**Is Seeing Believing? Misinformation & Incidental News Exposure News on Social Media**

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**Abstract**

Misinformation has significantly aided the rise of illiberal politicians and parties at home and abroad, and it is unclear whether incidental news exposure leads to increased likelihood of recall of misinformation or belief in political falsehoods. This study tests those relationships with a novel design featuring an online rolling cross-sectional survey linked with social media data collected from Facebook’s CrowdTangle. Results show that incidental news exposure plays a large role in recall of misinformation, but not in processes related to perceived credibility or false belief. We conclude that recall and credibility/false belief arise from two separate-but-related processes when it comes to the role news exposure.

*Keywords:* Misinformation, incidental news exposure, perceive credibility, false belief, information recall

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Misinformation has significantly aided the rise of illiberal politicians and parties at home and abroad. As seen in the wake of the 2020 U.S. Presidential Election, where claims of fraud encouraged an unprecedented insurrection aimed at overturning the legitimate results, misinformation erodes trust in democratic processes and institutions, creating an informational crisis in which journalism’s traditional role in bolstering the legitimacy of democratic practice has been undermined (Pickard, 2019). Social media platforms, in particular, are rife with misinformation, and these platforms are now regularly implicated as culpable actors in this crisis.

Some research has shown that highly engaged partisans are the most likely to share misinformation and/or believe political falsehoods (Valenzuela et al., 2019; Weeks, 2015). But most people engage with news content on a spectrum of cognitive involvement as they scan their various social feeds (Schäfer, 2020), and it is unclear whether *incidental* exposure leads to increased likelihood of recall of misinformation or belief in political falsehoods. One possibility is that passive scanners do not engage with news deeply enough to decipher fact and fiction. Alternatively, more detached scrolling may lead to exposure, but not necessarily belief in false stories, because people are not engaged enough to internalize the information. This study examines these possibilities by testing the links between incidental exposure to news on Facebook and three potential effects of misinformation: a) story recall, b) perceived credibility, and c) false belief. Incidental exposure itself arises from a variety of contextual, individual, and technological factors (Weeks & Lane, 2020), including social networks, individual-level habits and motivations, and Facebook’s news algorithm (Thorson et al., 2021). Therefore, this study will test how incidental exposure affects the outcomes above and beyond these factors.

The study relies on a novel design featuring an online rolling cross-sectional survey linked with social media data collected from Facebook’s CrowdTangle. For each sampling frame, we embedded a screenshot of the most popular fake and legitimate news articles in the previous three days (veracity determined by external fact checkers) with source cues photoshopped out of the image. After exposing respondents to the screenshot, three misinformation outcomes were measured, including story recognition (binary), perceived credibility (three-item scale), and false belief (single-item tailored to the story). The study will test the effects of incidental exposure on these outcomes, in addition to the effects of social media networks (e.g., size, diversity), and individual-level news habits and motivations (purposeful news use, news sharing, intention for using social media, political interest, partisanship, ideology). Finally, the study tests the role of Facebook’s news algorithm, as indicated by whether ‘politics’ and/or ‘news’ were listed in respondents’ interest categories in their Facebook settings.

**Incidental News Exposure and Misinformation**

Scholarship on the contemporary media environment has generally assumed that as individuals experience greater ability to choose, customize, and curate their media diets, the audience for news will become increasingly fragmented (Prior 2007; Thorson, 2015). This has been troubling from a normative perspective, as it threatens to deepen cleavages in political knowledge and engagement between those highly attuned to politics and those who are completely tuned out. Yet a burgeoning literature on so-called “incidental” exposure complicates this picture.

Researchers have typically argued that incidental exposure occurs when an individual encounters news or political information when they are using media for a non-news purpose (Weeks & Lane, 2020). Despite some evidence that digital media environments have increased the number of people who avoid news altogether (Karlsen et al., 2020), a number of studies have found that this type of incidental exposure is indeed commonly among samples of social media users (Fletcher & Nielsen, 2018; Weeks et al., 2021). Yet evidence of whether online incidental exposure leads users to engage with or learn from news content remains mixed. While a number of studies have found evidence that higher levels of incidental exposure are related to gains in political knowledge (Kobayashi & Inamasu, 2015; Weeks et al., 2021), other studies have failed to find such effects. (e.g., Feezell & Ortiz, 2021). As Kümpel (2020) has argued, some of these discrepancies may be explained by the degree to which people actually click on and engage with content they are incidentally exposed to. Further, the Political Incidental News Exposure Model (PINE) disaggregates incidental exposure into two levels, first-level passive appraisal of relevance of the content and second-level more intensive processing of the content (Matthes et al., 2020). These perspectives have established incidental exposure as a multifaceted phenomenon with consequences that are like highly contextual (Weeks & Lane, 2020).

One such context where incidental exposure may be consequential is political misinformation. On the one hand, the prevalence of misinformation on social media combined with the prevalence of incidental exposure hints at a potentially potent combination. If those with lower levels of political sophistication or access to mainstream news consumption encounter misinformation online incidentally, they may be more susceptible to believe or further spread falsehoods. On the other hand, the very nature of incidental exposure may limit potential negative misinformation effects. Research on the PINE model emphasizes that unless people appraise incidental information as relevant to their goals the effects of incidental exposure are likely to be limited (Matthes et al., 2020). It may be that people are incidentally exposed to misinformation, but only process it superficially because they were not motivated to seek it in the first place. Given these divergent possibilities an important goal of the present study is to try to disentangle mere incidental exposure to misinformation from subsequent recall, evaluation and belief of such information.

RQ1: How is incidental news exposure (motivation, encounters, and incidentality) related to recall of misinformation?

**Perceived Credibility**

Incidental news exposure could potentially affect three factors known to influence credibility judgments of online news stories: motivation, ability, and expectations. Metzger’s work (2007) elaborates on the classic dual processing model, which explains when and how individuals process information systematically or heuristically, and theorizes that systematic evaluation of the credibility of online information, including news stories, requires both individual motivation and ability. Otherwise, individuals rely on heuristics, or they do not evaluate credibility at all. These heuristic impressions are formed via online information cues, which could include a wide range of informational elements of the source, message, and medium (Metzger et al., 2003). Individuals’ expectations about online information are another key factor that shape credibility judgments. Developed to explain credibility in interpersonal interactions, expectancy violation theory suggests that individuals tend not to evaluate interpersonal interactions unless they in some way violate expectations (Burgoon, 1978). Applied to the credibility of online news, the theory suggests that news content that individuals will more actively evaluate the credibility of information that violates their expectations about the production and presentation of journalistic content (Lazer et al., 2018; Tandoc, 2020).

The concept of incidental news exposure implies a news-exposure scenario that could be described as unmotivated and non-violating. While news-related motivations (indicated by deeper interest in or engagement with news) can shape individuals’ choices and preferences that inform the algorithms that select news without our active input (Thorson, 2020), or developed immediately after exposure (Matthes et al., 2020), incidental exposure is generally characterized by a lack of background motivation to actively or purposefully seek out the news (Michelstein et al., 2020; Weeks & Lane, 2020). Therefore, it could be that individuals who primarily encounter the news incidentally, rather than purposefully, do not systematically process the information they encounter. Arguably, incidental exposure could also be related to individuals’ ability to assess the credibility of online news. Individuals who encounter news incidentally may receive lower volumes of news overall, and are therefore less knowledgeable about news production values and processes (Tully et al., 2020), and have a less clear idea about which informational cues to use for evaluating the credibility of information. Finally, these same individuals may not have specific expectations about news because they are less frequently engaged with news content (Tandoc, 2020), and therefore fake news stories may be less likely to violate their expectations about journalistic production and content.

In an unmotivated, non-violating informational scenario, people are more likely to (selectively) rely on heuristic cues to assess credibility (Metzger, 2007; Tandoc, 2020; Winter et al., 2016). Perhaps most importantly, these include partisan cues, as people more likely to believe information that is consistent with their prior attitudes (Metzger et al., 2020). However, saliency or relevance could also be important message features (Metzger, 2007). If the topic is close to that of a factually accurate news story that receives a substantial amount of coverage in other news media (i.e., the general topic is being covered for legitimate reasons), individuals may be more likely to believe false information about that same topic. Finally, visibility and repetition are important heuristics (Metzger, 2007). Therefore, if a person remembers seeing the story on social media, particularly more than once, they may be more likely to find it credible. These ideas lead us to pose the following research questions:

RQ2: How is incidental news exposure (motivation, encounters, and incidentality) related to perceived credibility?

**False Belief**

People are misinformed when they confidently hold false beliefs about political actors, issues and events that are objectively verifiable (Kuklinski et al. 2000, p. 790). In the context of normative theory, political knowledge is a necessary precondition for a heathy democracy, as people need accurate information to appropriately attend to the challenges and opportunities of public life (Delli Caprini & Keeter, 1996). Misperceptions hamper the acquisition of political knowledge and therefore undermine representative government. The study of the uninformed electorate is not new or novel (Bennett, 1988), but recent trends in both the information system and the political culture more broadly have accelerated scholarly interest in this area. First, as the gatekeeping power the traditional news media wanes, the information environment has become flooded with a range of politically themed content. From satirical late-night shows, to talk radio and hyper-partisan websites, the lines between fact and fiction are often blurred (Williams & Delli Caprini, 2011). Second, politicians and candidates are increasingly likely to embrace misinformation and conspiratorial thinking in their strategic framing of issues and events (Hameleers & Minihold, 2020). This phenomenon is exacerbated on social media, where news feeds may be inundated with politically relevant content, from professional news outlets and candidates to fake news and ‘news-like’ memes or posts from friends.

While emerging media platforms—along with other features of the media landscape that favor entertainment and virality over factual news narratives—have radically increased the supply of falsehoods, the study of false belief formation is concerned with the antecedent traits and cognitive processes of individual-level information reception and processing. Given that fake news often employs hyper-partisan themes and characters (DiResta et al., 2019) and in the 2016 election cycle in the United States uniquely targeted right-wing audiences (Benkler et al., 2018), much of the study of misperceptions is rooted in work on partisan motivated reasoning (e.g., Hollander, 2018; Kahan, 2012). This work shows that when presented with attitude-consistent falsehoods, people are more open to accepting them as fact, because people seek to reaffirm in-group affiliation, reduce cognitive effort, or both (Kahan, 2012). However, recent studies in this area suggest that cognitive involvement is more important than partisan bias in correctly identifying falsehoods (Pennycook & Rand, 2019). That is, a lack of effort or laziness in considering the veracity of information is a more reliable predictor of holding false beliefs, regardless of political affiliation (Pennycook & Rand, 2019; 2021).

Another line of thinking in this area draws on psychological models of memory and cognition to explain why false beliefs are so prevalent, and why corrections rarely stick (e.g., Lewandowski et al., 2012). When confronted with new information, people assess its veracity via a four-step process: compatibility with prior beliefs, coherence, source credibility, and group consensus (p. 112). People build mental models of current events and if the falsehood coheres to that narrative, it becomes a plausible stand-in when people fail to recall details of the story. This effect is stronger the more familiar one might be with the material, and therefore misperceptions are difficult to correct, unless an alternative narrative is provided and reenforced over time (Lewandowski et al., 2012). Given the role of cognition in determining misperceptions, several recent studies find that cognitive sophistication (commonly measured as skepticism, bullshit receptivity, cognitive reflection, science literacy, e.g., Pennycook et al, 2020) is inversely associated with holding false beliefs about a range of issues because people take the time to more deeply consider the veracity of new information (Littrell et al., 2021; Pennycook et al, 2020).

Selective attention to news in general has been implicated in holding politically valanced falsehoods (e.g., Cacciatore et al., 2014), but less is known about how reliance on social media for news might influence this phenomenon (c.f., Bode et al., 2020). Work in this area is still emergent, but since social media is a common source for political misinformation (DiResta et al., 2019) and people rely on various cues embedded in their news feeds to verify source credibility (Avram et al., 2020), it stands to reason that attention to news on social media might also influence false belief formation. A recent panel study of social media users across two presidential elections finds that except for strong partisans, there are either no effects, or mildly positive effects of social media use on belief accuracy (Garrett, 2019). However, that study did not account for the potential spectrum of engagement with the news on social media, from motivated attention to the various forms of incidental exposure.

Motivated users are more likely to seek learning gratifications from the news (Eveland, 2001) and are therefore more knowledgeable and less susceptible to false belief formation because they: a) are more familiar with factual narratives, and thus b) employ greater cognitive sophistication in assessing the veracity of news headlines. In contrast, dimensions of attention to news that represent incidental exposure may or may not lead to false belief formation. Serendipitous exposure may “fill in the gaps” for people’s knowledge of factual narratives and reduce false belief formation. Alternatively, these people may not recall the factual narrative, and thus rely on incomplete models of news events, making them susceptible to falsehoods when they fail to recall details (Lewandowski et al., 2012). Given the lack of findings in this area, we propose the following exploratory research questions:

RQ3: How is incidental news exposure (motivation, encounters, and incidentality) related to false belief?

**Methods**

**Survey Design**

This study relies on a novel design featuring an online rolling cross-sectional survey of adult social media users in the United States. The survey was administered in 17 sampling frames of 3-4 days each (with Saturday/Sunday counted as one day). This approaches affords us a unique opportunity to link survey responses and social media content, because we can “locate” responses in temporal proximity to actual content known to be circulating on social media. The research team collected external media data (~5,000 news stories per frame) from Facebook’s proprietary platform, CrowdTangle, and aggregate-level characteristics of these data were measured and matched with each sampling frame. Additionally, in each sampling frame we embedded a screenshot of the most popular fake and legitimate news articles in the previous three days (the veracity of the fake article was determined by external fact checkers) with source cues photoshopped out of the image. Respondents were told the stories have been “recently circulating on Facebook”—a true statement. This method affords us the ability to develop several cued recall and psychographic measures, which form the outcome variables for this study.

**Sample and Data**

Data were collected between September 3 and November 1, 2020. Quotas for age, race, gender, and census region were based on the 2018 American Community Survey. The survey has an incidence rate of 100% and a cooperation rate of 70%. It has an overall sample size of *N* = 2,006 with at least *n* = 100 for each sampling frame. The sample reflects the target population on the quota criteria. The average respondent is between 45 and 54 years old (measured on a 7-point scale where 1 = “18-24” and 7 = “85 or older”). Approximately 40% of the sample are persons of color, and 51% are female. Census regions were defined according to the U.S. Census Bureau’s map, and in our sample ~22% of respondents live in the Midwest, ~19% live in the Northeast, ~37% live in the South, and ~23% live in the West. In terms of non-criterion demographics, the average respondent has either “Some college” or a “2-year associate’s degree or trade school diploma” (*M* = 4.53 on a 7-point scale where 1 = “Some high school” and 7 = “Post-graduate degree”), and lives in a household that earns between $45,000 and $75,000 per year (*M* = 4.71 on an 8-point scale where 1 = “Less than $15,000” and 8 = “More than $150,000).

**Measures**

Key details for all measures are reported in Appendix A, including the number of items, measurement scales, reliability statistics (where appropriate), and descriptive statistics.

***Outcome Variables***

The study analyzes three outcome variables measured after respondents were exposed to the screenshot of the fake news article. First, *recall* was measured by reminding respondents that the story shown in the screenshot has been “circulating on Facebook recently,” and then asking them whether they have seen the story on Facebook (1 = Yes, 0 = No or Don’t Know). A follow-up question asked whether they had seen the story on some other social media platform, “such as Twitter, Instagram, YouTube, Snapchat, or Reddit.” Respondents who answered “Yes” to the follow-up question were also counted as having seen the story. Next, *perceived credibility* was measured after exposure to the screenshot with three items asking respondents to what extent the story is (1) credible, (2) accurate, (3) trustworthy (1 = “Not at all” and 5 = “Very”). The display order of these items was randomized to prevent ordering effects, and respondents’ scores on the three items were averaged to calculate the final variable. Finally, *false belief* was measured post-exposure by asking respondents to move a 7-point sliding scale toward one of two statements that “best describes [their] beliefs.” The true statement was shown on the left-hand side of the scale (1), and the false statement was shown on the right-hand side (7). Respondents were instructed to place the slider in the “exact middle” of the scale if they were “unsure of the truth.” The statements were derived from the fake news stories themselves. For example, one story headline read: “Biden says the Second Amendment is ‘Obsolete’. The statements thus read: (1) “Vice President Joe Biden’s campaign platform does NOT call for repealing the 2nd Amendment right to bear arms” [true] and (7) “Vice President Joe Biden’s campaign platform calls for the repealing the 2nd Amendment right to bear arms” [false].

***Incidental News Exposure***

We measured three dimensions of incidental news exposure based on prior literature (Weeks & Lane, 2020). First, *motivation* was measured by asking respondents which statement best describes their “typical reasons for accessing [their] social media accounts”: (a) “I mostly access social media to follow information about news and public affairs;” (b) “I mostly access social media for reasons unrelated to following information about news and public affairs;” and (c) “I don’t think very much about why I access social media.” Respondents who selected the first choice were scored a 1 to indicate purposeful news motivation, and respondents who selected one of the other choices were scored a 0 to indicate incidental news motivation. Second, *encounters* with political information was measured with six items (1 = “Never” and 5 = “Several times a day”) asking respondents how often they encounter (a) information critical of a presidential candidate they support, (b) information critical of a presidential candidate they oppose; (c) information critical supportive of a presidential candidate they support; (d) information supportive of a presidential candidate they oppose; (e) information that disagrees with their political views; and (f) information that agrees with their political views. Each respondents’ answers were averaged to calculate the final variable. Third, *incidentality* was measured with a single follow-up question that asked respondents: “On social media, some people intentionally search for news or political information, but others come across such information accidentally. What about you?” (1 = “Always intentionally” and 5 = “Always accidentally”).

***Political Interest and Preferences***

Four indicators of individuals’ political interest and preferences were measured. First, *political interest* was measured with three items asking respondents how interested they are in (a) news, (b) politics, and (c) local community (1 = “Not at all interested” and 5 = “Very interested”). Respondents’ answers to these questions were averaged. Second, we measured *algorithmic categorization* using a technique pioneered by Thorson and colleagues (2021). With the aim of obtaining an observable indicator of Facebook’s classification algorithm, we asked respondents at the end of the survey to open a web browser, navigate to the Settings menu of their Facebook accounts, and locate their Ad Interests section. We then asked them whether they saw the following categories included in their interests: (a) politics; (b) news or specific news organizations (e.g., the *New York Times*); or (c) neither. Respondents received 1 point for selecting either (a) or (b), resulting in a 3-point scale (0 = Neither, 1 = One, 2 = Both). Third, *political ideology* was measured with a single 11-point L-R scale (-5 = “Very liberal,” 0 = “Neither liberal nor conservative,” and 5 = “Very conservative”). Finally, *Trump evaluation* was measured with a 101-point feeling thermometer asking respondents how they feel about Donald Trump (0 = “Cold”, 50 = “Neither warm nor cold,” and 100 = “Warm”).

***News-Sharing Networks***

We measured three dimensions of social media networks relevant to news sharing. First, *network size* was measured by asking respondents how many people or accounts they are “friends with,” “follow,” or “subscribe to” for six social media platforms: Facebook, Twitter, Instagram, YouTube, Snapchat, and Reddit (1 = “None” and 7 = “2,001 or more”). Respondents’ answers were averaged to calculate the final variable. Next, *network diversity* was measured by asking respondents 8 questions about the prevalence of specific types of people in their social media networks: (1) people they know from your current work or school; (2) people they know from schools you’ve attended in the past or jobs you’ve held in the past; (3) family members or people they know through their family; (4) people they know socially; (5) people they have never met in person; (6) people in their city/town or immediate locality; (7) people in other cities or towns; and (8) people who live in other countries. Respondents’ answers were averaged. Finally, *news follows* was measured with three items asking them how often they follow social media accounts specifically because they are interested in what they post about (a) news or current affairs, (b) politics, and (c) social or community events (1 = “Never” and 5 = “Very frequently”). Respondents’ answers to these items were averaged.

***Control Variables***

The analysis controls for five demographic variables, including *age*, *race*, *gender*, *education*, and *income*. In addition, the analysis also controls for frequency of Facebook use (*Facebook frequency*). A single questionnaire item asked respondents: “In the past week, on average, how much time per day have you spent actively using Facebook.” Choices ranged from 1 = “Less than 10 minutes per day” to 6 = “More than three hours per day.”

***Second-Level Predictors***

The study also includes three second-level predictors, which are aggregate-level indicators of news content and audience engagement during each sampling frame and are based on external data collected from Facebook’s CrowdTangle platform. Taken together, these three metrics indicate for each sampling frame: (1) how much the Facebook audience engaged with news; (2) whether the news was generally positive or negative, and (3) the salience of the topic covered in the fake news story. First, *average engagement* was measured by calculating a weighted average of engagement metrics (likes, shares, and comments), then filtering out the bottom 80% of stories to leave only the top 20%, reflecting a “Pareto Rule” or “80:20 distribution” of audience attention. The resulting metric was rescaled from 0 to 1. Second, a measure of *net sentiment* was created by calculating the difference between positive and negative words in the headlines for these same articles (top 20% per frame), as measured by LIWC (Linguistic Inquiry and Wordcount). This metric was also rescaled from 0 to 1. Finally, *topic frequency* was measured by using a custom dictionary created by the study team that was used to computationally count the occurrence of keywords in the top 20% of articles. All keywords either appear in or are directly relevant to the topic of the fake news story for that frame. The final metric reflects the raw count for the frame, which was rescaled to run from 0 to 1.

**Analysis**

Linear mixed effects models were used to analyze the data, with logit models for the binary outcome (recall) and linear models for the interval-like outcomes (credibility and false belief). Prior to analysis, a series of model comparisons established that random-intercepts models are most appropriate for the data, as the means of the outcomes vary between sampling frames, but the effects of the primary predictors do not. After fitting the main models, interactions between the indicators of incidental news exposure were tested for each outcome.

**Results**

***Recall***

Results for the recall outcome are reported in Table 1. The table first shows the main-effects model, followed by two interaction models. Generally speaking, the Intraclass Coefficients (ICCs) for these models are low (~0.05), indicating that relatively little of variance in the outcome is explained by between-group (i.e., between time frames) effects. The main model shows that all three of the incidental news exposure variables are significantly related to story recall. The effect of motivation is positive *b* = 0.52, *SE* = 0.14, *p* < .01, indicating that respondents motivated by news use are 1.68 times more likely to recall the story than people motivated for other reasons. The coefficient for encounters is also positive (*b* = 0.14, *SE* = 0.06, *p* < .05), suggesting that each one-unit increase in the frequency of encountering political information is associated with a 1.15-times increase in the odds of recalling the fake story. Finally, incidentality is negative related to recall (*b* = -0.27, *SE* = 0.06, *p* < .001), suggesting that a one-unit increase in intentional news use is associated with a .76-times decline in the odds of recalling the fake story. The effects of these three incidental news exposure variables are visualized in Figure 1. Subsequent models show a positive interaction between encounters and incidentality (*b =* 0.11, *SE* = 0.04, *p* < .05), and visualization (see Figure 2) suggests that the positive effect of encountering political information is strongest where incidentality is high. Thus, while there is a negative main effect of incidentality, it also conditions news exposure such that people who frequently encounter political information incidentally are the most likely to recall the fake story.

It is also worth examining the other significant predictors of story recall. All three dimensions of news networks are positively and significantly related to the outcome (*OR*s range from 1.22 to 1.31), and three of four indicators of interests and preferences are positively related, with the highest odds ratios observed for algorithmic categorization (*OR* = 1.44) and Trump evaluation (*OR* = 1.97). Taken together, these results indicate that people with “newsy” networks, people who have been categorized by Facebook as having high interest in news and public affairs, and people who positively evaluated Trump are relatively more likely to recall the fake news story. Finally, recall is about 4 times more likely in sampling frames where net sentiment was negative (*b* = -1.34, *SE* = 0.49, *p* < .01, *OR* = 0.26), and about 3.5 times more likely sampling frames where the topic of the fake news story was salient in news coverage more broadly (*b* = 1.25, *SE* = 0.56, *p* < .05, *OR* = 3.49).

***Credibility***

Results for perceived credibility are reported in Table 2. There are no significant effects of the incidental news exposure variables, nor are there significant interactions between them. The strongest predictor in the model is story recall. The mean difference in credibility between respondents who recalled the story and respondents who did not is 0.66 (*b* = 0.66, *SE* = 0.07, *p* < .001), which is a difference of ~13% on the 5-point scale. Notably, Trump evaluation is the strongest predictor other than recall (*b* = 0.52, *SE* = 0.08, *p* < .001), and this result indicates that a one-unit change in Trump evaluation is associated with a 0.52 increase in perceived credibility, which is about 10% of the measurement scale. Other first-level effects are relatively weak, with coefficients of 0.09 for news diversity and news follows (network size is not significant), and coefficients of 0.03 for ideology and 0.10 for interest (algorithmic categorization is not significant). Of the second-level predictors, only net sentiment is related. Respondents perceive the story to be more credible in sampling frames where net sentiment is negative (*b* = -0.47, *SE* = 0.22, *p* < .05).

***False Belief***

Results for false belief (see Table 3) are similar to those for perceived credibility, with the exception of a significant negative effect of incidentality (*b* = -0.12\*\*\*, *SE* = 0.04, *p* < .001). Neither of the other two incidental news exposure variables are related, and there are no significant interactions between them. The strongest predictor in the model is Trump evaluation (*b* = 1.09, *SE* = 0.11, *p* < .001), and this result indicates a more than one-to-one connection between Trump evaluation and false belief. That is, a one-unit change in the favorability of Trump evaluation is associated with a 1.09 increase in false belief. The other strong predictors in the model are story recall (*b* = 0.39, *SE* = 0.10, *p* < .001) and perceived credibility (*b* = 0.57, *SE* = 0.03, *p* < .001). Relatively small effects are observed for network size (*b* = 0.10, *SE* = 0.05, *p* < .05), news follows (*b* = -0.13, *SE* = 0.04, *p* < .01), and political interest (*b* = -0.11, *SE* = 0.04, *p* < .05).

**Discussion**

To briefly recap the results, we find slightly different patterns of results for each of the three outcomes. For story recall, results show a relationship with all three incidental exposure variables, as well as consistent relationships with the indicators of news networks, individual preferences, and environmental factors such as sentiment and saliency. For perceived credibility, we find the strongest relationships with story recall and individual preferences, whereas we find no relationships with the incidental exposure variables, weak relationships with the network variables, and only one relationship with the environmental variables (sentiment). Finally, for false belief, we find the strongest results for individual preferences—particularly Trump evaluation—followed by story recall and perceived credibility. Findings for incidental news exposure, social networks, and environmental factors are relatively weak and or inconsistent.

From these results, we conclude that the data reflect at least two separate communicative processes—one for story recall and one for subsequent judgments and beliefs. Incidental news exposure appears to play a relatively prominent role in the first process, as there are clear and consistent relationships between the indicators of incidental exposure and story recall. However, incidental exposure plays almost no role in subsequent processes of evaluation and/or belief formation. Rather, these processes appear to be influenced more consistently by (a) memory and judgment further back in the causal chain (i.e., recall and credibility) and (b) individual preferences—presumably prior ideologies, attitudes, and orientations towards both specific political actors and politics, more generally. Thus, our results suggest that recollection of misinformation is influenced by the social media news feed and all the factors that govern flows of information through it, including not only individual preferences and behaviors, but also the structures of egocentric social networks and short-term characteristics of the news environment on Facebook. On the other hand, subsequent judgments and beliefs are influenced primarily by individuals “priors” and their acute processing of information—factors that are likely interrelated.

Aside from the incidental news exposure variables, the environmental factors were of particular interest to this study. A major strength of the study design is that it linked individual survey responses with aggregate-level data about news content on Facebook during the previous three days. Findings suggest that people are more likely to remember misinformation that is (a) negative and (b) salient. Neither of these findings is particularly surprising—social science has well documented the tendency toward a “negativity bias” (Rozin & Royzman, 2001), as well as the role for salience in shaping outcomes such as issue importance (McCombs & Shaw, 1972). That said, these results highlight the need for additional research into contextual factors that shape the content of individuals’ news feeds and their recollections of the content they saw. Our findings show that individual recall is not only influenced by factors that they themselves control, such as their social networks or their news consumption habits, but also by factors that are out of their control, such as whether the media covers a topic for legitimate reasons.

As with any research, this study is limited in important ways related to design, measurement, and analysis. The design is cross-sectional, and while we were able to link individual survey responses with external media data, these data are purely associational in nature, and we cannot make causal claims based on them. Another limitation relates to the linkage portion of the study. While it would be ideal to link individual survey responses with individual-level exposure data, these data are rarely available from Facebook itself, and the corporation has shut down recent efforts to circumvent their proprietary data collection platform. In terms of measurement, the study relies on self-reported survey data for key variables including incidental news exposure and social networks. It is possible that respondents have mis-estimated their news exposure and characteristics of their social networks. Finally, the analysis is also limited by the number of sampling frames. While some consider 15 second-level groups to be sufficient for detecting multilevel effects, others have argued that at least 30 such groups are required, particularly for detecting cross-level interactions. Future research should expand on this study by collecting data for longer periods of time across additional sampling frames.

Despite these limitations, this paper charts at least two interesting paths for future research on the role of Facebook’s news feed in shaping the recall and evaluation of, as well as the belief in, misinformation. The first pathway relates to the factors that shape individual-level patterns of news exposure and consumption, and how those patterns interact with environmental factors in the news to shape people’s recollection of misinformation. The second pathway is primarily psychological in nature, and charts a course for examining the ways in which individuals process misinformation in light of their prior beliefs. This second pathway is, of course, well trodden, as research has for some time documented the tendency for priors to shape information processing, perception, and judgment. For this reason, substantial theoretical legwork is needed to think through the specific dynamics of misinformation and the ways that well established psychological and communicative processes may differ as a result of it.

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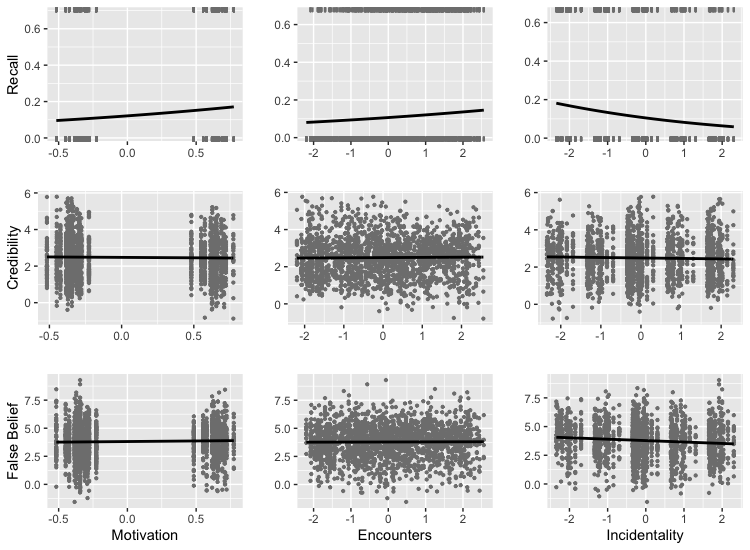
|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Table 1  *Predictors of False Story Recall* | | | | | | |
|  | Recall | | | | | |
| **Fixed Effects** | *b* | *SE* | *b* | *SE* | *b* | *SE* |
| Intercept | -0.84\*\* | 0.31 | -0.83\*\* | 0.31 | -0.83\*\* | 0.31 |
| Age | -0.03 | 0.05 | -0.03 | 0.05 | -0.03 | 0.05 |
| Gender (1 = Female) | -0.31\* | 0.13 | -0.31\* | 0.13 | -0.30\* | 0.13 |
| Race (1 = Person of Color) | 0.07 | 0.13 | 0.06 | 0.13 | 0.07 | 0.13 |
| Education | -0.04 | 0.04 | -0.04 | 0.04 | -0.04 | 0.04 |
| Income | 0.00 | 0.03 | 0.00 | 0.03 | 0.00 | 0.03 |
| Facebook Frequency | -0.05 | 0.04 | -0.04 | 0.04 | -0.04 | 0.04 |
| Network Size | 0.21\*\* | 0.07 | 0.21\*\* | 0.07 | 0.21\*\* | 0.07 |
| Network Diversity | 0.27\* | 0.12 | 0.29\* | 0.12 | 0.30\*\* | 0.12 |
| News Follows | 0.20\*\* | 0.08 | 0.20\*\* | 0.08 | 0.21\*\* | 0.08 |
| Algorithmic Categorization | 0.37\*\*\* | 0.10 | 0.36\*\*\* | 0.10 | 0.36\*\*\* | 0.10 |
| Political Interest | 0.18\* | 0.08 | 0.19\* | 0.08 | 0.20\* | 0.08 |
| Ideology (+ Conservative) | 0.05 | 0.02 | 0.05 | 0.02 | 0.05\* | 0.02 |
| Trump Evaluation | 0.68\*\*\* | 0.19 | 0.67\*\*\* | 0.19 | 0.69\*\*\* | 0.19 |
| Motivation (1 = Purposeful) | 0.52\*\* | 0.14 | 0.56\*\*\* | 0.14 | 0.53\*\*\* | 0.14 |
| Encounters | 0.14\* | 0.06 | 0.14\* | 0.06 | 0.15\* | 0.06 |
| Incidentality | -0.27\*\*\* | 0.06 | -0.27\*\*\* | 0.06 | -0.30\*\*\* | 0.06 |
| Average Engagement | 0.17 | 0.52 | 0.17 | 0.51 | 0.16 | 0.51 |
| Net Sentiment | -1.34\*\* | 0.49 | -1.34\*\* | 0.48 | -1.34\*\* | 0.48 |
| Topic Frequency | 1.25\* | 0.56 | 1.25\* | 0.55 | 1.26\* | 0.55 |
| Encounters x Motivation |  |  | -0.13 | 0.11 |  |  |
| Encounters x Incidentality |  |  |  |  | 0.11\* | 0.04 |
| **Random Effects** | *Var.* | *SD* | *Var.* | *SD* | *Var.* | *SD* |
| Intercept | 0.17 | 0.41 | 0.16 | 0.40 | 0.16 | 0.40 |
| ICC Adjusted | .05 | | .05 | | .05 | |
| ICC Conditional | .03 | | .03 | | .03 | |
| **Model Fit Statistics** | Value | | Value | | Value | |
| AIC | 1,724.10 | | 1,724.80 | | 1,719.90 | |
| BIC | 1,841.80 | | 1,848.10 | | 1,843.20 | |
| *G*2 | -841.10 | | -840.40 | | -838.00 | |
| *Note*: Cell entries are parameter estimates from a Generalized Linear Mixed Effects (GLME) model. All models estimated with Restricted Maximum Likelihood (REML) and Nelder-Mead optimization. *N* = 2,006. Groups = 17. \**p* < .05, \*\**p* < .01, \*\*\**p* < .001. | | | | | | |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Table 2  *Predictors of Perceived Credibility* | | | | | | |
|  | Perceived Credibility | | | | | |
| **Fixed Effects** | *b* | *SE* | *b* | *SE* | *b* | *SE* |
| Intercept | 3.01\*\*\* | 0.14 | 3.01\*\*\* | 0.14 | 3.00\*\*\* | 0.14 |
| Age | -0.03 | 0.02 | -0.03 | 0.02 | -0.04\* | 0.02 |
| Gender (1 = Female) | 0.06 | 0.05 | 0.06 | 0.05 | 0.06 | 0.05 |
| Race (1 = Person of Color) | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Education | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 |
| Income | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 |
| Facebook Frequency | 0.00 | 0.02 | 0.00 | 0.02 | 0.00 | 0.02 |
| Network Size | 0.04 | 0.03 | 0.04 | 0.03 | 0.03 | 0.03 |
| Network Diversity | 0.09\* | 0.05 | 0.09\* | 0.05 | 0.09 | 0.05 |
| News Follows | 0.09\*\* | 0.03 | 0.09\*\* | 0.03 | 0.09\*\* | 0.03 |
| Algorithmic Categorization | 0.05 | 0.04 | 0.05 | 0.04 | 0.04 | 0.04 |
| Political Interest | 0.10\*\*\* | 0.03 | 0.10\*\*\* | 0.03 | 0.09\*\* | 0.03 |
| Ideology (+ Conservative) | 0.03\*\*\* | 0.01 | 0.03\*\*\* | 0.01 | 0.03\*\*\* | 0.01 |
| Trump Evaluation | 0.52\*\*\* | 0.08 | 0.52\*\*\* | 0.08 | 0.52\*\*\* | 0.08 |
| Motivation | -0.05 | 0.06 | -0.04 | 0.06 | -0.05 | 0.06 |
| Encounters | 0.01 | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 |
| Incidentality | -0.02 | 0.02 | -0.02 | 0.02 | -0.03 | 0.02 |
| Recall | 0.66\*\*\* | 0.07 | 0.66\*\*\* | 0.07 | 0.66\*\*\* | 0.07 |
| Average Engagement | -0.23 | 0.23 | -0.23 | 0.23 | -0.23 | 0.23 |
| Net Sentiment | -0.47\* | 0.22 | -0.47\* | 0.22 | -0.47\* | 0.22 |
| Topic Frequency | 0.25 | 0.25 | 0.24 | 0.25 | 0.25 | 0.26 |
| Encounters x Motivation |  |  | -0.02 | 0.04 |  |  |
| Encounters x Incidentality |  |  |  |  | -0.02 | 0.02 |
| **Random Effects** | *Var.* | *SD* | *Var.* | *SD* | *Var.* | *SD* |
| Intercept | 0.04 | 0.19 | 0.04 | 0.19 | 0.04 | 0.20 |
| Residual | 1.18 | 1.08 | 1.18 | 1.09 | 1.18 | l.08 |
| ICC Adjusted | .03 | | .03 | | .03 | |
| ICC Conditional | .02 | | .02 | | .02 | |
| **Model Fit Statistics** | Value | | Value | | Value | |
| AIC | 6,168.45 | | 6,174.67 | | 6,175.70 | |
| BIC | 6,297.34 | | 6,309.16 | | 6,310.19 | |
| *G*2 | -3,061.23 | | -3,063.33 | | -3,063.85 | |
| *Note*: Cell entries are parameter estimates from a Generalized Linear Mixed Effects (GLME) model. All models estimated with Restricted Maximum Likelihood (REML) and Nelder-Mead optimization. *N* = 2,006. Groups = 17. \**p* < .05, \*\**p* < .01, \*\*\**p* < .001. | | | | | | |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Table 3  *Predictors of False Belief* | | | | | | |
|  | False Belief | | | | | |
| **Fixed Effects** | *b* | *SE* | *b* | *SE* | *b* | *SE* |
| Intercept | 4.13\*\*\* | 0.25 | 4.13\*\*\* | 0.25 | 4.13\*\*\* | 0.25 |
| Age | -0.09\*\* | 0.03 | -0.09\*\*\* | 0.03 | -0.09\*\*\* | 0.03 |
| Gender (1 = Female) | 0.10 | 0.07 | 0.10 | 0.07 | 0.10 | 0.07 |
| Race (1 = Person of Color) | 0.12 | 0.07 | 0.12 | 0.07 | 0.12 | 0.07 |
| Education | -0.01 | 0.02 | -0.01 | 0.02 | -0.01 | 0.02 |
| Income | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 | 0.02 |
| Facebook Frequency | 0.00 | 0.02 | 0.00 | 0.02 | 0.00 | 0.02 |
| Network Size | 0.10\* | 0.05 | 0.10\* | 0.05 | 0.10\* | 0.05 |
| Network Diversity | 0.05 | 0.07 | 0.05 | 0.07 | 0.05 | 0.07 |
| News Follows | -0.13\*\* | 0.04 | -0.13\*\* | 0.04 | -0.13\*\* | 0.04 |
| Algorithmic Categorization | 0.03 | 0.06 | 0.03 | 0.06 | 0.03 | 0.06 |
| Political Interest | -0.11\* | 0.04 | -0.11\* | 0.04 | -0.11\* | 0.04 |
| Ideology (+ Conservative) | 0.03 | 0.01 | 0.03 | 0.01 | 0.03 | 0.01 |
| Trump Evaluation | 1.09\*\*\* | 0.11 | 1.09\*\*\* | 0.11 | 1.09\*\*\* | 0.11 |
| Motivation | 0.10 | 0.09 | 0.10 | 0.09 | 0.10 | 0.09 |
| Encounters | 0.01 | 0.03 | 0.01 | 0.04 | 0.01 | 0.04 |
| Incidentality | -0.12\*\*\* | 0.04 | -0.12\*\*\* | 0.04 | -0.13\*\*\* | 0.04 |
| Recall | 0.39\*\*\* | 0.10 | 0.38\*\*\* | 0.10 | 0.39\*\*\* | 0.10 |
| Credibility | 0.57\*\*\* | 0.03 | 0.57\*\*\* | 0.03 | 0.57\*\*\* | 0.03 |
| Average Engagement | 0.00 | 0.41 | 0.00 | 0.41 | 0.00 | 0.40 |
| Net Sentiment | -0.21 | 0.39 | -0.21 | 0.39 | -0.21 | 0.39 |
| Topic Frequency | -0.01 | 0.45 | -0.01 | 0.45 | -0.01 | 0.45 |
| Encounters x Motivation |  |  | 0.02 | 0.06 |  |  |
| Encounters x Incidentality |  |  |  |  | -0.01 | 0.02 |
| **Random Effects** | *Var.* | *SD* | *Var.* | *SD* | *Var.* | *SD* |
| Intercept | 0.13 | 0.36 | 0.13 | 0.36 | 0.13 | 0.36 |
| Residual | 2.37 | 1.54 | 2.37 | 1.54 | 2.37 | 1.54 |
| ICC Adjusted | .05 | | .05 | | .05 | |
| ICC Conditional | .03 | | .03 | | .03 | |
| **Model Fit Statistics** | Value | | Value | | Value | |
| AIC | 7,569.79 | | 7,575.36 | | 7,577.16 | |
| BIC | 7,704.28 | | 7,715.45 | | 7,717.26 | |
| *G*2 | -3,760.89 | | -3,762.68 | | -3,763.58 | |
| *Note*: Cell entries are parameter estimates from a Generalized Linear Mixed Effects (GLME) model. All models estimated with Restricted Maximum Likelihood (REML) and Nelder-Mead optimization. *N* = 2,006. Groups = 17. \**p* < .05, \*\**p* < .01, \*\*\**p* < .001. | | | | | | |

Figure 1

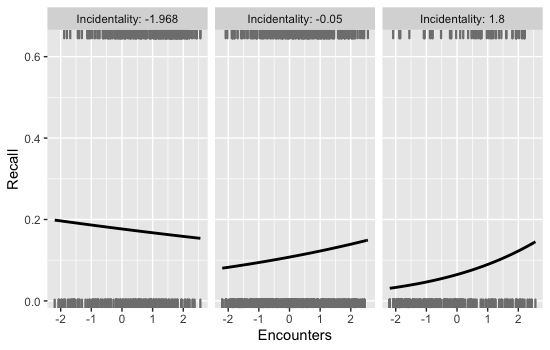
*Relationships Between Incidental Exposure Variables and Outcomes*



*Note*: Relationships estimated from “main effects” models in Tables 3-5.

Figure 2

*Conditional Relationship Between News Encounters and False Story Recall at Three Levels of News Incidentality*



*Note*: Relationship estimated from interaction models in Table 3.

Appendix A: Measurement Information

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table A1  *Measurement Information for Variables in Analysis* | | | | | |
| Variable | No. of Items | Scale | Cronbach’s Alpha | *M* | *SD* |
| Network Size | 6 | *Min*. = 1, *Max*. = 7 | .91 | 2.33 | 1.33 |
| Network Diversity | 8 | *Min*. = 1,  *Max*. = 5 | .89 | 2.41 | 0.82 |
| News Follows | 3 | *Min*. = 1,  *Max*. = 5 | .91 | 2.74 | 1.24 |
| Algorithmic Categorization | 2 | *Min*. = 0,  *Max*. = 2 | NA | 0.52 | 0.67 |
| Political Interest | 3 | *Min*. = 1,  *Max*. = 5 | .83 | 3.45 | 1.04 |
| Ideology (+ Conservative) | 1 | *Min*. = -5,  *Max*. = 5 | NA | 0.24 | 3.05 |
| Trump Evaluation | 1 | *Min*. = 0,  *Max*. = 1 | NA | 0.43 | 0.40 |
| Motivation | 1 | *Min*. = 0,  *Max*. = 1 | NA | 0.35 | 0.49 |
| Encounters | 6 | *Min*. = 1,  *Max*. = 5 | .96 | 2.84 | 1.29 |
| Incidentality | 1 | *Min*. = 1,  *Max*. = 5 | NA | 3.13 | 1.28 |
| Recall | 1 | *Min*. = 0,  *Max*. = 1 | NA | 0.28 | 0.45 |
| Credibility | 1 | *Min*. = 1,  *Max*. = 5 | NA | 2.71 | 1.28 |
| False Belief | 1 | *Min*. = 1,  *Max*. = 7 | NA | 4.02 | 1.96 |
| Average Engagement | NA | *Min*. = 0,  *Max*. = 1 | NA | 0.35 | 0.25 |
| Net Sentiment | NA | *Min*. = 0,  *Max*. = 1 | NA | 0.53 | 0.26 |
| Topic Frequency | NA | *Min*. = 0,  *Max*. = 1 | NA | 0.14 | 0.25 |

Appendix B: Model Comparisons

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Table B1  *Comparison of Fixed and Random-Intercepts “Null” Models* | | | | | | |
| Statistic | Recall | | Credibility | | False Belief | |
|  | Fixed  Intercepts | Random Intercepts | Fixed Intercepts | Random Intercepts | Fixed Intercepts | Random Intercepts |
| AIC | 2384.08 | 2349.16 | 6695.44 | 6673.69 | 8400.43 | 8378.10 |
| BIC | 2389.68 | 2360.36 | 6706.65 | 6690.50 | 8411.64 | 8394.91 |
| *G*2 | 36.92\* | | 23.75\* | | 24.33\* | |
| *N* | 2,007 | | 2,007 | | 2,006 | |
| *Note*: Cell entries in columns 2-3 compare model fit statistics from a logistic regression (logit) model and a Generalized Linear Mixed Effects (GLME) model. Columns 4-7 compare model fit statistics from Ordinary Least Squares (OLS) regression models and LME models. For all three comparisons, the mixed-effects models are a better fit to the data, indicating that the means of the three outcome variables vary across sampling frames.  Groups= 17. \**p* < .001. | | | | | | |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Table B2  *Comparison of “Full” Random-Intercepts and Random-Effects Models* | | | | | | |
| **Predictor: News Intention** | | | | | | |
| Statistic | Recall | | Credibility | | False Belief | |
|  | Random Intercepts | Random Effects | Random Intercepts | Random Effects | Random Intercepts | Random Effects |
| AIC | 2,093.29 | 2,095.05 | 6,564.48 | 6,566.77 | 8,295.18 | 8,299.13 |
| BIC | 2,110.10 | 2,123.07 | 6,586.89 | 6,600.40 | 8,317.60 | 8,332.76 |
| *G*2 | 2.24 | | 1.70 | | 0.05 | |
| *N* | 2,007 | | 2,007 | | 2,006 | |
| **Predictor: News Encounters** | | | | | | |
| Statistic | Recall | | Credibility | | False Belief | |
|  | Random Intercepts | Random Effects | Random Intercepts | Random Effects | Random Intercepts | Random Effects |
| AIC | 2,123.22 | 2,127.00 | 6,546.62 | 6,543.68 | 8,323.31 | 8,324.92 |
| BIC | 2,140.03 | 2,155.02 | 6,569.03 | 6,577.31 | 8,345.73 | 8,358.54 |
| *G*2 | 0.22 | | 6.94\* | | 2.40 | |
| *N* | 2,007 | | 2,007 | | 2,006 | |
| **Predictor: News Incidentality** | | | | | | |
| Statistic | Recall | | Credibility | | False Belief | |
|  | Random Intercepts | Random Effects | Random Intercepts | Random Effects | Random Intercepts | Random Effects |
| AIC | 2,038.06 | 2,039.91 | 6,515.79 | 6,519.78 | 8,233.03 | 8,231.97 |
| BIC | 2,054.87 | 2,067.93 | 6,538.21 | 6,553.41 | 8,255.45 | 8,265.59 |
| *G*2 | 2.15 | | 0.01 | | 5.06 | |
| *N* | 2,007 | | 2,007 | | 2,006 | |
| *Note*: Cell entries are model fit statistics comparing Linear Mixed Effects (LME) models with and without random effects. The comparisons establish that, with one exception, the models without random effects are a better fit to the data, indicating that the relationships between predictors and outcomes are largely stable across sampling frames.  Groups= 17. \**p* < .05. | | | | | | |