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Talking Past Each Other on Twitter: Thematic, Event, and Temporal Divergences in Polarized Partisan Expression on Immigration

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ABSTRACT

Extending literature on political polarization and political expression, we study patterns of polarized expression by vocal partisans from opposing camps on social media. Specifically, we argue that *polarized partisan expression* can be characterized by three divergences: 1) different thematic emphases on the same issue; 2) response to different real-world events on the same issue; and 3) a temporal disconnect at the aggregate level. Highlighting how online expression by different partisan groups is animated by discrete concerns and events and exhibits different temporality, the three divergences in polarized partisan expression not only reflect and explain existing polarization concepts but also speak to the epistemological chasm between partisan groups. Our empirical analysis is based on Twitter discussion about the issue of immigration in the U.S. and applies topic modeling and time series analysis. Results demonstrate that liberal and conservative tweets exhibit different thematic emphases, are often spurred by different event features, and remain largely temporally independent, though both Trump's tweets and emotionally evocative events can draw simultaneous reaction from both sides. These findings suggest that opposing partisan groups not only hold different views on the same issue, but also weave different events and facts about the issue into partisan expression in response to different exogenous factors. In short, they "talk past each other." These polarized partisan expression patterns indicate a splintered public sphere, a concerning quality for deliberative democracy.

KEYWORDS
Polarization; partisanship; partisan expression; social media; immigration

Contemporary American society is marked by growing levels of political polarization, through which the electorate is sorted into two oppositional conservative/Republican and liberal/Democratic camps (Abramowitz & Saunders, 2008; Baldassarri & Gelman, 2008; Boxell et al., 2020; Mason, 2015).[1] Increasingly, these two camps hold diverging issue positions and policy preferences (Jacobson, 2012) and develop dislike and distrust of each other (Iyengar et al., 2012, 2019). Although these tensions are not restricted to the U.S., they are particularly acute in the context of a two-party system that often rewards contention over coalition building.

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These ideological and affective forms of polarization are related to how *people with strong political opinions and identities* consume information and express opinions both offline and online (Iyengar et al., 2019). In the current high-choice media environment, partisans can selectively choose and internalize information to seek confirmation and avoid cognitive dissonance (Bennett & Iyengar, 2008; Frimer et al., 2017). Partisans are generally more comfortable having political conversations with like-minded others offline (Mutz, 2006) and might shut down cross-cutting talk in contentious times (Bode, 2016; Wells et al., 2017). Such information consumption and expression patterns, while not absolute, can nonetheless strengthen existing viewpoints and fuel opinion extremity and out-group animosity (Binder et al., 2009; Heiss & Matthes, 2020). These tendencies have intensified on social media platforms, which have become an important venue for information consumption, opinion expression, and discursive feuding on social and political issues (Bail, 2021; Settle, 2018; Shah, 2016). On social media, not only do partisans interact with like-minded others and expose themselves to congenial information (Kearney, 2019; Mukerjee & Yang, 2020), but they also engage in "selective sharing" of content to promote their claims and attack opponents (Shin & Thorson, 2017, p. 234).

These tendencies indicate the plausibility of *polarized expression patterns* among *outspoken partisans* on social media. In this study, we argue that *polarized partisan expression* is characterized by three divergences: 1) different thematic emphases on the same issue; 2) response to different real-world events on the same issue; and 3) temporal separation at the aggregate level, all of which lead to semantically divergent and temporally disconnected patterns of partisan expression on social media.[2] That is, when talking about the same issue online, opposing partisans often "stay in their own lane" and "talk past each other." It seems possible, for example, that among the various events triggering expression and discussion around U.S. immigration, outspoken liberals would react on social media to events related to Deferred Action for Childhood Arrivals (DACA) because of their strong support for this policy, while conservatives would remain largely quiescent on this matter; likewise, vocal conservatives may be motivated to express their opinions on the border wall policies that have long been promoted by Trump and GOP leaders. By foregrounding thematic, event, and temporal divergences in polarized partisan expression online, our study sheds light on several forms of political polarization – ideological, affective, interpretative, interactional, positional, and network polarization – while also pointing to the epistemological chasm between partisan groups.

To investigate the three divergences in polarized partisan expression, we focus on the issue of U.S. immigration, one that has drawn intense debate and media attention since Donald Trump made it a centerpiece of his 2016 presidential campaign and, later, of his presidency. In 2017, after Trump took office, a series of immigration executive orders, legal challenges, and social protests made news headlines. Given that this issue has ignited intense and widespread debate under the tumultuous Trump presidency, it provides a conservative test of the three proposed divergences in polarized partisan expression in the U.S. Analyses were conducted in three stages. First, we compiled a comprehensive list of immigration-related events, including (a) policy events that restricted or permitted immigration (e.g., Border Wall, Travel Ban, Sanctuary Cities, Family Separation, DACA and DAPA) and (b) immigrant-centered events (e.g., protests or boycotts in support of immigrants and instances where immigrants were perpetrators or victims of harm); and (c) Trump's bully pulpit of executive orders, policy announcements, and tweets concerning immigration. Second, we collected tweets related to immigration and conducted topic modeling using Latent Dirichlet Allocation (LDA) to identify patterns of expression aligned with conservatives and liberals, respectively. Third, we applied time series modeling to investigate how patterns of liberal and conservative expression were temporally related to event features and one another.

Before we move to this empirical analysis, we first explicate the three ways in which polarized partisan expression diverges by integrating several strands of literature, including political expression on social media, forms of political polarization, framing, and agenda-setting.

Expression and Polarization on Social Media

Public discussion is essential for a functioning and robust democracy (Habermas, 1994; Wells et al., 2017). Social media platforms seem to facilitate the free exchange of opinions and ideas between people from different backgrounds, but existing research shows that partisan expression dominates online spaces in the increasingly polarized U.S. society.

Partisan-ideological sorting has resulted in the convergence of partisan identity and ideological identity, with liberals aligned with the Democratic Party and conservatives aligned with the Republican Party (Mason, 2015). Increasing levels of ideological polarization in American society are evident in both internal ideological consistency and external ideological divergence (Lelkes, 2016). For over a decade, research has noted that the electorate gravitates toward the two extremes of the ideological spectrum (Abramowitz, 2010), with preferences on political and societal issues like civil rights, federal spending, and global warming increasingly split by political ideology (Abramowitz & Saunders, 2008; Baldassarri & Gelman, 2008; McCright & Dunlap, 2011). Moreover, strong partisan identities have led partisan groups to harbor increasingly negative feelings toward each other, a phenomenon described as affective polarization (Iyengar et al., 2012, 2019; Mason, 2015). Finkel et al. (2020) use "political sectarianism" to encapsulate this combination of "othering, aversion, and moralization" that now characterizes the negative feelings between partisans. Escalating affective polarization is supported by the fact that America experienced a substantial increase in out-party animosity from 1975 to 2017 (Boxell et al., 2020).

These forms of polarization suggest patterns of partisan expressiveness on social media. Strong partisans disproportionately contribute to political discussion on social media and develop more extreme views over time (Barberá, 2020). For them, self-identity is constituted by political beliefs and reinforced through self-expression (Ferrucci et al., 2020), which results in a greater need for expression and a stronger motivation to promote one's position (Heiss & Matthes, 2020; Kim, 2009). For partisans, information sharing and self-expression on social media are also inherently social activities to enhance in-group status (Shin & Thorson, 2017). Even when partisans consider self-censorship due to a fear of isolation, perceived issue importance can override this concern and encourage expression (Gearhart & Zhang, 2014).

Also, strong partisans' outspokenness is likely driven by their perception of an agreeable social network that provides a sense of perceived control and social validation (Chun & Lee, 2017), honed by unfriending disagreeable others to prune their social media feeds (Bode, 2016). Recent evidence suggests even people who are apolitical or moderate in their views cut social media ties during contentious times (Bozdag, 2020), potentially hollowing the middle.

Selective exposure further shapes divergence in partisan expressiveness. People tend to selectively access and process information, potentially to reduce cognitive dissonance, maintain the integrity of the political self, or protect their interpersonal relationships (Knobloch-Westerwick & Meng, 2011), a pattern especially pronounced among partisans (Frimer et al., 2017; Mukerjee & Yang, 2020). On social media, strong partisans are disproportionately exposed to like-minded information (Bakshy et al., 2015) and are averse to opposing information (Frimer et al., 2017). Additionally, on social media, selective exposure processes can be further aided by platform algorithms that up-rank and recommend pro-attitudinal content (Levy, 2021; Pariser, 2011). Such biased information intake increases attitude extremity on issues such as immigration (Heiss & Matthes, 2020). When highly polarized citizens self-select whom to interact with and what information to consume, all while viewing online expression as a facet of one's identity, the triggers for polarized partisan expression on social media appear to be in place.

Polarized Partisan Expression Patterns

As the discussion above shows, there is considerable theoretical support for the expectation that strong partisans exhibit different expression patterns on social media, particularly in the U.S. context. Focusing on strong partisans' tendency to express opinions only within a narrow range and in response to specific events based on partisanship/ideology, we emphasize three divergences in polarized partisan expression: 1) different thematic emphases by strong liberals and conservatives that reinforce partisan positions, 2) different offline event features of the same issue that drive expression by strong liberals and conservatives, and 3) different temporal patterns of expression indicating that their outspokenness does not occur in parallel. Together, these differences result in semantically divergent and temporally disconnected patterns of partisan expression on social media regarding the same issue. In what follows, we describe each divergence, provide prior empirical evidence, and tie it into established polarization and communication concepts.

Advancing Different Thematic Emphases

Thematic divergence describes how strong partisans with different political stances emphasize different aspects of the same issue. We use "thematic emphasis" to refer to an interpretive lens for understanding an issue and the resulting semantic coherence in expression, while acknowledging that this term can be used interchangeably with other variants like "thematic focus" (Baden et al., 2020) and "thematic domain" (Kligler-Vilenchik et al., 2020). Existing research, though not explicitly using the above terms, provides considerable empirical support for this pattern of expression. For example, while Democratic politicians' Twitter discourse centered on the public health risks posed by the COVID-19 pandemic, Republicans tended to emphasize China's role in the pandemic and its toll on the economy (Green et al., 2020). A similar divide can be observed in rank-and-file partisan discourse. Partisans on Twitter highlighted different concerns about COVID-19 vaccines (Jiang et al., 2021) and selectively shared fact-checking messages about the 2012 election to valorize their own party's candidates and diminish the opposing party (Shin & Thorson, 2017). Additionally, during the #Tarifazo protests in Argentina, pro- and anti-government communities on Twitter put forth different frames using hashtags, hyperlinks, and terms (Aruguete & Calvo, 2018).

The tendency to focus on different semantic strands is rooted in the existing polarization and framing literature. As a result of ideological and affective polarization (Lelkes, 2016; Mason, 2015; Van Bavel & Pereira, 2018), partisans are more motivated to speak out on controversial issues they care about and frame those issues differently in their expression on social media (Zhang, Shah, et al., 2022). This tendency is consistent with interpretative polarization, which posits that different groups apply different interpretative frames to make sense of an issue (Kligler-Vilenchik et al., 2020). For example, in social media discussion on an Israeli soldier who killed a wounded Palestinian assailant, supporters of the soldier expressed solidarity and highlighted his military duty, but opponents attended to the shooting itself (Kligler-Vilenchik et al., 2020). Partisans advancing different emphasis frames or issue attributes to discuss the same issue reflects the differential perspectives with which they approach, interpret, and construct messages on an issue in a competitive information environment (Chong & Druckman, 2007; McLeod et al., 2022; Pan & Kosicki, 1993). While this divergence is marked by different semantic strands, the other two divergences underscore events and temporality.

Responding to Different Events

Event divergence pertains to how online partisan expressiveness is triggered by offline events emblematic of different features that allow strong partisans to stick to their talking points. Specifically, strong partisans likely lean into talking about events that buttress their views while ignoring events that might undermine their positions. In this conceptualization, events are understood as happenings in the offline world that can potentially advance democratic deliberation, such as policy announcements and newsworthy incidents (Coleman & Gøtze, 2001). Other events, like a tweet storm started by a populist politician or an outrageous comment dropped by a provocateur, can reasonably provoke universal responsiveness (and rebukes) (Wells et al., 2020). Yet, they might have limited potential to facilitate deliberation or engagement over policy considerations. Empirical evidence lends support to this selectivity on external events: mass shootings with high casualties and child deaths are powerful predictors of gun control discourse from liberals, while mass shootings with random shooters consistently predict gun rights discourse from conservatives on Twitter (Zhang, Shah, et al., 2022). That is, rather than competing for superiority during each related event, strong partisans appear to selectively "join the chorus" on advantageous events, arguably to score political points and build solidarity.

This selectivity might be intentional. In the post-truth era, facts are selectively chosen to justify and promote one's own positions (Lewandowsky et al., 2017). Strong partisans may actively avoid chiming in on certain events, selecting to be expressive only when the triggering instances allow them to advance their agenda and "talking points" via social media (e.g., Green et al., 2020). Such a dynamic expands on the notion of issue ownership, which posits that different parties are motivated to promote issues on which they excel during campaigns (Arbour, 2014; Petrocik, 1996). This process might be further influenced by an awareness of social media algorithms that amplify content attracting attention and engagement from diverse groups: talking about events advantageous to the opposing side might only contribute to the algorithmic amplification of those events (Zhang et al., 2018).

Yet for some strong partisans, the selectivity in expression may be passive and unintentional, potentially explained by the second-level agenda-setting process in a polarized news ecology: partisans respond to particular events because they are exposed to a partisan media agenda and unaware of other events (Iyengar & Hahn, 2009; Romer & Jamieson, 2021). Exposure to one-sided events might also be a function of the homogenous social media networks in which people are embedded. Through patterns of unfollowing, partisans, moderates, and the apolitical all appear to trim their networks of those with whom they disagree (Bode, 2016; Bozdag, 2020).

Events triggering different patterns of expression among partisans on the left and right can be explained by and help explain established polarization concepts. As people hold more extreme attitudes about issues and social groups (i.e., ideological polarization and affective polarization), they are more motivated to engage in pro-attitudinal expression when an appropriate triggering event occurs. At the same time, event divergence might help explain interpretive polarization. How people contextualize an issue hinges on what facts they bring into consideration. As people attend and respond to events, they weave different features into their evaluation and interpretation of an issue (Zaller, 1992).

This pattern of expression also provides another perspective for considering the epistemological crisis in the current information ecology. Existing research illuminates the discrepancy between ground truths and expression that ignores or actively subverts them. For instance, while macroeconomic evidence shows that immigrants do not burden the economy of Western European countries, anti-immigration arguments promoting the supposed economic threat posed by immigrants still circulate widely (d'Albis et al., 2018). Our study highlights how partisans selectively evoke certain ground truths to discuss an issue, which is concerning because it poses a potentially bigger challenge for democratic deliberation than partisans selectively interpreting and framing certain events. When strong partisans do not wrestle with the same policy-relevant events and instead comment on certain events to score political points or build solidarity, public discourse further splinters.

Speaking at Different Times

As the first two divergences suggest, the third way in which polarized partisan expression diverges concerns the over-time pattern of speaking out at the aggregate level. If strong partisans from opposing camps focus on different thematic domains and select different events to talk about, their overall outspokenness regarding the same issue is unlikely to occur simultaneously. As a consequence, strong partisans talk about an issue passionately and profusely at different time points, as opposed to engaging in heated back-and-forth debates at one time. In other (more technical) words, opposing partisans' patterns of expression about the issue are temporally independent when aggregated over time. This pattern is observed though not theorized in the previous study of issue claims in Europe, such that societal issues have received an asymmetric number of claims from different actors and at different times (Koopmans et al., 2010).

This pattern of divergence relates to interactional polarization, which captures a gradual increase in like-minded interactions (Yarchi et al., 2021), as well as network polarization, which explains partisans' intensifying tendency to follow like-minded others as elections approach (Kearney, 2019). Given these forms of polarization, partisans are more likely to express opinions with considerable synchronicity: talking when cued by others in one's homophilous network to express themselves about an issue. This tendency also relates to counter-framing, which describes a frame that provides a competing interpretation in response to an earlier frame (Chong & Druckman, 2013), and the cascading activation model, which highlights the spread of interpretive frames among political actors (Entman, 2003). Notably, both theories emphasize how one frame spurs a response or an amplification. To the extent that framing discourses on the aggregate level do not engage each other, they can exhibit an over-time disconnect between patterns of expression advanced by different partisan camps.

This tendency to speak at different times instead of engaging in an ongoing discursive battle or deliberative exchange means that rather than confronting the same events and advancing disparate frames (e.g., Feldman & Hart, 2018), strong partisans in opposing camps stick to their own ideological narratives and limit effort to counter opponents when they are active. This lack of back-and-forth conversation between partisans may be a strategic action, geared toward avoiding confrontation and building support for action within ideological communities.

Building on existing polarization concepts and communication theories, our consideration of thematic emphases, event features, and temporal disconnection in polarized partisan expression extends scholarly attention *from* the way strong partisans in different camps possess increasingly polarized issue positions, hold negative feelings toward each other, and avoid cross-cutting interactions *to* how these trends can manifest into a tendency to "stay in one's political lane," "stick to practiced talking points," and end up "talking past each other." If observed, these patterns may illuminate how the epistemologies of different partisan groups differ and come into conflict, suggesting a splintered public discourse that misses chances for meaningful exchange.

Immigration During the Trump Presidency

The contentious nature of immigration serves as an appropriate context for examining the three divergences in polarized partisan expression. Studies suggest ideological concerns, including identity and religion, play a more significant role in shaping attitudes toward immigration, overshadowing self-interested calculations (Grover et al., 2019; Hainmueller & Hopkins, 2014). For example, instead of economic indicators, crime rates, and demographics, it is the conservative ideology that appears to drive state-level restrictive immigration legislation in the U.S (Chavez & Provine, 2009). Also, liberals' and conservatives' interpretations of the issue correspond to different moral judgments (Day et al., 2014) and their Twitter discussions on immigration exhibit different moral foundations and temporal patterns (Grover et al., 2019).

Upon taking office, Donald Trump signed three executive orders that impacted legal immigrants, undocumented immigrants, asylum seekers, and others – a U.S. policy change with global implications. These orders, the judicial decisions challenging them, and other policy announcements that followed, spanned border security and interior enforcement, including expanded detention, limited asylum access, enhanced border enforcement, construction of a U.S.-Mexico border, the barring of refugees and visa holders from seven prominently-Muslim nations, the repeal of DAPA, and the punishment of so-called sanctuary cities.

For this reason, we focus on the period from Trump's inauguration to the end of 2017, a time of intense attention to the issue of immigration among Republicans and Democrats. Trump's centrality within this ongoing debate provides an opportunity to examine whether partisan expression converges in response to these provocations, with his executive orders, policy announcements, and tweets concerning immigration often providing "raw meat" that may spur reactions from both sides of the partisan divide. If polarized partisan expression diverges on immigration during a tumultuous period that received widespread reaction, that would provide a strong confirmation of our expectations. In addition, we study what triggers liberal and conservative expression on Twitter, a platform known for political expression that can influence news production and political events (Kreiss, 2016; Lasorsa et al., 2012). We propose a hypothesis for each of the divergences.

H1: There are different thematic emphases in liberal and conservative expression about U.S. immigration on Twitter.

H2: Patterns of liberal and conservative expression about U.S. immigration on Twitter are driven by different features of immigration-related events.

H3: Patterns of liberal and conservative expression about U.S. immigration on Twitter are temporally independent of one another.

Methods

Data

Twitter Data

Immigration-related tweets throughout 2017, from January 1 to December 31, were collected from an archive containing a random 1% sample of Twitter's global stream. We searched for tweets ($N = 2{,}159{,}280$) containing a comprehensive list of terms spanning labels and language from the left, right, and center (e.g., "kids in cages," "asylum seeker," "build the wall," "anchor baby," "immigrant," "border wall") to capture a wide range of U.S. discourse. Using a language-detection algorithm, we excluded non-English tweets and ended up with 1,534,509 posts (see Appendix A for details about Twitter data collection and cleaning).

Event Timeline and Event Features

We compiled a comprehensive list of 63 immigration-related events in 2017, based on 1) policy announcements from the official websites of the White House and the Department of Homeland Security, 2) Ballotpedia's timeline of federal policy on immigration[3] and 3) immigration-related news from mainstream media sources including CNN, *The Washington Post*, *The New York Times*, *Time*, The Hill, *Wall Street Journal*, NBC news, ABC news, NPR news, BBC, Reuters, and CNBC.[4] Event selection was shaped by two considerations: policy shifts that received widespread media coverage (e.g., Trump's executive orders on sanctuary cities and the border wall, and the judicial decisions connected to these policies) and national news media stories centered on immigrants (e.g., death of an immigrant detainee in ICE custody; trial of the suspect in the shooting of Kate Steinle). Events that pertain to immigration policy but did not receive widespread news attention were not included. Each included event was cross-validated by reports from at least two of the media sources mentioned above. The full event list and event coding schemes are presented in Appendix B.

We developed a coding scheme to code these events for 22 features across three major categories, distinguishing (a) events about eight different policies coded for whether they restricted or allowed immigration (i.e., Border Wall, Travel Ban, Visa Restrictions, Sanctuary Cities, Family Separation, DACA and DAPA, ICE Efforts, and Refugees Admissions);[5] (b) four different types of immigrant-centered events (i.e., events centering on immigrants' experiences in terms of legal status and public life, immigrants as perpetrators or victims of harm); and (c) Trump initiated events, including his executive orders and announcements. The correlation between any pair of events was relatively low, ranging from the highest of 0.49 to the lowest of −0.03 (see Appendix C for correlations between event features). In the examination of the relationship between events and patterns of expression, we included Trump's tweets as a control variable because language cues from political elites can shape public opinion (Schneider & Jacoby, 2005) and Trump's tweets can trigger public expression (Lazarus & Thornton, 2021).

Analytic Strategy

Topic Modeling

To test H1, we applied topic modeling with Latent Dirichlet allocation (LDA) to allow unsupervised identification of topics. LDA is an established computational technique for investigating thematic structure in large text corpora (Guo et al., 2016; Maier et al., 2018).

Due to a large number of duplicate tweets (i.e., retweets), we took the unique tweets (n = 762,998 out of all 1,534,509 tweets) for topic modeling. First, the preprocessing step includes 1) removing URLs, handles, non-ASCII characters, numbers, and symbols, 2) tokenizing and lemmatizing words, and 3) removing stop words. Second, a document-term matrix was created, where each document represents a tweet and each term a token (i.e., word or unigram) that appears in the documents. Given that both infrequent terms and frequent terms bring noise and reduce model accuracy, infrequent terms (appearing in less than 0.005% of the documents) and frequent terms (appearing in over 90% of the documents) were removed (see Grinberg et al., 2019). Third, to find the statistically optimal number of topics (i.e., K), we relied on four metrics, lower bound, held-out likelihood, residuals, and semantic coherence. The first three metrics measure a model's goodness-of-fit, and the last metric evaluates the likelihood of highly probable words under a topic co-occurring within the same document.

We found the optimal K to be 24 as it yields the lowest residuals, relatively high semantic coherence, held-out likelihood, and lower bound (see Figure 1 for top-loading words of the 24 topics and Appendix D for the metrics). We performed topic modeling using the Gibbs method (Griffiths & Steyvers, 2004), with the starting alpha being 50/K, estimated beta (β) and prior distribution of delta (γ) being 0.1, and 1 repeated run with random initializations

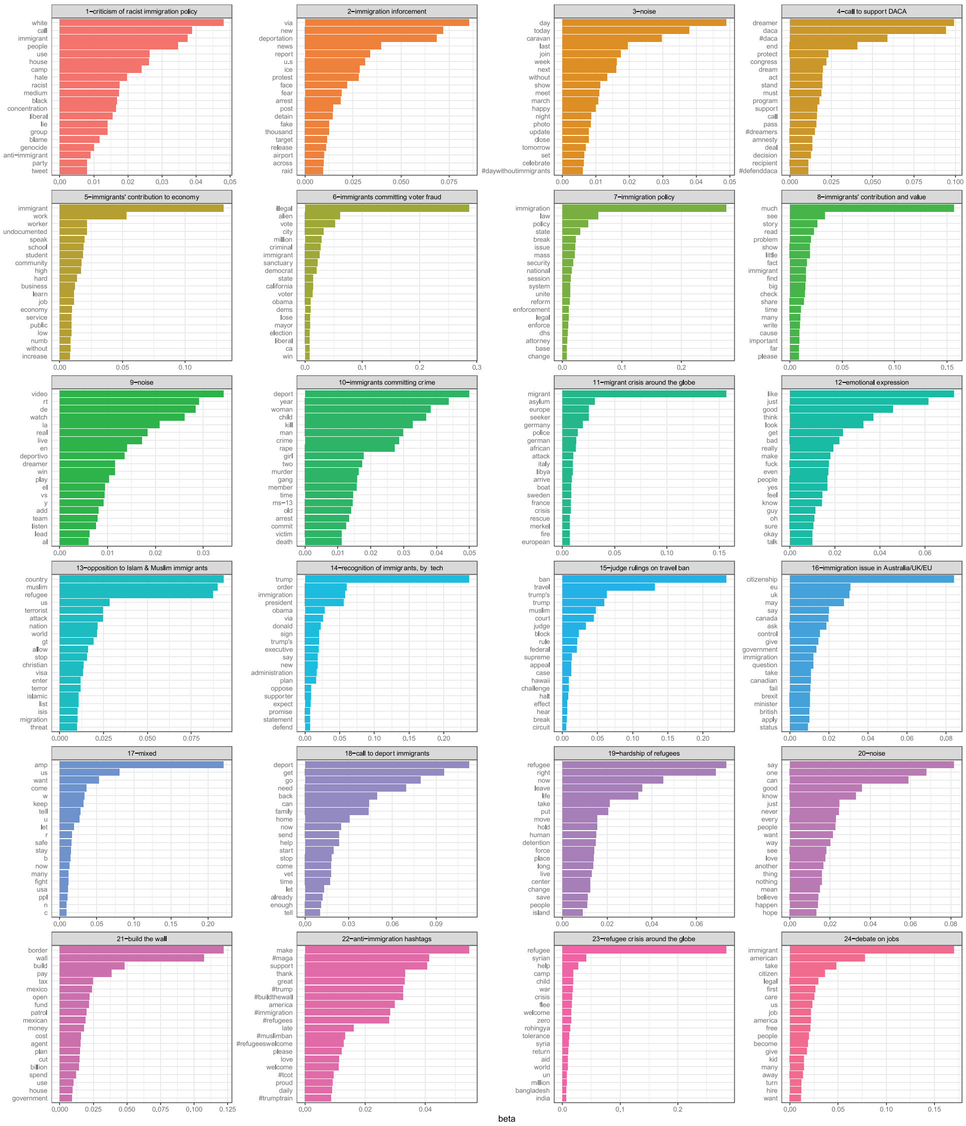


Figure 1. Top terms of the 24 topics.

and 2000 iterations. Topic modeling generates two main results: each term has a probability distribution (β) into each topic, and each document has a probability distribution (γ) into each topic. We interpreted and labeled each topic based on 20 terms with the highest β values; two authors interpreted each topic by examining the semantic meanings of 200 tweets with the highest γ values.

After each topic was labeled, we followed recommended practices (Baden et al., 2020; Kligler-Vilenchik et al., 2020; Yarchi et al., 2021) and took the followings steps: 1) removing mixed and irrelevant topics, 2) grouping similar topics that constellate together into a broader thematic emphasis, and 3) labeling the ideological leaning of the emergent thematic emphases, providing an even broader scope along partisan lines. For example, we grouped three topics, namely "immigrants" contribution to the economy", "immigrants" contribution and value", and "recognition of immigrants in tech," into the thematic emphasis of "immigrants" value," and ultimately merged this with other thematic emphases sharing a "liberal" ideological stance.

We found across topics that tweets with γ values lower than 0.1 tended to be less relevant. To prioritize the precision of topic assignment, we kept only tweets whose γ values were higher than 0.1 and assign each tweet to the topic with the highest γ. To validate the classification, two authors manually coded a random sample of 400 tweets for the accuracy of the liberal, conservative, and indeterminate labels. Liberal tweets have a precision rate of 77.8% (i.e., the percentage of instances that are relevant out of the total instances retrieved) and a recall rate of 82.4% (i.e., the percentage of instances that the model correctly identified as relevant out of the total relevant instances); conservative tweets have a precision of 85.0% and a recall of 84.2%; indeterminate tweets have a precision of 85.9%, a recall of 85.0% (see Appendix E).

Time Series Modeling

We tested whether the event features we coded for drove patterns of liberal and conservative expression (i.e., the daily number of tweets classified as liberal and conservative) in distinct manners (H2), using Prais-Winsten estimation, a type of GLS model that adjusts for the extent to which observations at one time point are related to observations at a previous time point (Park & Mitchell, 1980). To examine H3 concerning the temporal relationship between patterns of liberal and conservative expression, we first computed the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for each series (Appendix F for visualization of ACFs and PACFs). We confirmed the stationarity of the series using Augmented Dickey – Fuller (ADF) tests. We then conducted Granger causality tests to examine if the conservative and liberal time series Granger caused each other, based on a Vector Autoregression (VAR) model that includes the liberal and conservative series as endogenous variables.

For validation, we also applied Vector Autoregression (VAR) analysis for H2 & H3. This VAR model involved the liberal, conservative, and indeterminate time series as endogenous variables, and the event features as exogenous variables. The VAR estimates were then used to perform Granger causality tests and generate Impulse Response Functions (IRFs), which show the magnitude, significance, and temporal response of one endogenous variable to another.

Results

Topics, Thematic Emphases, and Ideologies of Tweets

Figure 1 displays the top loading words for each of the 24 immigration topics, which vary widely. Some topics concern threats posed by immigrants such as "Immigrants committing crimes;" others are about values they bring to American society, such as "Immigrants" contribution to the economy." Some topics directly call for restricting immigrants, like "opposition to Islam & Muslim immigrants" and "call to deport immigrants," while some topics express support of immigrants, like "call to support DACA" and "criticism of racist immigration policy." However, some topics do not exhibit clear political preferences, such

Table 1. Topics and the classification scheme.

Topic Number	Topic	Thematic Emphasis	Ideology
4	Call to support DACA	Call to support immigrants	Liberal
1	Criticism of racist immigration policy	Call to support immigrants	Liberal
19	Hardship of refugees	Call to support immigrants	Liberal
5	Immigrants' contribution to the economy	Immigrants' value	Liberal
8	Immigrants' contribution and value	Immigrants' value	Liberal
14	Recognition of immigrants in tech	Immigrants' value	Liberal
18	Call to deport immigrants	Call to restrict immigrants	Conservative
21	Build the wall	Call to restrict immigrants	Conservative
13	Opposition to Islam & Muslim immigrants	Call to restrict immigrants	Conservative
22	Anti-immigration hashtags	Call to restrict immigrants	Conservative
10	Immigrants committing crimes	Immigrants' threat	Conservative
6	Immigrants committing voter fraud	Immigrants' threat	Conservative
2	Immigration enforcement	News	Indeterminate
7	Immigration policy	News	Indeterminate
12	Judge rulings on travel ban	News	Indeterminate
15	Emotional expression	Emotional expression	Indeterminate
17	Debate on jobs	Mixed	Indeterminate
24	Mixed	Mixed	Indeterminate
11	Migrant crisis around the globe	Irrelevant	Irrelevant
16	Immigration issue in Australia/UK/EU	Irrelevant	Irrelevant
23	Refugee crisis around the globe	Irrelevant	Irrelevant
3	Noise	Noise	Noise
9	Noise	Noise	Noise
20	Noise	Noise	Noise

as news ("immigration policy" and "immigration enforcement") and emotional expression likely spanned the political spectrum ("emotional expression"). Topics outside the U.S. context (e.g., Immigration issue in Australia/UK/EU) are categorized as "irrelevant" and topics clearly caused by the introduction of noise during data collection are treated as "noise;" both are excluded from downstream analysis.

After the topics were clustered into thematic emphases, which were then grouped into ideological stances (see Table 1), we can observe a clear thematic divergence within the partisan expression. The majority of the relevant tweets (67.7%) display clear ideological leanings, with 27.3% liberal and 40.5% conservative tweets. Within liberal tweets, the thematic emphases include immigrants' value (with the following topics: "immigrants" contribution to the economy", "immigrants" contribution and value", and "recognition of immigrants in tech") and call to support immigrants (i.e., "call to support DACA," "criticism of racist immigration policy", and "hardship of refugees"), whereas the thematic emphases in conservative tweets pertain to immigrants' threat (i.e., "immigrants committing crimes" and "immigrants committing voter fraud") and call to restrict immigrants (i.e., "call to deport immigrant", "build the wall", "opposition to Islam & Muslim immigrants", and "anti-immigration hashtags"). These results lend support for thematic divergence in partisan expression (H1).

Relationship Between Partisan Expression and Event Features

Regression results with Prais-Winsten estimation show how the volume of liberal vs conservative tweets was associated with event features (Table 2). Liberal expression was driven by the family separation policy ($b = 723.28$, $p < .05$), DACA- and DAPA-related restrictions ($b = 729.53$, $p < .001$), Trump-initiated events ($b = 513.49$, $p < .001$), and Trump's immigration-related tweets ($b = 671.84$, $p < .001$), and suppressed by travel ban restrictions ($b = -813.01$, p

Table 2. The relationship between event features and partisan expression using prais-winsten estimation.

Events	Liberal	Conservative	Indeterminate
constant	183.05**	289.42***	218.21***
Border Wall – restrict	−41.87	465.61***	205.83
Border Wall – allow	1.96	7.74	7.00
Travel Ban – restrict	−813.01 ***	−480.54***	−322.60
Travel Ban – allow	7.86	3.60	575.67***
Visas – restrict	−744.23***	−79.94	88.17
Visas – allow	−21.88	−15.95	−5.90
Sanctuary Cities – restrict	−188.83	−82.03	−295.55
Sanctuary Cities. - allow	45.30	−104.55	25.55
Family Separation – restrict	723.28*	1531.84***	809.57*
DACA/DAPA – restrict	729.53***	124.10	230.60
DACA/DAPA – allow	334.65	−34.58	141.37
ICE Efforts – restrict	−53.93	−94.04	100.41
ICE Efforts – allow	385.95	24.71	−10.09
Refugee Admissions – restrict	−133.90	−78.99	−278.39*
Pro-immigrant Solidarity Events	76.15	52.72	24.51
Immigrants as Criminal	−180.08	1.19	−186.81
Immigrants as Victim of Crime	−38.03	49.73	7.17
Immigrants' Hardship	−364.43**	−11.96	−21.58
Trump Initiated	513.49***	10.56	−6.61
Trump Tweets	671.84***	225.82**	362.24*
R^2	.28	.20	.13
rho	.69	.67	.52
F (20, 343)	6.54	4.38	2.61

*$p < .05$, **$p < .01$, ***$p < .001$.

< .001), visa restrictions ($b = -744.23$, $p < .001$), and news about immigrants' hardships ($b = -364.43$, $p < .01$). Conservative expression was stimulated by border wall events ($b = 465.61$, $p < .001$) and the family separation policy that restricted immigration ($b = 1531.84$, $p < .001$) along with Trump's immigration-related tweets ($b = 225.82$, $p < .01$), but reduced by travel ban events that restricted immigration ($b = -480.54$, $p < .001$) (see Table 2).

A similar pattern can be observed with the VAR model that examines the contemporaneous relationship between event features and the expression time series while controlling for the mutual influence among the endogenous variables. Liberal expression was spurred by DACA- and DAPA-related restrictions ($b = 706.02$, $p < .001$), Trump initiated events ($b = 725.56$, $p < .001$), and Trump tweets ($b = 749.70$, $p < .001$). It was dampened by the travel ban that restricts immigration ($b = -611.53$, $p < .01$) and the visa policy that restricts immigration ($b = -997.93$, $p < .001$). Conservative expression was triggered by border wall events ($b = 594.51$, $p < .001$) and family separation policies that restrict immigration ($b = 1603.70$, $p < .001$), as well as Trump-initiated events ($b = 168.01$, $p < .05$) and Trump tweets ($b = 187.86$, $p < .05$). It was suppressed by travel ban events ($b = -303.38$, $p < .05$) and visa related events that restrict immigration ($b = -294.48$, $p < .05$) (see Table 3).

Both Prais-Winsten and VAR analyses show that the major event features predicting expression about immigration on the right differ from those predicting it on the left. DACA- and DAPA-related restrictions drove up liberal expression, while border wall events that restricted immigration spurred conservative expression. It is noticeable that a particular type of event, family separation, sparked expression across the political spectrum, likely because it violates moral values and evokes strong emotions. These results largely support H2. We also conducted an analysis at the level of thematic emphases on the liberal and conservative sides (see Appendix G).

Table 3. The relationship between event features and partisan expression using vector autoregressions (VARs).

Events	Liberal	Conservative	Indeterminate
Constant	21.26	93.31***	−14.54
Border Wall – restrict	−91.08	594.51***	9.98
Border Wall – allow	−13.31	0.02	−64.22
Travel Ban – restrict	−611.53**	−303.38*	−34.77
Travel Ban – allow	83.27	93.11	884.41***
Visas – restrict	−997.93***	−294.48*	−82.75
Visas – allow	−14.87	17.46	22.06
Sanctuary Cities – restrict	−82.37	191.01	−1.76
Sanctuary Cities. - allow	78.57	−170.80	40.85
Family Separation – restrict	342.19	1603.70***	360.33
DACA/DAPA – restrict	706.02***	−21.90	101.48
DACA/DAPA – allow	164.51	−164.83	−13.04
ICE Efforts – restrict	−154.66	−68.25	−138.20
ICE Efforts – allow	322.17	32.94	95.11
Refugee Admissions – restrict	−72.78	−31.12	−129.02
Pro-immigrant Solidarity Events	20.53	29.27	−15.57
Immigrants as Criminal	−208.43	82.56	−120.07
Immigrants as Victim of Crime	−91.06	61.14	−176.69
Immigrants' Hardship	−269.66	4.64	0.69
Trump Initiated	725.56***	168.01*	134.66
Trump Tweets	749.70***	187.86*	399.24**
R^2	.59	.58	.49

*$p < .05$, **$p < .01$, ***$p < .001$.

Temporal Disconnect in Patterns of Partisan Expression

The vector autoregression model of the liberal and conservative time series (Figure 2) suggested the best lag to be 1 according to the Bayesian Information Criterion (BIC). Thus, we conducted Granger Causality tests using liberal and conservative series, with the one-day lag. The Granger causality tests show that liberal expression did not Granger-cause conservative expression ($F = 0.20$, $p = .659$), nor did conservative expression Granger-cause liberal expression ($F = 0.00$, $p = .998$).

The VAR model with the liberal, conservative, and indeterminate time series as endogenous variables and events as exogenous variables produces slightly different findings. Under the best lag of 4 according to BIC, conservative expression Granger-caused liberal expression ($p < .01$), while liberal expression did not Granger-cause conservative expression ($p = .127$). IRFs show that liberal expression responded to conservative expression only starting from time $t + 3$ (Figure 3). These findings partially support H3.

Discussion

Building on existing polarization research, we theorize patterns of polarized partisan expression in terms of thematic emphases, event triggers, and temporal co-occurrence. These patterns capture how strong partisans "stay in their lane" and "talk past each other" on issues of public concern, drawing our attention to the texture of visible public discourse on social media. This focus on the nuanced online partisan discourse enriches our understanding of political polarization (its manifestation and outcomes in terms of online expression) and sheds light on the epistemological chasm between different partisan groups.

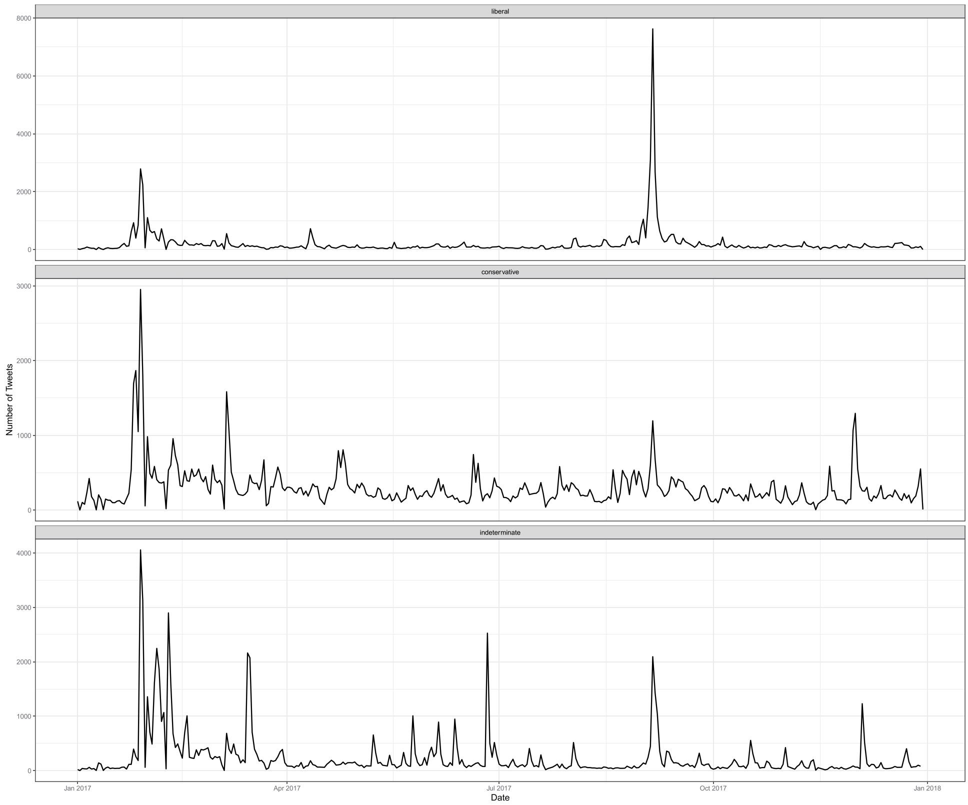
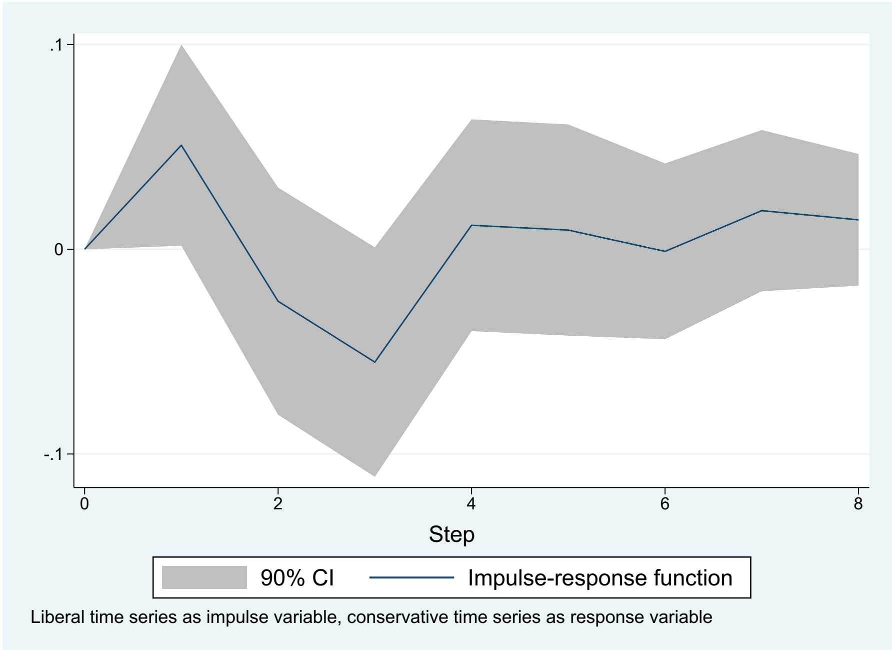


Figure 2. Time series of tweets by ideology.

Our analysis of immigration-related tweets lends some empirical support to patterns of divergence in polarized partisan expression on social media. We demonstrate how political expression about immigration emphasized different aspects of the issue depending on partisanship: the majority of the immigration-related expression on Twitter displayed clear ideological stances; and liberal and conservative expression exhibited different thematic emphases. Also, different event features drove expression on the left and right asymmetrically. Liberal expression spiked after events restricting DACA/DAPA, while no significant change was observed in the volume of conservative expression. In contrast, there was a surge in conservative expression after events supporting the border wall, while the volume of liberal expression remained unchanged. This might be explained by how DACA/DAPA and the border wall occupied a central role in the immigration reform agenda of liberals and conservatives, respectively, and thus were more likely to elicit specific responses among partisans. These findings provide some evidence of a partisan split in the outspokenness on the issue of immigration. The tendency of opposing partisans to advance distinct thematic emphases and respond to different events concerning U.S. immigration policy during the first year of the Trump administration results in semantically divergent and temporally disconnected partisan expression on Twitter.

It is noticeable that family separation, an emotionally evocative event, animated expression from both sides. The idea of kids being separated from their parents

(1) Impact of the liberal time series on the conservative time series



(2) Impact of the conservative time series on the liberal time series

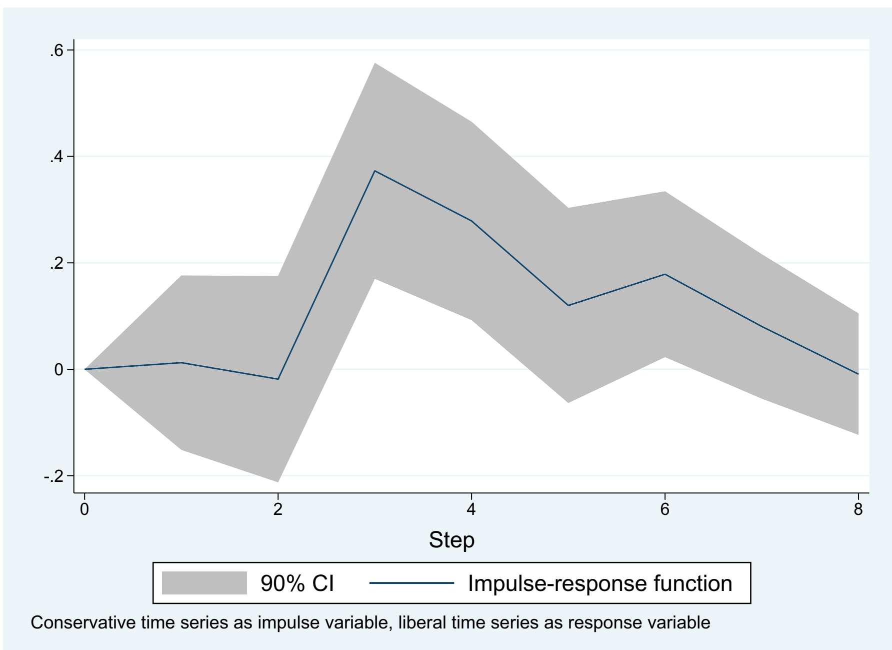


Figure 3. Impulse response functions for the liberal and conservative time series: (1) impact of the liberal time series on the conservative time series, (2) impact of the conservative time series on the liberal time series.

drew widespread public attention and intense debates. We also find that Trump's tweets, rich in political cues, drove both liberal and conservative expression, a pattern consistent with research on Trump's ability to use Twitter to attract broad attention and ignite heated public discussions (e.g., Wells et al., 2020; Zhang et al., 2018). These results suggest that emotionally evocative events and highly contentious remarks from a populist leader, especially the U.S. executive, can break through typically polarized partisan expression. And while we expect firebrands and evocative events to trigger bipartisan responses, they seem less likely to foster bipartisan deliberation and more likely to spur emotionally-charged and identity-based expression. What should serve as the basis for discursive engagement and acknowledgment of immigrant experiences, like policy announcements and immigrant-centered events, unfortunately, does not.

Lastly, patterns of liberal and conservative expression about immigration were temporally independent of each other when examined within a short time window. This suggests that the ideological expression from the two sides had distinct rhythms and responded to different sets of considerations. It is also noteworthy that when examining a longer period with a lag of four days, conservative expression Granger-caused liberal expression after a few days, but not vice versa. These findings indicate no contemporaneous relationship between liberal and conservative expression and an asymmetric pattern in a longer time window.

The lack of conversation between strong partisans speaks to a long line of research about political discussion in democratic societies, and it indicates a significant drift away from democratic ideals of cross-cutting talk. In a society grounded in pluralism, listening to diverse voices and engaging in conversation is essential (Eveland et al., 2020; Wells et al., 2017) for effective collaboration (Durkheim, 2014), tolerance of different views (Mutz, 2006), social integration (Friedland, 2001), and the strength of deliberative democracy (Habermas, 1994, 2009). However, when people who are passionate about politics "stay in their respective lane" and "talk past each other" only to remain fixated on certain aspects of an issue, the consequences are concerning. Research has already recorded real-world costs of the lack of inter-group communication marked by patterns of polarized expression. It impairs the country's ability to confront challenges like COVID-19 (Finkel et al., 2020), where social distancing and mask-wearing became a point of partisan contention during the pandemic (Borah et al., 2023; Stanley-Becker, 2020). These sharp divisions also generate group conflicts, as they impair pluralism in civic life and lead to the systematic underrepresentation of certain groups (Baldassarri & Gelman, 2008; Galston, 2002). Recent years have seen rising antipathy and distrust toward immigrants and religious minorities (Mooney, 2017; Suk et al., 2022), especially Muslims (Fox et al., 2019), Latinos (Cobb et al., 2017), and Asian Americans (Le et al., 2020; Ruiz et al., 2020). Social conflict may follow from increasingly violent political divides and civic unrest (Craig, 2020). In this context, our attention to three divergences in polarized partisan expression offer a new perspective to approach group conflicts in a social media era.

Our study shows how observational social media data can be used not only for methodical advancement but also for conceptual development. As social media platforms become a major vector for opinion measurement (Shah et al., 2015; Zhang, Chen, et al., 2022), a growing body of research uses social media data to observe and understand polarization.

While past studies mainly used social data to test established constructs like network homophily, we theorize patterns of polarized partisan expression, offering new avenues for the use of social media data in political communication research.

This study has several methodological limitations. First, we inferred ideological stances based on topics and tweets, which might lack precision. However, a supplementary analysis of the ideological stances of users posting liberal or conservative tweets based on a method advanced by Barberá et al. (2015) shows clear ideological differences between these groups of users (see Appendix H). Second, we examined divergences in patterns of partisan expression on Twitter, yet political polarization and discourse patterns are different across social media platforms (Yarchi et al., 2021). More research is needed on patterns of polarized expression on platforms such as Facebook, Reddit, and YouTube. Third, given the limited testing of these expressive tendencies in the U.S. context, with a single issue – immigration — that was the focus of a uniquely populist political figure, future research needs to gauge whether patterns observed in this article generalize to other countries, issues, or timeframes.

When it comes to theory development, we highlight three directions. First, this study fails to consider the asymmetry of political polarization. Research shows that conservatives are more ideologically polarized than liberals in general (Benkler et al., 2018; Grossmann & Hopkins, 2016). Therefore, conservatives may tend to display strong leanings in their opinion expression, particularly if they hold the belief that mass media and social media are biased against them. Future research should conduct user-level analysis to explore this possible dynamic.

Second, we do not claim that the online environment is inherently marked by polarized partisan expression and urge future research to investigate contexts in which the three divergences are less or more pronounced. For example, partisans might respond to the same events when the topic is of high personal relevance, such as when they are faced with controversial preventative measures amid a public health crisis (He et al., 2021), or in periods marked by heated debates, such as during presidential elections (Yaqub et al., 2017).

Third, future studies should incorporate the larger ecological context in which polarized partisan expression unfolds. For example, given that social media and news media adapt their operational strategies to maximize attention (Stroud, 2017; Webster, 2014), social media algorithms and news media production routines can form a structure of incentives for partisans to engage in expression on events that align with their own views so as to advance their agendas in both social and news media. Social media algorithms prioritize content, particularly emotionally charged and divisive content that spreads fast and wide to maximize engagement (Brady et al., 2017; DeVito, 2017), giving partisans an additional incentive to post "hot takes." Attention-maximizing social media algorithms might disincentivize partisan discussion of topics advantageous to the opposing side (Zhang et al., 2018). News media, especially partisan media, are increasingly attentive to social media expression, placing importance on popular topics to draw audience attention (McGregor, 2019). Such news reporting patterns further incentivize partisans to use polarized expression to advance their ideological stances.

Overall, the three divergences in polarized partisan expression on immigration in the U.S. are symptomatic of the post-truth era where facts are marginalized (Farkas & Schou, 2019), information is fragmented and customized, and realities are constructed, contested, and shaped by drastically different factors (Waisbord, 2018). Not only is information consumed and shared based on pre-conceptions and group identities (Shin & Thorson, 2017), but expression is also selective, at least in some respects, contributing to an ever-widening epistemological gap between sectarian groups. Polarized partisan expression further indicates a fractured public sphere marked by an inability to communicate across groups (Bennett & Pfetsch, 2018; Waisbord, 2018), speaking to mounting challenges for a functioning democracy, which requires common ground for debates, mutual understandings, and diverse perspectives (Habermas, 2009; Wessler, 2008).

Notes

1. We use conservatives/liberals from here on because 1) partisan-ideological sorting in the U.S. has resulted in the alignment of liberals with the Democratic Party and conservatives with the Republican Party; and 2) conservatives/liberals are more generalizable to the global context.
2. According to agenda-setting research, an issue is "whatever is in contention among a relevant public" (Lang & Lang, 1991, p.281), a definition that we adopt in this study. As discussed in the literature review, a "thematic emphasis" refers to an interpretive lens and the resulting semantic coherence in expression. As such, issues are what the first-level agenda-setting research is mainly concerned about, while thematic emphases are largely equivalent to frames or attributes in the second-level agenda-setting research (Ceron, Curini & Iacus, 2016).
3. https://ballotpedia.org/Timeline_of_federal_policy_on_immigration,_2017-2020
4. For international sources, we referred to U.S. editions or coverage.
5. Due to the lack of pro-immigration events concerning family separation and refugee admissions, the "Family Separation – allow" and "Refugee Admissions – allow" variables were dropped from the analysis.

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No potential conflict of interest was reported by the author(s).

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Data Availability Statement

Data is available upon request.

Open Scholarship

This article has earned the Center for Open Science badge for Open Materials. The materials are openly accessible at https://osf.io/3wqe4/

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