Political Psychology

Political Psychology, Vol. 42, No. 5, 2021
doi: 10.1111/pops.12774

The COVID-19–Social Identity–Digital Media Nexus in India: Polarization and Blame

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Drawing on social identity theory and research on digital media and polarization, this study uses a quasi-experimental design with a random sample (n = 3304) to provide causal evidence on perceptions of who is to blame for the initial spread of COVID-19 in India. According blame to three different social and political entities—Tablighi Jamaat (a Muslim group), the Modi government, and migrant workers (a heterogeneous group)—are the dependent variables in three OLS regression models testing the effect of the no-blame treatment, controlling for Facebook use, social identity (religion), vote in the 2019 national election, and other demographics. Results show respondents in the treatment group were more likely to allay blame, affective polarization (dislike for outgroup members) was social identity based, not partisan based, and Facebook/Instagram use was not significant. Congress and United Progressive Alliance voters in 2019 were less likely to blame the Modi government for the initial spread. Unlike extant research in western contexts, affective and political polarization appear to be distinct concepts in India where social identity complexity is important. This study of the first wave informs perceptions of blame in future waves, which are discussed in conclusion along with questions for future research.

KEY WORDS: affective and political polarization, blame, COVID-19, India, social and political identity

During times of global and national crises, all societies must come together to manage and mitigate suffering. Social solidarity that cuts across social differences, in the form of identities, is a force multiplier for any public policy response. Achieving social solidarity is especially challenging

Published by Wiley Periodicals, Inc., 350 Main Street, Malden, MA 02148, USA, 9600 Garsington Road, Oxford, OX4 2DQ, and PO Box 378 Carlton South, 3053 Victoria, Australia

Highlights

- Polarization can undermine social cohesion required to manage a public health crisis. This study aims to identify the factors that influenced according and allaying blame on the question of who is responsible for the initial spread of COVID-19 in India's first wave, and whether there was any evidence of affective and political polarization and social media impact.
- Using a quasi-experimental design with propensity score matching to combine two national random sample CATI surveys (that differed only in the 'blame' and 'no blame' versions of survey items), into one (n = 3304), three OLS models are used to predict blame for (1) Tablighi Jamaat, (2) the Modi government, and (3) migrant workers in big cities.
- Results show evidence of affective polarization among social groups in according and allaying blame but political polarization was absent, and there was no social media impact among our national sample of average Indians. Affective polarization among social groups and political polarization remain distinct concepts in India, contrary to extant research from the U.S.
- The findings have implications for subsequent COVID-19 waves and future national crises, as the attribution of responsibility or blame remains the focus of political competition.

in highly diverse societies with intergroup social conflict and an ascendent majoritarian politics that exploits affective polarization (Finkel et al., 2020). Political polarization's affective dimension privileges feelings about monolithic ingroup and outgroup identities over facts (Iyengar & Westwood, 2015). When India was reeling under the first wave of the COVID-19 pandemic in 2020, the above challenges to achieving social solidarity played out. In a climate of majoritarian politics and othering of minorities, scapegoating of Muslims in the news media and on social media increased especially on Facebook (Al Qaseemi, 2020; Harel, Jameson, & Maoz, 2020). In this study, we explore empirically how political partisanship, affective polarization, social identity, and social media influenced public opinion and attitudes about how to accord or allay blame. The studies on the affective dimension of polarization, separate from traditional political partisanship, suggest that majoritarian politics is a problem for any democratic society because it undercuts social solidarity especially when it is needed in times of crisis.

This study focuses on perceptions about the first wave of COVID-19, which emerged in India in March 2020, when the strict lockdown imposed by the Government of India was initially seen as effective in reducing the spread. The second wave emerged a year later in April 2021 and was bigger in terms of the alarming rise in cases, lives lost, and social pain. In February 2021, political parties and leaders were actively campaigning in Assam, Kerala, West Bengal, Tamil Nadu, and Puducherry for votes in the April legislative elections. In a March 17, 2021, meeting, the same day India recorded 28,003 cases, the highest number of cases in a single day, chief ministers were warned by the prime minister of an impending second wave (hindustantimes.com, 2021). However, facts on the pandemic put forward by experts were being processed from a politically polarized perspective given the context of legislative election campaigns. The prime minister himself, a star election campaigner for his party, was holding rallies, distracted from the supervision of COVID-19 management. In Uttar Pradesh, the opposition parties went to the court to force the government to hold local village elections by April 30, even though the elections had been planned for the following month, and numerous government poll workers died of COVID-19 (NDTV, 2021). By May 6, 2021, more than 414,000 cases were recorded in a single day. The results from this study on how the public accorded or allayed blame for the first wave of the pandemic has implications for understanding the role played by affective polarization in exacerbating the problem during the second wave.

This study examines how social identity became a central theme in the emergence and initial spread of COVID-19 in India in mid-March 2020, which led the BBC (2020b) to ask on April 2, "Who is the group blamed for India's new COVID-19 outbreak?" Al Jazeera reported on April 7, "How Tablighi Jamaat event became India's worst coronavirus vector" (Bisht & Sadiq, 2020). By April 18, India's leading liberal English-language newspaper *The Hindu* headlined, "Nearly 4300 cases were linked to Tablighi Jamaat event, says Health Ministry" (PTI, 2020), and on April 23, the United Kingdom's *The Independent* headlined "Why India has had to pass new law against attacks on healthcare workers" (Withnall, 2020). By December 15, 2020, the headline of a long investigative report on unemployed migrant workers returning home in early May 2020 by special government-run trains during the lockdown said it all: "The virus trains: How lockdown chaos spread COVID-19 across India" (Gettleman, Raj, Yasir, & Singh, 2020).

As the above headlines from international and domestic news outlets suggest, social identity and information at the time of the emergence of COVID-19 in the country provide the backdrop for this study on how the public accorded or allayed blame for the initial spread of the virus or what is now described as the first wave. This study draws on social identity theory and extant research on polarization and the contribution of social media to affective and political polarization to assess public opinion about who is to blame for the initial spread of the virus, with evidence from survey data using a quasi-experimental design. This study contributes to theory on social media, affective polarization, social identity, and partisanship, which has been predominantly focused on western contexts, with new evidence from the context of India.

Affective polarization fosters resentment and grievances based on perceived ingroup and outgroup identity, organized around social and political identities. This polarization—perceived distance separating partisans on issues and values—that is identity based, influences how polarized citizens emotionally process information and rely on motivated reasoning when expressing attitudes and opinions on issues and political leader approval (Druckman, Klar, Krupnikov, Levendusky, & Ryan, 2020; Finkel et al., 2020; Iyengar & Westwood, 2015; Lebo & Cassino, 2007). Because of dislike and resentment, and sometimes even hate, the affectively polarized often overestimate differences between ingroup and outgroup on issues and public policy. The affectively polarized, for the sake of homogeneity, even overestimate ingroup attitudes and opinions and are drawn to media and information sources that confirm their biases. Exposure to opposing views often leads to hostile reactions in the form of rejecting objectively presented facts. The process of self-selection on digital media leads to echo chambers of news and information and has normalized in the United States (Finkel et al., 2020).

Ideological distance and competing views on policy create clearly defined party identities and electoral competition in a democracy (Aldrich, 1995; Converse, 1964; Heath, 2005). Problems emerge in a democracy when polarization is either extreme or affective (shaped by negative feelings towards the outgroup), which makes it difficult to persuade the other side or change views in light of objectively presented facts. Abramowitz and McCoy (2019) discuss how negative partisanship in the United States makes political polarization unhealthy. However, in India, healthy polarization is vitiated by the proliferation of political parties based on social cleavages, which empowers the affective determination of political identities (Chhibber, Jensenius, & Suryanarayan, 2014; Heath, 2005). While some level of polarization is expected in competitive electoral politics, low levels of polarization allow for moderates in the middle to keep political debates over policy differences civil.

We begin with a discussion of social identity theory as it pertains to India, and recent research on political and affective polarization from other democracies. We then discuss the digital media landscape in India and the research design, methods, and analysis of the survey data and the results of our study. In conclusion, we discuss the important contributions of this study to research on social identity, social media, and affective and political polarization and identify areas for future research.

Social Identity and Political Identity

Social identity theory outlines how group members come to identify themselves with the members of an ingroup in relation to outgroups (Billig & Tajfel, 1973; Tajfel, 1978, 1982; Tajfel & Turner, 1979). Group identities acquire their social meaning in relation to other groups. A key premise of the social identity–nationalist imagination literature is that social identity is carefully constructed by identity entrepreneurs who invoke particular renderings of history (Reicher, Haslam, & Hopkins, 2005) to construct and mobilize ingroup and outgroup identities to serve their cause (Liu & Hilton, 2005). Identity entrepreneurs define the boundaries of inclusion and exclusion by careful use of history and rhetorical devices to influence the cognitive and psychological processes of group members. Group salience becomes important in this context, and individuals think and act in conformity with established stereotypes against the outgroup members. According to this theory, ingroup solidarity is accompanied by a negative outgroup bias and—in extreme cases—outright hostility toward outgroup members. This theory of social identity has been applied to understand ethno-religious conflicts in many parts of the world, including India (Kakkar, 1996; Khan, Svensson, Jogdand, & Liu, 2017; Liu & Khan, 2014). However, we must also consider the possibility that subjectively internalized group membership may be a hybrid or overlap of two or more social/political identities. Roccas and Brewer (2002) introduced the concept of social identity complexity to explain membership or multiple group identities. For example, in the context of India, political identity as the Left Front (a combination of Communist and left parties) may overlap with religious, caste, and ethnic identities. Such complexity may confound predicted and observed findings.

While social identity theory has been the basis for analysis of historical political texts in India (Khan et al., 2017; Liu & Khan, 2014), there is little empirical research on India, social identity, and polarization. A notable exception is Yang et al. (2016), a cross-national comparative study measuring perceived political polarization on political issues and the impact of online news use across 10 countries, in which the India sample surveyed in 2010 was limited to those in urban areas and participants were recruited from an online panel. A model predicting perceived polarization revealed that of the 10 countries, India was the exception with a weak negative relationship between online news use and perceived polarization, in contrast to a positive relationship in the remaining nine countries. Perceived polarization may be less evident among average Indians because of the lack of strong party identity evidenced by vote switching.

Electoral volatility, or vote switching, is common in India for a variety of reasons identified in extant research including the fiscal space of a state incumbent government (Nooruddin & Chhibber, 2008), new parties entering and exiting (Heath & Ziegfeld, 2018), and economic growth rates, which have been found to affect vote shifting even more than between exiting parties and newcomers (Dash & Ferris, 2020). As Indian voters in different subnational and national electoral contexts may often switch parties, the term "party identification," which has been central to research on affective polarization in the United States --where political science has measured and defined affective polarization as a sense of *partisan* group identity --may have less applicability to India (Druckman & Levendusky, 2019). Affective polarization has also been described as the tendency of people identifying as belonging to one political party to view the other (outgroup members) negatively and copartisans (ingroup members) positively, drawing on the U.S. case (Iyengar & Westwood, 2015). The primacy of "partyism" was also supported by a comparative study focusing on Great Britain, the United States, Belgium, and Spain, which found that partisan discrimination against opponents "to a degree that exceeds discrimination against members of religious, linguistic, ethnic or regional out-groups…[with a pattern that]…holds even when social cleavages are intense and the basis for prolonged political conflict" (Westwood et al., 2018, p. 333).

Westwood and Peterson (2020) posit an important link between race and partisanship in the United States. They use behavioral games to demonstrate that events which trigger partisan identity or racial group identity can also activate the other. Although no direct comparison exists with a racial group and partisan identity in India, it is important to recognize that longitudinal voting data shows that Muslim voters have historically preferred the Indian National Congress (INC) or Congress party, whereas the Bharatiya Janata Party (BJP) historically attracted support from upper-caste Hindus (Roy & Sopariwala, 2019). The preference of Muslim voters for the INC has been strategically exploited by the BJP to consolidate the Hindu vote, which historically had been split with upper-caste Hindus voting BJP and lower-caste Hindus voting for other parties (Yadav, 1999). In 2019, however, the BJP received a larger vote share than 2014, which included significant increases in the levels of support from Dalits and lower-caste Hindus across the country, in addition to the upper-caste Hindus the party had attracted for decades (Aiyar, 2019). The electoral strategy to consolidate the Hindu vote that historically was split along caste lines has been an important factor in determining the BJP's vote share and seat margins in the 2014 and 2019 national elections and may be due in part to the fact that the party's leader, Narendra Modi, comes from a lower-caste, low-income family, and the BJP has used tropes of majoritarian politics. Recalling Westwood and Peterson's (2020) finding that race is inseparable from partisanship in the United States, in India there appears to be the potential for a similar partisan polarization to take root with the BJP being largely identified with by the majority Hindu community.

India's diverse media systems in ethno-linguistically bordered states that are home to different parties and party systems and give rise to pre- or postelection alliances that may also change from one election to the next (Kumar, 2011). These circumstances make the BJP's hold on power uncertain. The State of Maharashtra where the BJP held the Chief Minister position is one recent example where, in the Assembly election in late 2019, Shiv Sena, having won in a preelectoral alliance with incumbent BJP, demanded the Chief Minister post. The alliance ended between BJP and Shiv Sena, who now holds the Chief Minister post and is in power because of a coalition with the INC and the Nationalist Congress Party (NCP), which was formed in 1999 (by three men who were expelled from the Congress party because they were opposed to Italian-born Sonia Gandhi leading the party).

Digital Media

India completed the transition from analogue to digital television in several phases spanning 2013 to 2017. The latest data from India's Broadcast Audience Research Council (BARC, 2020, p. 6) showed 836 million individuals with access to television, 46% average growth in news viewing minutes and high variance across states in growth of TV viewership over the past four years from a low of 5% in Kerala to the highest growth of 119% in Assam, Sikkim, and the North East, with mid-range growth including 48%–60% in Delhi, Karnataka, West Bengal, Maharashtra/Goa, and Odisha, and 70%–80% in Madhya Pradesh, Chhattisgarh, and Gujarat. Viewing minutes of news programs grew 23% over 2018–19. Vernacular television news is most popular in South Indian states where over 90% of news viewership was on local-language news channels (BARC, 2020, p. 11). The number of local vernacular news channels in South India varied from a high of 19 (Telugu) in Andhra Pradesh and Telangana, 14 (Tamil) in Tamil Nadu and Pondicherry, 12 (Kannada) in Karnataka, to 8 (Malayalam) in Kerala. The number of news channels in other regional languages in 2019 include 10 (Bangla) in West Bengal, 10 (Gujarati) in Gujarat, 8 (Asomiya) in Assam, 7 (Odia) in Odisha, 7 (Marathi) in Maharashtra, and 4 (Punjabi) in Punjab. The growth of vernacular news outlets in number and in viewing time is extraordinary. India's high-choice media environment is beyond anything found elsewhere in terms of the number of outlets, languages, and reach, and TV remains most often named as the first choice for news. There are some 400 news channels in India's "hybrid" media environment in which social media posts may become headline news and traditional media use new media to attract audiences (Chadwick, 2017; Neyazi, Kumar, & Semetko, 2016).

Since 2016, when low-cost smartphones and data plans were launched in India, they have become increasingly used for online shopping, watching and reading news, and streaming entertainment. According to one report: "Industry sources say the definition of what is considered television is rapidly changing… now any screen has the potential to function as one. With mobile phones growing at a much faster rate than the number of traditional TV screens, there is a possibility that TV penetration in the country in future could outstrip the actual number of TV sets that households own" (Kausik, 2019).

A 2018 Pew Research Center survey on Mobile Technology and its Social Impact speaks to the question of contact and found smartphone users in India are similar to those in 10 other "emerging economies" in having broader social networks than nonusers, with the percentage of adults who said they frequently or occasionally interact with people having different religious views at 70% among India's smartphone users compared to 58% for nonusers (Silver, Huang, & Taylor, 2019).

Digital Media and Affective Polarization

Empirical research on the contribution of social and digital media to polarization has been heavily focused on U.S. and UK contexts, especially since the 2016 U.S. presidential election and the Brexit referendum. Despite the many empirical studies in higher-income democracies, findings continue to provide mixed evidence on whether or not social media increases polarization through echo chambers (Barbera, 2020). Garrett et al. (2014) provide compelling evidence that exposure to "pro- and counter-attitudinal" information has an influence on perceptions of members supporting the opposing party. Experiments on social identity, media, and affective polarization by Wojcieszak and Garrett (2018) found that when national identity is primed, animosity toward immigrants increases, and the high-choice media environment serves to further amplify polarization.

A number of recent studies have confirmed past findings that partisan media foster political polarization (Garrett, Long, & Jeong, 2020). Robison and Moskowitz (2019) find that feelings towards social groups perceived to be part of political support base of parties is an important factor driving affective polarization. There is a causal link between emotionally laden political conversations and affective polarization (Hutchens, Hmielowski, & Beam, 2019; Yarchi, Baden, & Kligler-Vilenchik, 2020). Yarchi et al. (2020) use computational methods to report how social media exacerbates polarization and found that ingroup and outgroup polarization has an important affective dimension on Facebook, even though among all social media platforms Facebook users are more likely to have communicative interactions with outgroup members. India is Facebook's largest country when measured by the number of users, over 400 million, and the platform has emerged as a major source of information for many (Government of India, Ministry of Electronics & IT, 2021).

Harel et al. (2020) found that hate speech online can lead to violence especially in a polarized climate. Hate speech posted online in India may take different forms. Two recent examples are given here to show how perceived hate speech on religious grounds can lead to protests and violence (Lowe & Muldoon, 2010). In Allahabad, in Uttar Pradesh, well past COVID-19's arrival, a Muslim woman who had been posting controversial videos on Facebook and YouTube posted one with hate speech against Hindu gods that obtained 10,000 views in a few hours; many condemned the video, and the police arrested her, charging her with hate speech (Abishiek, 2020). In another recent incident, the nephew of a state-level Congress party politician in Bengaluru posted comments slandering the Prophet on Facebook, which resulted in mass riots in which the home of his uncle, a Member of the Legislative Assembly (MLA) in Karnataka, and two police stations, were burned down (Kalkod, 2020). Despite these anecdotal examples, and apart from the aforementioned 2010 comparative study across 10 countries in which India was the outlier displaying a negative relationship between online news use and polarization (Yang et al., 2016), there is a dearth of empirical research on digital media and polarization in India.

Context

According to social identity theory, long-standing conflict among communities, in this case Hindus and Muslims in India, shapes the ingroup and outgroup feelings. The preexisting perception among India's largest minority, that the current Indian government led by the BJP is antagonistic to the Muslim community, may foster negative feelings towards the government and its policies. This social-identity-driven polarization is likely further exacerbated by polarization on social media, which has emerged as a major source of information and news. To understand polarization with respect to blaming Tablighi Jamaat specifically and Muslims more generally for the initial spread of the virus in spring 2020, it is important to recover the sociopolitical context in the months before the pandemic.

Over the nine months prior to the emergence of the COVID-19 in India, events put the spotlight on Muslims in different contexts such as in August 2019 with the ending of special status for Jammu and Kashmir, India's only Muslim majority state; then with protests over the December 2019 passage of the controversial Citizenship Amendment Act, that fast-tracked citizenship applications for persecuted religious refugees who arrived before 2015 from Bangladesh, Pakistan, and Afghanistan, which excludes Muslims; and finally the tragic violence and communal riots in Delhi in February 2020. Social identity featured prominently in the public debate during this period leading up to March 24, 2020, when the Government of India, led by Prime Minister Narendra Modi, put the country under a very strict 21-day lockdown that banned all gatherings and shut down all economic activity.

A global conference in Delhi in mid-March 2020, attended by some 8000 members of Tablighi Jamaat—a global Islamic revivalist and missionary movement launched in India in the 1920s, with members in many states—was identified as a major cluster for the spread of the virus, and that information served as a catalyst for anti-Muslim sentiment and allegations of Islamophobia (Al Qaseemi, 2020; Mishra, 2020). Al Jazeera and many news outlets reported that many participants, some of whom were COVID-19 positive, had left for different parts of the country and were described online and in the news, with Islamophobic overtones, as superspreaders in India (BBC, 2020a, 2020b; Bisht & Sadiq, 2020). After weeks of testing and tracing, public health officials estimated that 30% of India's confirmed cases were directly related to the Tablighi Jamaat event, as members returning to their homes across India (PTI, 2020). News was used to stoke religious intolerance especially on social media, which served up ideologically motivated conspiracy theories that painted members of the Muslim community as a vector of the disease (Sahoo, 2020). False reports of Muslims acting with intent to infect, such as spitting or coughing in public places, became viral (Tribune India, 2020; Withnall, 2020). The Twitter hashtag "#coronajihad" was shared over 300,000 times and was possibly viewed by 300 million people (Sahoo, 2020).

In contrast to Tablighi Jamaat members who were often referred to as Muslims, suggestive of the perception of a homogeneous Muslim community, migrant workers are perceived as a more heterogeneous group that includes all faiths and middle and lower classes. Some 600,000 internal migrants in India work in a state that is far away from their home state. Migrant workers in major cities who had lost income and support began defying the lockdown after the first week by going to bus stations to try and find a way home. By April 14, the expected end of the 21-day lockdown, thousands of migrant workers gathered at Bandra West railway station in Mumbai and in other cities, but the lockdown was extended to May 3. Conditions facing the migrant workers attracted empathetic coverage in the media, leading the Government to run special trains and buses to take migrant workers home to their villages. However, many also criticized migrant workers for becoming potential superspreaders.

In view of the sociopolitical context, we expect to see evidence of affective polarization among Muslims and Hindus in the form of significant differences between the two groups on according and allaying blame for the spread of the virus. Tablighi Jamaat could be blamed for breaking the lockdown rules and contributing to the acceleration of viral spread. Given that the Citizenship Amendment Act was perceived to be discriminatory against Muslims, Prime Minister Modi and his government may be blamed for the spread of the virus by Muslims and INC/UPA voters. As migrant workers are a heterogeneous group including all religious social and political party identities, we do not expect to find that Muslim or Hindu social and political identity will predict blaming this group for the spread.

Research Questions

Given the literature on affective and political polarization, and the information environment in the first months of COVID-19 in the country, the study asks several research questions with respect to according or allaying blame for the initial spread of the virus.

RQ1: Do the "no blame" framed survey items encourage respondents in this (treatment) group to be significantly different from the group receiving the "blame" framed survey items, in allaying blame for the spread of the virus?

RQ2: Is social identity (religion) significant for according or allaying blame?

RQ3: Is party identity (measured by reported vote in 2019) significant for according or allaying blame?

RQ4: Is the use of Facebook or Instagram a significant predictor of blame?

Method

CVoter, a leading survey agency in India, tracks public opinion on timely political issues using Computer Assisted Telephone Interviewing (CATI). CVoter Foundation provided us with survey data from two nationally representative samples, with respondents selected by the CATI software with automated Random Digit Dialing (RDD). Age skewed as the country's younger population with 27% in the 18–25 age group and 29% in the 26–35 age group, for example; with respect to location, 45% reported living in a rural area, 39% urban, and 15% semi-urban; and 75% reported using Facebook or Instagram. Additional demographics are provided in the supporting information. These two short CATI surveys were fielded from August 2 to August 12, 2020, and differed only in how the COVID-19 related questions were framed: One survey had the "blame" version of the questions, and another had the "no blame" version. Respondents were asked about whether each of the three different groups should be blamed or not blamed: Tablighi Jamaat, the Modi government, and migrant workers. Use of Facebook or Instagram, past vote in the 2019 national parliamentary election, and demographic questions were included in these short national surveys that ran less than 15 minutes. The surveys had response rates of approximately 40%, using World Association for Public Opinion Research (WAPOR) and American Association for Public Opinion Research (AAPOR) RR1. The surveys were conducted in 11 national languages including Asomiya, Bangla, Gujarati, Hindi, Kannada, Malayalam, Marathi, Oriya, Punjabi, Tamil, and Telugu, which cover most of India. The survey data used in the models were weighted to reflect national demographics.

Questions

Respondents on both surveys were asked about Facebook and Instagram use as follows:

Q1: "Now I would like to ask you some questions thinking back to the first lockdown in late March and early April. How often did you use Facebook or Instagram in a typical week during the first lockdown? Multiple times a day, most days, some days, once a week, never"

Q2: "And what about over the past month, how often did you use Facebook or Instagram in a typical week? Multiple times a day, most days, some days, once a week, never"

One survey included a set of blame-related questions on the spread of COVID-19, and the other survey included the no-blame version of the same questions. The questions were prefaced by:

Thinking back to the first lockdown in late March and early April, how much do you disagree or agree with the following statements? Using a scale from 0 to 10, where 0 means strongly disagree and 10 means strongly agree.

Blame Version (*N* = 1707)

Q3: "The Modi government's failure to enforce an earlier lockdown in February–March played a significant role in spreading COVID in India."

Q4: "Migrant workers who did not follow the lockdown and started returning to their home states played a significant role in spreading COVID in India."

Q5: "Tablighi Jamaat, a religious group, played a significant role in spreading COVID in India following an international meeting in early March in Delhi, in which at least a few thousand people were infected by Coronavirus."

No Blame Version (*N* = 1652)

Q3: "It is unfair to blame the Modi government for not enforcing an earlier lockdown in February–March to stop the spread of COVID in India."

Q4: "Migrant workers who did not follow the lockdown and started returning to their home states were unfairly blamed for playing a significant role in spreading COVID."

Q5: "Tablighi Jamaat, a religious group, was unfairly blamed for playing a significant role in spreading COVID in India following an international meeting in early March in Delhi, in which at least a few thousand people were infected by Coronavirus."

Respondents from the two cross-sectional surveys were merged into one dataset, and one set of the blame questions was reverse coded, resulting in the quasi-experimental design with blame (control) and nonblame (treatment) groups in one pool of respondents. Because the distribution of the covariates between the blame sample and the no-blame sample may not be similar in the observational data, propensity score matching was used to match treatment and control groups (Austin, 2011; Ho, Imai, King, & Stuart, 2004, 2011), based on the covariates: use of Facebook/Instagram, Religion, Vote in 2019, Gender, and Age. Propensity score matching is a statistical technique to match the treatment cases and control cases based on the propensity score, to reduce selection bias and strengthen estimation of treatment effects (Adelson, 2013). The propensity score is the likelihood of an individual participating in a treatment group based on their observable characteristics, example age, sex, and religion (White & Sabarwal, 2014). A total of 1652 observations from each survey were matched between the blame and no-blame groups—using nearest neighbor-matching method—and 55 observations were unmatched (see supporting information). The 55 unmatched observations were dropped, and the merged dataset had 3304 observations.

We use the "Zelig" package in R to estimate the average treatment effect (Choirat, Honaker, Imai, King, & Lau, 2017; Imai, King, & Lau, 2008). Three ordinary least squares (OLS) regression models, one for each of the three Blame versions as the dependent variable were run, with the no-blame treatment variable in each model, controlling for Facebook use, social identity based on religion, political identity based on 2019 vote in the general election, gender, age, and location.

Measurement

To estimate the change in attitude with time and effect of treatment and other control variables on blaming the Tablighi Jamaat, the Modi government, and migrant workers, we use an OLS model, which is given by:

$$y_{ji} = \alpha + \beta \text{Treatment}_i + \gamma X_i + u_i$$

where y_{ji} is the outcome for question j (=3) related to Tablighi Jamaat, the Modi government, and migrant workers; Treatment is a dummy variable indicating 1 for treatment group and 0 for control group. X_i is a vector of control variables: the use of Facebook/Instagram, religion, gender, party vote in the 2019 general election, and age.

The use of Facebook/Instagram is an ordered categorical variable with five response categories, combining the first two questions above. Self-reported religion has five groups: Hindus, Muslims, Christians, Sikhs, and Others, with Hindus as the reference category in the models. For gender, women are coded 1, men 0. Vote in 2019 is coded with two dummy variables: 1 is voted for BJP/National Democratic Alliance (NDA) and 0 for others, and 1 if voted for INC/United Progressive Alliance (UPA) and 0 for others. Age is an ordered categorical variable with five groups, with the under-25 group iass the reference category: <25, 25–34, 35–44, 45–54, 55+.

Results

Evidence on the effect of the treatment variable or the no-blame-framed questions suggests respondents in the treatment or the no-blame group significantly allayed blame for the spread of the virus in two of the three cases, providing an affirmative answer to RQ1 based on our expectations. Table 1 displays the group means and *t*-test results for the matched dataset.

The comparison of means for the blame and no-blame groups for the three questions reveals that the differently framed questions resulted in significant differences between means for Tablighi Jamaat and for the Modi government but was not significant for migrant workers. Those receiving the no-blame frame (treatment group) were significantly less likely to blame both Tablighi Jamaat and the Modi government for the spread of the virus, but there was no treatment effect on blaming migrant workers, a heterogenous group of different faiths. Predicted blame for each of these three actors in control (blame) and treatment (no blame) groups is also in Figure 1, which displays those in the treatment group as significantly less likely than the control group to blame Tablighi Jamaat and Prime Minister Modi's government, with no effect on migrant workers.

Table 2 displays the estimates of the three OLS regression models, predicting according blame to Tablighi Jamaat, the Modi government, and migrant workers for the initial spread of the virus, which is the dependent variable in each model. From the estimates it is clear that the treatment variable (the nonblame version of the questions) was significant for Tablighi Jamaat and the Modi government and was not significant for migrant workers, controlling for all other variables in the model, in line with our expectations.

Table 1. Group Means and *t*-Test Results

	Group Means				
	Blame	No Blame	*t*-Test	*df*	*p*
Tablighi Jamaat	5.83	5.01	5.62	3300.1	.000
PM Modi government	5.11	4.71	3.007	3296.5	.002
Migrant workers	5.1	5.32	−1.55	3296	.11

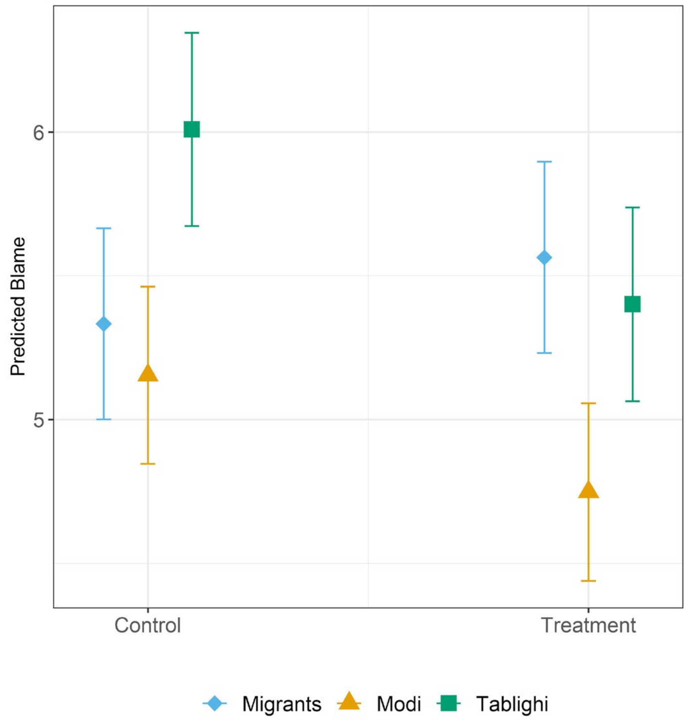

Figure 1. Treatment effect on predicting allocating or allaying blame. [Colour figure can be viewed at wileyonlinelibrary.com]

The average treatment effect (ATE) for the models according blame to Tablighi Jamaat was −0.61 (95% CI, −0.89 to −0.35), to the Modi government was −0.42(95% CI, −0.67 to −0.13), and to migrant workers was 0.25 (95% CI, −0.07 to 0.51). Blame for Tablighi Jamaat and the Modi government for the initial spread of the virus was slightly reduced by the treatment compared with that of migrant workers, which was not statistically significant.

In addressing RQ2 on social identity and RQ3 on party identity, expected as well as unexpected findings emerged. Beyond the significant treatment effect, which showed that those in the treatment group—which is the group that received the nonblame version of the questions—were less likely to accord blame to Tablighi Jamaat and to the Modi government, the models in Table 2 indicate that compared to Hindus (the reference category), Muslims were less likely to blame Tablighi Jamaat for the spread of COVID-19 and more likely to blame the Modi government for the initial spread. Differences between Hindus and Muslims on blame was expected. However, this finding should not be interpreted by the reader as one of primordial differences between these two large groups. Indian Muslims are in fact a quite heterogeneous group with different sects, places of worship, and social status. The same can be said of Indian Hindus.

Compared to Hindus (the reference category), Sikhs were also less likely to blame Tablighi Jamaat and migrant workers, but there was no effect on blaming the Modi government. Christians were more likely to blame the Modi government and migrant workers for the spread of the virus, but there was no effect on blaming Tablighi Jamaat. Christians blaming the Modi government's handling of COVID-19 for the initial spread of the virus may be related to a growing perception of discrimination among those in the religious community because proselytizing and missionary activities in the

Table 2. Predicting Who Is to Blame for the Initial Spread of COVID-19 in India, 2020: Tablighi Jamaat, Prime Minister Modi's Government, and Migrant Workers (OLS Regression Estimates)

	Blame		
	Tablighi Jamaat	PM Modi Government	Migrant Workers
Treatment (no blame)	**−0.61*****	**−0.42****	0.23#
	(0.14)	(0.13)	(0.14)
Facebook/Instagram	0.002	0.02	−0.03
	(0.05)	(0.04)	(0.05)
Religion (Hindu reference group)			
Muslims	**−1.33*****	**0.53****	0.08
	(0.21)	(0.19)	(0.21)
Christians	−0.04	**0.93***	**1.03***
	(0.49)	(0.45)	(0.48)
Sikhs	**−1.47****	−0.01	**−1.17***
	(0.54)	(0.49)	(0.53)
Others	−1.002#	0.11	0.73
	(0.53)	(0.48)	(0.51)
Women	**−0.36***	0.05	−0.11
	(0.14)	(0.13)	(0.14)
Voted BJP/NDA	−0.12	0.063	0.17
	(0.15)	(0.14)	(0.15)
Voted INC/UPA	**−0.46***	**−0.41***	−0.05
	(0.21)	(0.19)	(0.21)
Age Group (<25 reference group)			
25–34	**−0.41***	**−0.31***	**−0.58*****
	(0.17)	(0.15)	(0.16)
35–44	−0.15	0.001	0.02
	(0.16)	(0.15)	(0.16)
45–54	0.01	0.09	−0.006
	(0.16)	(0.15)	(0.16)
55+	−0.11	0.27#	0.38*
	(0.16)	(0.14)	(0.16)
Urban	−0.17	0.01	0.22
	(0.15)	(0.14)	(0.15)
Constant	6.16***	4.9***	4.87***
	(0.18)	(0.16)	(0.17)
N	3304	3304	3304
Adj. R^2	0.02734	0.00965	0.01014

Note. Estimates in bold are significant.
****p* < .001; ***p* < .01; **p* < .05; #*p* < .1.

country have been restricted. Compared with men, women were less likely to blame Tablighi Jamaat for the spread. There was no gender effect on blaming the Modi government or migrant workers.

The clear evidence of polarization between Hindus and Muslims on blaming Tablighi Jamaat and the Modi government affirms empirically that social identity was an important source of affective polarization in India at the moment of this study, the emergence of COVID-19 in spring 2020. This is a statistic from a quasi-experimental design and should not be read as Muslims think alike and Hindus think or behave alike.

Despite debates in the news media and on social media about who to blame for the initial spread of the virus in spring 2020, this study found that although most respondents used Facebook or Instagram (some 75%), using these social media had no effect on perceptions of blame, controlling for all other variables in the model. In response to RQ4, Facebook or Instagram use was not a significant source of influence on according or allaying blame.

Partisanship was measured here by one's reported vote in the national Lok Sabha election in 2019, which also yielded interesting results. Compared to voting for Others (the reference category, referring to non-BJP/NDA or non-INC/UPA parties), voting BJP or for a party in the NDA had no effect on blame in any of the three question conditions. However, compared to Others, those voting for the INC or for a party in the UPA in 2019 were less likely to blame Tablighi Jamaat and also less likely to blame the Modi government for the spread of the virus. The state of political polarization in the context of the emergence of the virus in the country was at an insignificant level among respondents whereas affective polarization in the form of social identity (Hindu/Muslim religion) was significant.

As a control variable in the model, it is surprising to find that compared to those in the 18–24-year-old age group (the reference category), those in the 25–34-year-old age group were less likely to blame all three actors for the spread of the virus. Compared to 18–24 year olds, those in the 55-plus age group were unique in being more likely than the youngest cohort to blame migrant workers for the spread of the virus. The wisdom of this 55-plus age group in our study suggests that they already understood what we know now, that the virus spreads easily indoors and in enclosed spaces (such as the trains and busses the migrant workers were given by the government to get home) and is less likely to spread outdoors as easily. The study finds no location (urban/rural) effect on blame.

Discussion

Social identity was already of heightened interest when COVID-19 emerged in India in March 2020. The spread of the virus was quickly connected to a Delhi conference of Tablighi Jamaat, an international Muslim missionary group, and with members returning home to many states in India, health authorities in April 2020 estimated that the group was responsible for 30% of the cases at that early stage (Bisht & Sadiq, 2020). Using a quasi-experimental design, this study provides causal evidence that affective polarization based on social identity (religion Hindu/Muslim) was a significant factor in according or allaying blame for the initial spread of the virus in India. In light of the paucity of empirical research on affective polarization based on social identity in India, the findings from this study open the door to further exploration in this important area of inquiry.

This study makes an important contribution to theory on affective and political polarization, given that in much of the extant research, the former is seen as a subset of the latter. This study finds that affective and political polarization are two distinct concepts in India. While affective polarization based on social identity was evident for Hindus and Muslims in according or allaying blame for the initial spread of the virus to Tablighi Jamaat and the Modi government, in ways expected, it was a surprise to find that political polarization was not evident. Instead, Congress party and UPA voters were significantly less likely to blame the Modi government for the initial spread, compared with voters for other parties. Although the findings are limited to the initial emergence of COVID-19, the lack of political polarization among respondents in this study stands in stark contrast to what one often sees in prime-time news discussion programs, as well as news from parliamentary debates and street protests. More research on what triggers polarization online and in public opinion is needed. The concept of partisan-driven animus common in the western political science literature appears to be not easily transferable to India; not only because voters have demonstrated a propensity to switch in large numbers, as the examples of electoral volatility mentioned earlier suggest, but also because in a developing country like India, there may be little difference between the main parties on social welfare policy, even though the political identity of the Left is congruent with strong welfare policies and subsidies (see Appendix S3 in the supporting information).

Two groups—members of Tablighi Jamaat, a Muslim missionary organization, and migrant workers, a heterogeneous group of all faiths—both faced the plight to get home during the first lockdown, but migrant workers were reported on empathetically by many news organizations in contrast to news on Tablighi Jamaat, which also included fake news stories based on misinformation on social media. This study found that Facebook use had no effect on according or allaying blame in all three models. Facebook use remained not significant when interacted with social identity (religion), gender, and age group, and those interactions were therefore not presented. This finding is in line with Yang et al. (2016), who found India was the exception in a 10-nation comparative study, as survey respondents in India who used online media were not significantly more likely to perceive political polarization, whereas the opposite emerged in the other nine countries.

The lack of strong party identification, evidenced by electoral volatility, may be another reason why political polarization was absent among our survey respondents. These findings also suggest that the average voter in our sample may be far away from the online activists and protestors on the streets often seen in the news. These findings on a lack of party polarization in according or allaying blame also dovetail with Roccas and Brewer (2002) who introduced the concept of social identity complexity and found initial studies support the prediction is “affected by stress and is related to personal value priorities and to tolerance of outgroup members” (p. 88).

Affective political polarization compounds and exacerbates problems in a large densely populated country such as India with huge disparities, insufficient health care, and other infrastructure and state capacity issues. The media reports and anecdotal evidence suggest how desperate situations can become when the second wave of COVID-19 struck and hospitals in the country were overwhelmed as demand for oxygen outstripped supply. As of May 12, 2021, the World Health Organization blamed religious festivals (Kumbh Mela) and campaign rallies for the second wave (effectively echoing India’s Opposition parties and blaming the central Government), whereas the U.S. infectious disease specialist Dr. Anthony Fauci blamed opening up too soon as the reason for India’s second wave spread. By May 14, the BJP rebutted the Opposition’s allegation that the Government had ignored the risk of a second wave and provided a list of six meetings the Prime Minister had with Chief Ministers between September 2020 and April 2021 in which he initially asked to focus on the 60 districts with the highest number of cases and to increase testing substantially and utilize the state disaster response fund for COVID-19 infrastructure that had been increased from 35% to 50% (Singh, 2021). BJP also criticized the Congress party for promoting vaccine hesitancy and blamed leading spokespersons and health ministers in Congress-ruled Chhattisgarh and Jharkhand for raising questions about the efficacy of “made-in India” Covaxin.

Although much has changed since the first wave emerged in March 2020, it is clear that a major political issue concerns the attribution of responsibility or blame for India’s second wave in spring 2021, which speaks to the relevance of our study that investigated how the average Indian accorded or allayed blame for the initial spread of the virus in the country. Research in a European context using survey experiments found that “partisan loyalties have pervasive effects on responsibility attributions,” in other words, on according blame, and “somewhat weaker effects on evaluations of performance” (Tilley & Hobolt, 2011, p. 316). However, partisan loyalties are less common in India, where political elites in elected office switch parties and their voters follow, and voters themselves often switch parties between elections. India’s current BJP-led National Democratic Alliance (NDA) government increased its vote and seat share substantially in 2019 after a campaign in which Prime Minister Modi and his party were repeatedly blamed for the implementation of the demonetization and General Services Tax (GST) policies and repeatedly accused of corruption with the purchase from France of the Rafale fighter jet. However, that political communication strategy resulted in an increase of only eight seats for the Congress party, up from 44 seats to 52 out of 543 seats in the Lok Sabha. Outcomes from the April and May 2021 Assembly elections suggest many Indian voters are pragmatic rather than partisan by voting BJP in 2019 for the Lok Sabha and for an opposition party in the 2021 elections in West Bengal, Tamil Nadu, and Kerala. How political parties and candidates attribute responsibility and accord blame, and whether this influences voters, is an important question for future research.

This study also raises questions about India's Facebook and Instagram users, who now number 410 million and 210 million respectively, and political engagement online (Government of India, Ministry of Electronics & IT, 2020). In this study. unlike social identity and voting behavior which were significant influences on allaying or according blame for the initial spread of COVID-19, Facebook and Instagram use had no effect. A growing number of citizen-initiated Facebook groups launched to promote peace between India and Pakistan emphasize the shared culture of Hindus, Sikhs, and Muslims in the subcontinent (Kumar & Semetko, 2018). How prosocial content competes for user attention with polarizing content on digital social media platforms merits more scholarly attention. Another important area for research in India is the prevalence and influence of misinformation online. We hope to see more empirical research on social identity theory, social media, and polarization in India in the future.

ACKNOWLEDGMENTS

The authors would like to thank CVoter Foundation and CVoter News Services for providing the data used in this study. Correspondence concerning this article should be addressed to Holli A. Semetko, Emory University, 1555 Dickey Drive, Atlanta, GA 30322-1007, USA. E-mail: holli.semetko@emory.edu

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Table S1. Proportion of Respondents in Each Group (Unweighted)

Table S2. Number of Respondents in Each Group

Appendix S3. Two key social welfare policies