Title

Twitter Misinformation and Political Donations in the 2020 US Election:The Blue Canary in the Coal Mine

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The Blue Canary in the Coal Mine

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Abstract

While American politics have in recent years been marked by rising polarization, well-documented cases of election misinformation spread through social media, and the violent January 6 “Stop the Steal” riot at the US capitol, little is known about the impact of unsubstantiated allegations of election irregularities on voter behavior. By utilizing a Twitter corpus of election misinformation and public FEC donations data from the 2020 US presidential election, I develop a novel longitudinal dataset of voter donation behavior and offer new insights into the relationship between online political misinformation and individual political donations in a developed, diverse democracy such as the United States. While this descriptive statistical analysis of an unusual election cycle should be interpreted with caution, the results suggest that people who interacted with unsubstantiated voter fraud claims on Twitter in the run-up to the 2020 US presidential election donated *more* frequently but *not* in significantly different amounts than donors at large. The positive correlation between Twitter interactions with election misinformation and altered donor behavior furthermore appears to be mediated through partisan pathways and overall Twitter activity. Individuals located in zip codes where a majority of the electorate supported Joe Biden in the 2020 election donated *more* frequently and in *larger* amounts than the people located in zip codes where the majority supported Donald Trump. Compared to other donors exposed to election misinformation on Twitter, people with more Twitter followers gave *more* frequently and in *greater* amounts, while citizens who repeatedly interacted with election misinformation contributed *smaller* amounts at *similar* rates.[1]

Keywords Political misinformation; voter fraud; social media; voter behavior; individual political contributions

[1] My ability to share data is limited by Twitter's Terms of Service and FEC regulations. For the foreseeable future, I will make replication data and code available on a case-by-case basis, likely subject to data-use agreements. To request access to replication data and/or code, contact me at lucasro19@g.ucla.edu. Last updated April 7, 2023.

Introduction

While conspiratorial thinking has been a staple of American society across time and demographics,[2] misleading or unsupported factual claims spread by political candidates today constitute normal and accepted features of elections in the United States, Western Europe, and beyond.[3] In recent years, elections held in countries ranging from established democracies such as the United States[4] to younger democracies such as the Philippines[5] have been marked by widespread political misinformation. Against this backdrop, several recent studies argue that America's polarized electorate is becoming less committed to democratic values.[6,7]

The electoral campaigns and presidency of Donald Trump feature prominently in discussions regarding the impact of political misinformation on voter behavior and the future development of American politics. Starting from April 2020,[8] Trump made sweeping and unsupported claims that the 2020 US presidential election could be stolen through voter fraud. As noted by Berlinski et al.,[9] these unfounded assertions ranged from familiar tropes (e.g., claims that illegitimate ballots were submitted by deceased voters and fraudulent mail-in ballots) to novel conspiracy theories (e.g., claims that voting machines were manipulated by the late Venezuelan leader Hugo Chávez). After he lost the election in November 2020, Trump and his allies doubled down on voter fraud claims that were at best dubious or inconsequential and at worst knowingly false.[10] Amid increasingly heated and unsubstantiated rhetoric, the "Stop the

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[2] Uscinski and Parent, *American Conspiracy Theories*.
[3] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[4] U.S. Congress, Senate, "Senate Report on 2016 Russian Interference."
[5] Sharma, "Meta Removes Facebook Accounts to Tackle Misinformation Ahead of Philippines Polls."
[6] Mounk and Foa, "The Danger of Deconsolidation: The Democratic Disconnect"; Wike and Fetterolf, "Liberal Democracy's Crisis of Confidence."
[7] Cf., Voeten, "Are People Really Turning Away from Democracy?"
[8] Inskeep, "Timeline: What Trump Told Supporters For Months Before They Attacked."
[9] Berlinski et al., "The Effects of Unsubstantiated Claims of Voter Fraud on Confidence in Elections."
[10] E.g., Yoon, "What to Know About the $787.5 Million Fox News-Dominion Settlement."

Steal" rally on January 6, 2021, devolved into a violent riot at the US capitol that sought to disrupt the certification of President-elect Biden's victory. Given that Trump's unsubstantiated allegations of a stolen election were the primary theme of the January 6 riot, it is vital for researchers and citizens alike to better understand the relationship between election misinformation and voter behavior.

The need to investigate the impact of political misinformation transcends American borders. Politicians regularly accuse opponents of election fraud, especially outside the United States.[11] In February 2021, the Myanmar military justified its coup against the country's democratic government by alleging voter fraud in the country's November 2020 election.[12] Apart from Trump, elites in other democracies have also made unsubstantiated claims of voter fraud to cast doubt on unfavorable electoral results, both preceding and following elections. For example, Jair Bolsonaro, the president of Brazil between 2019 and 2022, expressed fears of voter fraud during his presidential campaigns in both 2018[13] and 2022[14] to preemptively cast doubt on an unfavorable electoral outcome. Upon losing the 2019 Indonesian presidential election, Prabowo Subianto claimed that he had been the victim of voter fraud and refused to concede.[15] Even in Israel, an advanced and established democracy,[16] Prime Minister Benjamin Netanyahu made unfounded claims of election fraud when facing imminent electoral defeat during contentious elections in June 2021.[17]

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[11] The following examples are inspired by Berlinski et al., "The Effects of Unsubstantiated Claims of Voter Fraud on Confidence in Elections."
[12] Goodman, "Myanmar Coup: Does the Army Have Evidence of Voter Fraud?"
[13] Savarese, "Leading Brazil Candidate Says He Fears Electoral Fraud."
[14] Kahn, "Supporters of Brazil's Far-Right President Say He Was the the Subject of Fraud."
[15] Paddock, "Indonesia Court Rejects Presidential Candidate's Voting Fraud Claims."
[16] Wiatr, *Political Leadership Between Democracy and Authoritarianism*.
[17] Oren Liebermann and Eliza Mackintosh, "Israel: Netanyahu Alleges Elections Fraud as Political Rhetoric."

Evidently, accusations of misconduct and election irregularities are a common thread in electoral politics across space and time. However, the impact of election misinformation on voter behavior in developed democracies has not been extensively studied.[18] To date, research has largely focused on identifying voter misperceptions[19] and understanding the directionally motivated pathways by which voters interact with conspiracy theories and unfounded rumors.[20] Even research into the impact of *confirmed* cases of election irregularities on voter confidence has primarily examined democratic regimes that are younger and less established than Western democracies.[21] While political scientists have in recent years started to devote more resources to studying the impact of misinformation on electoral politics, the existing literature emphasizes effects on voter *beliefs* instead of voter *behavioral outcomes* such as voting and donation rates. Since voter turnout[22] and small-donor support[23] shape electoral outcomes, the direction and magnitude of the impact of misinformation on voter behavior, if any, has significant practical implications for voter representation and the long-term health of democratic institutions.

By analyzing the political contributions of US citizens[24] who interacted with unfounded voter fraud claims on Twitter during the 2020 general election, I offer new insights into the relationship between exposure to election misinformation and voter behavior in established democracies. Since this analysis is based on an unweighted national sample of select Twitter

[18] Berlinski et al., "The Effects of Unsubstantiated Claims of Voter Fraud on Confidence in Elections."
[19] E.g., Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."
[20] E.g., Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions"; Guess, Nyhan, and Reifler, "Selective Exposure to Misinformation: Evidence from the Consumption of Fake News during the 2016 U.S. Presidential Campaign."
[21] Norris, *Why Electoral Integrity Matters*; Hyde, *The Pseudo-Democrat's Dilemma*.
[22] Hansford and Gomez, "Estimating the Electoral Effects of Voter Turnout"; Holbrook and McClurg, "The Mobilization of Core Supporters"; Martinez and Gill, "The Effects of Turnout on Partisan Outcomes in U.S. Presidential Elections 1960–2000."
[23] Alexander, "Good Money and Bad Money: Do Funding Sources Affect Electoral Outcomes?"; Hua, "Campaign Finance: How Did Money Influence 2020 U.S. Senate Elections?"
[24] Foreign nationals are prohibited from donating to US political candidates. See FEC, "Who Can and Can't Contribute."

users, the results presented below must be interpreted with great caution. These concerns notwithstanding, however, my descriptive analysis of the *VoterFraud2020*[25] Twitter corpus and Federal Election Commission (FEC) data does suggest strong statistically and practically significant findings regarding the *direction* of the impact of misinformation on voter behavior. First, I find that people who tweeted or retweeted messages containing phrases associated with unsupported voter fraud claims during the 2020 election donated *more* frequently but *not* in significantly different amounts than individual donors at large (see Figure 1 below).

The results of this analysis moreover indicate that partisan identity mediates the effects of online exposure to election misinformation. Of the individuals who interacted with election

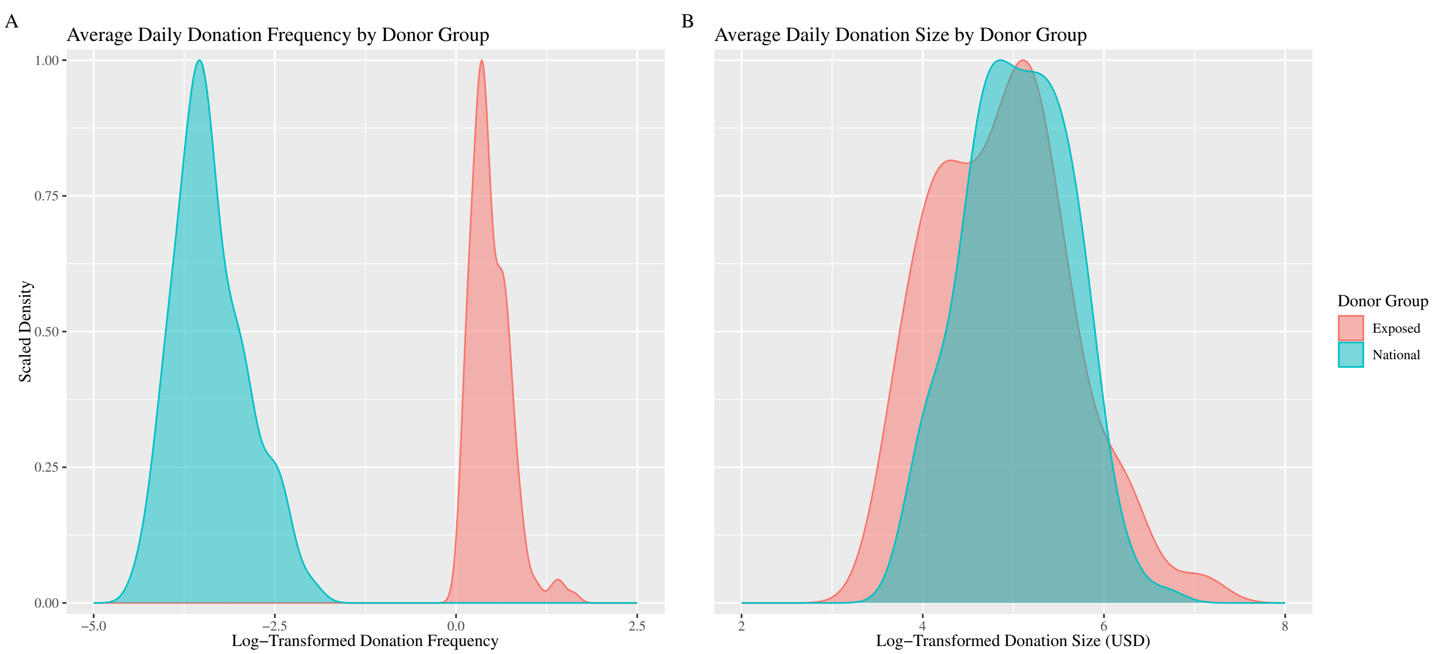

Figure 1. Relative distributions of the size and frequency of contributions from all donors and donors exposed to election misinformation on Twitter. Given the severely skewed nature of average daily donations (in number and size), the log-transformed frequencies and amounts are displayed. While there is a significant degree of overlap in average donation size between the two groups (Fig. 1-B), donors who engaged with unfounded voter fraud claims on Twitter gave much more frequently per day, on average, in the 2020 general election than donors at large (Fig. 1-A).

[25] Abilov et al., "VoterFraud2020."

misinformation on Twitter and donated to political causes during the 2020 presidential election, people located in zip codes that supported the Democratic candidate (Joe Biden) donated *more* frequently and *larger* amounts throughout the general election, on average, than citizens located in zip codes that supported the Republican candidate (Donald Trump). In competitive zip codes where either candidate won with a margin of 5% or less, however, people who interacted with voter fraud claims on Twitter contributed *less* frequently and in *smaller* amounts to political campaigns than other donors who engaged with similar election information on Twitter. Since Green et al. find that Democratic voters who interacted with tweets in the *VoterFraud2020* Twitter corpus turned out at higher rates in the 2021 Georgia Senate runoff races than Republican voters exposed to the same tweets,[26] these results provide additional empirical evidence to suggest that political misinformation impacts voter behavior differently across the ideological spectrum.

Relative Twitter status and activity also appear to mediate the impact of exposure to unfounded voter fraud allegations on the social media platform. The donation behavior of people with a significantly above-average Twitter following (i.e., popular voices) as well as citizens who repeatedly tweeted election misinformation (i.e., active users) markedly diverged from the donation patterns observed among other Twitter users who interacted with unsupported election fraud claims and donated to political causes. Donors with Twitter accounts ranking in the upper quartile with respect to their number of followers (relative to people in my sample) gave *more* frequently and in *larger* amounts than other donors exposed to misinformation on Twitter during the 2020 general election. At the same time, people who repeatedly tweeted or retweeted

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[26] Green et al., "Online Engagement with 2020 Election Misinformation and Turnout in the 2021 Georgia Runoff Election."

messages associated with voter fraud claims in the immediate run-up to Election Day[27] donated at *similar* daily frequencies but in *smaller* amounts than donors who interacted with election misinformation less often on Twitter. While these heterogenous outcomes require further analysis, they do suggest two notable patterns. First, Twitter interactions with political misinformation appear to have a more significant and sizable impact on elites (i.e., people with very many Twitter followers) than non-elites, though the magnitude of this effect may be partially explained by the greater political engagement and financial resources of elites in general. Second, increases in the number of Twitter interactions with election misinformation appear to be linked to smaller daily political donations.

Given the rising levels of polarization and skepticism of democratic norms such as free and fair elections within contemporary American politics,[28] my findings regarding the potential impact of exposure to Twitter election misinformation on individual political contributions represent a proverbial (blue) canary in the coal mine. To the best of my knowledge, no published study has similarly examined the connection between Twitter misinformation and individual donations during a US presidential election. While uncovering worrying signs that indicate exposure to election misinformation disproportionately dampens political contributions among moderates in competitive districts and non-elites, I also identify a promising lode of new data that may pave the way for deeper mining of existing Twitter corpora and highlight the need for continued research into political misinformation spread through social media and voter behavior.

[27] November 3, 2020.
[28] Mounk and Foa, "The Danger of Deconsolidation: The Democratic Disconnect."

Defining Misinformation

Before discussing the results of any analysis on the impact of misinformation, it is essential to define misinformation. Misperceptions, or specific inaccurate or unsupported viewpoints, are ubiquitous both in[29] and outside[30] the United States and precede the covid-19 pandemic.[31] Misinformation is reflected in our perceptions of topics as diverse as the economy,[32] foreign policy,[33] and gun control.[34] Flynn et al. offer a concise and broadly accepted definition of misinformation, describing misinformation at its most basic level as a set of factual statements not supported by the best available evidence in the public domain.[35] Misperceptions are also marked by great certainty, distinguishing them from simple ignorance or lack of information.[36] In developed democracies, reliable evidence in the public domain often includes but is not necessarily limited to government reports, investigations by mainstream media, and studies published by independent researchers. While most citizens do not closely follow either public- or private-sector researchers, their work is frequently published online or disseminated through reputable news sources that have online platforms. As such, we can think of online access as a key metric of accessibility in the public domain. Since numerous researchers and journalists utilize Twitter to share their work, Twitter as a platform in particular serves as a reasonable proxy for online access.[37] Although most Twitter users do not frequently tweet, many users still use the

[29] Kull, Ramsay, and Lewis, "Misperceptions, the Media, and the Iraq War."
[30] Institut Publique de Sondage d'Opinion Secteur, "The Perils of Perception and the EU: Public Misperceptions About the EU."
[31] Uscinski and Parent, *American Conspiracy Theories*.
[32] Bartels, "Uninformed Votes."
[33] Kull, Ramsay, and Lewis, "Misperceptions, the Media, and the Iraq War."
[34] Aronow and Miller, "Policy Misperceptions and Support for Gun Control Legislation."
[35] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[36] Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship"; Pasek, Sood, and Krosnick, "Misinformed About the Affordable Care Act?"
[37] Howoldt et al., "Understanding Researchers' Twitter Uptake, Activity and Popularity—an Analysis of Applied Research in Germany."

platform as a source of political information.[38] Recent changes to Twitter's research API policies notwithstanding,[39] studies of political information (regardless of veracity) and voter behavior therefore frequently benefit from incorporating Twitter data.

The Flynn et al. definition of misperceptions clarifies distinctions between misinformation and related terms that have entered the public lexicon – namely, interpretations, rumors, and conspiracy theories.[40] Interpretations describe how we categorize or contextualize information.[41] If our interpretation runs counter to the best available evidence, our interpretation constitutes a misperception. A rumor is unverified yet relevant information that arises and spreads rapidly in contexts of ambiguity, danger, or potential threat. While rumors help us make sense of uncertain situations, they fail to meet widely agreed-upon standards of evidence and therefore fall under misperceptions.[42] Conspiracy theories are claims that seek to explain events by reference to covert activities at the hands of powerful people[43] working against the public good for their own benefit. If their predictions fail to materialize and corroborating evidence does not appear, conspiracy theories constitute misinformation.[44]

While the terms disinformation and misinformation are often used interchangeably in public discourse, disinformation is misinformation spread intentionally with the knowledge that the relevant statements are misleading or even demonstrably false.[45] As illustrated by the Russian interference efforts in the 2016 US presidential election, disinformation operations are often

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[38] McClain et al., "The Behaviors and Attitudes of U.S. Adults on Twitter."
[39] Twitter Developer Platform, "Twitter API: Academic Research Access."
[40] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[41] Gaines et al., "Same Facts, Different Interpretations."
[42] Bordia and DiFonzo, "When Social Psychology Became Less Social."
[43] Sunstein and Vermeule, "Conspiracy Theories."
[44] Uscinski and Parent, *American Conspiracy Theories*.
[45] Wardle and Derkhshan, *Module 2: Thinking about 'Information Disorder': Formats of Misinformation, Disinformation, and Mal-Information*.

covert activities under the direction of foreign actors.[46] Since disinformation campaigns do employ the same platforms as reputable news sources and researchers to spread their messages (e.g., Twitter), researchers must be cautious when utilizing data from Twitter accounts to investigate the relationship between information and voter behavior. To address this concern, my analysis expands on the innovative approach developed by Hughes et al.[47] and Green et al.[48] to combine Twitter data with government records by solely focusing on Twitter users who can be reliably identified and matched to public FEC records. Since federal law bars foreign nationals and American minors[49] from donating to political campaigns within the US, we can reasonably infer that all Twitter users reliably matched to FEC records are adult Americans. Consequently, we can safely assume that the dataset used in this analysis solely consists of (voting-age) American citizens.[50]

Literature Review

The existing literature provides both theoretical and empirical motivations to expect a measurable relationship between Twitter interactions with political misinformation and voter behavior. The field of psychology offers two theoretical frameworks known as rationalization and reactance theory to understand the ways humans interact with information. By combining insights derived from these frameworks with evidence from political science,[51] researchers have developed several structural models of voter behavior, ranging from the calculus of voter models

[46] U.S. Congress, Senate, "Senate Report on 2016 Russian Interference."
[47] Hughes et al., "Using Administrative Records and Survey Data to Construct Samples of Tweeters and Tweets."
[48] Green et al., "Online Engagement with 2020 Election Misinformation and Turnout in the 2021 Georgia Runoff Election."
[49] Minors can only contribute under very specific circumstances. See FEC, "Who Can and Can't Contribute."
[50] FEC, "Foreign Nationals."
[51] Degan and Merlo, "A Structural Model of Turnout and Voting in Multiple Elections."

originally proposed by Downs[52] and Rikers and Ordeshook[53] to motivated-reasoning frameworks.[54] While these models present intuitive theoretical explanations of voter behavior, empirical results from the 2016 and 2020 US presidential elections indicate that existing voter models do not adequately address the practical effects that political misinformation may have on voter decision-making and behavior.

Rationalization Theory and Reactance Theory

In general, people act upon a set of personal convictions – and are very effective at resisting efforts to alter strongly held beliefs.[55] The field of psychology offers two frameworks for conceptualizing interactions between our beliefs and information: namely, rationalization theory and reactance theory. Since our beliefs and policy preferences are closely related, these general frameworks provide a necessary background to the more targeted theories we discuss below.[56] On the one side, rationalization theory suggests that when we encounter new circumstances or information that may change the status quo, we tend to frame the development in the most positive light or as an extension of our current situation.[57] In short, we strive for consistency in our beliefs and attitudes,[58] even if that requires acquiescing to limits on our previous range of options.[59] In contrast, reactance theory posits that we react against infringements on our behavioral freedoms or intellectual options by attaching greater value to the

[52] Downs, "An Economic Theory of Political Action in a Democracy."
[53] Riker and Ordeshook, "A Theory of the Calculus of Voting."
[54] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[55] McGuire, "Resistance to Persuasion Conferred by Active and Passive Prior Refutation of the Same and Alternative Counterarguments."
[56] Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."
[57] Aranson, "The Rationalizing Animal" in Leavitt, Pondy, and Boje, *Readings in Managerial Psychology*.
[58] Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."
[59] Cooper, *Cognitive Dissonance: Fifty Years of a Classic Theory.*

status quo.[60] While empirical evidence supports both theories, research indicates that they are most relevant in different situations. We tend to rationalize behavioral and intellectual constraints when the restriction is definitive but react negatively when it is possible that the change may not come into effect.[61]

Since messages spread by political campaigns typically contain broadly defined promises (or threats) that may or may not come into effect depending on the outcome of a given election, the psychology literature suggests that voters will be inclined to resist electoral campaigns that attempt to reshape strongly held viewpoints. Reactance theory implies political misinformation such as unfounded voter fraud claims would be difficult to spread among subgroups of the electorate where the misinformation contradicts attitudes widely held in the community. At the same time, similar misinformation may provoke a counterreaction among voters who fear the implications of the unsupported claims (e.g., an election stolen through voter fraud). Election misinformation could therefore find a fertile ground among voters who (1) are already inclined to believe the underlying unproven claims or (2) are uncertain about their prospects of electoral defeat (or victory) and the subsequent policy failures (or successes).

Among voters who are not well-informed or do not hold firm positions on relevant campaign promises – which is relatively uncommon among active Twitter users[62] – rationalization theory suggests that voters are willing to adapt to changing circumstances to preserve consistency in their worldviews and would therefore predict limited interest in and opposition to the relevant campaign messages.[63] However, research has shown that people often

[60] Brehm and Brehm, *Psychological Reactance*.
[61] Laurin, Kay, and Fitzsimons, "Reactance Versus Rationalization."
[62] Bestvater et al., "Politics on Twitter."
[63] Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."

are not *un*informed about policy debates but rather *mis*informed.[64] Since even minor differences at the margins of aggregate public opinion can lead to markedly different government policies,[65] misperceptions among voters likely play a more significant role in shaping electoral politics than public ignorance.[66]

Voter Models and Misinformed Voters

Political scientists have developed several frameworks of voting behavior based on the calculus of voting models originally proposed by Downs[67] and Riker and Ordeshook,[68] which estimate the likelihood that a voter will turn out based on the net value she could derive by voting. Since the presence and quality of information shapes the perceived costs and benefits of voting,[69] incorporating the information environment in which voters operate constitutes a natural extension of these models. While mathematicians have adapted SIR (Susceptible, Infected, and Recovered) models from the field of epidemiology to model rumor spreading through both verbal communication and social media platforms,[70] I have not identified voter models within the political science literature that similarly incorporate the SIR rumor-spreading framework adapted for online social media.

Calculus of voting models can be divided into three broad categories: pivotal-, ethical-, and uncertain-voter models.[71] Pivotal-voter models focus on the perceived likelihood that a citizen's vote will decide the election, while ethical-voter models emphasize a voter's sense of

[64] Kuklinski et al.
[65] Stimson, Mackuen, and Erikson, "Dynamic Representation."
[66] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[67] Downs, "An Economic Theory of Political Action in a Democracy."
[68] Riker and Ordeshook, "A Theory of the Calculus of Voting."
[69] Riker and Ordeshook.
[70] E.g., Zhao et al., "SIR Rumor Spreading Model in the New Media Age."
[71] See the overview provided by Degan and Merlo, "A Structural Model of Turnout and Voting in Multiple Elections."

civic duty. While these models are useful tools, both pivotal- and ethical-voter models do not adequately account for misinformation. For example, misperceptions regarding the support of a particular candidate or one's civic responsibilities could easily alter our perception of the value of participating in a given election. Uncertain-voter models highlight the cost of voting as it relates to the information available to citizens and the corresponding probability that we mistakenly vote for candidates not aligned with our views. Since misperceptions can distort policy preferences[72] and reshape the distribution of collective opinion,[73] incorporating the impact of misinformation would be a valuable addition to these models.

Recognizing both the valuable insights from psychology as well as extensive evidence from empirical research,[74] political scientists have in recent years shifted toward paradigms focused on directionally motivated reasoning.[75] As expected under rationalization and reactance theory, studies show that our interpretation of facts depends on whether the information reinforces or contradicts beliefs stemming from our ideological or partisan preferences.[76] While it remains difficult to evaluate whether misperceptions affect opinions or vice versa, directional reasoning does have measurable implications,[77] ranging from information consumption choices[78] to the information we remember,[79] even if that information contains statements that have been proven false.[80] For example, if we overestimate the number of people relying on welfare programs, we also tend to overestimate the percentage of the federal budget dedicated to such

[72] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[73] Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."
[74] E.g., Kuklinski et al.; Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[75] Kunda, "The Case for Motivated Reasoning."
[76] Lodge and Taber, *The Rationalizing Voter*.
[77] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
[78] Stroud, "Media Use and Political Predispositions."
[79] Kahan et al., "Science Curiosity and Political Information Processing."
[80] Thorson, "Belief Echoes."

programs.[81] Since our policy preferences are closely connected to our beliefs and by extension our political identity, voters tend to rationalize their response to information in accordance with their political identity.[82] At the same time, voters likely resist facts that are perceived as sufficiently threatening to their identity.[83] As such, voters' perception of the value of voting is likely related to the ideological distance between their viewpoints and candidate positions in an election cycle. Given time constraints and recent changes to Twitter API policies, I was unable to classify the Twitter users in my sample into distinct groups based on their news consumption choices (e.g., based on the news media or political commentators they follow on Twitter). By incorporating estimates of regional ideological leanings from the American Ideology Project,[84] however, I can at least partially control for the degree of ideological differences between voters and candidate positions in the 2020 election.

Election Misinformation and Voter Misperceptions

When Kuklinski et al. published their work demonstrating the extent of misperceptions among the American electorate, they challenged two established streams of literature that focused heavily on the *un*informed voter: the study of political heuristics, which argues that citizens can perform their civic responsibilities well even without information, and the study of elite discourse, which views public opinion as a malleable concept responsive to external factors.[85] As part of this ongoing discussion, some political scientists argue that apathetic and uninformed voters are crucial to the health of an electoral system, since these voters are unlikely

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81 Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."
82 Greene, "Social Identity Theory and Party Identification*"; Berinsky, "Rumors and Health Care Reform."
83 Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions."
84 Tausanovitch and Warshaw, "Subnational Ideology and Presidential Vote Estimates (V2022)."
85 Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."

to instigate electoral conflicts and serve a moderating force when such conflicts do appear.[86] Most researchers, however, argue that citizens should be factually informed to fulfill their responsibilities as voters.[87] While this debate is worthwhile, it would benefit from an analysis of the impact of misinformation, particularly baseless claims of election irregularities spread by both political elites and ordinary citizens. For example, some argue that citizens must have access to accurate information to evaluate public policy.[88] However, access to facts alone does not necessarily minimize the influence of misperceptions. Voters must not only access but also utilize these facts to inform their policy preferences.[89] Since fact-checks are associated with greater political knowledge in general[90] and appear to be read primarily by the people who do not need the counter-attitudinal treatment,[91] it is doubtful whether many voters will utilize the requisite facts to shape their policy preferences, even if evidence is directly provided to them in the form of fact-checks.

While the elite cues literature challenged by Kuklinski et al. suggests misinformation spread by social elites can negatively shape citizen beliefs and attitudes,[92] recent empirical evidence appear to confirm Kuklinski et al.'s argument that public opinion is highly resistant to persuasion attempts by political elites. Findings from the Obama and Trump presidencies indicate that political leaders have limited capacity to alter citizens' attitudes regarding fundamental democratic institutions such as elections and the legislative process.[93]

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[86] Berelson, "Democratic Theory and Public Opinion."
[87] Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."
[88] Carpini and Keeter, *What Americans Know about Politics and Why It Matters*.
[89] Lupia and McCubbins, *The Democratic Dilemma*.
[90] Gottfried et al., "Did Fact Checking Matter in the 2012 Presidential Campaign?"
[91] Shin and Thorson, "Partisan Selective Sharing"; Guess, Nyhan, and Reifler, "Selective Exposure to Misinformation: Evidence from the Consumption of Fake News during the 2016 U.S. Presidential Campaign."
[92] E.g., Zaller, *The Nature and Origins of Mass Opinion*.
[93] The following argument is inspired by Berlinski et al., "The Effects of Unsubstantiated Claims of Voter Fraud on Confidence in Elections."

First, panel design studies of the 2016 and 2020 US presidential elections provide mixed evidence on the effect of unfounded voter-fraud claims by political elites on voter behavior. While Trump also spread unsupported voter fraud allegations before the 2016 election, Trump supporters' confidence in elections did not measurably change while Democrats' confidence in elections actually increased before election.[94] Following Trump's victory in the 2016 election, Trump voters' confidence in elections increased while their belief in unfounded claims of illicit voting decreased. Clinton voters' confidence remain unchanged[95] – a classic case of "winner effect" retroactively shaping voter perceptions of electoral integrity and fairness.[96] While Trump's voter fraud claims in the run-up to the 2020 election were better publicized than his 2016 claims, a similar partisan phenomenon was observed among voters who interacted with his allegations. Among panel survey respondents who approved of Trump's presidential job performance, exposure to Trump's election fraud claims eroded trust and confidence in democratic institutions. Among respondents who disapproved of Trump's performance, interactions with Trump's claims increased voter confidence in elections.[97]

Second, existing evidence strongly indicates that most presidents fail to meaningfully alter public opinion on most topics[98] and face electoral punishments for attempting to change public views on established democratic norms.[99] According to data from six nationally representative surveys conducted between 2013 and 2015, voters oppose unilateral presidential power (though they are much more supportive in matters concerning national security). These findings remained consistent despite varying levels of politicization of presidential power and

[94] Sinclair, Smith, and Tucker, "'It's Largely a Rigged System.'"
[95] Levy, "Winning Cures Everything?"
[96] E.g., Anderson and Tverdova, "Winners, Losers, and Attitudes about Government in Contemporary Democracies."
[97] Sinclair, Smith, and Tucker, "'It's Largely a Rigged System.'"
[98] Edwards, *On Deaf Ears*; Franco, Grimmer, and Lim, "The Limited Effect of Presidential Public Appeals."
[99] Reeves and Rogowski, "Unilateral Powers, Public Opinion, and the Presidency."

rising polarization during the Obama presidency.[100] In three other nationally representative survey experiments conducted across a range of policy domains during the Obama presidency, Reeves and Rogowski also find that the public reacts negatively when the president achieves policies through unilateral action (i.e., by side-stepping established norms such as the legislative process in Congress). Notably, these opinion costs are greatest among respondents who support the relevant policy goal pursued by the president.[101] While partisan and policy considerations play a much stronger role in shaping voters' candidate preferences than actions and statements that challenge democratic norms,[102] both Democratic-leaning and Republican-leaning citizens and donors tend to withdraw support from candidates who violate democratic norms associated with judicial deference, impartial investigations, and compromise.[103] Although Carey et al. do identify substantial polarization by party on voter identification laws (i.e., ballot access), their overall findings indicate that both regular citizens as well as the most invested and motivated voters (i.e., donors) are highly critical of norm violations. Empirical evidence from the 2022 US midterm election reinforces Carey et al.'s findings. Republican candidates denying the outcome of the 2020 election disproportionately lost their races, even in districts that otherwise would have been expected to firmly support Republican candidates.[104]

Since the available evidence regarding the influence of elite political rhetoric on voter behavior is inconclusive, the existing literature would benefit from a rigorous analysis of the impact of (misleading) political messaging by elites *and* non-elites on voter beliefs and activity. By analyzing a novel dataset that combines highly political and inaccurate messages shared by

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[100] Reeves and Rogowski.
[101] Reeves and Rogowski, "The Public Cost of Unilateral Action."
[102] Graham and Svolik, "Democracy in America?"
[103] Carey et al., "Party, Policy, Democracy and Candidate Choice in U.S. Elections."
[104] Cohn, "Election Denial Didn't Play as Well as Republicans Hoped"; Blake, "How Badly Election Deniers Cost the GOP, in 9 Stats"; Cf., Carey et al., "Who Will Defend Democracy?"

elites (e.g., Donald Trump) and ordinary citizens on Twitter, I strive to provide valuable insights to help inform ongoing debates regarding the impact of election misinformation, and political information more broadly, on voter behavior in developed democracies. Indeed, my analysis suggests that Twitter interactions with political misinformation are associated with greater increases in donation behavior among elites (i.e., people with very many Twitter followers) than among other politically active citizens (i.e., people sharing political (mis)information on Twitter and providing financial support to political campaigns).

Argument

We should expect some relationship between exposure to political misinformation during elections and voter behavior. Indeed, Green et al. find that Twitter interactions with election misinformation during the 2020 US election season are linked to measurable, albeit small, changes in voter turnout rates in the 2021 Georgia Senate runoff races. Based on their analysis of 40,000 Twitter users registered to vote in Georgia who also interacted with tweets in the *VoterFraud2020* corpus, voters who liked or retweeted messages opposed to conspiracy theories were more likely to turn out than other voters. In contrast, voters who liked or retweeted posts promoting conspiracy theories related to voter fraud were less likely to vote than other voters.[105] To the best of my knowledge, the Green et al. study is the first attempt to quantify the impact of election misinformation on voter behavior (and not beliefs or attitudes[106]) using Twitter data in general and the *VoterFraud2020* corpus in particular.

[105] Green et al., "Online Engagement with 2020 Election Misinformation and Turnout in the 2021 Georgia Runoff Election."
[106] E.g., Berlinski et al., "The Effects of Unsubstantiated Claims of Voter Fraud on Confidence in Elections."

There are three reasons to expect some relationship between misinformation and voter behavior. At an individual level, emotions shape people's decisions. If we have a stance on a topic based on misperceptions, we could be motivated to vote because of the confidence with which we hold that belief.[107] Additionally, candidates and issues are affect-laden, and people update beliefs toward objects using their existing affective evaluations.[108] Hence, voters may become more likely to participate in an election if they perceive candidates to be aligned with their own stances[109] – which could very well consist of or be based on misperceptions.[110] Lastly, conspiracy beliefs are more likely to emerge in response to identity-threatening events such as electoral loss.[111] In other words, the anticipated or actual disappointment of losing an election may make voters more inclined to not only form but also act upon conspiracy theories in the next election.[112]

While Green et al. employ similar arguments to explain potential relationships between election conspiracies and voter turnout,[113] these reasons can also be applied to account for associations between election misinformation with voter donation behavior. The concept of voter encompasses general civic activities ranging from membership in political associations to voting and donating to political causes.[114] Since both voting and donating are fundamental means by which voters can express their support (or opposition) to the political statements spread during an electoral cycle, individual voter donations during a general election represent an accepted

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[107] Valentino et al., "Election Night's Alright for Fighting."
[108] Flynn, Nyhan, and Reifler, "The Nature and Origins of Misperceptions"; See also Phillips, "Affective Polarization."
[109] Green et al., "Online Engagement with 2020 Election Misinformation and Turnout in the 2021 Georgia Runoff Election."
[110] Kuklinski et al., "Misinformation and the Currency of Democratic Citizenship."
[111] Taber and Lodge, "Motivated Skepticism in the Evaluation of Political Beliefs."
[112] Green et al., "Online Engagement with 2020 Election Misinformation and Turnout in the 2021 Georgia Runoff Election."
[113] Green et al.
[114] Putnam, Leonardi, and Nanetti, *Making Democracy Work*.

measurement of voter behavior.[115] However, since donating to political causes imposes greater and more immediate costs on voters, individual political contributions arguably constitute a higher level of voter participation than voter turnout.

Based on historic voter turnout rates, there is evidence to suggest that increased exposure to political misinformation does not alter the behavior of the general electorate. Since suffrage was expanded to most groups of the U.S. population, the share of registered voters who turn out in presidential and midterm elections has remained relatively stable.[116] As such, the political

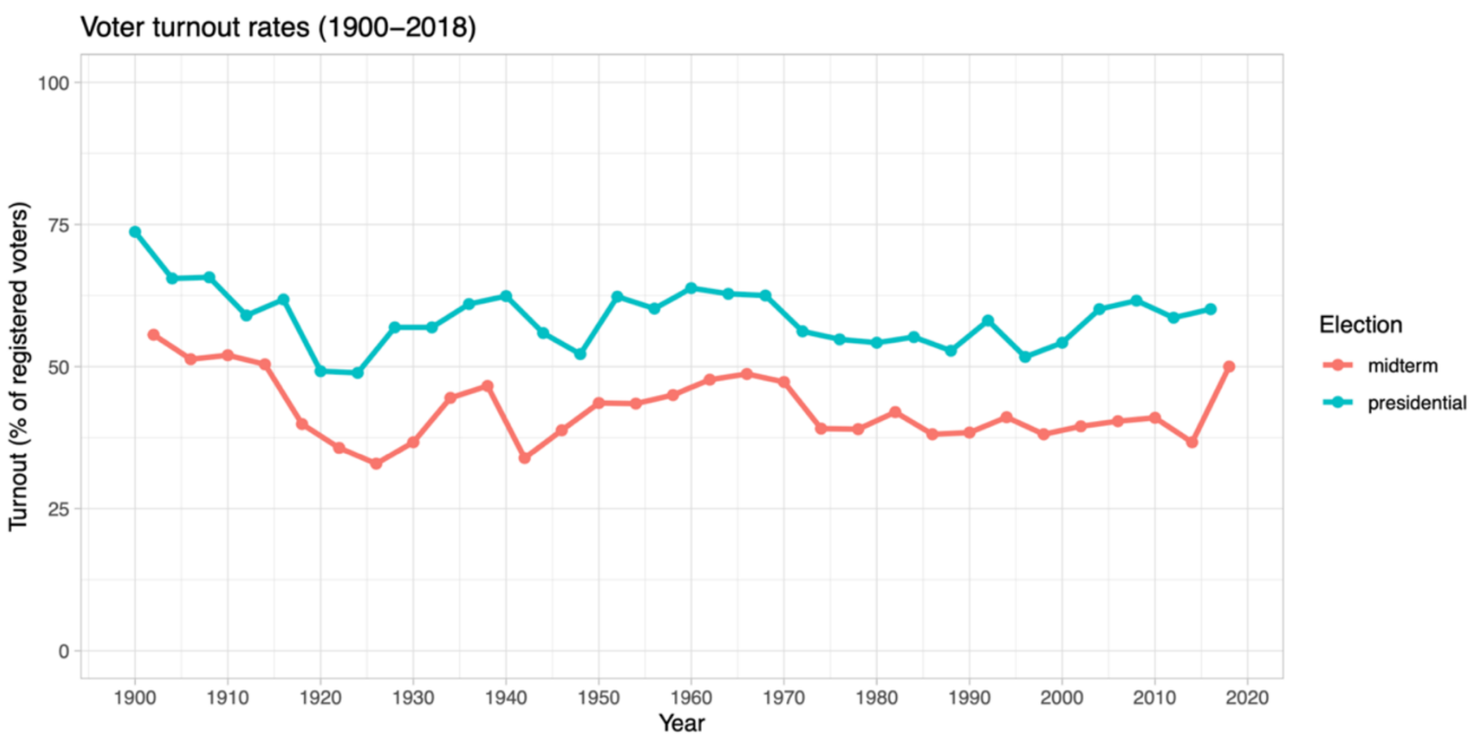

Figure 2. National voter turnout rates among registered voters have remained constant over time. Since ballot access was expanded to most groups of the US population following the passage of the 19th Amendment (1920) and the civil rights movement (1954-1968), the share of registered voters who turn out in presidential and midterm elections has remained relatively stable. This suggests that changes in the level of political (mis)information in public discourse have limited, if any, impact on overall voter behavior. Given pandemic-related changes to ballot access in 2020 (e.g., streamlined access to mail-in ballots), I do not include the 2020 voter turnout rates in Figure 2.

[115] E.g., Kujala, "Donors, Primary Elections, and Polarization in the United States."
[116] U.S. Census Bureau, "Historical Reported Voting Rates."

participation of the general electorate, which since the passage of the 19th Amendment in 1920 roughly mirrors the adult U.S. population, has not changed significantly over time (see Figure 2). Based on a review of 104,823 letters sent to the editors of the New York Times between 1890 and 2010 (and compared to a validating sample from the Chicago Tribune), Uscinski and Parent argue that conspiratorial thinking and misperceptions have been common across demographics and partisan leanings, and time.[117] Since voter participation in the form of turnout appears to have remained stable regardless of several fluctuations in the frequency of misinformation in American public discourse over time,[118] changes in the level of exposure to misinformation appears to have limited, if any, impact on a fundamental form of political behavior – namely, voter turnout among the overall electorate.

While there is limited evidence that misinformation alters the behavior of the general electorate, we should expect that exposure to political misinformation regarding electoral promises and election irregularities influences subgroups of voters. Applying reactance theory, we should expect that citizens strongly opposed to the implications of specific false electoral statements will react negatively when exposed to such claims. Apart from physically protesting on the street, voting "no" or donating to competing campaigns are the most concrete tools voters have at their disposal to voice their disapproval of electoral statements and agendas – including electoral messages containing baseless factual claims that raise the specter of unjustified electoral loss. Established research finds that donors are highly passionate about politics and hold very strong views on candidates.[119] Since individual donors as a group are logically the most

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[117] Uscinski and Parent, *American Conspiracy Theories*.
[118] Uscinski and Parent.
[119] Francia et al., *The Financiers of Congressional Elections*; Francia et al., "Limousine Liberals and Corporate Conservatives"; Panagopoulos and Bergan, "Contributions and Contributors in the 2004 Presidential Election Cycle"; Rhodes, Schaffner, and La Raja, "Detecting and Understanding Donor Strategies in Midterm Elections."

invested in the electoral success of their preferred candidate and therefore very sensitive to misperceptions regarding the odds of electoral victory (or defeat), the effects of interactions with election misinformation are likely most measurable among individual donors. As such, my analysis is well-positioned to evaluate the direction of the impact of political misinformation on highly motivated voters.

Holding all else equal, we should therefore expect that exposure to election misinformation – whether spread by political elites such as Trump or non-elites such as fellow Twitter users – tends to (1) increase voter participation as measured through donation behavior, (2) with especially measurable effects among people opposed to the unsupported or misleading statements regarding election irregularities.

Data

To carry out my analysis, I synthesized three public datasets to construct a novel dataset containing 1,802 unique observations of voting-age American citizens who interacted with unsubstantiated claims of voter fraud on Twitter in the run-up to the 2020 US presidential election, together with longitudinal measurements of their donation behavior and proxy estimates of their partisan identity and ideological preferences: namely, the *VoterFraud2020* Twitter corpus, FEC individual contributions records, and the American Ideology Project.

VoterFraud2020 Twitter Corpus

The *VoterFraud2020* corpus is a multi-modal Twitter dataset compiled by Abilov et al. in 2021 that contains 7.6 million tweets and 25.6 million retweets from 2.6 million Twitter users who were selected because they interacted with keywords linked to voter fraud claims between

October 23, 2020, and December 16, 2020. While Abilov et al. initially used manually curated keywords (e.g., "voter fraud" and "#stopthesteal") to identify relevant tweets, these phrases and hashtags were later expanded and modified using a data-driven approach. Based on various validations performed by Abilov et al., the *VoterFraud2020* corpus contains an estimated 60% of the Twitter data containing their crawled keywords.[120] While the *VoterFraud2020* corpus is based on a rigorous set of keywords, these keywords do not take the ideological position of the user tweeting, retweeting, or liking the selected tweets into account. As such, this corpus contains statements *regarding* unsubstantiated voter fraud claims but not exclusively statements evaluating unfounded allegations of election irregularities. As such, my dataset is best viewed as a collection of citizens who *interacted* with election misinformation rather than a group of people who promoted inaccurate or misleading allegations of voter fraud.

As noted by Abilov et al., *VoterFraud2020* was collected and made available according to Twitter's Terms of Service for academic researchers, following established guidelines for ethical Twitter data use. The *VoterFraud2020* corpus is freely accessible but does not directly share content of individual tweets. By using Tweet IDs as the main data element, the dataset does not expose information about users whose data has been removed from the platform following account suspension or deletion, which ensures greater user privacy but also distorts the number and type of observations available to current researchers. Following Abilov et al.'s example, I utilized an Electron-based desktop application called Hydrator to convert (i.e., hydrate) the *VoterFraud2020* data into an analyzable format. While Twitter's Terms of Service do not allow full JSON datasets of tweets to be distributed to third parties, they do allow datasets of tweet IDs to be shared. Hydrator enables academic researchers to transform tweet IDs provided by fellow

[120] Abilov et al., "VoterFraud2020."

scholars such as Abilov et al. into analyzable JSON and CSV files. Unfortunately, Twitter's recent changes to their API greatly reduce the amount of read-only access to Twitter data. As of April 18, 2023, Twitter has moreover rescinded Hydrator's application keys, making the application unfit for continued use.[121]

Given time constraints and uncertainty regarding changes in Twitter's API policies,[122] I focused on hydrating *VoterFraud2020* tweets posted in the run-up to Election Day to identify Twitter users who tweeted or retweeted messages linked to unsupported voter fraud allegations between October 23, 2020, and November 2, 2020.[123] Since likes on Twitter are not as public as tweets and retweets, they carry lower audience costs and can therefore be viewed as cheap talk. Given my interest in concrete changes in voter behavior, I concentrated on users who tweeted or retweeted rather than simply liked claims associated with election misinformation. This pre-election subset of the Twitter data consisted of 286,589 tweet IDs. By iteratively loading tweet ID files into Hydrator to identify deleted accounts (which could not be analyzed in this project due to the lack of available data) and hydrate tweet IDs, I obtained a dataset of 56,788 unique Twitter accounts belonging to individual citizens, groups such as political campaigns, and organizations such as news media, various non-profits, and private companies.

Using a custom-written R script to clean and standardize names,[124,125] I extracted 29,648 identifiable names consisting of a first name, up to two middle names, and a last name (including suffixes such as "Sr." and "Jr." but excluding titles such as "MD" or "PhD") from these 56,788 unique Twitter users. This identifiable group is not limited to actual individuals but also contains

[121] Summers and Ruest, "Hydrator."
[122] Twitter Developer Platform, "Twitter API: Academic Research Access."
[123] I did not incorporate likes or track Twitter activity over time to anonymize observations as much as possible.
[124] A major note of thanks to Kate Lyons (2017) for publishing a dictionary of emojis with prose names for emojis, UTF-8 codepoints, UTF-8 representations, and corresponding R encodings to enable identification of emojis in mined social media data. See https://github.com/lyons7/emojidictionary
[125] I intend to make most of my code publicly available on GitHub in the coming months.

at least several organizations that were not removed during the automated filtering. To maximize the number of potential linkages with FEC records, I split shared accounts (i.e., accounts with names joined by “and” or “&”) into distinct observations to maximize the number of potential linkages with FEC records. Combining these names with location data obtained from account metadata or scraped from user-written profile descriptions, I ultimately identified 1,802 Twitter users who fully matched distinct FEC records by all 4 name components and at least one geographic identifier such as zip code, city, or county. Of these 1,802 accounts, 130 (or 7.2%) were verified users.[126]

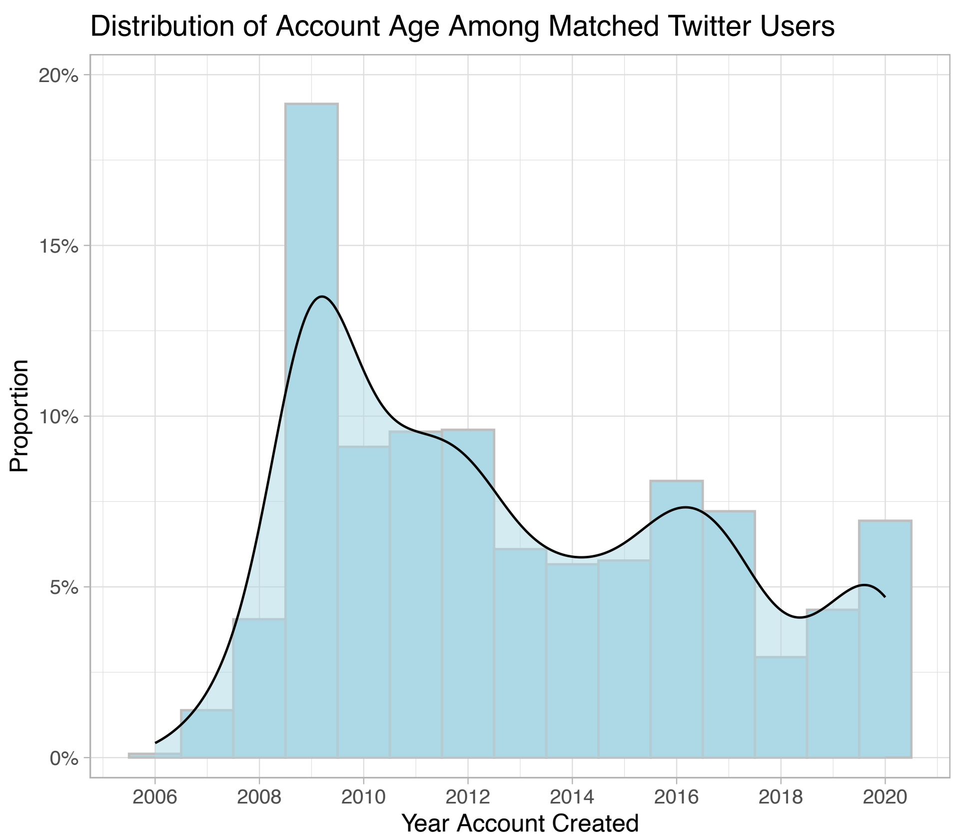

Figure 3. Relatively uniform Twitter account ages. Apart from the 2006-2009 period during which Twitter launched and rapidly spread, the accounts in my sample were created relatively uniformly across time. This pattern provides reassurance that the Twitter accounts in my sample were most likely matched to actual people (of various ages).

[126] To the best of my knowledge, these 130 users had verified status in during the 2020 presidential election.

These Twitter users together constitute the dataset used for my analysis. In cases where Twitter users matched multiple distinct FEC records, I gave priority to verified users and names that matched at the smallest geographic level. For example, if a Twitter user with username "@johndoe123" with screenname "J Doe" (i.e., extracted name components based on synthesizing username and screenname are "john" and "doe") matches to one "John Doe" located in the same city and another "John Doe" residing in the same county or state, then I (1) merged the city-level matches and (2) removed that "John Doe" record from the FEC data to prevent double-matching to the same name. To increase sample size, I considered linking Twitter accounts to FEC records through partial matching text algorithms. Given the significant number of accounts that partially match multiple names in the FEC database without clear geographic distinctions, however, I have not included these observations in the current data but may include them in a future iteration of the dataset if I can reliably link them to unique FEC donors. Refer to Appendix A for additional details on the strategy I implemented to extract and match names across Twitter and the FEC records.

The average age of the matched Twitter accounts was about 7 years at the time of the 2020 election, with a plurality (19.2%) of accounts in my sample created in 2009. Additionally, the matched accounts appear to have been created at similar annual rates between the launch of Twitter in 2006 and the election in 2020 (see Figure 3). Consequently, we can reasonably infer that the observations in my sample do constitute people of various ages and not bots or accounts created solely for the purposes of the 2020 election. Given the FEC restrictions on foreign nationals and American minors, we can furthermore safely assume that all observations in my data represent US citizens who are most likely voting-age adults.[127] Since Twitter users in

[127] FEC, "Who Can and Can't Contribute."

general tend be more politically active than the general public[128] and the Twitter users in my sample also donated to various political causes during the 2020 general election my final dataset (1) most likely consists solely of people who are registered to vote and (2) quite probably consists entirely of active voters.

While there is sizable variation in Twitter status and activity among the users in my final sample, the Twitter users matched to FEC records on average have markedly more followers than the national average. If we define active or frequent Twitter users as people who have posted at least five times per month since activating their account, frequent and infrequent users across the US Twitter userbase had an average of 159 and 15 followers, respectively, as of May 2021.[129] Among matched Twitter accounts, however, users had an average of 27,534 and median of 561 followers. As a group, the number of followers per account ranges from a low of 0 to a high of 9,630,160. In other words, people who interacted with election misinformation on Twitter and donated to political causes during the 2020 presidential election appear to have had larger online social networks than most Twitter users. While this phenomenon may be at least partially explained by my focus on users who tweeted or retweeted messages associated with election misinformation (instead of all users who liked these messages), the magnitude of difference in average Twitter following does indicate that the persons in my final dataset – while not all social elites – tend to reach more people on Twitter than most American Twitter users, much less most American citizens.[130]

The donors who interacted with election misinformation on Twitter between October 23 and November 2 on average tweeted or retweeted 1.31 messages with *VoterFraud2020*

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[128] E.g., Wojcik and Hughes, "Sizing Up Twitter Users."
[129] Statista, "Average Number of Followers and Accounts Followed by Twitter Users in the United States as of May 2021, by Tweet Volume."
[130] For additional information on the US Twitter userbase, see Odabas, "10 Facts about Americans and Twitter."

keywords. While 83.6% (n = 1,506) of matched donors actively interacted with election misinformation on Twitter only once, about 16.4% (n = 296) of donors actively interacted with unsubstantiated voter fraud claims more than once, with some users sharing messages associated with such claims as many as 33 separate times in that 11-day period. On average, the people who repeatedly tweeted or retweeted posts containing such claims shared similar posts 2.88 times.

FEC Individual Political Contributions Data

The Federal Election Commission (FEC) provides freely downloadable data files summarizing the financial reports of political campaigns in federal elections across the US. Public FEC data provide the amount, date, and recipient of each transaction per individual donor as well as more refined location data such as the zip code where a donor was located when making a political contribution. Since 2015, individual contributions are included in FEC files if the donor contributes more than $200 to candidate committees in a given cycle or gives more than $200 to political action committees (PACs) and party committees in a given calendar-year.[131] As such, this analysis examines Twitter users who donated at least $200 to various political campaigns throughout the entirety of 2020, including but not limited to either the general election season included in my data or the primaries in the beginning of the year excluded from this analysis. Since I include donations made up till December 31, 2020, however, the FEC records I utilized should include almost everyone who donated at least $200 to political campaigns throughout 2020. As noted by the FEC on its website,[132] anyone may inspect and download reports filed by political committees. The names and addresses of individual contributors may not be sold or used for commercial purposed or to solicit contributions or

[131] FEC, "Contributions by Individuals File Description."
[132] FEC, "FEC Bulk Data."

donations. While this analysis matches a sizable group of donors to Twitter accounts that interacted with election misinformation and therefore uncovers potentially sensitive patterns about individual Americans, I do not (1) identify Twitter users beyond their zip code; (2) will not share my final dataset with parties who may be inclined to use the data for commercial or political purposes; and (3) retained only anonymized Twitter user IDs when performing the actual analysis. As such, I have fully adhered to Twitter's Terms of Service and FEC regulations while processing this data and implemented additional measures on my own accord to maximize the privacy of all individuals matched to Twitter accounts present in the *VoterFraud2020* corpus.

To match Twitter users from the *VoterFraud2020* corpus with FEC donations data, I utilized the same method used to clean the Twitter data to extract name components (i.e., first name, up to two middle names, and last name with suffixes) and location data from the FEC records. By utilizing the same overall procedure to extract names with both the Twitter and FEC data, I consistently standardized names across disparate data sources. Since exposure to election misinformation likely impacts subgroups of the electorate differently, I strove to maximize the pool of Twitter observations that could be matched to FEC records to enable cross-group comparisons. As a result, I focused on the general election period of the 2020 electoral cycle, when voters that do participate in an electoral cycle become increasingly exposed to political information, including political misinformation. Since Trump and his allies doubled down on unsubstantiated claims of voter fraud after his defeat in the 2020 election, leading to even greater voter exposure to false and misleading claims regarding the election, I include FEC donations data up till the end of the calendar year in my analysis. Given that the Democratic[133] and Republican[134] national conventions that confirmed Biden and Trump, respectively, as the official

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[133] Mullin, "Remote Democratic Convention Drew 18.7 Million Viewers on First Night."
[134] Lucey and Restuccia, "RNC Nominates Trump, Warns Against Biden Victory."

nominees of their parties occurred in August of 2020, I initially treated August 1 as the approximate start of the general election season. Since Biden and Trump were already the clear party nominees by July 2020,[135] the weeks surrounding August 1 form a reasonable albeit fluid cutoff for analyzing the general election. Given the structure of FEC files, I ultimately focused on FEC records ranging from July 24 to December 31. During this 5-month period surrounding the 2020 presidential election,[136] the FEC recorded 25,506,468 transactions from 4,063,731 unique individual donors to various political campaigns. Out of these four million donors, 1,802 individuals were reliably matched to Twitter users who interacted with election misinformation on the social media platform in the 11 days preceding Election Day.

American Ideology Project Data

Given the existence of motivated political reasoning,[137] my analysis is strengthened by controlling for polarization and partisanship through estimates of regional ideological leanings. For example, polarization may confound the impact of misinformation on donations by motivating voters to act more on partisan identity than information or interpret (unsupported) factual statements along partisan lines.[138] A review of polarization research suggests ideological divergences has occurred mostly among partisans rather than voters at large.[139] Since my sample consists solely of people who are both Twitter users and political donors – two of the most partisan and politically active groups within American politics – we must account for heterogenous outcomes by ideological leaning. To control for partisan identity and affective

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[135] Sparks, "Biden Maintains Double-Digit Lead over Trump Nationally, with Coronavirus a Top Issue."
[136] Election Day was November 3, 2020.
[137] Taber and Lodge, "The Illusion of Choice in Democratic Politics"; Anson, "Partisanship, Political Knowledge, and the Dunning-Kruger Effect."
[138] Nyhan, "Facts and Myths about Misperceptions."
[139] Lelkes, "Mass Polarization."

polarization,[140] I utilized the zip codes provided by the FEC to merge the Twitter-FEC dataset with data from the American Ideology Project (AIP)[141] and thereby obtain rigorous estimates of both the mass public's ideology as well as 2020 presidential voting behavior in zip codes across the US.

Since Americans increasingly tend to cluster in cities and neighborhoods with people who align with their political preferences[142] and politically active Twitter users presumably are even more likely than the general public to sort themselves into geographic clusters by partisan identity, local estimates of ideological leaning serve as reasonable proxies for the political preferences of matched Twitter users in my sample. As opportunity arises, I intend to provide a more rigorous estimate of the partisan preferences of donors in my sample by supplementing my analysis with both (1) voting history data from official voter records as well as (2) the partisan labels of the beneficiaries of the contributions given by relevant donors (e.g., as listed on official 2020 ballots).

The AIP estimates are derived using a multilevel regression and post-stratification (MRP) model that takes local race, education, and gender distributions into account. Since research has shown that voters of different sex or gender, race or ethnicity, income or education levels, and voting history do vote at different rates,[143] citizens of varying demographic backgrounds most likely also donate to political causes at varying rates.[144] Because the MRP estimates are adjusted for race, education, and gender, they implicitly account for key demographic information without adding more proxy variables to the data. As noted by Tausanovitch and Warshaw,[145] the MRP

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[140] Phillips, "Affective Polarization."
[141] Tausanovitch and Warshaw, "Subnational Ideology and Presidential Vote Estimates (V2022)."
[142] Bishop and Cushing, *The Big Sort*.
[143] Leighley and Nagler, *Who Votes Now?*
[144] E.g., Rhodes, Schaffner, and La Raja, "Detecting and Understanding Donor Strategies in Midterm Elections."
[145] Tausanovitch and Warshaw, "Subnational Ideology and Presidential Vote Estimates (V2022)."

estimates are most useful for descriptive analyses and analyses that use public opinion as an independent variable.[146] The AIP estimates of overall ideological preferences by zip code are therefore well-suited to the purposes of my analysis.

Final Data

After merging the *VoterFraud2020*, FEC, and AIP data, I obtained a sample of 1,802 Twitter users who (1) tweeted or retweeted messages containing phrases associated with unsubstantiated election fraud claims and (2) donated at least $200 to political committees in 2020. While my sample is moderately sizable, it is by no means randomized or necessarily representative of the national population. By construction, my final dataset only contains a subset of all individual political donors: namely, donors who were active on Twitter in October 2020; have not deleted their accounts since 2020; were all exposed to tweets that contained the misinformation keywords utilized by Abilov et al.; and shared sufficient name and geographic information in their Twitter profiles to be merged with FEC records. As shown in Figure 4-A, the geographic distribution of all donations to political causes during the 2020 general election approximately mirrors the distribution of the overall US adult population, with significant clusters in California, Texas, Florida, New York, and the states surrounding Washington, D.C. As evidenced by Figure 4-B, the distribution of contributions from donors exposed to election misinformation on Twitter closely mirrors this national distribution, though there is a noticeable drop in donations from donors in the Washington, D.C. area and New England states and an increase in contributions from donors in California. In fact, there is no statistically significant difference ($p \approx 1$) in the state-level distributions of donations from all donors (Figure 4-A),

[146] Caughey and Warshaw, "Public Opinion in Subnational Politics."

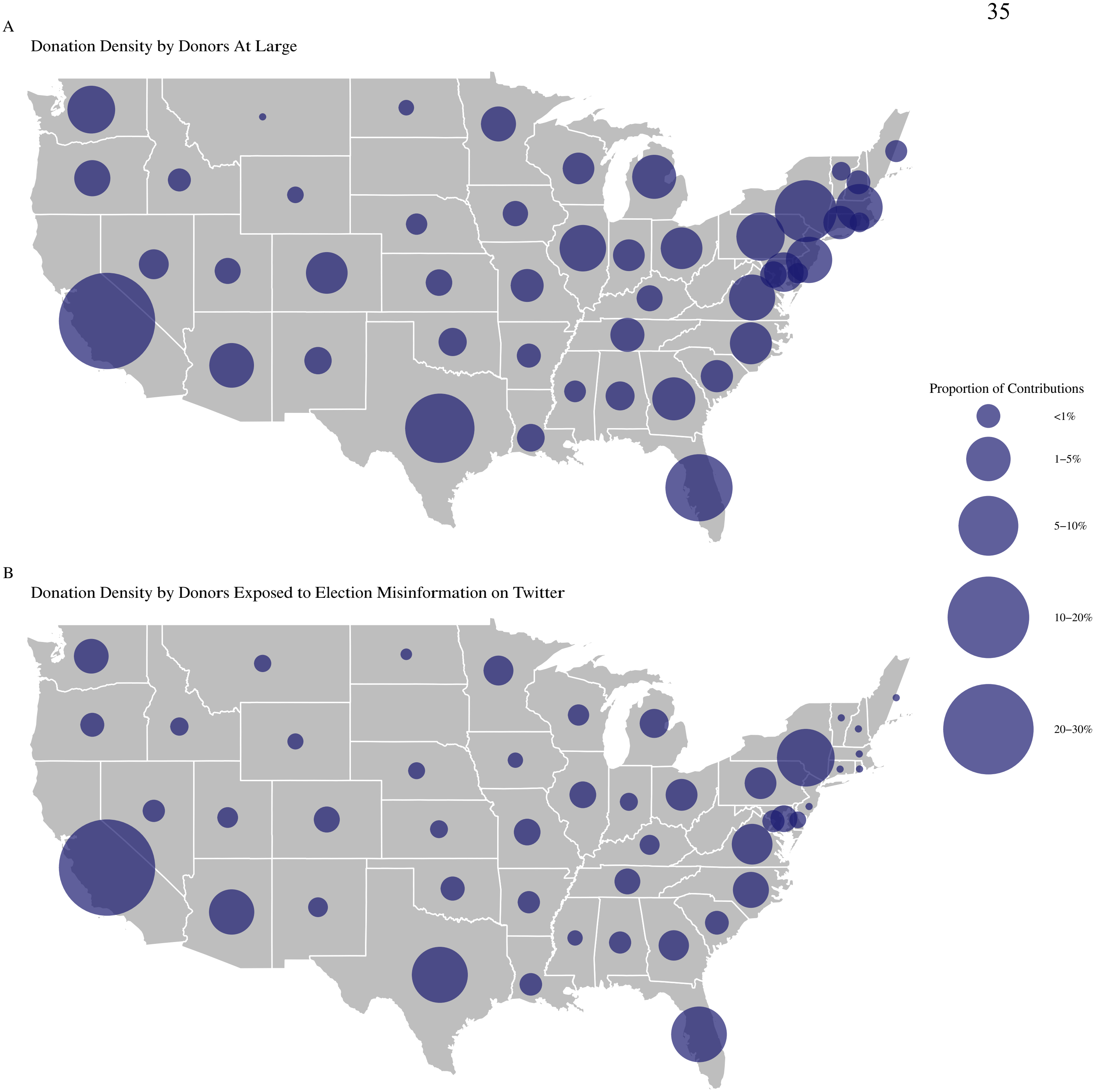

Figure 4. Sample accurately reflects the 2020 state-level distribution of both the US population as well as the national donor population. The geographic distributions of individual donors at large (Fig. 4-A) and donors who interacted with voter fraud claims on Twitter during the 2020 presidential election (Fig. 4-B) closely mirror each other, with major clusters in population centers such as California, Texas, Florida, and New York. While there is a noticeable drop in donations from donors exposed to misinformation in the DC area, relative to the national donor population, a Chi-squared test finds no significant difference in the 2020 state-level distributions of either group or the national US population.

donations from donors exposed to voter fraud claims on Twitter (Figure 4-B), and the 2020 US population based on a Chi-squared test with 10,000 Monte Carlo simulations. The mean squared error (MSE) between the state-level distribution of the national population and the state-level distributions of the national and misinformation-exposed donor populations, is only about 6.7 x 10^{-5} and 7.3 x 10^{-4}, respectively, with the largest gap in both samples observed in California. While I do not claim that my dataset constitutes a nationality representative sample, it does accurately reflect the state-level distribution of the US national population.

Given the limited demographic information that can be gleaned from Twitter accounts or FEC records, it is not possible to consistently infer demographic information such as education and income levels – much less sex, age, and ethnicity – concerning the Twitter users in my sample. If my sample was larger, I would use zip code-level demographic data from the Census Bureau to estimate the demographic distribution of the donors exposed to election misinformation on Twitter. Given the present lack of reliably accurate demographic information, I have not manually reweighted observations to better reflect national demographic distributions.[147] Since observations in the data collectively do match the state-level distribution of the national population, this is not a severe problem. As noted by Rhodes et al.,[148] the existing consensus within political science argues that people donate money to express support for a preferred political "team" and enjoy the emotional benefits of participating in politics.[149] Both directionally motivated reasoning frameworks as well as empirical evidence support this theory, as individual donors tend to contribute passionately rather than strategically to candidates who

[147] E.g., Census Bureau, "CPS: Technical Documentation: Methodology: Weighting."
[148] Rhodes, Schaffner, and La Raja, "Detecting and Understanding Donor Strategies in Midterm Elections."
[149] Ansolabehere, De Figueiredo, and Snyder, "Why Is There So Little Money in Politics?"

align with their own political ideology.[150] While precise demographic data could be a valuable addition to my sample, the AIP's estimates of political preferences by zip code – which incorporate survey respondents' demographics and geography to estimate public opinion – therefore provide sufficiently robust contextual information for the purposes of this analysis.

Research design

To evaluate the overall magnitude, direction, and statistical significance of the relationships between the voter donation behavior and interactions with election misinformation on Twitter, I utilize general summary statistics, (paired) t-tests, and non-parametric correlation tests. I analyze differences in both average donation size and frequency throughout the general election between 10 different groups of donors, ranging from subgroups within my donor sample based on likely partisan identity and Twitter account characteristics to individual political donors at large. I chose to rely on t-tests and non-parametric correlation tests for two key reasons. Since I cannot guarantee whether my sample is representative of individual donors active on Twitter, I am primarily interested in determining the *direction* of the impact of political misinformation on voter donation behavior, rather than modeling the expected change in behavior as very specific donor characteristics shift. Second, since donation sizes and frequencies are highly right-skewed (Cf., Appendix B), candidate statistical models such as multivariate linear regression or logistic regression require variable transformations or the removal of outliers, which significantly undercut the interpretability of these models for the purposes of this analysis.

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[150] Bonica, "Database on Ideology, Money in Politics, and Elections: Public Version 2.0"; Bonica, "Mapping the Ideological Marketplace"; Ensley, "Individual Campaign Contributions and Candidate Ideology"; McCarty, Poole, and Rosenthal, *Polarized America*.

Comparing Donation Behavior of National and VoterFraud2020 Donors

Paired t-tests are a simple statistical tool that allow us to compare averages between two related groups such as the donors matched to Twitter accounts (n = 1,802) and donors in the original FEC dataset that contains both the Twitter users and non-Twitters users (n = 4,063,731). While the original FEC dataset and my processed dataset overlap, I am primarily interested in comparing patterns in my data to national averages to determine whether the patterns we observe are both statistically and practically significant. I obtained national average donation rates from the full original FEC dataset. Since I compare metrics measured on a daily basis (e.g., average daily size of contributions) for the 160 days between July 24, 2020, and December 31, 2020, all t-tests tests regarding differences in daily average measurements ultimately involve two samples of 160 measurements (regardless of the size of the underlying donor population). Since the dates are the same throughout the general election, a paired t-test is the appropriate method to assess the differences in mean donation size and frequency between two groups of donors. When comparing the total amount donated and total number of political contributions across the general election between the Twitter and national donors, however, regular t-tests may be used. Unless otherwise noted, all t-tests described below involve one-tailed tests to determine whether group A donates significantly more often and in significantly larger amounts than group B.

Comparing Impacted Donation Behavior by Partisan Identity

In addition to testing differences between closely related groups, paired t-tests also enable us to evaluate differences among subgroups within a sample. In this analysis, I utilize paired t-tests to compare the frequency and size of political contributions made by identified individual donors located in Democratic- versus Republican-leaning zip codes, using zip code-level estimates of the Democratic share of the 2020 presidential vote provided by the Tausanovitch and Warshaw.[151] Since presidential vote distributions are not available for every zip code, this part of the analysis involves 1,633 rather than 1,802 observations. I code zip codes where at least 50% of voters supported the Democratic presidential nominee (Joe Biden) as Democratic-leaning regions (*n* = 921 or 56.4%). Similarly, I treat zip codes where less than 50% of voters supported the Democratic presidential candidate as Republican-leaning regions (*n* = 712 or 43.6%). Using the definition of electoral competitiveness that is commonly used by mainstream news media[152] and that aligns with standard definitions of electoral competitiveness in the political science literature,[153] I moreover define competitive regions as zip codes where the Democratic presidential candidate won (or lost) by at most five percentage points. In other words, competitive zip codes – which presumably contain many more moderates than partisans – represent districts where the Democratic presidential vote share falls between 45% and 55%, inclusive.

To strengthen my analysis of partisan donor behavior, I also utilize the American Ideology Project's MRP zip code-level estimates of local ideological preferences. Tausanovitch and Warshaw orient local ideal points, a synthesized measure of the local public's preferences on each policy dimension, so that lower values are associated with politically left preferences and higher values with politically right preferences. Since ideal points lack a real scale, Tausanovitch and Warshaw standardize the MRP estimates to mean 0 and standard deviation 1. In other words, an ideal point of 0 represents a policy preference that falls approximately in the center of the

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[151] Tausanovitch and Warshaw, "Subnational Ideology and Presidential Vote Estimates (V2022)."
[152] E.g., Wolf, "What Redistricting Looks Like Across the Country"; See also Drutman, "What We Lose When We Lose Competitive Congressional Districts."
[153] Cox, Fiva, and Smith, "Measuring the Competitiveness of Elections"; See also Blais and Lago, "A General Measure of District Competitiveness"; Grofman and Selb, "A Fully General Index of Political Competition"; Folke, "Shades of Brown and Green."

American ideological spectrum. By extension, negative MRP ideal point estimates indicate left-leaning ideological preferences, whereas positive MRP ideal point estimates represent right-leaning ideological preferences. Since ideal point estimates are not available for every zip code, this part of the analysis involves 1,653 observations split across 966 (or 58.4%) left-leaning and 687 (or 41.6%) right-leaning zip codes.

To apply a consistent lens when comparing differences in donor behavior in (1) Democratic-leaning versus Republican-leaning zip codes (i.e., by presidential vote) and (2) left-leaning versus right-leaning zip codes (i.e., by estimated local ideal points), I reverse the ideological scale provided by Tausanovitch and Warshaw by multiplying all MRP estimates by negative one (-1). In other words, I focus on changes in the behavior of donors exposed to Twitter election misinformation relative to the baseline provided by donors exposed to similar messages who hold right-leaning policy preferences or supported Trump in the 2020 election. Accounting for directionally motivated reasoning, these donors were more likely to accept voter fraud claims such as those spread by Trump and his allies than Democratic-leaning donors. As a result, I define left-leaning zip codes as communities where the adjusted MRP estimate of the local ideal point lies above zero. Similarly, I treat zip codes where the adjusted MRP estimate of the ideal point lies below zero as right-leaning neighborhoods.

Across all 1,633 donors for which zip code-level presidential vote shares are provided, approximately 55.2% of the electorate, on average, supported Biden in 2020. Likewise, the average (adjusted) estimated ideal points of donors who interacted with voter fraud claims on Twitter appears to lie only slightly to the left of American ideological center (0.0681, 95% CI: [0550. 0.0811]). While the average Democratic share of the presidential vote across all zip codes appears to fall just barely outside the definition of a competitive district, potentially implying that matched donors are primarily located in politically competitive or moderate communities, this average score belies a more nuanced situation. Only 16.1% (n = 263) of donors matched to *VoterFraud2020* Twitter accounts in fact in fact reside in electorally competitive neighborhoods. On average, Biden won zip codes where he was victorious in my sample by a margin of about 20.8 percentage points and lost zip codes where he was defeated in my data by a margin of approximately 14.9 percentage points. Since the Democratic presidential candidate won more zip codes with a greater margin of the victory than the Republican presidential candidate, donors in my sample appear to be primarily located in communities that strongly lean toward the Democratic Party in national elections.

Comparing Impacted Donor Behavior by Twitter Profile

I utilize not only paired t-tests but also non-parametric correlation tests to compare donation patterns between subgroups within my sample based on key Twitter profile attributes: in short, verified user status, account age in 2020 (in years), existence of account before the 2020 election, number of voter fraud-related tweets, and the number of followers.

Non-parametric correlation tests enable researchers to analyze the association between variables that are not normally distributed (Cf., Pearson's correlation coefficient). Since Twitter donation rates are not normally distributed (see Appendix B), I use the Spearman's rank correlation and Kendall's rank correlation tests to estimate the correlation between Twitter donor behavior and variables such as the likely partisan leaning and age of the associated Twitter user (see Tables 1 and 2 below). Although the two tests are nearly identical, Kendall's method examines the ordinal association among all possible pairwise events while Spearman's method focuses on linear associations between pairs of observations. To use these tests, three assumptions must be met: First, pairs of observations must be independent. While I compare characteristics of the same person, my sample size is sufficiently large that we can safely assume independence between the Twitter users in my sample. Secondly, variables must be measured on interval, ordinal, or ratio scales. Since I evaluate associations between variables such as user verified status (ordinal), account age (interval), ideological leaning (interval), and donation outcomes (ratio), this assumption is also satisfied. Lastly, the Kendall and Spearman methods assume monotonic relationships between variables. A visual analysis of the relationships among the variables of interest indicates that this assumption is met.[154] As such, I can safely utilize the Kendall and Spearman correlation tests to estimate the magnitude and significance of correlations within the Twitter data.

Results: Overview

Based on FEC records from August to December 2020, about 1.6% (n = 4,063,731) of all adult Americans (n = 257,915,956)[155] donated at least $200 to various political committees during the 2020 general election. During the same five months, more than 6% (n = 1,802) of all the Twitter users in my cleaned Twitter data (n = 29,648) donated similar amounts to political campaigns and candidates. In short, Twitter users who interacted with election misinformation in the run-up to the 2020 election appear to have been almost four times as likely to donate to political campaigns than their fellow American citizens. While Twitter users tend to be more politically active than non-Twitter users and may therefore also be more likely to contribute to political causes in general, this major difference does provide practical motivation to suspect

[154] To conserve space, these graphics are not shown here.
[155] U.S. Census Bureau, "Population and Housing Unit Estimates."

significant changes in voter behavior following interactions with voter misinformation on Twitter.

Results: Differences in Average Daily Donor Behavior

Donors At Large Versus Donors Exposed to Misinformation: Consumers Count

People who consumed and shared unsubstantiated voter fraud claims on Twitter in the run-up to the 2020 US presidential election donated *more* frequently but *not* in significantly different amounts than the average individual donor. Paired t-tests indicate that the Twitter users in my sample donated about 1.67 more times per day, on average, than all individual donors at large (see Figure 5). This difference is statistically significant ($p < 0.0001$). While an additional 1.67 transactions per day may not appear to be a major figure, it is important to note that this number describes the average difference in the daily number of transactions per person in the Twitter and FEC samples. In other words, the 1,802 Twitter users exposed to election misinformation in my sample together donated about 3,009 more times, on average, each day of the general election. Since this effect is mediated by ideological leanings (see results below), this figure holds important implications for local elections. Given the heterogenous effects by partisan identity, this increase in the number of political contributions could be highly concentrated among specific donors in a given geographic area – potentially leading to very different electoral outcomes as candidates gain or lose financial support from donors who interact with election misinformation on Twitter.

While tweeting or retweeting keywords linked to election misinformation is associated with more frequent donations, paired t-tests suggest there is no statistically significant difference

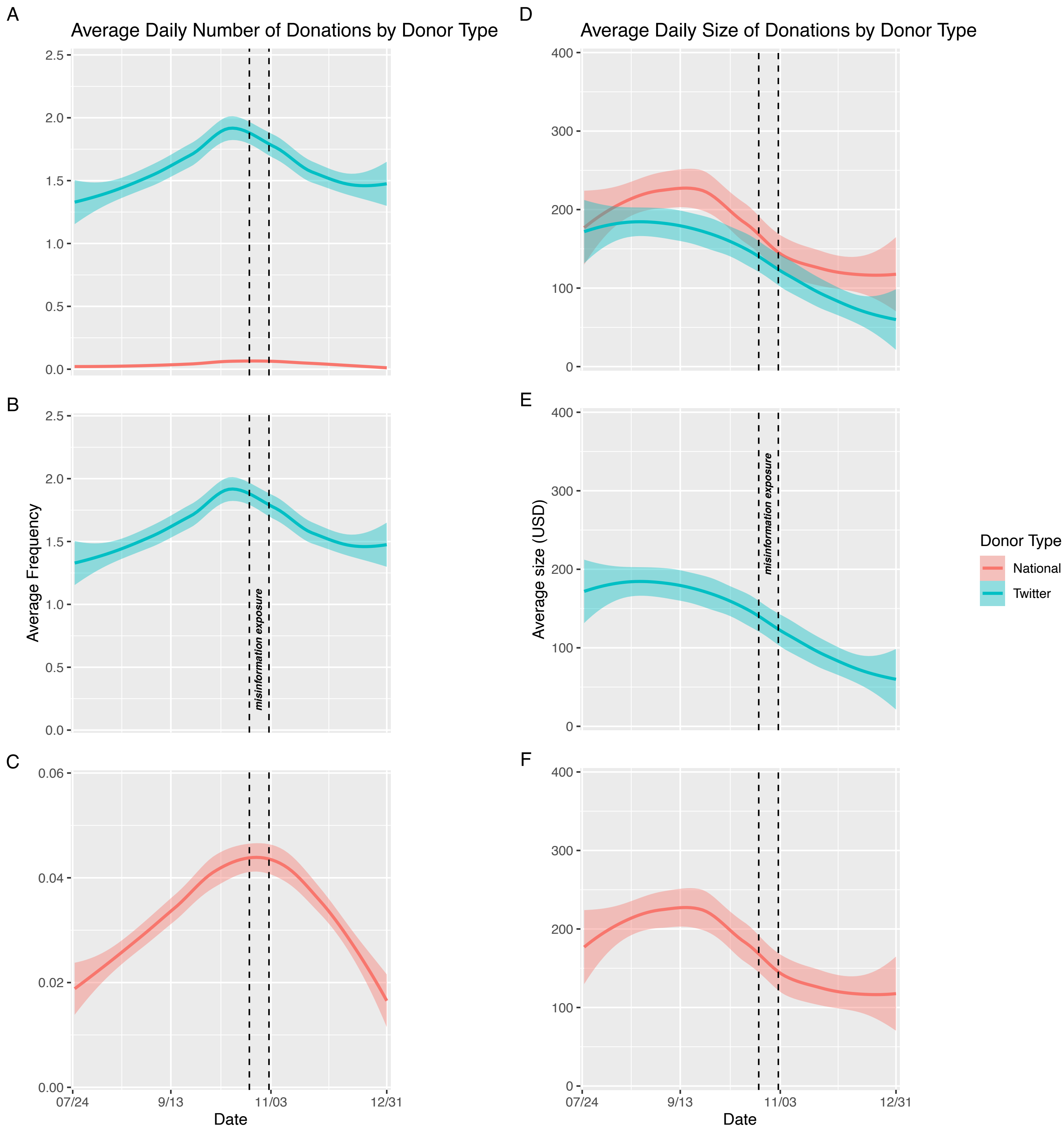

Figure 5. Consumers Count. Twitter users exposed to misinformation donate more frequently but in similar amounts as other donors. While the political contribution frequency of both Twitter and general FEC donors follows a similar distribution over time, the actual rate of donations is much higher among the donors who interacted with election misinformation on Twitter. Note the magnitude of the scale on the y-axis in Figure 5-C.

(*p* = 0.8327) in the average size of political contributions made by Twitter or general FEC donors (see Figure 5). Although not statistically significant, the direction of the average difference in donation size between the two sample is notable. On average, individual donors who interacted with unfounded voter fraud claims on Twitter contributed *less* money than other individual donors. The average amount donated by the Twitter users in my sample is about $180.38 (95% CI: [$152.17, $208.59]), about $3.02 less than the $183.40 average donated by all individual donors across the U.S. (95% CI: [$165.83, $200.96]) during the general election. Even though donors exposed to Twitter election misinformation on average contributed smaller amounts than other donors, they still donated more money per person throughout the entire general election season ($1,630.99) than donors at large ($1,153.16) due to their elevated rate of giving. Future research will need to determine whether the donors exposed to election misinformation on Twitter gave to a larger or smaller number of campaigns than their fellow donors across the US. If the people who interacted with online political misinformation contributed to more political causes, their aggregate impact may very well be diluted relative to the combined influence of all individual political donors. On the other hand, if they contributed to fewer candidates, the overall impact of people exposed to online political misinformation is likely concentrated among a small number of elections and may therefore outweigh the aggregate influence of their fellow individual donors in those elections.

Impacted Donation Behavior by Partisan Identity: Partisans Pay

Of the donors matched to Twitter accounts that interacted with political misinformation during the 2020 US presidential election, individuals located in zip codes where a majority of the electorate supported the Democratic presidential candidate (Joe Biden) in the 2020 election

A

Measurement Variable	Difference in Means Donation Size	95% CI	n	Correlation Kendall's Tau	Spearman's Rho	n
Overall						
Relative to national donors	-3.0144	[-Inf, 20.5574]	1802	—	—	—
Partisan identity						
Democratic zip code	+87.1905 ****	[50.3574, Inf]	1633 (921)	+0.0881 ****	+0.1065 ****	1633 (921)
Competitive zip code	-70.9803 ***	[-Inf, -36.4573]	1633 (263)	-0.0322	-0.0390	1633 (263)
Left-leaning zip code	+86.2220 ****	[49.9758, Inf]	1653 (966)	+0.1273 ****	+0.1904 ****	1653
Twitter profile						
Verified user	+177.6287 ***	[78.1811, Inf]	1802 (130)	+0.1434 ****	+0.1734 ****	1802 (130)
Account age	—	—	—	+0.0490 ***	+0.0692 ***	1802
New account	-52.8915 *	[-Inf, -14.2994]	1802 (125)	-0.0212	-0.0256	1802 (125)
Multiple fraud tweets	-58.1252 **	[-Inf, -24.1646]	1802 (296)	-0.0093	-0.0112	1802 (296)
Major number of followers	+9.2910	[-16.0887, Inf]	1802 (901)	+0.0607 **	+0.0733 **	1802 (901)
Elite number of followers	+58.3697 **	[26.0962, Inf]	1802 (451)	+0.1043 ****	+0.1260 ****	1802 (451)

Note: *p < 0.05, **p < 0.01, ***p < 0.001, ****p < 0.0001

B

Measurement Variable	Difference in Means Donation Frequency	95% CI	n	Correlation Kendall's Tau	Spearman's Rho	n
Overall						
Relative to national donors	+1.6366 ****	[1.5633, Inf]	1802	—	—	—
Partisan identity						
Democratic zip code	+0.1591 **	[0.0604, Inf]	1633 (921)	+0.0548 *	+0.0620 *	1633 (921)
Competitive zip code	-0.3484 ****	[-Inf, -0.2291]	1633 (263)	-0.0394	-0.0445	1633 (263)
Left-leaning zip code	+0.1883 ***	[0.0831, Inf]	1653 (966)	+0.0763 ****	+0.1050 ****	1653
Twitter profile						
Verified user	+0.3441 ***	[0.1939, Inf]	1802 (130)	+0.0412 *	+0.0468 *	1802 (130)
Account age	—	—	—	+0.0089	+0.0118	1802
New account	+0.1812	[-Inf, 0.3718]	1802 (125)	-0.0166	-0.0189	1802 (125)
Multiple fraud tweets	-0.0242	[-Inf, 0.0854]	1802 (296)	+0.0039	+0.0045	1802 (296)
Major number of followers	+0.0438	[-0.0541, Inf]	1802 (901)	+0.0423 *	+0.0481 *	1802 (901)
Elite number of followers	+0.2360 ***	[0.1163, Inf]	1802 (451)	+0.0363	+0.0412	1802 (451)

Note: *p < 0.05, **p < 0.01, ***p < 0.001, ****p < 0.0001

Table 1. Mean difference in daily donation behavior and correlations between daily donation behavior and select variables. While the average donation size of matched Twitter users is slightly lower than that of donors at large, there is no statistically significant difference in the average daily size of contributions between matched donors in my sample and donors at large. Notably, most variables and binary categories among the matched Twitter users were significantly associated with changes in daily donation size. Donors who interacted with Twitter election misinformation donated significantly more often each day throughout the general election, on average, than donors at large. Note that all p-values listed above are the result of one-tailed hypothesis tests, which here yield infinite intervals.

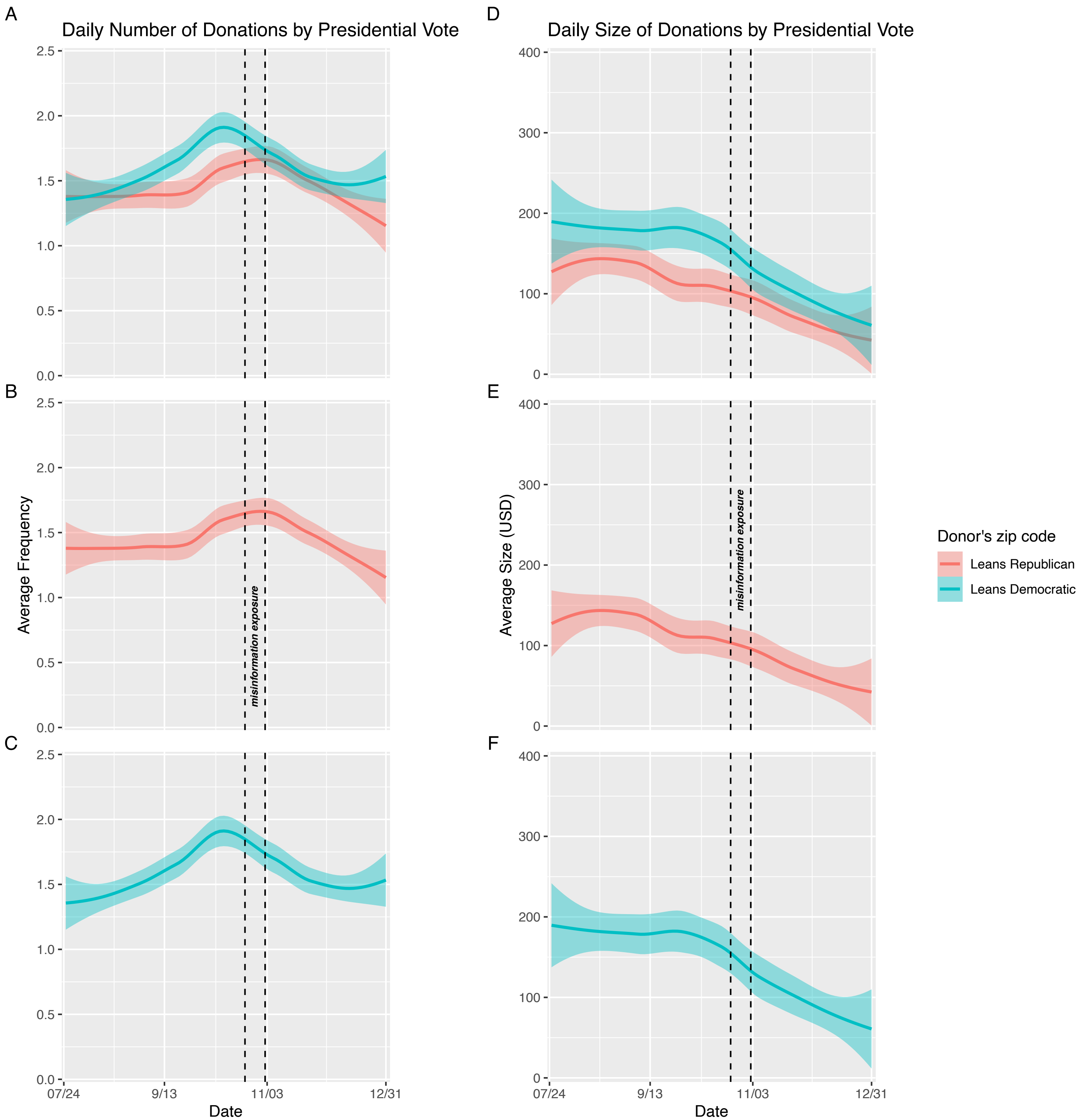

Figure 6. Partisans Pay. Donors exposed to misinformation on Twitter located in Democratic-leaning zip codes donated more frequently and in larger amounts than similar donors located in Republican-leaning zip codes.

donated significantly *more* frequently ($p < 0.01$) and in significantly *larger* amounts ($p < 0.0001$) than the people located in zip codes where the majority supported the Republican presidential candidate (Trump). On average, donors from Democratic-leaning zip codes contributed to campaigns about 0.16 more times and about $87.20 more per day throughout the general election. Likewise, donors exposed to voter fraud information on Twitter who resided in left-leaning zip codes contributed *more* often ($p < 0.001$) and in *greater* amounts ($p < 0.0001$) than similar donors situated in right-leaning zip codes (see Figure 6).

As such, the impact of exposure to election misinformation on Twitter appears to be mediated by the partisan identity of the person interacting with the unsupported or misleading allegations of election irregularities. While this finding aligns with expectations under the framework provided by reactance theory and directionally motivated reasoning, the direction of the partisan effect is somewhat surprising. I expected a strong negative reaction (i.e., higher donation rates) among people who (1) supported Trump and (2) desired to prevent the electoral implications that could come about if the voter fraud claims were borne out. However, this pattern is not observed in my data. At the same time, people who (1) opposed Trump in 2020 and (2) interacted with unsubstantiated claims implying Democrats could steal Trump's victory – a viewpoint not widely held in Democratic circles – appear to have partially countered these allegations by donating more to various candidates in federal elections.

Granted, the people in Democratic-leaning zip codes who on average donated more than people in Republican-leaning zip codes may have been Republicans who were extra motivated by all the presence of nearby Democrats to donate to Republican causes such as Trump's presidential campaign. Since I have not tracked the recipients of individual donations but rather

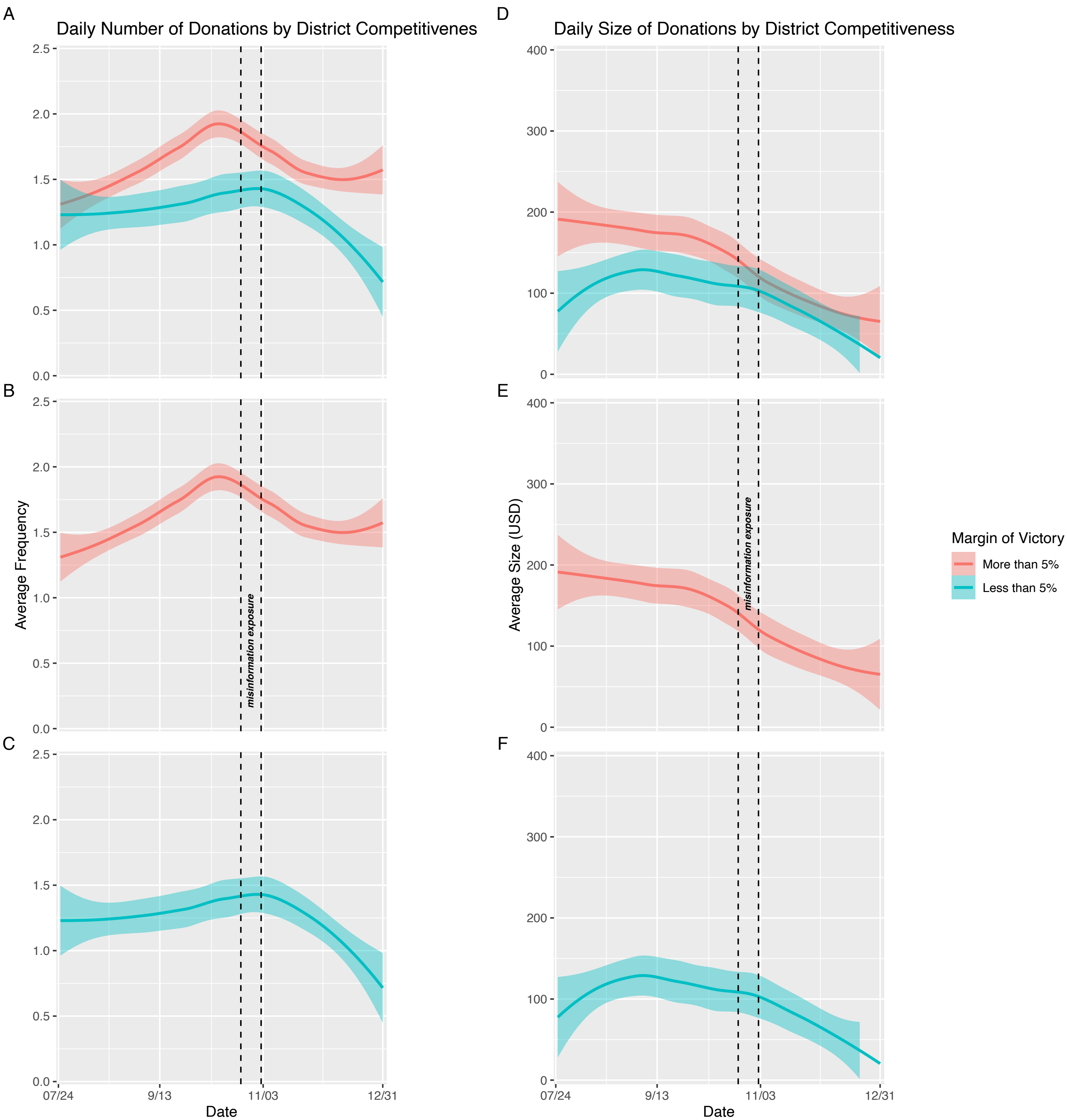

Figure 7. Centrists Cost. Donors exposed to misinformation on Twitter located in competitive zip codes donated less frequently and in smaller amounts than similar donors located in zip codes where the Biden or Trump won with a margin greater than 5%.

examined aggregate trends, I cannot refute this possibility with complete confidence. Pending further analysis of the partisan labels of the recipients of the contributions in my data, however, there is sufficient reason to doubt that this is the case. First, Democratic-leaning communities logically contain a larger number of Democratic-leaning than Republican-leaning individual donors. As such, if the above hypothetical situation truly was the case, I would also expect that the donations of at least some Democratic donors would balance out the giving of Republican donors, leading to a small or even negligible difference in the average amount contributed to political causes. Given the significant and sizable difference in donation patterns in Democratic- and Republican-leaning zip codes observed in my sample, this does not appear to be the case.

Impacted Donation Behavior by District Competitiveness: Centrists Cost

Since Twitter users do tend to lean slightly Democratic,[156] the slight overrepresentation of donors from zip codes won by Biden (56.4%) relative to donors from zip codes lost by Biden (44.6%) in the 2020 election could theoretically drive the partisan effects of election misinformation on donor behavior. However, an analysis of the donor behavior in competitive districts – which presumably contain similar shares of Democratic and Republican voters – suggests that the observed heterogenous partisan effects likely hold regardless of the partisan composition of a district or election. On average, donors located in communities that Biden or Trump won with a margin of less than 5% and who were exposed to unsubstantiated allegations of voter fraud on Twitter contributed 0.35 *fewer* times ($p < 0.0001$) and $70.98 *less* per donation ($p < 0.001$) throughout the general election than similar donors located in districts that Biden or Trump won with more than 5% (see Figure 7). In other words, as the share of likely moderate

[156] Wojcik and Hughes, "Sizing Up Twitter Users."

and Republican voters *increased* and the share of Democratic voters *decreased* in a given zip code, donors interacting with election misinformation on social media also *decreased* their relative donation activity. Since this is the inverse of the pattern observed in overwhelmingly Democratic-leaning zip codes, where similar donors *increased* their activity as the likely share of Democratic voters *increased* (see Tables 1 and 2), it appears that different partisan identities do lead to different changes in donor behavior in conjunction with exposure to election misinformation on Twitter.

Impacted Donor Behavior by Twitter Status: Socialites Spend (Part I)

Apart from likely partisan identity, relative Twitter status and activity also appear to mediate the impact of Twitter exposure to political misinformation on donor behavior. For example, verified users who interacted with voter fraud claims on the platform in the 11 days before Election Day and donated to federal political campaigns during the 2020 general election gave about 0.34 *more* times ($p < 0.001$) and approximately $177.63 *more* per contribution ($p < 0.001$) each day of the election than unverified users exposed to similar claims on the platform. Since verified Twitter users at the time of the 2020 election (before recent changes to the Twitter blue program)[157] tended to be social elites, journalists, or political commentators who are also more politically engaged than the general public, this pattern is not surprising. Pending future investigation, the elevated donation rates among verified users could very well reflect self-identification of political engagement by the elite (through Twitter blue) instead of the impact of exposure to election misinformation on elite voices.[158] Since donors exposed to election

[157] Twitter, "Twitter Blue."
[158] Cf., Guess, Nyhan, and Reifler, "Selective Exposure to Misinformation: Evidence from the Consumption of Fake News during the 2016 U.S. Presidential Campaign."

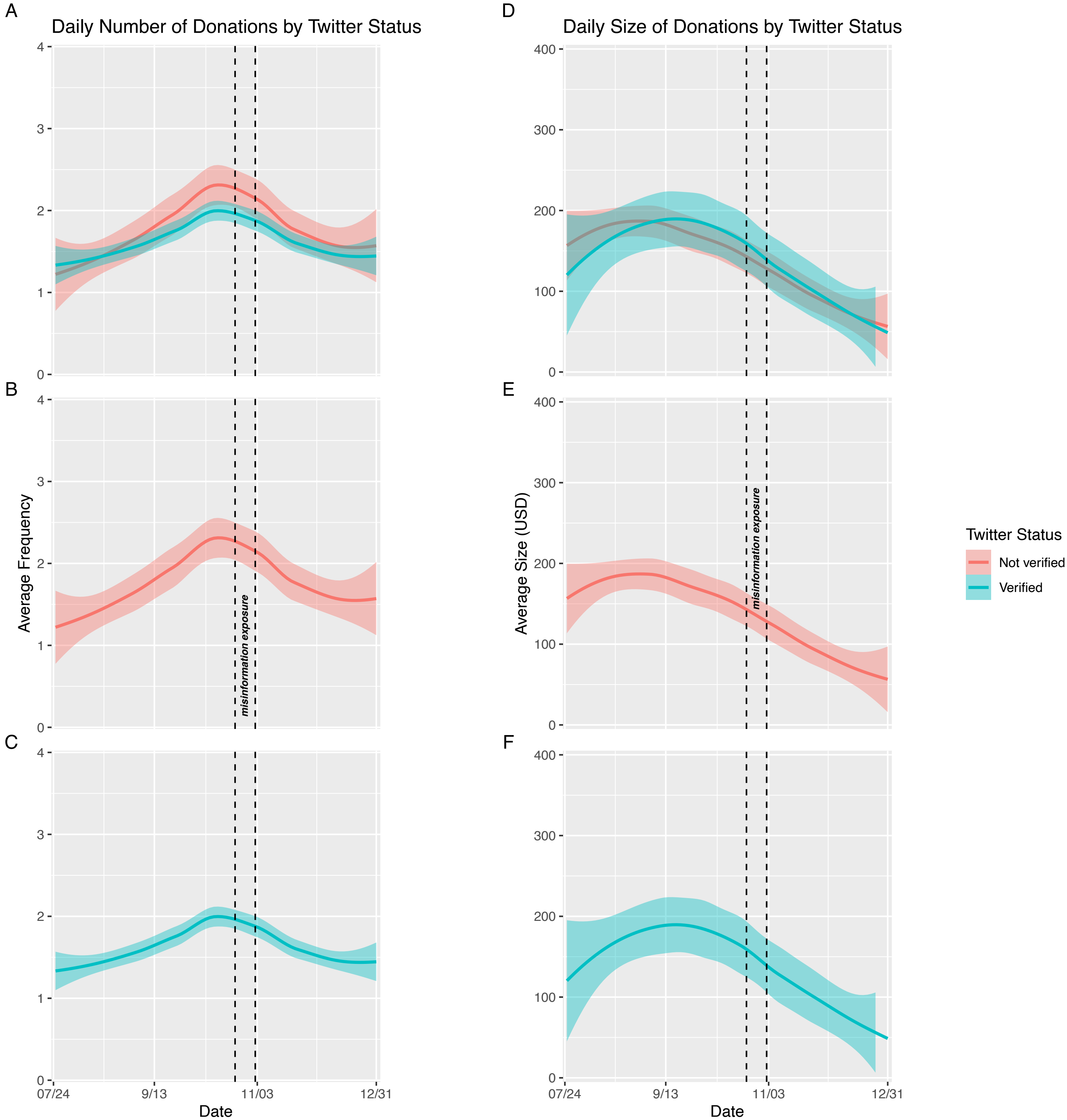

Figure 8. Socialites Spend (Part I). Donors matched to verified Twitter accounts that engaged with unsubstantiated voter fraud claims donated more less frequently and in larger amounts than donors matched to non-verified Twitter accounts exposed to similar election misinformation. Since these plots display (loess) smoothed trends, they inadvertently obscure very high variability in the daily average donation sizes of verified Twitter users.

misinformation on Twitter with an unusually large number of Twitter followers also gave *more* frequently and in *greater* amounts than similar donors, however, there does appear to be a link between a donor's relative reach on Twitter and their response to interactions with political misinformation on the platform (see discussion below).

Impacted Donor Behavior by Twitter Activity: Proselytizers Pinch

Although there was no significant difference in the size of daily contributions from donors at large and donors exposed to election misinformation on Twitter, there does appear to be a *negative* association between the number of interactions with such misinformation and the size of daily donations. On average, donors who (re)tweeted messages associated with voter fraud claims more than once in the run-up to the presidential election gave $58.13 less per contribution than donors who shared such tweets just once ($p < 0.01$). At the same time, there was *no* significant difference in the daily number of individual contributions between these two groups, indicating that people who repeatedly engaged with and attempted to publicize election misinformation donated less money to federal candidates across the entire 2020 general election. Since the negative correlation between average total donation size and a donor's total number of tweets linked to election misinformation is not statistically significant (see Table 2), it appears that interacting with more than one – versus just one – tweet regarding unsubstantiated voter fraud claims constitutes a key threshold for changes in donation behavior.

Impacted Donor Behavior by Twitter Following: Socialites Spend (Part II)

Of the donors matched to Twitter accounts that interacted with election misinformation during the 2020 election, people with more Twitter followers than 75% of similar donors gave about 0.23 *more* times per day ($p < 0.001$) and almost $58.37 *more* per political donation than other donors exposed to election misinformation. Donors in the upper quartile with respect to their number of followers (relative to other people in my sample) had between 2,297 and 9,630,160 followers, with an average of 108,474 followers. While there is about 27%[159] degree overlap between the donors with verified Twitter accounts and the donors with an elite number of followers, donors with such sizable numbers of Twitter followers evidently represent major voices on the platform. Since numerous people and organizations have independently decided to follow these donors, these 451 donors are evidently perceived by the Twitter community to be elite voices worth engaging with. In contrast to donors with more followers than 75% of their peers, people with a major or above-median number of followers (i.e., above 561) do not demonstrate a statistically significant different Twitter activity (e.g., number of tweets) or donation behavior compared to individuals with a below-median number of followers. As such, it appears that donors with very many followers (and not just a major number of followers) can be reasonably viewed as a group of elite voices on Twitter. As shown in Table 2, both Twitter verified status and Twitter following are moderately and *positively* correlated with the total amount donated ($p < 0.0001$) and the total number of contributions ($p < 0.05$) donated by individuals who interacted with election misinformation the platform. Combining these results, it appears that exposure to election misinformation on Twitter is especially linked and may partially drive the donation behavior of the most prominent voices on the social media platform.

[159] Recall that verified users ($n = 130$) only compose about 7% of the entire sample.

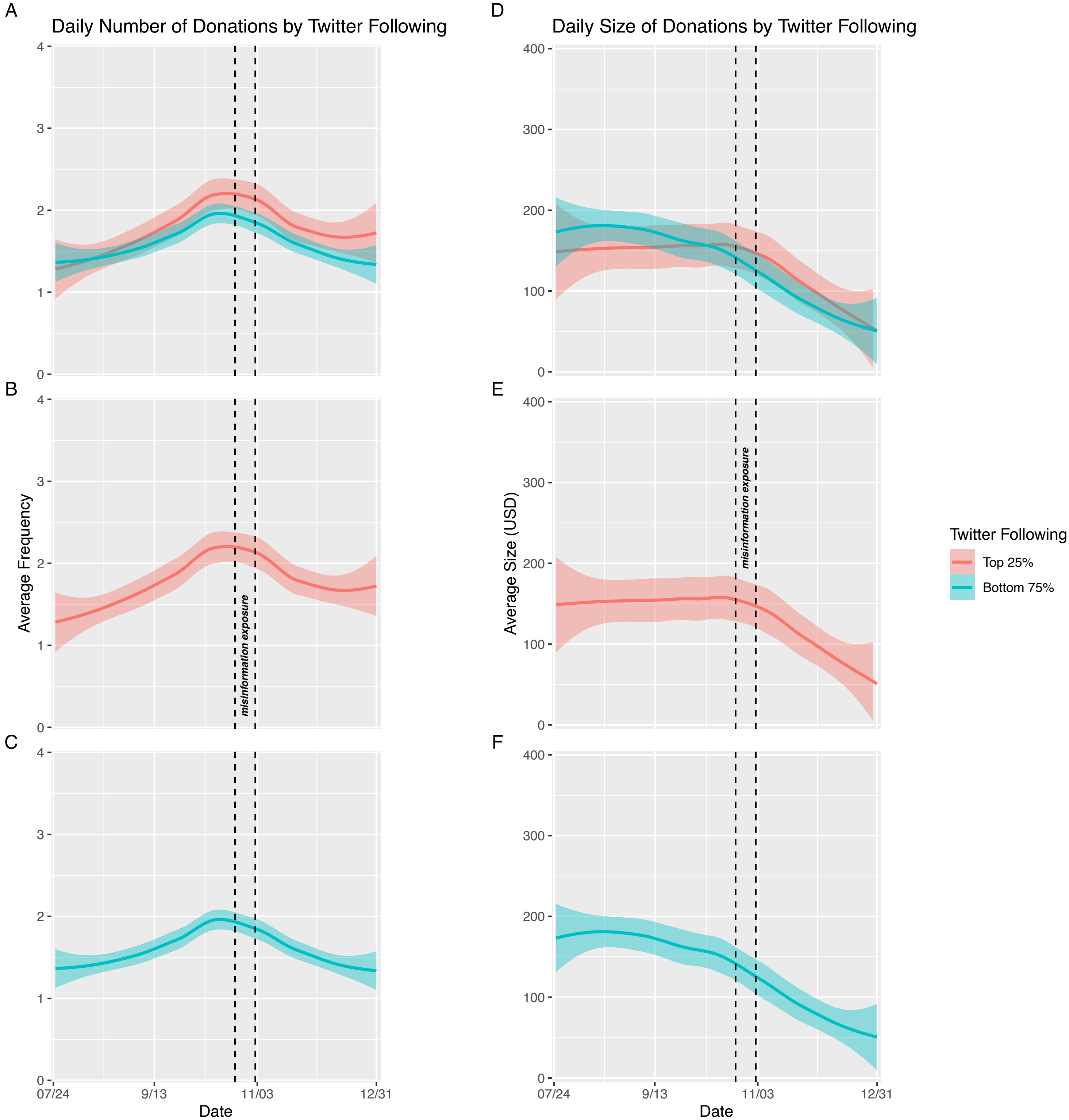

Figure 9. Socialites Spend (Part II). Donors who engaged with matched to Twitter and have an elite number of followers donated more frequently and in larger amounts than similar donors who with few Twitter followers. Since these plots display (loess) smoothed trends, they inadvertently hide very variability in the daily average donation sizes of verified Twitter users (especially in Fig. 9-D). Donors in the top 25% of accounts in term of following (relative to other donors in my sample), have at least 2,297 followers.

Results: Differences in Cumulative Donor Behavior

Non-parametric correlations tests not only confirm the results from above but also provide additional insights into the strength and direction of the association between donation behavior following exposure to election misinformation and Twitter account age and the likely ideological leaning of donors in my sample (see Table 2).

First, Twitter account age is weakly but *positively* (about 0.05) correlated with the total amount donated ($p < 0.01$) but is *not* associated with the total number of contributions ($p = 0.61$) by an individual exposed to election misinformation on Twitter. This phenomenon could have one of two explanations. First, as a Twitter user gains experience on the platform and the age of the corresponding account increases, the Twitter user may consume more political news through the platform and subsequently become more politically engaged in general, leading to higher political donation rates. Second, as a Twitter account ages, the owner of that account also ages. As such, the positive correlation between Twitter account age and total contribution may also reflect existing patterns of political engagement of older citizens or increased susceptibility[160] to election misinformation that encourages political donations. Since there is only a significant correlation between account age and the total amount and not number of amounts given to political campaigns, this relationship may moreover reflect the larger average disposable income available to middle-aged Americans (45-55 years old) who adopted Twitter when they were in their thirties compared to the contemporary young professionals (35-45 years old) who have only recently become active on Twitter.

Confirming the trend observed with daily average donation frequencies and sizes, both the total amount ($p < 0.0001$) as well as number of contributions ($p < 0.0001$) donated per

[160] Guess and Munger, "Digital Literacy and Online Political Behavior."

individual donor exposed to Twitter election misinformation are moderately and *positively* correlated with zip codes that lean more toward the left side of the American ideological spectrum. As the adjusted MRP estimates of zip code-level ideal points increase (i.e., local political preferences move left), the total number of donations and total size of donations of Twitter users in the relevant zip codes who interacted with election misinformation also tend to increase. In other words, the heterogenous partisan impact of Twitter exposure to election misinformation is not limited to daily donor behavior, which can be highly variable, but also appears in election-wide donor behavior, which is relatively stable.

In addition to confirming the existence of heterogenous partisan effects, Tausanovitch and Warhsaw's estimates of local ideological preferences also provide an insight into the potential influence of polarization on donor behavior in the context of online interactions with political misinformation. Since the zip code-level ideal point estimates have been scaled to mean 0 and standard deviation 1, the absolute values of these estimated ideal points describe the approximate ideological distance between the average political preferences in a given zip code and the average political preferences across the entire US. In other words, a higher absolute ideal point corresponds to a more ideologically extreme position (relative to other Americans). While there is *no* significant relationship between donors' expected ideological distance from the center (p = 0.2), more extreme ideological positions are moderately and *positively* ($p < 0.0001$) associated with larger total contributions among donors who interacted with voter fraud claims on Twitter. Granted, people who are more ideologically extreme are likely also more motivated to support political causes and should therefore be expected to generally donate more often to campaigns than people who are relatively politically moderate. Pending future research, however, this finding holds potentially worrisome implications for the future development of electoral politics in many Western democracies facing rising levels of polarization and partisanship. Since (1) more extreme and partisan actors exposed to political misinformation on Twitter donate greater amounts to political causes than similar individual donors and (2) the number of highly partisan citizens appears to be increasing, the relative financial influence of these donors will likely increase in coming elections. Given the importance of small-dollar donors in contemporary

A

Measurement Variable	Correlation with Total Size Kendall's Tau	Spearman's Rho	n
Partisan identity			
Ideological position (raw)	+0.1273 ****	+0.1904 ****	1633
Ideological distance (abs)	+0.0799 ****	+0.1178 ****	1633
Twitter profile			
Verified user	+0.1434 ****	+0.1734 ****	1802 (130)
Account age	+0.0490 **	+0.0692 **	1802
Number of tweets	-0.0089	-0.0110	1802
Number of followers	+0.0821 ****	+0.1211 ****	1802

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, ****$p < 0.0001$

B

Measurement Variable	Correlation with Total Frequency Kendall's Tau	Spearman's Rho	n
Partisan identity			
Ideological position (raw)	+0.0763 ****	+0.1050 ****	1633
Ideological distance (abs)	+0.0227	+0.0311	1633
Twitter profile			
Verified user	+0.0412 *	+0.0468 *	1802 (130)
Account age	+0.0089	+0.0118	1802
Number of tweets	+0.0044	+0.0051	1802
Number of followers	+0.0348 *	+0.0482 *	1802

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, ****$p < 0.0001$

Table 1. Correlations between select variables and cumulative donation behavior of donors exposed to election misinformation. Table 2-A and Table 2-B display the magnitude, sign, and significance of the correlations between variables related to a donor's profile (e.g., likely partisan identity and Twitter usage) and average total amount donated to political campaigns and average total number of political contributions, respectively.

primaries and general elections,[161] major shifts in the ideological composition of the donor base (weighted by the amounts contributed) may yield fewer candidates that align with the average policy preferences of the region (i.e., district, state, or country) that they are elected to represent.

Discussion

Significance

My analysis provides two significant contributions to the existing political science literature. First, I expand on the existing understanding of online political misinformation and voter behavior by specifically analyzing the donation behavior of people who interacted with unsubstantiated claims of election irregularities on a prominent social media platform. In general, it appears that individuals who tweeted or retweeted voter fraud claims and donated money to candidates in federal elections during the 2020 US presidential election donated *similar* amounts *more* frequently than all other donors across the country. As a result, donors exposed to Twitter election misinformation ultimately contributed more money in total to various political causes than donors at large, suggesting that donors who interact with political misinformation on Twitter may wield a greater relative influence on the fundraising of candidates in federal elections than most donors.

Second, I provide a novel and scalable dataset of use to future researchers that tracks longitudinal donation behavior and interactions with election misinformation on Twitter. Since contemporary political campaigns rely heavily on fundraising from small donors,[162] datasets such as this present a prime opportunity for deeper analyses of the relationship between campaign

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[161] Alexander, “Good Money and Bad Money: Do Funding Sources Affect Electoral Outcomes?”; Hua, “Campaign Finance: How Did Money Influence 2020 U.S. Senate Elections?”
[162] Alexander, “Good Money and Bad Money: Do Funding Sources Affect Electoral Outcomes?”; Hua, “Campaign Finance: How Did Money Influence 2020 U.S. Senate Elections?”

fundraising (and subsequent electoral outcomes), online political messaging, and voter behavior. Given recent changes to Twitter's policies that severely restrict research access to the Twitter API, this dataset also provides a potential way for continued linkages across existing public Twitter corpora through tweets IDs. As a proof of concept, this dataset moreover demonstrates that linking diverse public records with available social media data can yield fascinating descriptive analyses of ongoing trends in voter behavior.

Limitations

At the same time, my analysis also suffers from significant limitations, ranging from sample selection to potentially confounding variables. First, the data on which this analysis was performed is by no means randomized or necessarily representative of the broader pool of individual American donors, much less the general US population.[163] Second, my data heavily relies on the *VoterFraud2020* corpus. Although this corpus is one of the most comprehensive public archives of Twitter activity linked to unfounded voter fraud claims in the 2020 election, this corpus is also very narrowly focused on (1) a select number of keywords and (2) a relatively short timeframe. Since my sample is moderately sizable and my analysis focuses on the direction of mean differences in behavioral outcomes, I am confident that my analysis remains significantly robust, even if it could theoretically miss some nuances in the magnitude of the changes in donor behavior.

By utilizing the *VoterFraud2020* corpus, however, this analysis solely focuses on Twitter users – who make up a small portion of the US population and lean slightly Democratic – and

[163] Cf., Hughes et al., "Using Administrative Records and Survey Data to Construct Samples of Tweeters and Tweets."

donors – who by definition are the most politically invested voters.[164] While my emphasis on Twitter users and donors creates an implicit bias within the data, my analysis can still inform future research. Since my analysis shows that interactions with election misinformation on Twitter are (1) associated with *statistically* and *practically* significant changes in voter behavior among the voters most likely to have strong stances on political issues and that (2) these measurable changes are marked by heterogenous effects mediated through ideological pathways, my results provide both novel insights into the intersection of online political misinformation and voter donations as well as robust empirical justification to continue mining social media data for longitudinal analyses of the impact of misinformation on voter behavior.

Third, this analysis does not examine either changes in donor behavior immediately preceding and following exposure to election misinformation or the relative intensity of these interactions. Given the widespread and well-publicized nature of the baseless claims regarding election irregularities in the 2020 presidential election, it is difficult to isolate the impact of interactions with election misinformation on Twitter from other types of misinformation (e.g., misperceptions regarding the covid-19 pandemic), misinformation on other platforms (e.g., Facebook[165]), or increased voter susceptibility to election misinformation in the context of evolving pandemic conditions.[166] While we can reasonably assume that people who interacted with voter fraud claims on Twitter in the immediate run-up to the 2020 election were more likely to engage with such statement online in general, continued research is required to test the validity of this assumption.[167]

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[164] Wojcik and Hughes, "Sizing Up Twitter Users."
[165] Guess, Nyhan, and Reifler, "Selective Exposure to Misinformation: Evidence from the Consumption of Fake News during the 2016 U.S. Presidential Campaign."
[166] Berlinski et al., "The Effects of Unsubstantiated Claims of Voter Fraud on Confidence in Elections"; Green et al., "Online Engagement with 2020 Election Misinformation and Turnout in the 2021 Georgia Runoff Election."
[167] Guess, Nyhan, and Reifler, "Selective Exposure to Misinformation: Evidence from the Consumption of Fake News during the 2016 U.S. Presidential Campaign."

Next Steps

While this analysis offers new insights into the potential impact of online political misinformation on voter behavior, it is best viewed as a (blue) canary in the coal mine. Given the potentially worrying intersections between rising polarization, increased political misinformation spread through social media, and voter behavior in not only young but also established democracies, the results presented above indicate that both safety precautions and deeper mining of relevant data is needed. In addition to expanding my dataset with voter records or names identified through partial-matching algorithms, I urge fellow scholars to (1) investigate the longitudinal impact of exposure to online political misinformation, including across electoral cycles and different types of elections; (2) examine differences, if any, in the direction, magnitude, and significance of the impact of interactions with political misinformation on voter behavior on distinct social media platforms; (3) develop more public archives and transparent, standardized statistical tools for detecting misinformation online, a monumental task but one that could yield major synergies with social media companies currently developing tools to identify and flag misinformation on their platforms; and (4) identify and analyze federal elections with similar voter fraud claims not dominated by Trump and his allies to determine the relative influence of Trump on the impact of misinformation in American electoral politics and test the strength of the partisan heterogenous partisan effects identified above.

Given pandemic circumstances, 2020 was a highly unusual election year.[168] As a result, this project would greatly benefit from a rigorous analysis of donation patterns in other recent federal elections. Since Obama's 2008 presidential campaign was one of the first to incorporate social media platforms,[169] the presidential and Congressional elections between 2008 and 2018

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[168] Census Bureau, "Record High Turnout in 2020 General Election."
[169] Zavattaro, "Brand Obama."

represent well-suited candidates for such an analysis, with both FEC records and voter turnout data relatively accessible for these electoral cycles.[170]

Since Guess et al. find that Facebook was a key vector for exposure to fake news during the 2016 presidential election,[171] the literature would also benefit from a deeper investigation into the impact of political misinformation on voter behavior *between* and *across* social media platforms. For example, do donors who interact with unsubstantiated voter fraud claims on Twitter demonstrate different behavioral outcomes than donors who interact with similar claims on other platforms such as Facebook, Instagram, or TikTok? Does the combined effect of exposure to the same or different pieces of political misinformation across multiple social media platforms lead to greater changes in voter and donor behavior?

While Abilov et al. have made a very valuable contribution to the literature by making *VoterFraud2020* publicly accessible, research into political misinformation and voter behavior would be greatly enhanced by additional language processing tools and data points, including misinformation corpora containing information from other social media platforms and countries outside the United States. Expanding the breadth and depth of data that is available concerning online misinformation would streamline cross-country and longitudinal analyses, and thereby yield much stronger and more generalizable findings of use to scholars, policymakers, and citizens alike. As natural language processing (NLP) tools continue to be improved and refined, the political science literature could benefit tremendously from NLP tools that are adapted and standardized for use in social science research. Given such tools, for example, we could consistently identify and analyze political misinformation across existing Twitter corpora (and

[170] Cf., Bond et al., "A 61-Million-Person Experiment in Social Influence and Political Mobilization."
[171] Guess, Nyhan, and Reifler, "Selective Exposure to Misinformation: Evidence from the Consumption of Fake News during the 2016 U.S. Presidential Campaign."

social media platforms in general) with tweets from recent US elections,[172] both expanding our time horizon as well as potentially increasing the number of observations per electoral cycle.

As noted above, Trump features prominently in discussions regarding the apparent rise and impact of political misinformation on American citizens. Trump himself could theoretically drive a significant part of the observed changes in donor behavior among left-leaning donors who engaged with election misinformation spread on Twitter (by people such as Trump) and strongly opposed his presidential candidacy in 2020. Given Trump's continued role in public life as a well-known and controversial figure as well as current presidential candidate, however, it remains challenging to identify case studies for analyzing the impact of unfounded voter fraud claims on American voters outside of Trump. While Stacy Abrams is by no means equivalent to Trump, her gubernatorial campaigns in Georgia in 2018 and 2022, related claims regarding voter suppression – claims found to be invalid or unsupported by empirical evidence in federal court – as well as prolonged refusal to explicitly concede the 2018 gubernatorial race could serve as a reasonable test case to evaluate the relative importance of the person spreading election misinformation on the actual impact of that misinformation, especially along partisan lines.[173]

Conclusion

By analyzing the political contributions of US citizens who interacted with unfounded voter fraud claims on Twitter during the 2020 general election, I offer new insights into the relationship between exposure to election misinformation and voter behavior in established democracies. I hope my analysis and corresponding novel dataset will inspire other social

[172] E.g., Chen, Deb, and Ferrara, "#Election2020."
[173] E.g., Kessler, "Stacy Abrams's Rhetorical Twist on Being an Election Denier"; Associated Press, "Federal Judge Rules Against Stacy Abrams Group in Voting Rights Lawsuit."

scientists to delve into the understudied connections between political misinformation, social media platforms and voter behavior, and will serve as the groundwork for continued and more in-depth mining of text-based data sources on social media. By quantifying the direction of the impact of Twitter engagement with voter fraud claims on donor behavior by partisan and platform-specific factors, I hope that this analysis provides both scholars and policymakers with a valuable tool for evaluating the impact of misinformation on members of their communities and will help them calibrate potential policy interventions to the needs of their constituents.

Appendix A

Matching Twitter and FEC data

This appendix provides a general overview of the process I used to (1) hydrate *VoterFraud2020* files, (2) extract name components from the Twitter accounts corresponding to the hydrated tweets, (3) clean those extracted name components, (4) adapt and repeat steps (2)-(3) for FEC data, and (5) match the cleaned Twitter and FEC records.

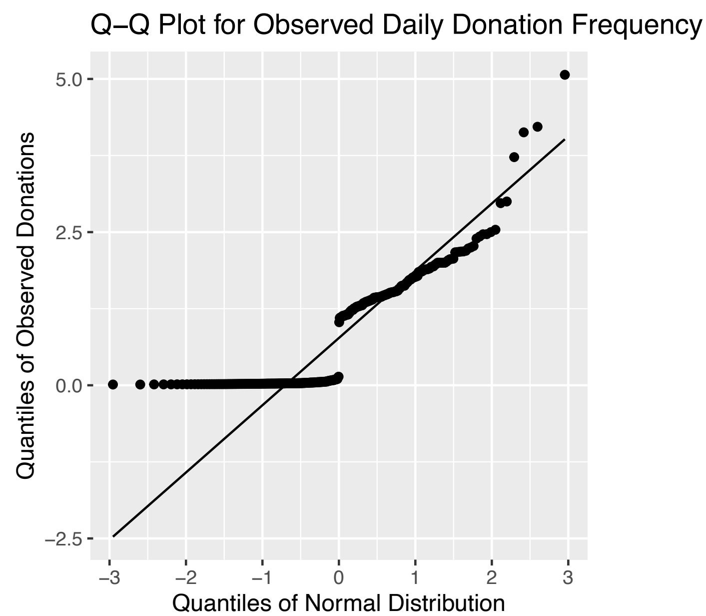
1. Download all tweets from the *VoterFraud2020* that fall within the study period (10/23/20-11/02/20). This data is freely accessible at https://voterfraud2020.io
2. Merge all tweet IDs from all relevant tweet files together into a .txt file with no row or column names.
3. Download and install the Hydrator application from https://github.com/DocNow/hydrator
4. Input file from step 2 into Hydrator application.
5. If Hydrator returns error messages, remove the tweet ID at the index specified in the error message. Repeat this process until all available tweet IDs have been hydrated into JSON and CSV files.
6. Subset hydrated tweets by selecting the Twitter user ID, user screen name, user name, and user description variables. Filter this data to only retain distinct Twitter user IDs.
7. Strip Twitter usernames of emojis, using dictionary and strategy developed by Kate Lyons. This dictionary is freely accessible at https://lyons7.github.io/portfolio/2017-03-10-emoji-maps/

8. Strip Twitter username of hashtags and "non-name" punctuation such as comma's, parentheses, semicolons, and similar symbols that do not form standard components of names.
9. Strip Twitter usernames of titles such as "Dr." and "PhD" while retaining suffixes such as "Jr." and "Sr."
10. Use regex to split CamelCase words at the second capitalized letter if the word does not involve "Mc"-like components.
11. Use regex to split username strings into separate words based on spaces.
12. Retain the first four identified words as name components.
13. Adapt process to extract names from general election FEC data (07/24/20-12/31/20).
14. Since most matched Twitter names match more than one FEC name, matched names using the following hierarchy:
    a. Verified Twitter users that uniquely match one FEC name
    b. Non-verified Twitter users that uniquely match one FEC name
    c. Verified Twitter users that match first and last FEC names (exact match)
    d. Verified Twitter users that match first and last FEC names (fuzzy match)
    e. Verified Twitter users that match first, middle, and last FEC names (fuzzy match)
15. Loop through names to retain matched names that also match in general location data, where location data is matched using the following hierarchy: zip code > county > city > state.

Note: Even though numerous portions of this process can be automated or run in parallel, cleaning, and matching Twitter and FEC records requires significant manual data processing and control, particularly at steps 5 and 15.

Appendix B

Non-Normality of *VoterFraud2020* Donations



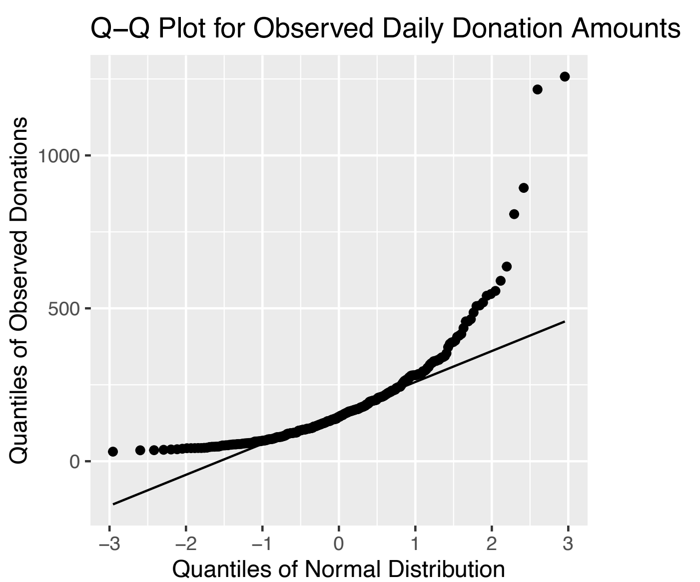


Figure A. Q-Q plots of the daily donation rates and sizes demonstrate visually that these variables are not normally distributed. As a result, we utilize non-parametric correlation tests such as Kendall's and Spearman's methods to estimate the correlation coefficients describing the associations among variables in my sample and donor behavior. Note that the total donation frequencies and sizes follow a similar empirical distribution.

Appendix C

Non-smoothed Longitudinal Donation Behavior

Most of the density plots displayed above rely on a loess (i.e., local regression technique) smoothing algorithm to provide a clean, visible trend in donation size and frequency across time. While these plots provide a helpful intuition to support the findings from the paired t-tests and non-parametric correlation tests, they do not accurately reflect the reality, where donation patterns are highly skewed and fluctuate drastically from day to day. For readers who desire a more in-depth understanding of the longitudinal donation behavior of the donor groups discussed above, I replicate the plots from above but plot them with non-smoothed curves below.

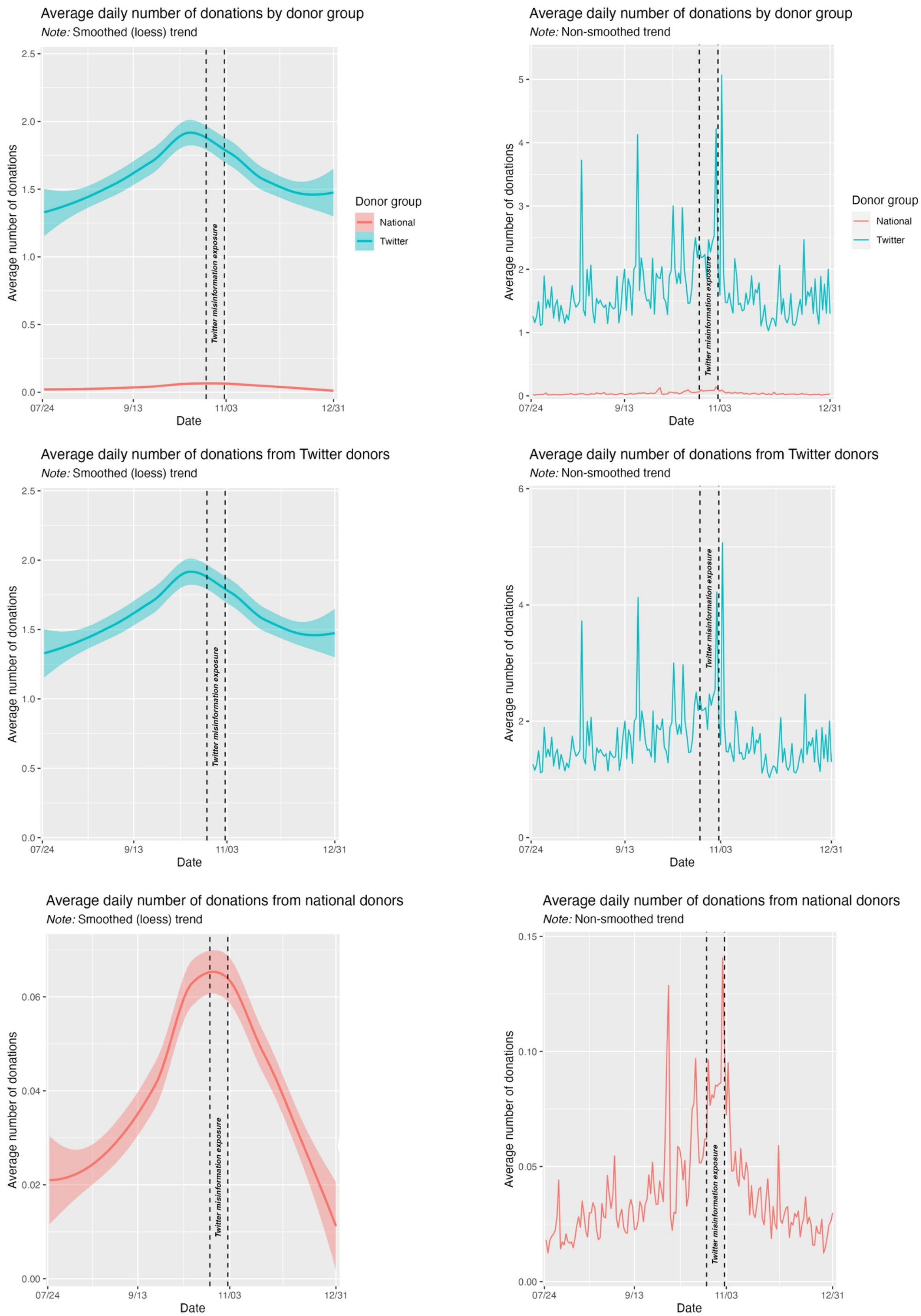


Figure B. Smoothed and non-smoothed average daily *number* of donations among donors who engaged with to *VoterFraud2020* tweets in the run-up to the 2020 presidential election and donors at large.

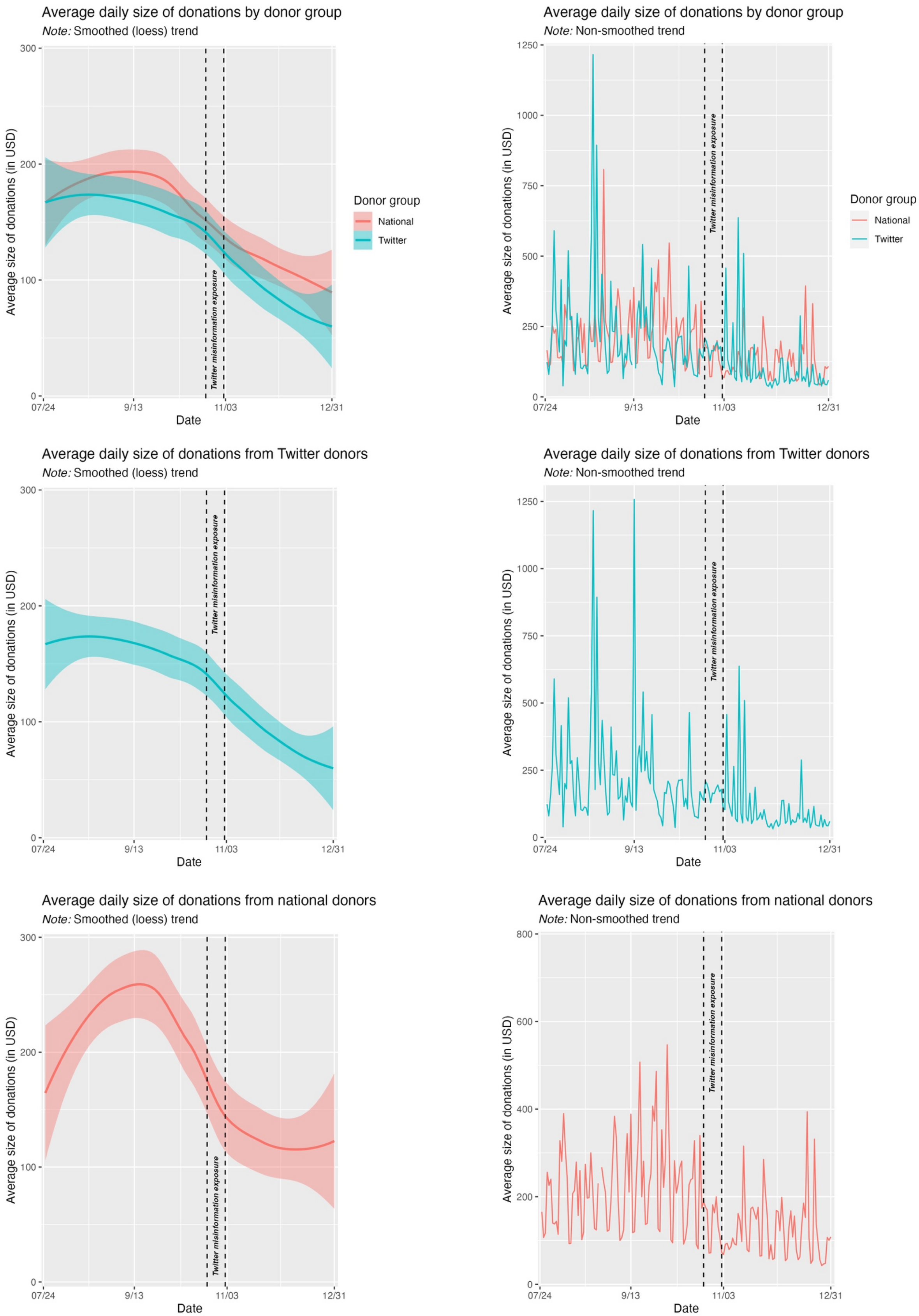


Figure C. Figure Smoothed and non-smoothed average daily *size* of donations among donors who engaged with to *VoterFraud2020* tweets in the run-up to the 2020 presidential election and donors at large.

Appendix D

Expanded Summary Tables

A

Measurement Variable	Difference in Means: Donation Size	95% CI	n	Correlation: Kendall's Tau	Spearman's Rho	n	p-value: $p1$	$p2$	$p3$
Overall									
Relative to national donors	-3.0144	[-Inf, 20.5574]	1802	—	—	—	0.4164	n/a	n/a
Partisan identity									
Democratic zip code	+87.1905 ****	[50.3574, Inf]	1633 (921)	+0.0881 ****	+0.1065 ****	1633 (921)	6.65E-05	1.68E-05	1.61E-05
Competitive zip code	-70.9803 ***	[-Inf, -36.4573]	1633 (263)	-0.0322	-0.0390	1633 (263)	0.0004271	0.1156	0.1156
Left-leaning zip code	+86.2220 ****	[49.9758, Inf]	1653 (966)	+0.1273 ****	+0.1904 ****	1653	6.19E-05	1.85E-14	5.92E-15
Twitter profile									
Verified user	+177.6287 ***	[78.1811, Inf]	1802 (130)	+0.1434 ****	+0.1734 ****	1802 (130)	0.001818	1.88E-13	1.26E-13
Account age	—	—	—	+0.0490 ***	+0.0692 ***	1802	n/a	3.24E-03	0.003285
New account	-52.8915 *	[-Inf, -14.2994]	1802 (125)	-0.0212	-0.0256	1802 (125)	0.01239	0.2775	0.2776
Multiple fraud tweets	-58.1252 **	[-Inf, -24.1646]	1802 (296)	-0.0093	-0.0112	1802 (296)	0.002617	0.634	0.6341
Major number of followers	+9.2910	[-16.0887, Inf]	1802 (901)	+0.0607 **	+0.0733 **	1802 (901)	0.2728	0.001864	0.001846
Elite number of followers	+58.3697 **	[26.0962, Inf]	1802 (451)	+0.1043 ****	+0.1260 ****	1802 (451)	1.61E-03	8.84E-08	7.95E-08

Note: *p < 0.05, **p < 0.01, ***p < 0.001, ****p < 0.0001

B

Measurement Variable	Difference in Means: Donation Frequency	95% CI	n	Correlation: Kendall's Tau	Spearman's Rho	n	p-value: $p1$	$p2$	$p3$
Overall									
Relative to national donors	+1.6366 ****	[1.5633, Inf]	1802	—	—	—	2.20E-16	n/a	n/a
Partisan identity									
Democratic zip code	+0.1591 **	[0.0604, Inf]	1633 (921)	+0.0548 *	+0.0620 *	1633 (921)	0.00422	0.0123	0.01226
Competitive zip code	-0.3484 ****	[-Inf, -0.2291]	1633 (263)	-0.0394	-0.0445	1633 (263)	1.57E-06	0.07193	0.07192
Left-leaning zip code	+0.1883 ***	[0.0831, Inf]	1653 (966)	+0.0763 ****	+0.1050 ****	1653	1.77E-03	1.78E-05	1.88E-05
Twitter profile									
Verified user	+0.3441 ***	[0.1939, Inf]	1802 (130)	+0.0412 *	+0.0468 *	1802 (130)	0.0001102	0.04711	0.04708
Account age	—	—	—	+0.0089	+0.0118	1802	n/a	0.6132	0.6155
New account	+0.1812	[-Inf, 0.3718]	1802 (125)	-0.0166	-0.0189	1802 (125)	0.9412	0.4225	0.4226
Multiple fraud tweets	-0.0242	[-Inf, 0.0854]	1802 (296)	+0.0039	+0.0045	1802 (296)	0.3577	0.8496	0.8496
Major number of followers	+0.0438	[-0.0541, Inf]	1802 (901)	+0.0423 *	+0.0481 *	1802 (901)	0.2302	0.04134	0.04131
Elite number of followers	+0.2360 ***	[0.1163, Inf]	1802 (451)	+0.0363	+0.0412	1802 (451)	0.0006795	0.08043	0.08043

Note: *p < 0.05, **p < 0.01, ***p < 0.001, ****p < 0.0001

Variable Definitions

Average difference in daily donations between matched Twitter users and all donors

Whether 2020 Democratic presidential vote share was above 50%
Whether 2020 Democratic and Republican presidential vote share was within 5%
American Ideology Project MRP ideology estimate

Whether Twitter user had verified status in 2020-2022
Number of years account was created before 2020
Whether acount was created in 2020
Whether donor (re)tweeted voter fraud claims more than once in study period
Whether donor had more than the median number (561) of followers in sample
Whether donor had more followers (>561) than 50% of sample
Whether donor had more followers (>2,297) than 75% of sample

Figure D. Summary Table 1 with exact *p*-values and variable descriptions.

A

Measurement	Correlation with Total Size			p-value	
Variable	**Kendall's Tau**	**Spearman's Rho**	***n***	***p1***	***p2***
Partisan identity					
Ideological position (raw)	+0.1273 ****	+0.1904 ****	1633	1.85E-14	5.92E-15
Ideological distance (abs)	+0.0799 ****	+0.1178 ****	1633	1.54E-06	1.58E-06
Twitter profile					
Verified user	+0.1434 ****	+0.1734 ****	1802 (130)	1.88E-13	1.26E-13
Account age	+0.0490 **	+0.0692 **	1802	0.003236	3.29E-03
Number of tweets	-0.0089	-0.0110	1802	0.6392	6.41E-01
Number of followers	+0.0821 ****	+0.1211 ****	1802	2.57E-07	2.51E-07

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, ****$p < 0.0001$

B

Measurement	Correlation with Total Frequency			p-value	
Variable	**Kendall's Tau**	**Spearman's Rho**	***n***	***p1***	***p2***
Partisan identity					
Ideological position (raw)	+0.0763 ****	+0.1050 ****	1633	1.78E-05	1.88E-05
Ideological distance (abs)	+0.0227	+0.0311	1633	0.2022	2.06E-01
Twitter profile					
Verified user	+0.0412 *	+0.0468 *	1802 (130)	4.71E-02	4.71E-02
Account age	+0.0089	+0.0118	1802	0.6132	6.16E-01
Number of tweets	+0.0044	+0.0051	1802	0.828	8.27E-01
Number of followers	+0.0348 *	+0.0482 *	1802	0.04007	4.06E-02

Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, ****$p < 0.0001$

Figure E. Summary Table 2 with exact *p*-values.

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