4. The formula is as follows:  $r = \beta + 0.05\lambda$ , where  $\lambda$  is an indicator variable that equals 1 when  $\beta$  is nonnegative and 0 when  $\beta$  is negative (Peterson & Brown, 2005). Since Pearson’s  $r$  is a bidirectional measure, our dataset also includes some studies reporting the standardized effect of knowledge on discussion (rather than the other way around).
5. Since Peterson and Brown’s formula only applies to standardized regression coefficients, when studies reported unstandardized coefficients, we converted these to beta coefficients using the formula for standardizing regression coefficients:  $(SD_x \times b)/SD_y$ . These betas were then converted to correlation coefficients using Peterson and Brown’s formula. The latter procedure was only possible for studies reporting the standard deviations of both the dependent and independent variables.
6. Many studies ask respondents about multiple discussion partners and then combine the responses into a single discussion index. Since the relative contribution of each discussion partner to knowledge cannot be teased apart in these studies, they were coded as “other.”
7. This number is lower than 134 because some papers report on more than one study.
8. While we do have 37 studies examining the effects of discussion heterogeneity, this number proved insufficient, as we did not have enough studies coded at each level of the moderating factors. For instance, for the moderator comparing youth and adult samples, we had 34 studies examining this effect on adult samples compared with only *three* studies examining this effect on youths. This power problem persists for most other moderators of this effect.
9. As this Online Appendix shows, in all cases, the subgroup-level estimates presented in Table 2 are robust to the comprehensive battery of sensitivity analyses we have used.
10. The only exception to this rule is when we model discussion heterogeneity as having severe one-tailed publication bias. In this case, the effect size changes from  $r = .1$  to  $r = -.26$ . We do not interpret this large change because it is most likely driven by outliers (Kepes, Banks, McDaniel, & Whetzel, 2012).
11. We were able to locate a total of four experimental studies manipulating discussion and testing effects on political knowledge (e.g., Eveland & Schmitt, 2015). Due to their fundamentally different research design, these studies were excluded from the meta-analysis. Yet, when including them, all of our conclusions remain virtually identical (details on these studies are available from the authors).

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### Author Biographies

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