From Maoism to MAGA: Embracing Democracy with Authoritarian Imprints

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Abstract

Right-wing populism, notably Trumpism, has presented a formidable challenge to democracy. We explore the historical roots of Trumpism among the Chinese diaspora by analyzing nearly one million tweets from approximately 200 Chinese overseas opinion leaders between 2019 and early 2021. We develop a novel measure of authoritarian imprints, drawing on the usage of high-frequency words from the political discourse of China's Cultural Revolution (1966–1976). Leveraging computational text analysis, we identify both pro-Trump and anti-democratic stances in these tweets. Our analysis reveals that Chinese opinion leaders with strong authoritarian imprints are significantly more likely to support Trump and endorse anti-democratic actions, such as rejecting the 2020 presidential election result and advocating for unconstitutional means to overturn the result. This study contributes to the understanding of support for right-wing populism among immigrants and ethnic minority groups, and the impact of historical legacies on contemporary political attitudes.

Keywords: populism, Trumpism, immigrants, social media

1 Introduction

Populism, most notably right-wing populism, has gained momentum across the globe over the past decade or so, posing a formidable threat to democratic institutions and values. A booming body of literature has been dedicated to investigating the roots of populism.[1] Scholars are generally divided into two main camps: one highlighting economic grievances as the breeding ground for populists,[2] and the other pinpointing cultural backlash as a vital catalyst.[3] Taken together, this line of research focuses primarily on how traditionally white-dominated societies react to trade and technology shocks and the influx of immigrants.

Yet less is known about why immigrants or ethnic minority groups support populist leaders or parties. Understanding this phenomenon has become especially crucial for American politics in light of the country's ongoing demographic shift toward a more diverse population. This research question has gained particular relevance following Trump's 2024 victory, which drew unprecedented support from minority communities, despite his anti-immigration and xenophobic rhetoric. Hispanic support surged to 46% — a notable 14% increase from 2020 — while Asian American voters shifted significantly to the right, reaching approximately 40%. [4]

Between 2000 and 2019, over 1.38 million Chinese emigrants settled in the United States, making China the second-largest source of U.S. immigrants and the largest source among authoritarian countries (see Figure A1 of the Online Appendix). Surprisingly, a sizable segment of the Chinese diaspora — especially first-generation Chinese immigrants — emerged as ardent supporters of Donald Trump.[5] This support was strikingly evident in December 2020, when the Proud Boys, a far-right group championing Donald Trump, received nearly $100,000 in donations for medical expenses in the wake of a clash with Black Lives Matter protesters in Washington, D.C. Remarkably, over 80% of this amount was contributed by Chinese Americans and the Chinese diaspora.[6] Considering Trump's anti-China rhetoric, such as references to the COVID-19 pandemic as "kung flu" and "China virus," the support he garnered from the Chinese diaspora was particularly puzzling. To be sure, Trumpism epitomizes the global rise of right-wing populism. While Trumpism has been extensively studied within the context of the U.S. general electorate,[7] far less is known about what explains the Chinese diaspora's embrace of Trumpism.

To address this important gap, we explore the historical roots of Trumpism in the Chinese diaspora. Historical institutions or events exert a lasting impact on a broad range of contemporary attitudinal and behavioral outcomes, such as cultural values,[8] political and social trust,[9] voting behaviors,[10] and attitudes toward out-groups.[11] In particular, in post-communist countries, the experience of living through communist regimes leads people to exhibit left-authoritarian attitudes, express less support for democracy and market economy, yet advocate more for state-provided social welfare.[12] Even different autocratic ruling strategies leave a lasting imprint on the political attitudes of ordinary citizens long after the breakdown of the regime.[13]

When it comes to immigrants, it is worth highlighting that their political attitudes can be shaped by their socialization experiences and collective memories from their countries of origin.[14] Notably, authoritarian imprints, which we define as "deeply ingrained behavioral and cognitive patterns formed through socialization experiences in authoritarian regimes," can persist long after migration, even in democratic settings. Consequently, immigrants from non-democratic countries, despite their democratic desires, tend to support strong, unaccountable leaders in democracies.[15] Building on this growing body of work, we contend that authoritarian imprints led many in the Chinese diaspora, especially first-generation immigrants, to support Trump, who appeared to follow an authoritarian playbook during his presidency.

This study focuses on Chinese overseas opinion leaders on Twitter — individuals born in China but currently residing abroad — who actively participated in heated debates surrounding the 2020 U.S. presidential election and Donald Trump. We collected nearly one million tweets posted by approximately 200 Chinese opinion leaders between January 2019 and January 2021. By leveraging the word frequency of *People's Daily*, the mouthpiece of the Chinese Communist Party (CCP), we created a dictionary of high-frequency words from the political discourse during the Cultural Revolution (1966–1976), a period characterized by intense ideological indoctrination and political conflicts in contemporary China. The rhetoric of the Cultural Revolution has left an enduring imprint on the Chinese people.[16] The Cultural Revolution represented Mao's permanent revolution and continuous purification endeavors, marking the apex of Maoist authoritarian culture, which sought to preserve the ideology of the CCP through an intensified form of Maoism.[17] We then developed a novel measure of authoritarian imprints based on the frequency of Cultural Revolution (CR) words normalized by the total word count in the tweets of Chinese opinion leaders. Our findings demonstrate the remarkable persistence of these authoritarian imprints, also referred to as CR imprints in this study, throughout the sample period. Specifically, opinion leaders who frequently used CR words in 2019 consistently continued to do so from January 2020 to January 2021.

In the following analysis, we employ supervised machine learning methods, such as support vector machines (SVMs), to identify tweets expressing pro-Trump and anti-democratic stances. We find that the authoritarian imprints of Chinese opinion leaders strongly predict their pro-Trump and anti-democratic stances. Specifically, Chinese opinion leaders with deep authoritarian imprints not only tend to support Trump, but also contest the 2020 presidential election result and advocate for unconstitutional or violent means to overturn it. These findings remain robust even when accounting for tweet sentiments and several key personal characteristics of the opinion leaders. Moreover, the authoritarian imprints of opinion leaders have a broad impact on the Chinese diaspora on Twitter. We provide suggestive evidence of spillover effects, demonstrating that tweets containing a higher proportion of CR words are more likely to be retweeted, replied to, and liked. Furthermore, in a quasi-experimental fashion, we show that Twitter users who were exposed to and subsequently retweeted tweets containing CR language tended to post an increasing number of tweets advocating for the unconstitutional overthrow of the election result.

Our research advances the existing scholarship in several important ways. First, while the vast majority of literature on populism focuses primarily on the dominant social or ethnic groups in Western societies and underscores economic and cultural threats as key drivers, support for populists among immigrants or ethnic minority groups is relatively understudied. To fill this empirical lacuna, we investigate why a considerable number of Chinese immigrants fervently supported Donald Trump, a right-wing populist, during the 2020 presidential election. More broadly, we contribute to the understanding of the political ideology and behavior among diaspora communities,[18] as well as among ethnic minority groups, particularly Asians.[19] Second, we offer a novel perspective on the support for populist leaders among immigrants in a democratic regime. Specifically, we demonstrate that the political attitudes of immigrants from authoritarian countries have deeper historical roots, thereby enriching the literature on the impact of historical legacies on contemporary political attitudes. Third, our study has crucial implications for understanding the cross-border transmission of values.[20] Through the process of immigration, immigrants have imported their authoritarian values from their home countries to democratic settings, which in turn reshapes the political landscape in their new homes.[21] Our research provides new evidence to this line of inquiry and highlights the potential of immigrants to act as agents of value transmission, deepening our understanding of the complex interplay between immigration and the transmission of cultural and political values.[22] Finally, prior research typically employs indicators such as geographic proximity,[23] population composition,[24] or duration of exposure[25] to assess the long-term effects of historical events, assuming individuals exposed to the same historical event share the same attitudinal legacies. As an alternative approach, we have developed a novel measure that leverages the political discourse during the Cultural Revolution to analyze the language styles of social media users, enabling us to capture the authoritarian imprints at the individual level.

2 Authoritarian Imprints and Trumpism

2.1 Echoes of the Past: Value Transmission under Authoritarian Rule

Despite the widespread belief that China's economic reforms and opening-up would relegate Maoism to the annals of history, the resurgence of Maoist authoritarian culture in contemporary China challenges these expectations,[26] highlighting Maoism's lasting influence and continued relevance.[27] While existing studies insightfully note the enduring impact of the Maoist legacy on China's adaptive governance and political system in the post-revolutionary era, albeit in a "tamed, tweaked, and transformed" form,[28] the question of how Maoist authoritarian culture continues to shape contemporary beliefs and attitudes remains understudied.

Prior research has identified several plausible channels through which historical events or institutions can have long-lasting effects on contemporary political attitudes. First, the government has played a vital role in the political socialization of individual citizens. In particular, authoritarian governments typically impose strict control over the propaganda apparatus, media, and education systems to monopolize public discourse, silence dissident voices, and indoctrinate citizens with a singular pro-regime worldview.[29] Second, social and religious organizations serve as alternative institutions for education and mobilization, often outlasting individual families and political regimes and transmitting ideas and values to group members.[30] Third, families, friends, and communities exert a large influence on people's identities and attitudes, which can be passed down from generation to generation.[31]

The first two channels are associated with "institutional reinforcement," whereas the third channel involves "intergenerational socialization".[32] These "mechanisms of reproduction" give rise to behavioral path dependence, referring to the pattern where "once a community's social and political psychology has gone down a certain path, its behaviors and culture become entrenched and hard to reverse".[33] While we acknowledge that social organizations, communities, and individuals can be crucial sources of attitudinal transmission and persistence, we emphasize the authoritarian government's role in reinforcing people's authoritarian imprints and reviving Maoist authoritarian culture. Even individuals who did not directly experience the Maoist era may still carry Maoist cultural imprints through indirect channels such as state propaganda, education, family socialization, and broader sociopolitical discourses.

Despite the end of the Cultural Revolution, the Chinese Communist Party (CCP) has maintained its hold on power and continued to shape people's worldviews in its favor. The language and rhetoric frequently used during the Maoist era, particularly during the Cultural Revolution, periodically reemerges in official propaganda, especially when the CCP leadership encounters internal and external challenges. The revival of such language serves to denounce foreign states with strained relations with China and stigmatize potential challengers to the leadership within the ruling elite.

For instance, in the late 1990s, the CCP leadership considered Falun Gong a serious threat and launched a political crackdown campaign.[34] Phrases from the Cultural Revolution, such as "contemptible scoundrel" (*tiaoliang xiaochou*), "vicious political motive" (*xian'e zhengzhi yongxin*), and "a last-ditch struggle"(*chuisi zhengzha*), were invoked to denounce Falun Gong.[35] Moreover, when the CCP's top leaders purge political rivals during anti-corruption campaigns, certain political labels are often used to discredit these corrupt officials. One salient example is that Zhou Yongkang, Sun Zhengcai, and Ling Jihua indicted on corruption-related charges — were labelled "ambitious schemers" (*yexin jia*) and "conspirators" (*yinmou jia*) by the 2017 work report of the Central Commission for Discipline Inspection, the CCP's anticorruption watchdog, and in state media coverage.[36] These two terms, in fact, were used during the Cultural Revolution to condemn Lin Biao, Mao's handpicked successor, who ultimately fell out of Mao's favor and died in a mysterious plane crash while allegedly fleeing China. [37]

Furthermore, during periods of tension between China and the U.S., Chinese propaganda authorities have been known to employ derogatory language, including terms like "ugly face" (*chou'e zuilian*) and "bandit's logic" (*qiangdao luoji*), to denounce the U.S. and provoke anti-American sentiment.[38] There words also figured prominently during the Cultural Revolution, when anti-foreignism and xenophobic sentiments echoed the intense xenophobia of the Boxer Rebellion in 1900.[39] Consider, for example, following the intrusion of a U.S. military aircraft into Hainan Island's airspace in 1967, the *People's Daily* dismissed the U.S.'s official explanation as "an outright lie and bandit logic" and went on to assert that "this incident completely exposes the ugly face of American imperialism as a bandit and a liar to the people of the world." [40]

Maoist authoritarian culture, perpetuated and invoked by the CCP's ideological control and propaganda, has left enduring imprints on the Chinese people. Language and narratives, as vehicles for culture, have a profound impact on people's emotions, beliefs, and preferences.[41] In the context of China, the political discourse from the Mao era, most notably the rhetoric during the Cultural Revolution,[42] has played a crucial role in shaping people's worldviews and ideologies.[43] As Yang notes, cultural products about the Cultural Revolution like poems, novels, and TV dramas led to "Mao fever" and nostalgia among sent-down youth in the 1990s.[44] Similarly, the songs from the Cultural Revolution era have constructed collective memories that still resonate in Chinese society today.[45] In the post-Mao era, social problems, such as corruption and economic inequality, have evoked collective memories of the Cultural Revolution among peasants and workers, thereby fuelling their mobilization in protests.[46] In recent years, disgruntled youth are increasingly embracing Maoist anti-establishment tenets and calling for struggle against the capitalist class. [47]

2.2 Revival of Authoritarian Imprints in Trump's Populist America

The influence of collective memory on individuals' attitudes and behaviors also hinges on associativeness of memory. Associativeness implies that events affect beliefs not only through conveyed information but also through evoked memories.[48] When current events bear resemblance to past events, history becomes more salient in people's minds, thereby shaping their beliefs and behaviors. This occurs because the resemblance facilitates the recall of past events at the individual level,[49] and structures the collective memory at the group level, even if not all individuals have personally experienced the shared past.[50]

The Cultural Revolution, launched by China's paramount leader Mao Zedong in 1966, is regarded as one of the most tumultuous social-political movements in contemporary China. The Cultural Revolution represents the apex of Maoist authoritarian culture, aiming to preserve the ideology of the CCP through an intensified form of Maoism.[51] The imprints cast by the shadow of the Cultural Revolution resonate well with contemporary populist rhetoric. Populism can be commonly understood as an ideology that considers society to be separated into two antithetic groups, "the pure people" versus "the corrupt elite," and politics should be on behalf of the interests of "the people".[52] Populist leaders and parties claim that they, and they alone, represent the people.[53] Ordinary people, however, do not truly represent themselves in populist politics; instead, populist leaders take radical actions in the name of the majority, which "opens the door to authoritarian solutions and even dictatorship".[54] Populist leaders underscore the importance of popular sovereignty and typically view formal democratic institutions as "the creatures of corrupt elite deals and exploitation, rather than as autonomous institutions of democratic accountability and legal constraint".[55] They adopt a political strategy that relies on "direct, unmediated, uninstitutionalized support from large numbers of mostly unorganized followers".[56] Formal institutions become obstacles for populist leaders to augment their personalistic power and maintain direct and uninstitutionalized mass support. Therefore, formal institutions, in the eyes of populists, must be circumvented or even compromised to represent the general will of the "people."

Stuart Schram posited that Mao recognized the power of the masses in his essay entitled *The Great Union of the Popular Masses (minzhong de da lianhe)*, and thus was a populist in a broad sense.[57] Similarly, Benjamin Schwartz, in his analysis of Mao's *Report on an Investigation of the Peasant Movement in Hunan (Hunan nongmin yundong kaocha baogao)* in 1927, associated Mao's ideas with populism in the sense that Mao emphasized the importance of the masses, particularly the peasantry, as a revolutionary force.[58] Maurice Meisner notes:

> "Many other features of the Maoist mentality were typically populist: a hostility to occupational specialization; an acute distrust of intellectuals and specialists; a profound antipathy to bureaucracy; an antiurban bias; and a romantic mood of heroic revolutionary self-sacrifice. Mao was not simply a populist in Marxist guise (any more than he was simply a Chinese nationalist in Communist dress), but populist ideas and impulses profoundly influenced the manner in which he adapted and employed Marxism."[59]

The Cultural Revolution, the apex of Maoism, manifests anti-elite and anti-establishment ideologies. In the mid-1960s, Mao was dissatisfied with post-Stalin Soviet policies and "was unwilling to permit his party-state to evolve into a stable bureaucracy ruled by bureaucrats who lorded over subordinates and paid lip service to revolutionary ideals motivated by career advancement and material comfort".[60] On August 5, 1966, Mao's big-character poster on *People's Daily* called to "bombard the headquarters," a call to denounce the ruling elites within the CCP. Mao's blueprint for the Cultural Revolution, the "Decision of the CCP Central Committee concerning the Great Proletarian Cultural Revolution," stated that the objective was "to struggle against and overthrow those persons in authority who are taking the capitalist road, to criticize and repudiate the reactionary bourgeois academic authorities and the ideology of the bourgeoisie and all other exploiting classes...".[61] The Cultural Revolution represents a vivid example of Mao's willingness to embrace populist rhetoric, such as the mass line, and advocate for popular support.[62] During the Cultural Revolution, students and industrial workers were mobilized from below to attack state bureaucracies and criticize officials with revisionist tendencies.[63] Within the party-state, officials also seized the opportunity to turn against their superiors.[64] In short, the Cultural Revolution saw the "anti-bureaucratic ghost" at its height, leading to devastation of the state machinery and its functionaries.[65]

In such a mass movement against an entrenched elite, violence is regarded as a necessary means. Mao firmly believed that "only violent conflict could bring about genuine social change and liberate the oppressed" and "violence and humiliation of elites is necessary for a decisive break from the old to the new".[66] Consequently, of 49 ministers of the State Council, approximately 75% were purged or removed from the State Council during the Cultural Revolution.[67] The Central Party apparatus's departments were dismantled into small working groups and the bulk of Party cadres were purged so that civilian Party organizations ceased to function by the end of 1966.[68] As Walder notes, "Offices throughout urban China were almost emptied from 1969 to 1971. Large majorities of administrators and staff spent long periods in manual labor. The emptied offices operated with skeleton staffs, covering only minimal functions. Research virtually ceased, and government services were slashed to a bare minimum."[69]

The political discourse of the Cultural Revolution has left enduring imprints on the Chinese people. The rhetoric frequently invoked throughout this tumultuous period fostered a climate of hostility and hatred among the Chinese people. The Cultural Revolution stressed the paramount importance of class struggle, with the slogan "Never forget the class struggle" (*qianwan buyao wangji jieji douzheng*) being used widely to divide lines between friends and enemies, between good and evil, and to legitimize violence against those labeled as class enemies.[70] It thus comes as no surprise that the word "struggle" (*douzheng*) is one of the most frequently used words during the Cultural Revolution, as will be discussed in subsequent sections. In contemporary America, pro-Trump opinion leaders from the Chinese diaspora often resorted to this word in their efforts to mobilize netizens on Twitter to challenge the results of the 2020 presidential election. One influential opinion leader, for instance, posted a tweet on December 3, 2020: "We must dare to struggle and at the same time be good at fighting. At this time, we should strive to gain as many allies as possible. Venting anger is a secondary matter." By the same token, another opinion leader tweeted on December 16, 2020: "The lawsuit has just entered its peak, how can one speak of victory or defeat? Even if Trump is no longer the president, his influence endures. The struggle against evil forces must never cease. The darker the society, the more force we need to resist."

Another notable feature of political discourse during the Cultural Revolution involved the "vilification of the other".[71] Curses and other crude expressions were employed to dehumanize and attack individuals deemed as "enemies of the people." A prime example is the phrase "cow demons and snake spirits" (*niu gui she shen*), which was widely used to refer to all class enemies. Once individuals were labeled as "cow demons and snake spirits," they were dehumanized and regarded as animals and evil creatures rather than fellow human beings, thereby legitimizing violent actions against them.[72] On 1 June 1966, *People's Daily* published an editorial titled "Sweep Out all the Cow Demons and Snake Spirits," calling for the masses to "completely eradicate the old thoughts, old culture, old customs, and old habits that have harmed the people inflicted by all exploitative classes over the course of thousands of years." [73] Afterward, the Cultural Revolution swept across the entire country. Interestingly, this phrase was also employed by Trump supporters to denounce supporters of the Democratic Party during the election. Before the "Million MAGA March" on November 14, 2020, where Trump supporters rallied in Washington, D.C. to contest the election result, a prominent opinion leader posted a tweet: "The rally in DC will begin tomorrow. The American people will come in a torrential force, striking fear into all the big and small cow demons and snake spirits involved in this election coup." To take another example, one opinion leader was reluctant to accept the election result and questioned the election's legitimacy on December 6, 2020: "When the video of the Georgia State election fraud was released, some Biden supporters have turned silent, while others keep insisting that everyone should respect the election results. This isn't an election, it's outright theft. I have to admire the executive order on foreign interference in the election issued by Trump two years ago, which paved the way for sweeping out all the cow demons and snake spirits through a legal framework."

[Figure 1 about here]

To illustrate the assault on democratic norms through the use of Cultural Revolution rhetoric following Trump's defeat in the 2020 US presidential election, we focus on five prototypical Cultural Revolution words: cow demons and snake spirits (*niu gui she shen*), leader (*lingxiu*), struggle (*douzheng*), defending (*hanwei*), and devils (*mogui*). We examine the usage trends of these words during the Cultural Revolution and the 2020 election period. Figure 1 displays the frequency of these terms in both the *People's Daily* corpus and the tweet corpus. The left panel reveals that the usage of these five terms peaked during the Cultural Revolution. The right panel indicates that, after the election day, opinion leaders increasingly employed these words to support Trump, attack Democrats, and contest the election results. Many opinion leaders praised Donald Trump as a great "leader" who could "make America great again." After Trump's loss in the 2020 election, they claimed it was a rigged election and mobilized Trump supporters to "defend" their great leader and confront the "cow demons and snake spirits" and "devils," referring to Democrats and those opposing Trump. In the following empirical analysis, we will systematically examine the usage of the Cultural Revolution words among pro-Trump opinion leaders.

3 Data

3.1 The Sample of Overseas Chinese Opinion Leaders

To construct a sample of overseas Chinese opinion leaders, our study specifically targets individuals who demonstrate active engagement and influence on Twitter. As is often the case, opinion leaders closely follow current events and promptly express their views. Typically, they follow major media outlets on Twitter to stay informed about the latest news. With few exceptions, Chinese opinion leaders follow at least one major news outlet on Twitter. To identify these opinion leaders, we leverage the follower lists of major news outlets' Twitter accounts. Given our specific focus on Chinese opinion leaders, we pay particular attention to Chinese media outlets and the Chinese editions of international media. Using web scraping techniques, we obtained the follower lists of 16 media outlets' official Twitter accounts in November 2021. [74]

Approximately 10.3 million Twitter accounts followed at least one of these 16 media outlets. After sorting this list based on each account's number of followers, we removed accounts that did not tweet in Chinese or had fewer than 10,000 followers, resulting in about 4,300 accounts. To ensure these accounts were owned by overseas Chinese opinion leaders with a primary focus on public affairs, we excluded accounts affiliated with Chinese government agencies and state media, accounts owned by individuals born in Hong Kong, Macau, or Taiwan who were not directly exposed to Maoist authoritarian culture, and accounts unrelated to public affairs, resulting in 271 accounts. Given our interest in the political attitudes of overseas Chinese opinion leaders as immigrants or minority groups residing in democratic settings, we further excluded 45 accounts owned by individuals currently residing in Mainland China, Hong Kong, and Macau. Using the Twitter API, we attempted to collect all tweets from these accounts but were unable to access 27 of them. Ultimately, our sample consists of 817,216 tweets from 199 opinion leaders between January 2019 and January 2021. In the Online Appendix, Figure A2 presents the distribution of account creation dates time of these opinion leaders, Figure A3 visualizes the networks among these opinion leaders based on their mutual following relationships, and Figure A4 displays the number of tweets in our sample over time. Table A2 of the Online Appendix presents relevant information about the top 10 accounts ranked by their number of followers.

3.2 Authoritarian Imprints: Measurement and Validation

To quantify the authoritarian imprints of overseas Chinese opinion leaders, we investigate the frequency of their usage of Cultural Revolution rhetoric in their regular tweets. As noted earlier, the Cultural Revolution represents the apex of Maoism. The political discourse from the Mao era, particularly the rhetoric during the Cultural Revolution,[75] has profoundly shaped people's worldviews and ideologies.[76] Language acquisition is deeply embedded in socialization, serving as both the medium and outcome of how individuals internalize and reproduce social norms and cultural patterns.[77] Linguistic practices manifest beliefs and ideologies shaped by diverse socialization experiences, including age, education, and geography. In authoritarian contexts, prolonged exposure to authoritarian culture leaves distinct linguistic imprints, revealing the internalization of its values and norms.

We use the *People's Daily* corpus to identify terms that were commonly used in political discourse during the Cultural Revolution (CR) period and develop a dictionary of CR-related terms. The *People's Daily*, the official mouthpiece of the CCP, has long served as the most influential propaganda outlet in China. Drawing upon the *People's Daily* database covering the years 1949 to 2003, we collected approximately 1.2 million articles during this period. For data preprocessing, we used the "jieba" tokenizer, a widely used Chinese tokenization module, to segment Chinese sentences into word sequences and remove stopwords from our corpus. We split the corpus into two periods: the Cultural Revolution period (1966–1976) and the non-Cultural Revolution period (1949–1965 and 1977–2003). We calculate the relative frequency of a term j during the Cultural Revolution period as follows:

$$\frac{T_j^{CR}}{\sum_{i=1}^{N} T_i^{CR}} - \frac{T_j^{Non-CR}}{\sum_{i=1}^{N} T_i^{Non-CR}} \tag{1}$$

where $T^{CR}j$ denotes the frequency of term j — the total number of times term j appeared in *People's Daily* — during the CR period. $\sum_{i=1}^{N} T_i^{CR}$ is the sum of all term frequencies during the CR period. T_j^{Non-CR} represents the frequency of term j in the non-CR period. $\sum_{i=1}^{N} T_i^{Non-CR}$ is the sum of all term frequencies in the non-CR period. Equation (1) captures how frequently term j was used during the CR period compared to other periods. Table A3 of the Online Appendix presents the top 30 frequently used CR words.

Using Equation (1), we rank all terms by their relative frequency. Using these rankings, we experiment with four different cut-off points to develop the CR dictionary. The first two dictionaries include terms/words with a relative frequency greater than 1/10,000 and 1/1,000, respectively; whereas the latter two dictionaries contain the top 1,000 and 500 terms/words, respectively. Figure A5 of the Online Appendix illustrates the proportion of CR words in the total number of words in *People's Daily* from 1949 to 2003 for each cut-off point, with the CR period (1966–1976) shaded in grey. As illustrated, the results remain consistent regardless of the chosen cut-off. Throughout this paper, our primary analysis employs the CR dictionary consisting of the top 1,000 words. We also perform robustness checks with alternative cut-offs. The summary statistics of CR imprints are reported in Table A4 of the Online Appendix. The validation exercises are detailed in Section C of the Online Appendix.

3.3 Quantifying Pro-Trump and Anti-Democratic Stances

Our study focuses on examining the pro-Trump and anti-democratic stances of opinion leaders. We employed supervised learning to classify tweets posted during the most intense period of the 2020 presidential election, between September 2020 and January 2021. Specifically, we randomly selected 2,400 tweets (approximately 1% of the total tweets during this period) from the tweet corpus to build our training sample. We then trained research assistants to manually label these tweets into three categories, each represented by a binary variable: support for Trump (YES=1, Otherwise=0), denying the election result (YES=1, Otherwise=0), and advocating for overturning the election result (YES=1, Otherwise=0). In the subsequent analysis, we created a new variable, "anti-democratic stance," coded as "1" if either or both denial of the election result or advocacy for overturning the election result is coded as "1." We meticulously cross-checked the coding results to ensure accuracy (for examples of manually coded tweets, please refer to Section G in the Online Appendix). After testing five widely adopted supervised learning algorithms for classification, we selected support vector machine (SVM) to process the remaining tweets in our sample due to its superior classification accuracy among the five algorithms (see Table A5 of the Online Appendix). Throughout this paper, we employ the F1 score to evaluate model performance. The F1 score maintains a balance between precision and recall, making it an effective metric for imbalanced classification where correctly identifying positive cases is particularly important.

To assess the extent of support for Trump and anti-democratic actions across various accounts, we calculate the proportion of pro-Trump and anti-democratic tweets relative to the total number of tweets for each account by date. In essence, an opinion leader who posts a greater percentage of tweets endorsing Trump or challenging the election results is regarded as more pro-Trump and anti-democratic. Figure A6 of the Online Appendix displays the proportion of pro-Trump and anti-democratic tweets relative to the total tweets over time, revealing a noticeable surge after Election Day and amidst the Capitol riot. To provide insight into the anti-democratic rhetoric used by Trump supporters in contesting the election result, we examine the 1,000 most-retweeted tweets from September 2020 through January 2021 and generate a word cloud, as illustrated in Figure A7 of the Online Appendix. It becomes evident that terms such as "revolution" (*geming*), "fake" (*zaojia*), and "fraud" (*wubi*) were frequently employed to challenge the election result.

3.4 Control Variables

We control for a set of variables related to the personal attributes of opinion leaders. We collected personal details for 199 opinion leaders, including age and educational background, from online sources. While renowned opinion leaders often have a Wikipedia page providing easy access to personal details, those less well-known usually do not. We control for an opinion leader's reputation by using a dummy variable indicating whether the individual has a Wikipedia page. For individuals without a Wikipedia page, we gather biographical information from other online sources. Nonetheless, information about certain opinion leaders remains limited. We tackle this problem by employing machine learning algorithms to impute missing values (see Table A6 of the Online Appendix for details). Figure A8 of the Online Appendix shows the distribution of age, education, and Wikipedia page presence among the opinion leaders in our sample. The vast majority of these opinion leaders were born after 1960, do not hold PhD degrees, and do not have Wikipedia pages. One potential concern is that the CR language may coincidentally carry strong positive or negative sentiments, which could drive our results. To address this concern, we also control for the sentiment of each tweet in our analysis. We use the Chinese emotional vocabulary ontology database, developed by Dalian University of Technology,[78] as a dictionary to measure sentiment across the tweet corpus.

4 Research Design and Results

4.1 The Persistence of CR Imprints

To begin with, we split the tweet corpus into two parts. The first part consists of tweets produced in 2019, which are used to construct a measure of CR imprints at the account level to alleviate endogeneity concerns. The second part comprises tweets from January 2020 to January 2021 and is used for our main analysis. To measure the CR imprints of each account i, we calculate the ratio of CR words to the total number of words used by each account i as follows:

$$CR\ Imprints_i = \frac{CR\ words_i}{Total\ words_i} \tag{2}$$

Figure A9 of the Online Appendix illustrates the dynamic changes in CR imprints across the tweet corpus (see Figure A10 using an alternative dictionary). It becomes evident that the spikes of CR imprints are associated with significant socio-political events in China or the United States, including Hong Kong's anti-ELAB movement, the Black Lives Matter (BLM) movement, and the 2020 US presidential election. Figure A11 and Table A4 of the Online Appendix provide density plots and summary statistics of CR imprints at the account level, tweet level, and account by date level, respectively.

Our empirical analysis begins by exploring the persistence of CR imprints. We use the following model specification:

$$CR\ Imprints_{it} = \beta_0 + \ \beta_1 CR\ Imprints_{it'} + \ \lambda_t + \varepsilon_{it} \tag{3}$$

where $CR\ Imprints_{it}$ denotes the CR imprints of account i on date t between January 2020 and January 2021; $CR\ Imprints_{it'}$ represents the average level of CR imprints for account i throughout 2019; λ_t accounts for time fixed effects; and ε_{it} is an idiosyncratic error term. β_1 is the quantity of interest, which captures the effect of the account's average level of CR imprints in 2019 on its CR imprints in daily tweets from January 2020 to January 2021.

[Table 1 about here]

In Table 1, columns (1)–(2) indicate a significant and positive correlation between the CR imprints in 2019 and the CR imprints during 2020–2021. In columns (3)–(6), we use the CR imprints from the first and second half-year of 2019 as predictors and find a positive association between these two predictors and the CR imprints during 2020–2021. Overall, the results demonstrate a striking persistence of CR imprints among the opinion leaders. Specifically, the opinion leaders who frequently used CR words in their tweets during 2019 were significantly more likely to continue doing so in 2020 and early 2021. Given the evident persistence of CR imprints, we use the 2019 CR imprints as the primary explanatory variable in our subsequent analysis of 2020–2021 to mitigate simultaneity concerns.

4.2 CR Imprints and Pro-Trump and Anti-Democratic Stances

In this section, we assess the impact of opinion leaders' CR imprints on their pro-Trump and anti-democratic stances. To estimate this effect, we use a baseline model as follows:

$$Y_{it} = \beta_0 + \beta_1 CR\ Imprint_{it'} + \beta_2 Age_i + \beta_3 Edu_i + \beta_4 Wiki_i + \beta_5 Sentiment_{it} + \lambda_t + \varepsilon_{it} \quad (4)$$

where Y_{it} denotes account i's pro-Trump and anti-democratic stances on date t, calculated as the proportion of pro-Trump and anti-democratic tweets in account i's total tweets on date t. $CR\ Imprint_{it'}$ represents the average level of CR imprints for account i in 2019. In some specifications, we include dummy variables Age_i, Edu_i, and $Wiki_i$ to control for account i's age (born pre- or post-1960), education level (Ph.D. degree holder or not), and reputation (presence of a Wikipedia page or not), respectively. We also control for the overall sentiment of account i's tweets on date t, $Sentiment_{it}$. λ_t indicates time fixed effects; and ε_{it} is an idiosyncratic error term.

Column (1) of Table 2 indicates a positive association between CR imprints and pro-Trump tendencies when only controlling for date fixed effects. Substantially, a one standard deviation increase in opinion leaders' CR imprints is associated with an approximately 14% increase in their pro-Trump tendencies relative to the mean. Column (2) adds control variables, such as opinion leaders' age, education level, the presence of a Wikipedia page, and tweet sentiment. The results remain largely unchanged.

[Table 2 about here]

Columns (3)–(4) investigate the effect of CR imprints on denying the election result, whereas columns (5)–(6) focus on advocating for overturning the election result through unconstitutional or violent means. Both denying the election result and advocating for its overturning are considered anti-democratic stances. Columns (7)–(8) estimate the impact of CR imprints on anti-democratic stances, defined as engaging in either or both of these behaviors. The results in columns (3)–(8) show a positive and statistically significant relationship between CR imprints and anti-democratic tendencies, regardless of whether control variables are included. Notably, a one standard deviation increase in opinion leaders' CR imprints is associated with an approximately 20% increase in the likelihood of denying the election result and a 13% increase in the likelihood of advocating for its overturning. When using the top 500 words from the *People's Daily* CR word rankings as an alternative CR dictionary, we obtain quantitatively similar results (see Table A7 in the Online Appendix).

Additionally, we conduct a falsification test. Instead of using the top 1000 words in the *People's Daily* CR word rankings to measure CR imprints, we select the 500 words above and below the median in the CR word rankings to create a new measure. This new measure is expected to have little relevance to CR imprints. Reassuringly, Table A8 of the Online

Appendix shows that this new measure has no predictive power in determining the political stances of opinion leaders.

We further explore the heterogeneous effects by opinion leaders' age and education levels. One could argue that the impact of CR imprints would be more pronounced among opinion leaders born before 1960, as their socialization — internalizing the norms, culture, values, and customs of the society — was heavily influenced by the propaganda and political movements during the Cultural Revolution. Another plausible conjecture is that the effects of CR imprints on anti-democratic stances would be stronger among less educated individuals compared to those who obtained Ph.D. degrees, mostly in the United States. However, the results in Table A9 of the Online Appendix indicate that the effects of CR imprints do not vary significantly by age and education levels, suggesting that even those who did not directly experience the Cultural Revolution or who earned Ph.D. degrees in the Western world are no less influenced by the enduring Maoist authoritarian culture.

Unlike the research on post-communist states,[79] where individual exposure to communism can be precisely quantified by years lived under communist regimes, China's enduring authoritarian system means that individuals remain susceptible to authoritarian rhetoric in state propaganda and educational indoctrination well beyond the Cultural Revolution period, as previously discussed. The words of the Cultural Revolution represent Maoist authoritarian culture, but this does not mean they are exclusively used in that period. Instead, Maoist cultural symbols continue to permeate contemporary Chinese society. Therefore, we do not see that the effect varies by age. An additional reason may be that an overwhelming 85% of the opinion leaders in our study were born after 1960 (see Figure A8 of the Online Appendix), indicating that their primary socialization occurred after the most violent and chaotic period (1966–1969) of the Cultural Revolution. This concentration of post-1960 births results in insufficient variation in our age variable, further limiting our ability to detect age-specific effects.

4.3 Alternative Explanations

Thus far, we have established the empirical linkage between CR imprints and support for Trump. However, an alternative explanation for Trump's support among the Chinese diaspora is that individuals who oppose the CCP are inclined to support Trump due to his tough approach towards China and the resulting irreversible momentum against China in US foreign policies. To address this concern, we control for each account's stance against the CCP. Using supervised learning methods, we identify opinion leaders' views on the CCP. Specifically, we randomly select 3,200 tweets from January 2020 to January 2021 as our training sample and manually code them as "1" if their content involves denouncing the CCP, Chinese government, or China's top leadership, and "0" otherwise, with the help of a research assistant. We employ five commonly used supervised learning algorithms to train our classifier, and find that the SVM performs the best (see Table A10 in the Online Appendix for details). We thus use the SVM to process approximately 220,000 tweets from September 2020 to January 2021. We create a binary variable indicating opinion leaders' anti-CCP positions, with a value of "1" if they posted at least one tweet denouncing the CCP in the sample period and "0" otherwise.

Table A11 demonstrates that the effects of CR imprints remain robust when controlling for accounts' anti-CCP stances, whereas the effects of anti-CCP stances are not statistically significant. Our data demonstrates that over 90% of the opinion leaders in our sample had criticized the CCP, the Chinese government, or the CCP's top leadership (see Figure A13 of the Online Appendix). While it is true that almost all Trump supporters are critics of the CCP, those opposing Trump demonstrate equally strong criticism of the Chinese regime. This widespread anti-CCP sentiment across both camps suggests that anti-CCP stance alone cannot explain their divergent attitudes toward Trump.

Beliefs about Western democracy also fail to adequately account for Trumpism among Chinese opinion leaders. While Zhang contends that Chinese internet users are disenchanted with the ideal of democracy and increasingly adopt right-wing populist rhetoric and ideology,[80] Lin argues that "political beaconism" — the idealization of Western political systems — drives Chinese intellectuals toward Trumpism.[81] Our findings suggest authoritarian imprints play a fundamental role in shaping how individuals conceptualize and approach democracy. Paradoxically, Trump supporters may maintain abstract democratic ideals, shaped by their experiences under authoritarian regimes, while simultaneously exhibiting anti-democratic behaviors, as evidenced by their rejection of election results and support for extra-constitutional actions, which they claim serve to defend democracy. This contradiction stems from their limited socialization experience in democratic systems and the deep-seated influence of authoritarian imprints on their political behavior.

4.4 The Impact of Trump's Defeat on Anti-Democratic Stances

We employ a generalized difference-in-differences (DID) design to examine the impact of the 2020 presidential election on anti-democratic stances among the opinion leaders with high levels of CR imprints compared to those with low levels of CR imprints. Following Trump's defeat in the election, his supporters increasingly adopted anti-democratic rhetoric in an attempt to delegitimize the election result and advocate for overturning it. This scenario resonates with research suggesting that authoritarian tendencies can be "activated" when individuals perceive threats to social order or stability.[82] We leverage Trump's electoral defeat as an exogenous shock to analyze how opinion leaders with varying degrees of CR imprints responded to this event.

In this setting, we expect that opinion leaders with higher levels of CR imprints would be more likely to use anti-democratic language. The generalized DID model is specified in the following form:

$$\begin{aligned} Y_{it} = \beta_0 &+ \beta_1 \text{CR Imprint}_{it'} + \beta_2 \text{Post-Election}_t \\ &+ \beta_3 \text{CR Imprint}_{it'} \times \text{Post-Election}_t + \beta_4 \mathbf{C}_{it} + \eta_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where Y_{it} represents account i's anti-democratic stances, namely denying and advocating for overturning the election result, at time t. *Post-Election*$_t$ is a dummy variable that takes a value of "1" after the election day and "0" otherwise. $\mathbf{C}_{it}$ comprises a set of control variables, including tweet-level sentiment. η_i represents account fixed effects, allowing us to control for unobservable time-invariant individual characteristics of opinion leaders; λ_t denotes time fixed effects to control for common shocks; and ε_{it} is an idiosyncratic error term. β_3, the coefficient of the interaction term between *CR Imprint*$_{it'}$ and *Post-Election*$_t$, is the quantity of interest, capturing the effect of Trump's defeat on the change in anti-democratic rhetoric among opinion leaders with high levels of CR imprints compared to those with low levels of CR imprints. The constituent terms CR Imprint$_{it'}$ and Post-Election$_t$ are absorbed by account and date fixed effects receptively.

[Table 3 about here]

As shown in Table 3, all interaction terms between CR imprints and the post-election day dummy variable are statistically significant at the 1% or 5% level. This suggests that opinion leaders with stronger CR imprints were more likely to exhibit anti-democratic tendencies after Trump's election defeat. To further investigate this relationship, we estimate the dynamic treatment effects of CR imprints on anti-democratic stances and plot the results in Figure A12 of the Online Appendix. Prior to the election day, the differences in denying the election result or advocating for its overthrow among Chinese opinion leaders with varying CR imprints are negligible and statistically insignificant. After the election day, however, opinion leaders with stronger CR imprints demonstrated a marked increase in anti-democratic tendencies.

In fact, the pro-Trump stances of Chinese opinion leaders were also evident during the 2020 Black Lives Matter (BLM) movement, prior to the US presidential election (as elaborated in Section E of the Online Appendix). The BLM movement drew attention to racism, discrimination, and inequality endured by Black people in the United States. Racial attitudes are a crucial dimension for understanding partisan polarization.[83] The 2020 George

Floyd Protests intensified partisan polarization of attitudes in the United States.[84] Thus, our findings indicate that opinion leaders' views on race and affirmative action — potential alternative explanations for Trumpism — are also shaped by their underlying authoritarian imprints.

4.5 Spillover Effects

An important question worth exploring is whether the CR imprints of opinion leaders have a broader impact. As an initial step, we delve into the potential spillover effects of these opinion leaders' tweets. We first examine whether a tweet with more CR words is more likely to be retweeted, responded to, or liked on Twitter. The results, displayed in Table A12 of the Online Appendix, indicate a positive correlation between the proportion of CR words in a tweet and the number of retweets, replies, and likes, even when controlling for the tweet's sentiment. In other words, tweets with a greater prevalence of CR language tend to elicit more engagement from Twitter users.

[Figure 2 about here]

Furthermore, we explore the extent to which exposure to tweets containing the CR language influences the anti-democratic attitudes of social media users. We identified the ten most widely circulated tweets with CR language posted between September 2020 and January 2021 based on the number of retweets (see Section F of the Online Appendix). These tweets were posted by the opinion leaders who used CR language to attack Democrats and either deny the election result or advocate for its overturn. We compiled a list of all Twitter accounts that retweeted these ten posts, yielding a total of 5,663 unique accounts. In this "natural" experiment, the treatment involves exposing social media users to tweets featuring the CR language. To minimize pre-treatment effects, namely, the likelihood of users being influenced by opinion leaders before they viewed and retweeted these tweets, we excluded accounts that were followers of any of the 199 opinion leaders, retaining only those accounts

($N = 691$) that did not directly follow them. Through the Twitter API, we collected all tweets posted by these 691 accounts from September 2020 to March 2021, resulting in nearly 600,000 tweets. Using the Support Vector Machine (SVM) algorithm, these tweets were classified based on whether they involved denying the election result or not, and whether they advocated for overturning the election result or not. We then assembled the data into an account-by-week panel dataset. For the outcome variable, to measure the anti-democratic stances of each account, we calculate the proportion of tweets that either contested the election result or advocated for its reversal, relative to the total number of tweets per account on a weekly basis. We conduct a staggered DID analysis following the method developed by.[85] Figure 2 shows that after being exposed to a tweet featuring CR language, Twitter users in our sample posted more tweets calling for the unconstitutional overthrow of the election result, whereas the tweets denying the election result did not significantly increase. Taken together, the use of CR language by Chinese opinion leaders to disseminate anti-democratic messages has considerable repercussions on social media, shaping public opinions towards Donald Trump, perceptions of election legitimacy, and crucially, faith in the U.S. democratic system.

5 Conclusion

Our study on the Chinese diaspora's support for Trumpism has offered insights into the relationship between authoritarian imprints and support for right-wing populism. We find that the Chinese diaspora's support for Trumpism is deeply rooted in the experience of authoritarianism in their home country. Our research underscores the enduring influence of authoritarian imprints, particularly among first-generation immigrants, which shapes their political attitudes long after they have emigrated to a democratic country.

By leveraging individual language styles on social media, our novel measure captures variation in authoritarian imprints within the Chinese diaspora. We demonstrate these imprints strongly predict pro-Trump and anti-democratic stances among overseas Chinese opinion leaders during and after the 2020 US presidential election. Our findings highlight the lasting influence of home country authoritarian regimes in shaping immigrant political behavior in new contexts. This enriches our understanding of populism's drivers among minority groups and diaspora communities beyond economic or cultural grievances. It also underscores how immigration transmits political values across borders. Future research could further investigate the extent to which similar authoritarian imprints from home countries endure across other immigrant communities and shape political ideology over time. As countries become more diverse, understanding immigrant political socialization will gain greater importance.

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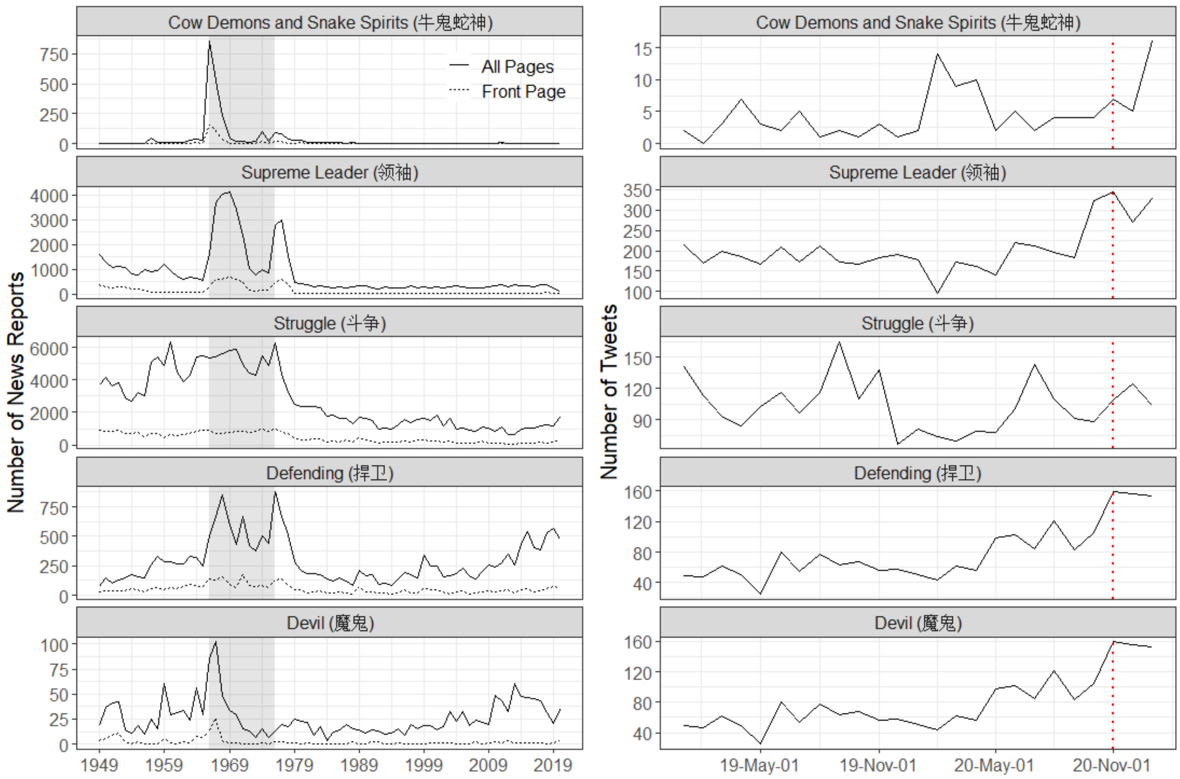
Figure 1: The Usage Trends of Five Prototypical Cultural Revolution Words



Notes: The left panel presents the usage trends of these five words across the front page and all pages of *People' s Daily*, with the grey area indicating the CR period. The right panel illustrates the usage trends of these words within the tweet corpus, with the dotted line representing Election Day. The two peaks in the usage trend of the word "struggle" before the dotted line correspond to Hong Kong's Anti-extradition Law Amendment Bill (ELAB) movement and the Black Lives Matter (BLM) movement, respectively.

Table 1: The Persistence of the Cultural Revolution Imprints

Panel A. Summary Statistics

Variables	Observations	Mean	Median	Std. Dev.
CR Imprints (2019.01–2019.12)	33,091	0.082	0.072	0.069
CR Imprints 1 (2019.01–2019.06)	15,664	0.079	0.069	0.068
CR Imprints 2 (2019.07–2019.12)	17,427	0.085	0.075	0.070
CR Imprints (2020.01–2021.01)	48,324	0.080	0.072	0.065

Panel B. CR Imprints Persistence

	Dependent variable: CR Imprints (2020.01–2021.01)					
	(1)	(2)	(3)	(4)	(5)	(6)
CR Imprints	0.698***	0.696***				
	(0.053)	(0.053)				
CR Imprints 1			0.492***	0.490***		
			(0.079)	(0.079)		
CR Imprints 2					0.617***	0.616***
					(0.058)	(0.059)
Observations	45,566	45,566	41,615	41,615	45,335	45,335
Date FE	NO	YES	NO	YES	NO	YES

Notes: We measure the CR imprints in 2019 by using different time periods, including the entire year of 2019 (i.e., 2019.01–2019.12), the first half-year of 2019 (i.e., 2019.01–2019.06), and the second half-year of 2019 (i.e., 2019.07–2019.12). The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Table 2: CR Imprints and Pro-Trump and Anti-Democratic Stances

	Dependent Variable							
	Supporting Trump		Denying the result		Overthrowing the result		Anti-Democracy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CR Imprints	0.091*	0.090*	0.127***	0.131***	0.014*	0.013*	0.140***	0.144***
	(0.048)	(0.048)	(0.039)	(0.039)	(0.007)	(0.007)	(0.043)	(0.043)
Age		-0.001		-0.001		0.000		-0.001
		(0.003)		(0.003)		(0.001)		(0.003)
Education		0.006*		0.006*		0.000		0.006
		(0.003)		(0.003)		(0.001)		(0.004)
Wikipedia		0.000		0.000		-0.000		0.000
		(0.002)		(0.002)		(0.000)		(0.002)
Sentiment		-0.001***		-0.001***		0.000**		-0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
Observations	24,118	24,118	24,118	24,118	24,118	24,118	24,118	24,118
Mean of DV	0.013	0.013	0.013	0.013	0.002	0.002	0.015	0.015
Date FE	YES	YES	YES	YES	YES	YES	YES	YES

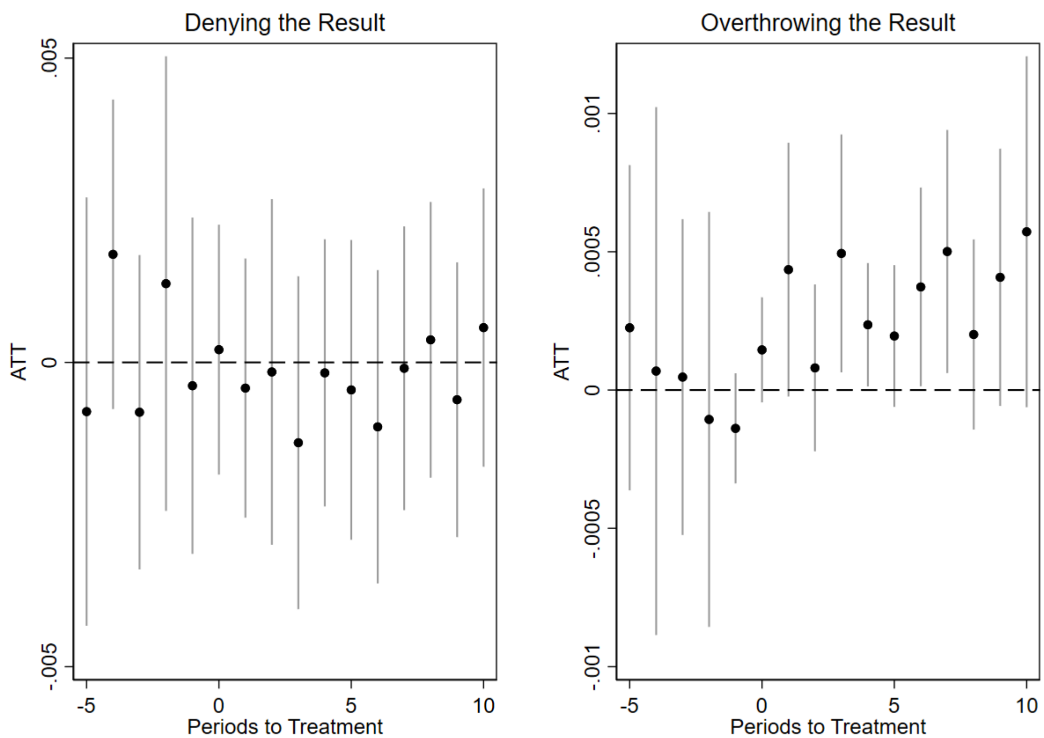
Notes: The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Table 3: CR Imprints and Anti-Democratic Stances:
A Difference-in-Differences Analysis

	Dependent Variable					
	Denying the result		Overthrowing the result		Anti-Democracy	
	(1)	(2)	(3)	(4)	(5)	(6)
CR Imprints × Post-Election	0.134**	0.133**	0.021*	0.022*	0.156***	0.155***
	(0.051)	(0.052)	(0.012)	(0.012)	(0.055)	(0.055)
Observations	24,117	24,117	24,117	24,117	24,117	24,117
Controls	NO	YES	NO	YES	NO	YES
Account FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES

Notes: The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Figure 2: The Spillover Effects on Twitter Users' Anti-Democratic Stances



Notes: The coefficients obtained from the staggered DID analysis are plotted, with the 95% confidence interval represented by the grey vertical line.

Online Appendix

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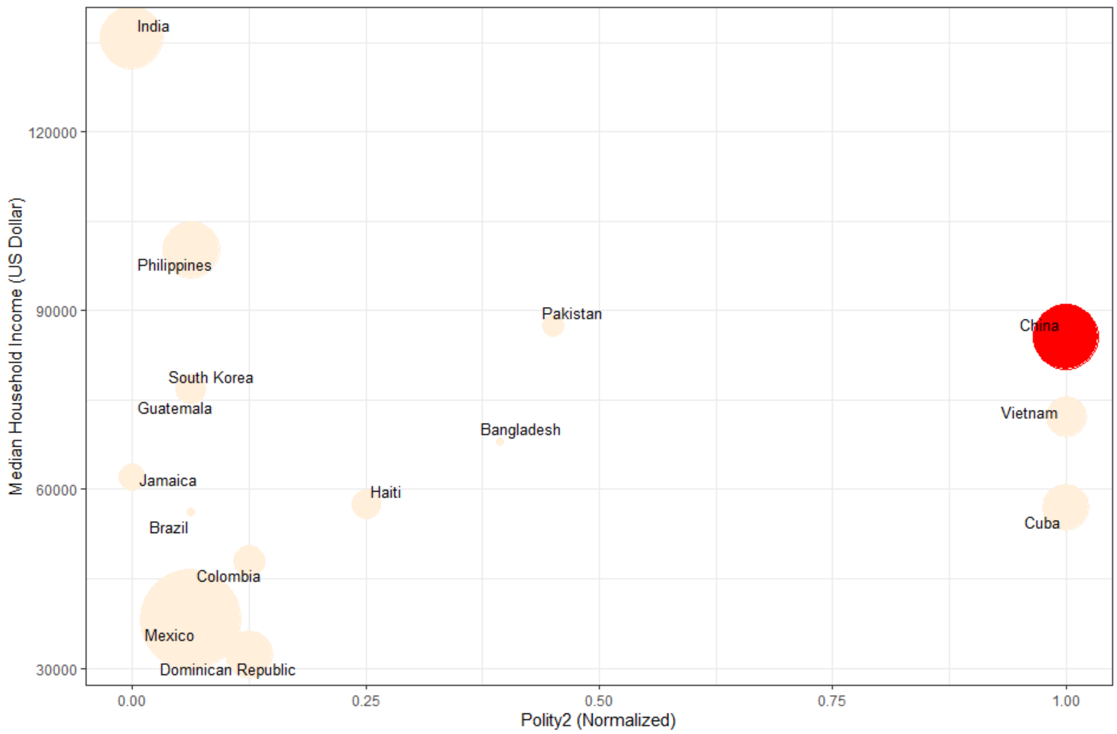
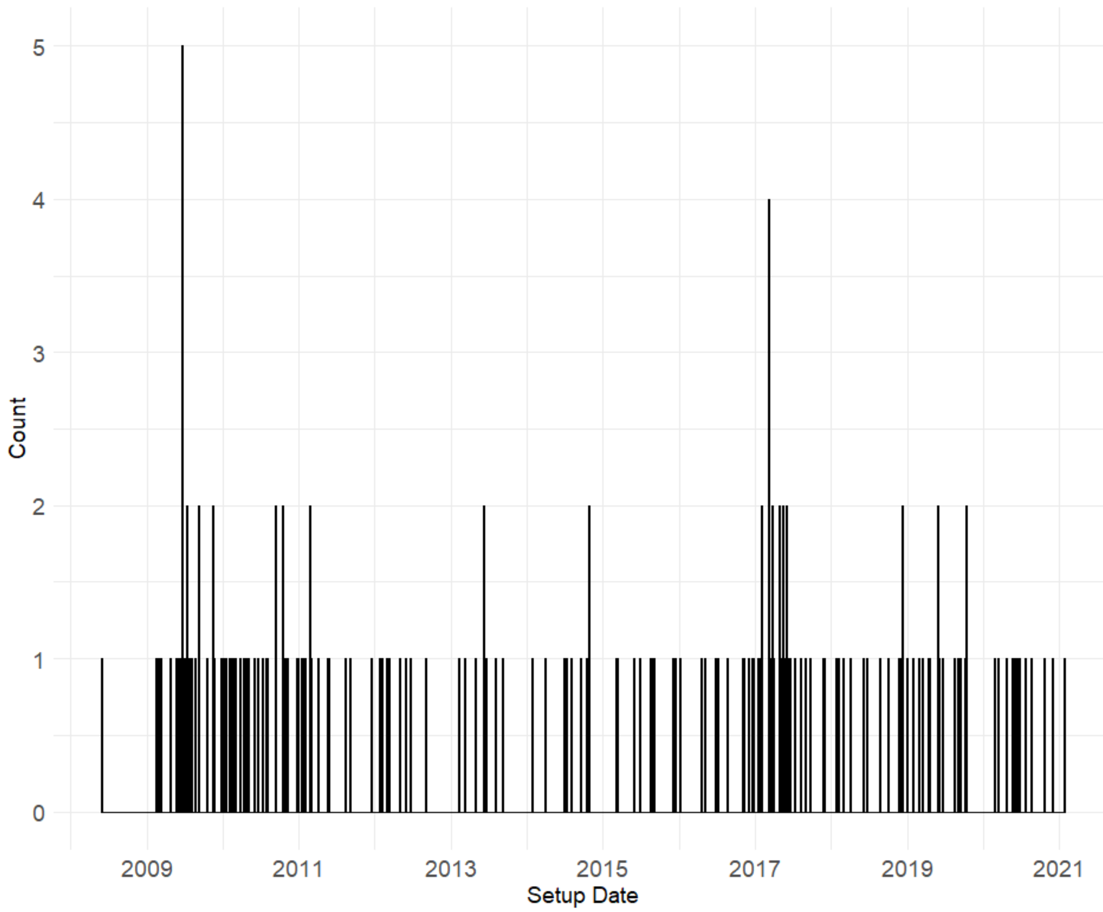
A Supplementary Figures

Figure A1: Top 15 Countries of Origin for Immigrants in the United States (2000–2019)



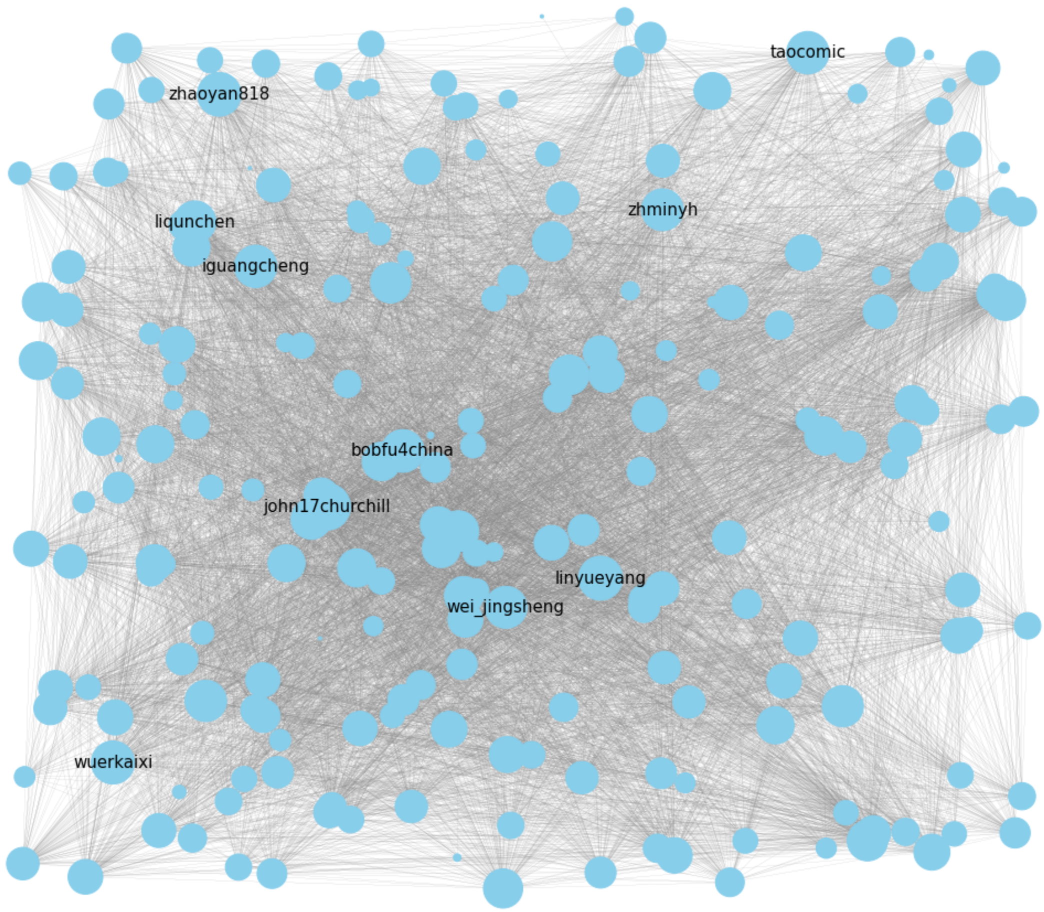
Notes: The x-axis represents a normalized Policy2 score, where "0" indicates full democracy and "1" denotes full autocracy. The y-axis indicates the median household income. The size of the circles corresponds to the number of immigrants from 2000 to 2019. Notably, China is the second-largest source of U.S. immigrants and the largest source among authoritarian countries.
Data source: the U.S. Department of Homeland Security

Figure A2: Distribution of Set-Up Dates for 199 Twitter Accounts



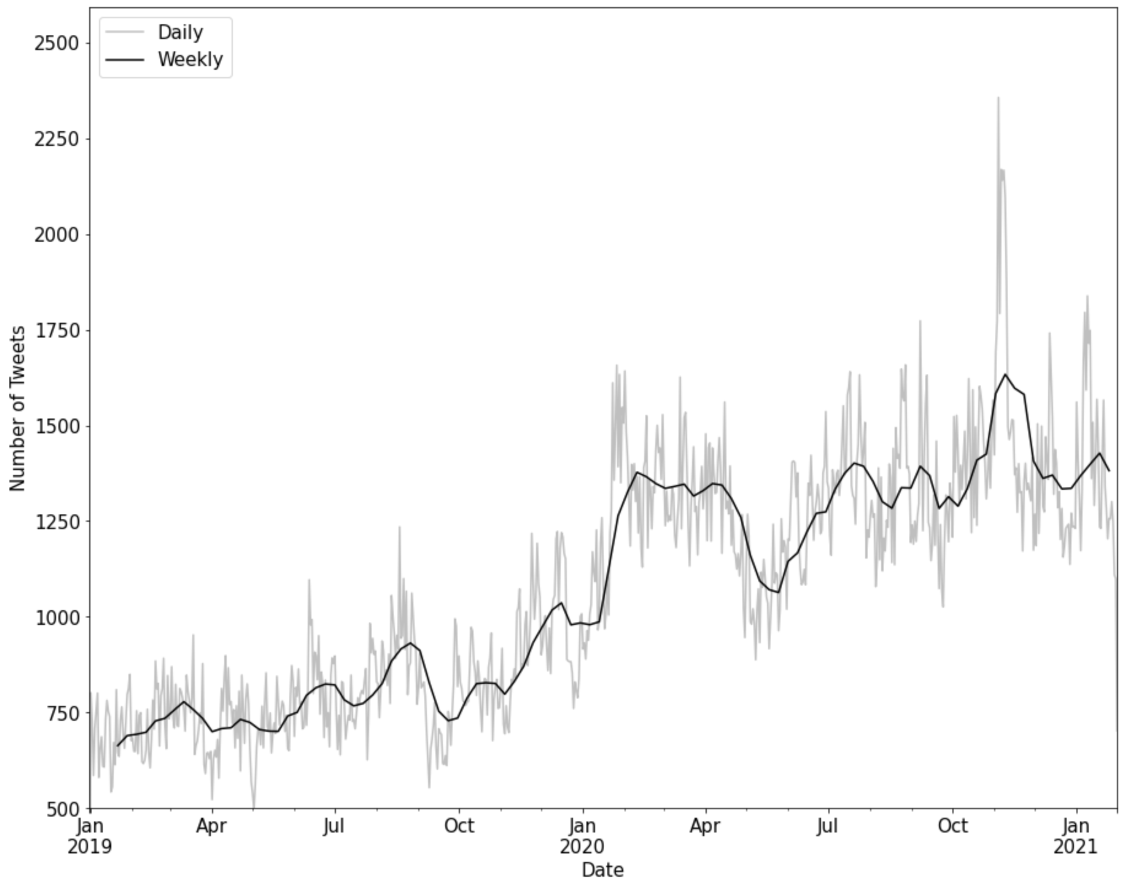
Notes: This histogram shows the set-up date of each account in our research. As can be seen, most of them were created before 2019.

Figure A3: Interconnection Network of Opinion Leader Accounts



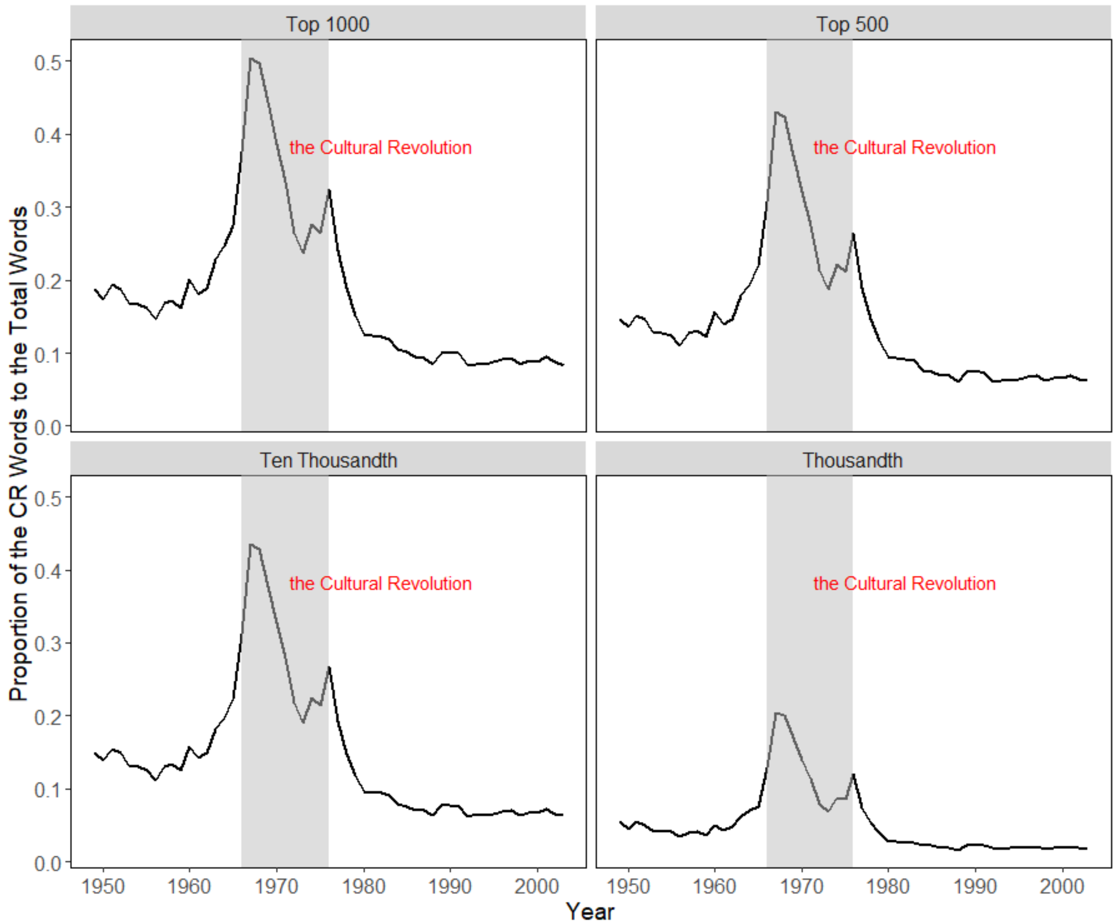
Notes: The figure shows the interconnection network among the 199 Twitter accounts based on their mutual following relationships. The size of each node refers to its centrality in the network. Labels for the top ten accounts are shown.

Figure A4: The Number of Tweets in the Sample Over Time



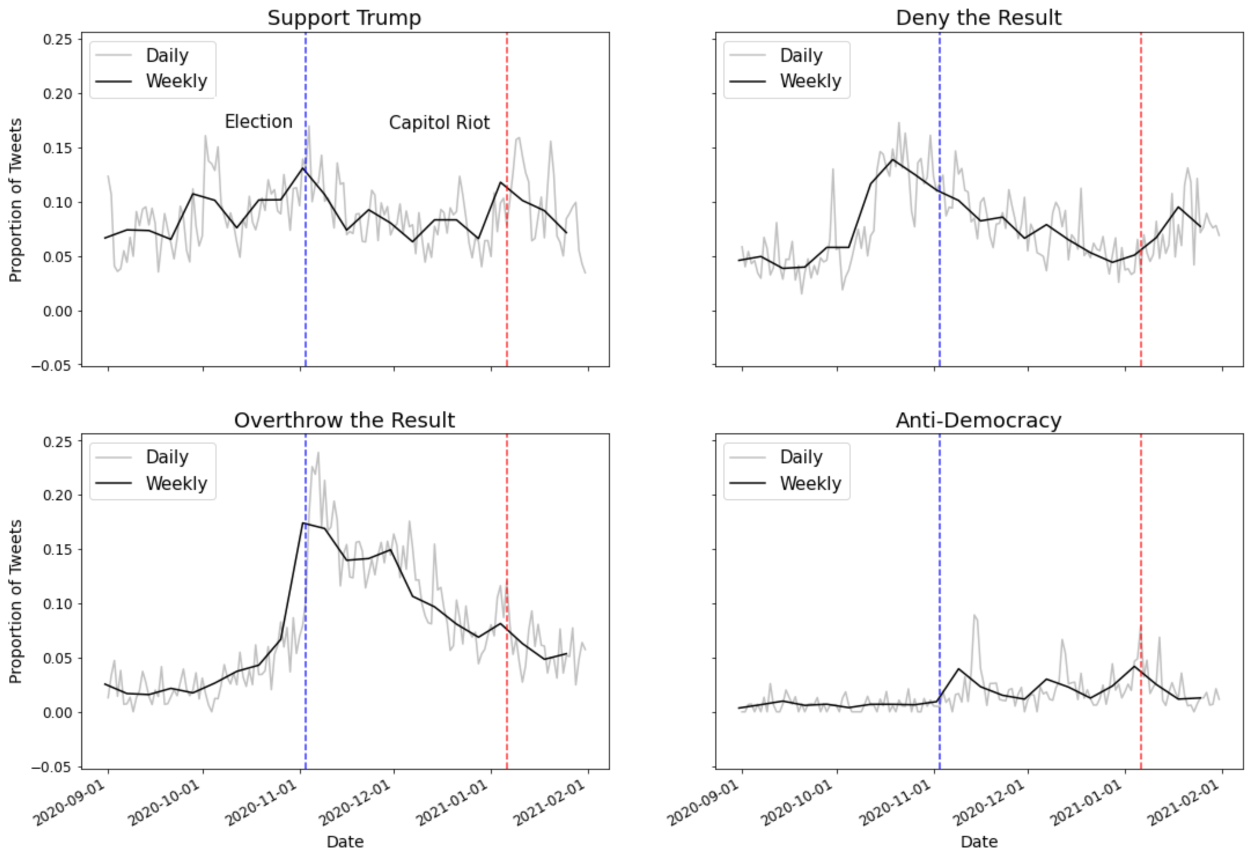
Notes: The grey and black lines represent the daily and weekly total number of tweets released by 199 Twitter accounts in our sample, respectively. Notably, in November 2020, when the U.S. presidential election took place, the number of tweets reached its peak.

Figure A5: The Distribution of Cultural Revolution (CR) Words in *People's Daily*



Notes: The *People's Daily* corpus includes all news articles published between 1949 and 2003. The four panels plot the proportions of CR words relative to the total word count over time, using the top 1,000, the top 500, a relative frequency greater than 1/10,000, and a relative frequency greater than 1/1,000 as cut-off points, respectively. The grey areas denote the Cultural Revolution period (1966–1976). It is evident that regardless of the chosen cut-off, the patterns remain strikingly similar.

Figure A6: The Proportions of Pro-Trump and Anti-Democratic Tweets



Notes: According to the supervised learning results, the four subfigures depict the daily and weekly proportions of pro-Trump and anti-democratic tweets relative to the total number of tweets over time. Notably, both on Election Day and during the Capitol riot, the proportions of pro-Trump and anti-democratic tweets exhibit a substantial increase.

Figure A7: Top 1,000 Retweeted Tweets Word Cloud (Sep 2020–Jan 2021)

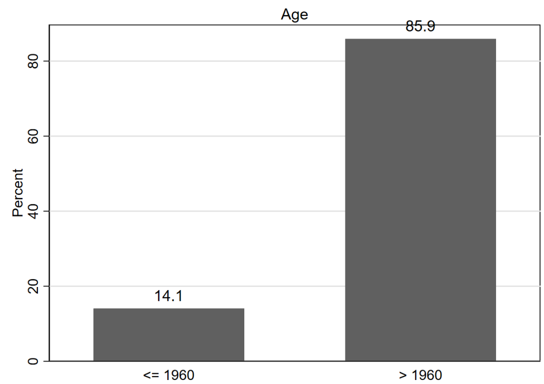
(a) Chinese Word Cloud

(b) English Word Cloud (Translated)

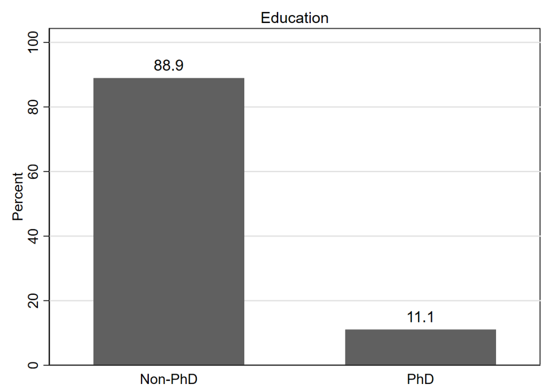
Notes: The Word Cloud depicts the 1,000 tweets with the highest number of retweets between September 2020 and January 2021. The size of each term in the cloud corresponds to the frequency of its usage. In addition to election-related words such as “America”(美国), “Baiden”(拜登),“Trump”(川普), “president” (总统), “election”(大选), “votes”(选票), it becomes evident that terms such as “revolution” (革命), “fake” (造假), and “fraud” (舞弊) were frequently employed to challenge the election result.

Figure A8: Distribution of Covariates

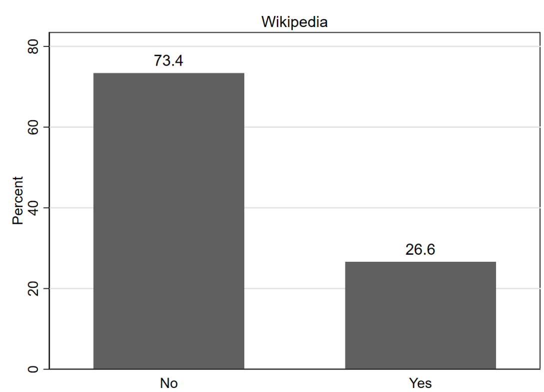
Panel A. Age



Panel B. Education

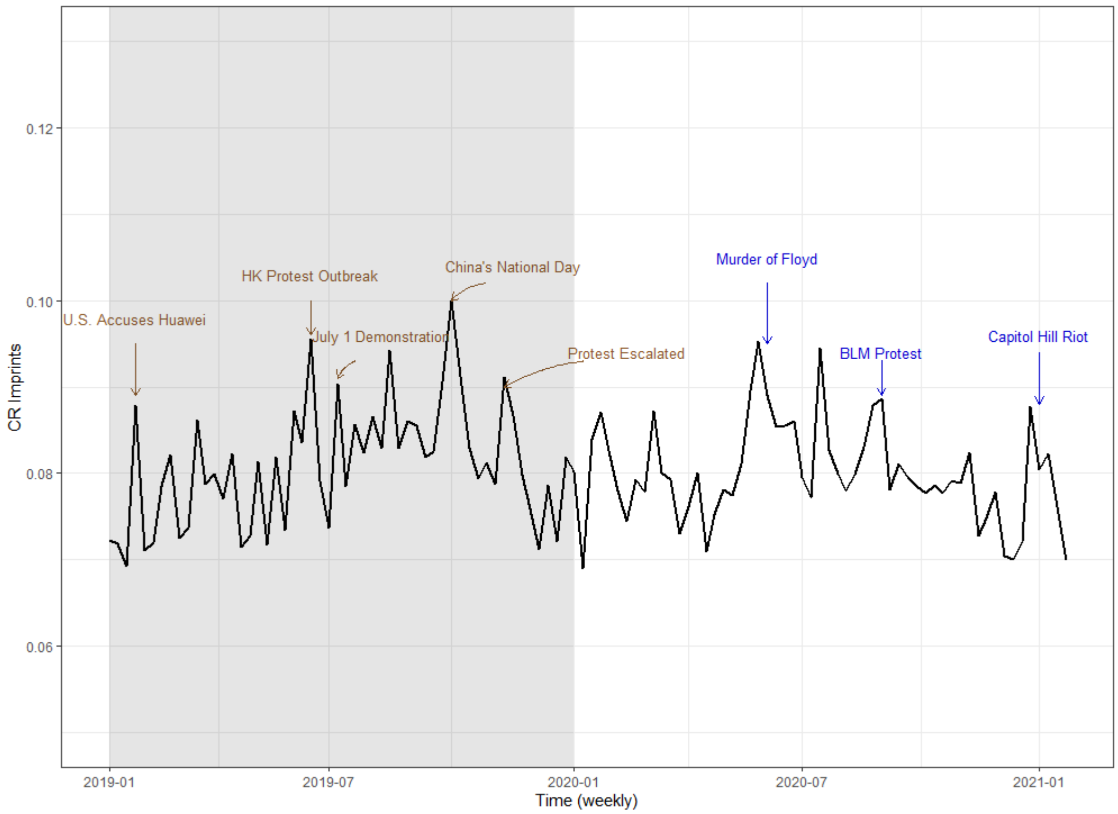


Panel C. Wikipedia



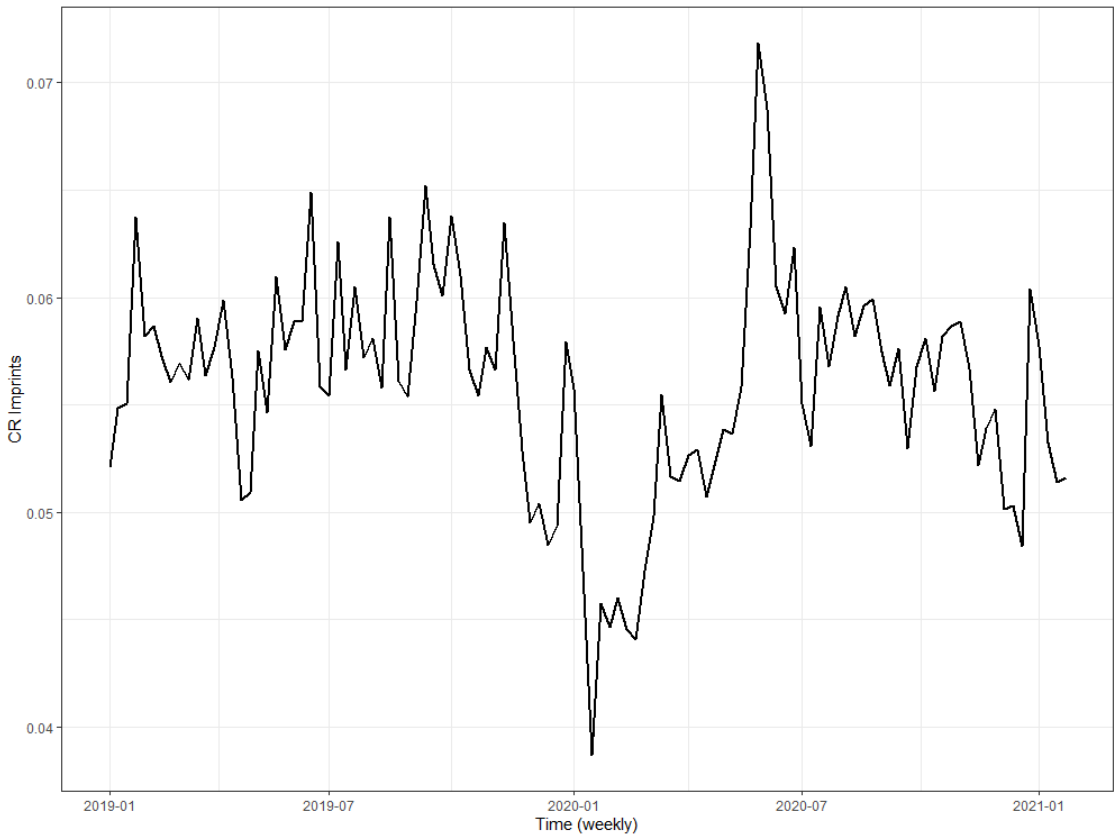
Notes: The three covariates are binary variables. Bar charts show the percentage distribution of each variable.

Figure A9: The Cultural Revolution Imprints in Tweets



Notes: We first calculate the proportion of CR words to the total number of words in each tweet. Then, we compute the mean value of CR imprints on a weekly basis. The results show that the spikes of CR imprints in the tweet corpus are associated with significant events related to China or the US.

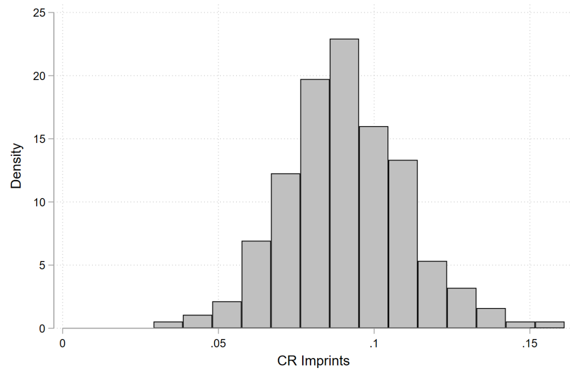
Figure A10: The Cultural Revolution Imprints in Tweets (Top 500 Words)



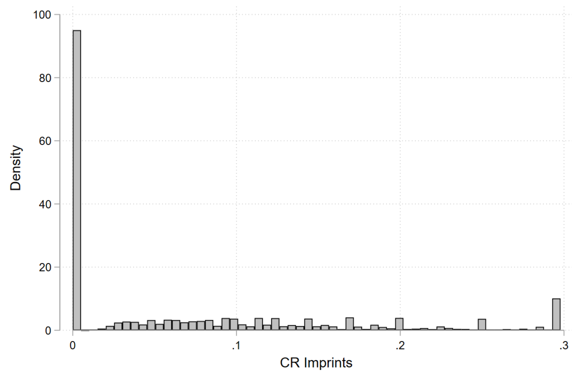
Notes: In this table, we use the top 500 words from the *People's Daily* CR word rankings as an alternative CR dictionary.

Figure A11: The Density of Cultural Revolution Imprints Across Different Samples

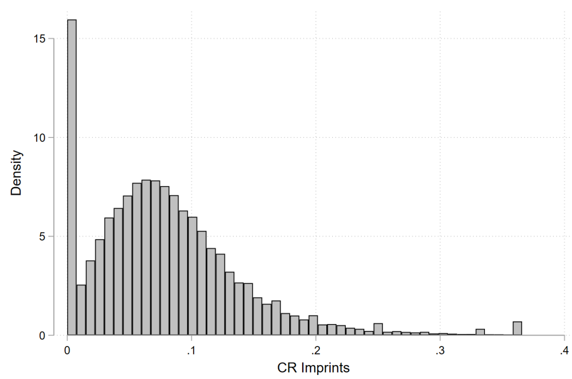
Panel A. Account Sample



Panel B. Tweet Sample



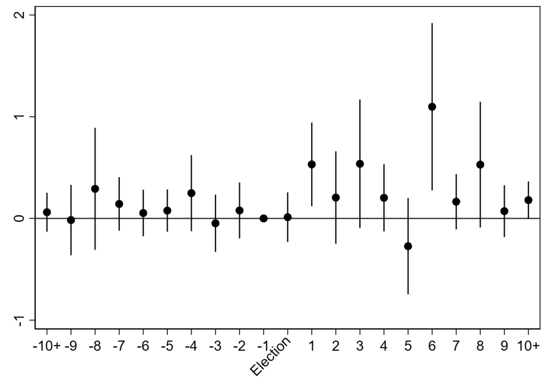
Panel C. Account-Date Sample



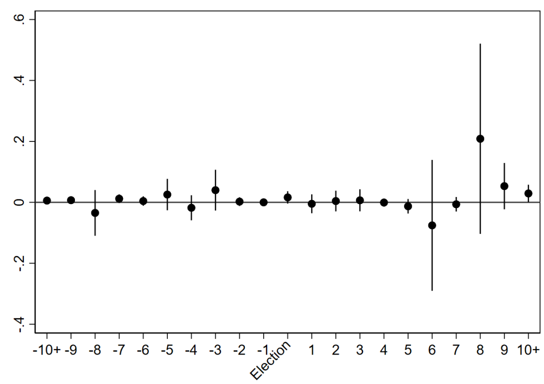
Notes: The density plots in the three panels illustrate the distribution of the CR imprints at the account, tweet, and account-by-date levels. In the second and third panels, we have winsorized the data at levels of 0.05 and 0.005, respectively.

Figure A12: Dynamic Effects of CR Imprints on Anti-Democratic Stances

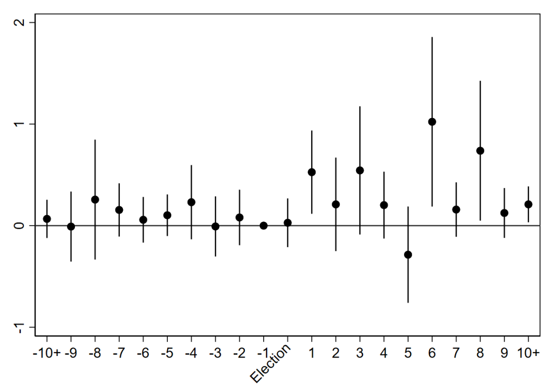
Panel A. Denying the Result



Panel B. Overthrowing the Result

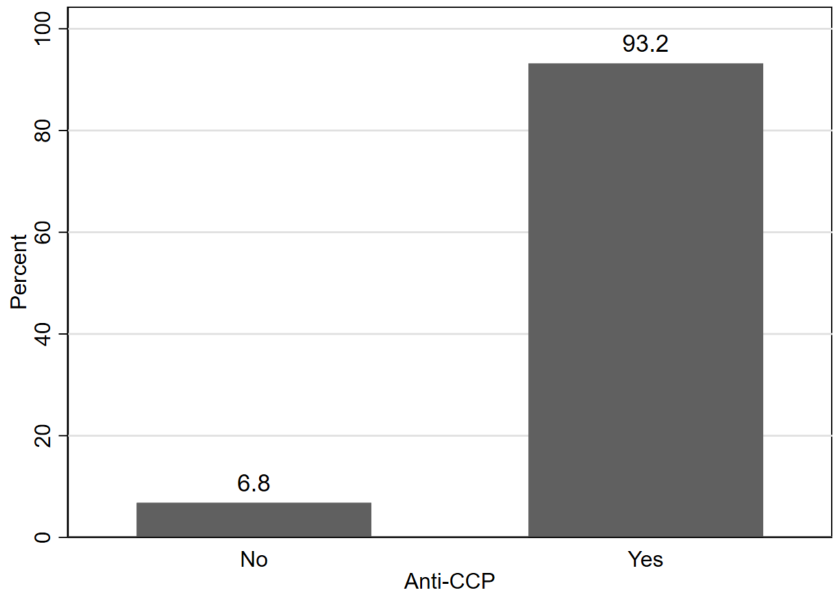


Panel C. Anti-Democracy



Notes: The coefficients of the interaction terms between CR imprints and day dummies are plotted, with 95% confidence interval represented by vertical lines. Our treatment period begins on November 3rd, 2020, the day of the US presidential election.

Figure A13: Distribution of Anti-CCP Stances



Notes: This figure depicts the proportion of accounts that had ever posted anti-CCP tweets during this period.

B Supplementary Tables

Table A1: Media Outlets Used in Sample Construction

Twitter Account Name	Twitter Handle	Account Registration Time	Number of Followers
BBC News 中文	@bbcchinese	February 2007	2,232,559
纽约时报中文网	@nytchinese	June 2012	1,698,372
华尔街日报中文网	@ChineseWSJ	June 2009	1,428,267
美国之音中文网	@VOAChinese	August 2007	1,306,554
自由亚洲电台	@RFA_Chinese	November 2008	726,336
DW 中文- 德国之声	@dw_chinese	May 2010	582,613
联合早报 Lianhe Zaobao	@zaobaosg	May 2009	556,583
FT 中文网	@FTChinese	March 2009	353,506
RFI 華語 - 法國國際廣播電台	@RFI_TradCn	April 2009	330,290
明镜新闻网	@MingJingNews	December 2011	318,959
博讯新闻网	@boxun	June 2009	232,877
日经中文网	@rijingzhongwen	November 2017	205,785
大纪元新闻网	@dajiyuan	July 2009	169,275
ABC 中文	@ABCChinese	December 2010	142,163
KBS World Chinese	@KBSChinese	May 2010	51,240
加拿大国际广播	@RCIZhongwen	April 2010	28,645
		Total	10,364,024

Notes: This table displays the details of media outlets that we used to construct the sample of overseas Chinese opinion leaders. The media outlets in the table, from top to bottom, are BBC News Chinese, the New York Times Chinese, the Wall Street Journal Chinese, Voice of America Chinese, Radio Free Asia, Deutsche Welle Chinese, Lianhe Zaobao, Financial Times Chinese, Radio France Internationale Chinese, Mirror Media, Boxun News, Nikkei Chinese, Epoch Times, Australian Broadcasting Corporation (ABC) Chinese, Korean Broadcasting System (KBS) Chinese, Radio Canada International (RCI) Chinese. We chose the top 16 media outlets by the number of followers because those ranked 17th and below were non-mainstream and less influential, with fewer than 20,000 followers. We have collected detailed information about these followers, including account IDs, the number of follower and following accounts, as well as profile descriptions.

Table A2: **Key Social Media Metrics of the Top 10 Opinion Leaders**

Rank	Twitter Account Handle	Number of Followers	Tweets	Retweets	Replies	Likes
1	@remonwangxt	421,946	3,697	243,151	85,535	1,027,980
2	@aiww	372,989	13,275	79,107	23,186	169,050
3	@xiayeliang	290,050	4,203	8,156	13,877	62,109
4	@shifeike	249,913	654	9,325	5,452	30,136
5	@wangzhian8848	244,373	3,048	124,578	258,673	758,339
6	@heqinglian	228,729	14,625	153,202	70,230	645,693
7	@tengbiao	213,136	1,449	19,945	15,862	60,727
8	@wangdan1989	211,567	2,645	48,409	40,837	270,091
9	@mjtvhopin	202,451	14,404	69,372	93,801	218,053
10	@xchen156	200,482	181	2,449	2,560	11,927
	Sum of the top 10	2,635,636	58,181	757,694	610,013	3,254,105
	Average of the top 10	263,564	5,818	75,769	61,001	325,411
	Average of all in the sample	59,231	4,017	37,698	17,310	129,055

Notes: This table outlines the key metrics of the 10 most-followed accounts. The retweets, replies, and likes columns indicate the total number of times the tweets of each account were retweeted, replied, and liked between January 2019 and January 2021. In addition, the sum and average values of the key metrics for the top 10 and all opinion leaders in the sample are presented. These metrics suggest that the overseas Chinese opinion leaders in our sample are not only influential within the overseas Chinese community but are also highly active on social media. The total number of followers for these 199 opinion leaders is about 12 million, with the most influential leader having 421,946 followers. Each opinion leader, on average, had roughly 59,231 followers. Moreover, these opinion leaders generated 817,216 tweets during the two-year sample period. This translates to an average of about 145 tweets per account each month. As expected, opinion leaders' tweets attracted considerable attention from Twitter users, with the total number of retweets, replies, and likes reaching around 7.5 million, 3.4 million, and 25.7 million, respectively. On average, each tweet received 9.2 retweets, 4.2 replies, and 31.4 likes.

Table A3: Top 30 Frequently Used CR Words

1	革命 (revolution)	16	思想 (thought)
2	毛主席 (Chairman Mao)	17	路线 (political line)
3	无产阶级 (proletariat)	18	贫下中农 (poor and lower-middle peasants)
4	人民 (people)	19	学习 (study)
5	毛泽东思想 (Mao Zedong thought)	20	著作 (works)
6	斗争 (struggle)	21	阶级 (class)
7	群众 (the masses)	22	革委会 (revolutionary committee)
8	伟大 (great)	23	美帝国主义 (American imperialism)
9	文化大革命 (the Cultural Revolution)	24	反动 (reactionary)
10	资产阶级 (bourgeoisie)	25	苏修 (Soviet revisionism)
11	修正主义 (revisionism)	26	指示 (directives)
12	敌人 (enemy)	27	伟大领袖 (great leader)
13	教导 (teach and instruct)	28	资本主义 (capitalism)
14	胜利 (victory)	29	阶级斗争 (class struggle)
15	同志 (comrade)	30	道路 (road)

Notes: This table presents the 30 most frequently used words in the *People's Daily* during the Cultural Revolution period.

Table A4: Summary Statistics of CR Imprints Across Different Samples

Panel A. Account Sample				
Variables	Observations	Mean	Median	Std. Dev.
CR Imprints	199	0.091	0.090	0.020
Panel B. Tweets Sample				
Variables	Observations	Mean	Median	Std. Dev.
CR Imprints	817,216	0.079	0.029	0.120
Panel C. Account-Date Sample				
Variables	Observations	Mean	Median	Std. Dev.
CR Imprints (2019.01–2019.12)	33,091	0.082	0.072	0.069
CR Imprints 1 (2019.01–2019.06)	15,664	0.079	0.069	0.068
CR Imprints 2 (2019.07–2019.12)	17,427	0.085	0.075	0.070

Notes: The summary statistics of CR imprints are presented across three panels, each representing different levels of analysis: account level, tweet level, and account by date level.

Table A5: Performance Comparison of Supervised Learning Algorithms for Classifying Pro-Trump and Anti-Democratic Tweets

	Logistic Regression	K-nearest Neighbor	Multinomial Naive Bayes	Support Vector Machine	Random Forest
Precision	0.85	0.85	0.85	**0.87**	0.85
Recall	0.92	0.92	0.92	**0.92**	0.92
F1-score	0.89	0.89	0.89	**0.89**	0.89

Notes: During the 2020 U.S. presidential election period, overseas Chinese opinion leaders posted a substantial number of tweets related to the election. We randomly selected 2,400 tweets from the period between September 2020 and January 2021 and had research assistants manually classify them into the following categories, including "supporting Trump," "denying the election result," "advocating for overthrowing the result," and others. We then employed supervised machine learning algorithms to train a classifier that could categorize the remaining approximately 220,000 tweets. These metrics are the results of k-fold cross-validation based on the manually coded tweets. After evaluating several classification algorithms, we find that the support vector machine (SVM) performs the best, as shown in this table.

Table A6: Performance Comparison of Supervised Learning Algorithms for Imputing Missing Values

			Age (Born Pre- or Post-1960)		
	Logit Regression	Decision Tree	XGBoost	Support Vector Machine	Deep Neural Networks
F1-score	0.78	0.78	**0.85**	0.82	0.78
			Education (Ph.D. Degree Holder or Not)		
	Logit Regression	Decision Tree	XGBoost	Support Vector Machine	Deep Neural Networks
F1-score	0.67	0.67	**0.74**	0.72	0.70

Notes: Despite the wealth of information on opinion leaders through open-access websites, some data still remains incomplete. To address this challenge, we employ supervised learning methods by training a classifier with available information to estimate the missing values. To enhance accuracy, age is recoded as a binary variable, with a value of "1" indicating individuals born after 1960 and a value of "0" indicating those born earlier. Education is also recoded in binary form, with a value of "1" indicating individuals holding a Ph.D. degree and a value of "0" indicating those without. These metrics are the results of k-fold cross-validation based on the manually coded tweets. After evaluating various classification algorithms as shown in this table, we selected XGBoost to train the classifier and impute the missing values.

Table A7: Results Using Top 500 CR Words as an Alternative Dictionary

	Supporting Trump		Denying the result		Overthrowing the result		Anti-Democracy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CR Imprints	0.350***	0.354***	0.321***	0.333***	0.067***	0.067***	0.388***	0.400***
	(0.053)	(0.052)	(0.066)	(0.067)	(0.014)	(0.014)	(0.076)	(0.078)
Age		-0.001		-0.001		0.000		-0.001
		(0.003)		(0.002)		(0.000)		(0.002)
Education		0.001		0.006*		-0.000		0.005
		(0.002)		(0.003)		(0.001)		(0.003)
Wikipedia		-0.003		-0.001		-0.000		-0.002
		(0.002)		(0.002)		(0.000)		(0.002)
Sentiment		0.001***		-0.001***		0.000		-0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
Observations	26,360	26,360	26,360	26,360	26,360	26,360	26,360	26,360
Mean of DV	0.013		0.013		0.002		0.015	
Date FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: An alternative CR dictionary is created using the top 500 words as the cut-off point. The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Table A8: Results of the Falsification Test

	(1) Supporting Trump	(2) Denying the result	(3) Overthrowing the result	(4) Anti-Democracy
Non-CR Imprints	0.005	0.042	0.009	0.051
	(0.012)	(0.038)	(0.007)	(0.045)
Observations	24,118	24,118	24,118	24,118
Controls	YES	YES	YES	YES
Date FE	YES	YES	YES	YES

Notes: A falsification test is conducted by developing a dictionary of non-Cultural Revolution (non-CR) words. We select the 500 words both above and below the median from a word list ranked by relative frequency during the Cultural Revolution to create a new dictionary. We then compute non-CR imprints as the proportion of non-CR words in this dictionary to the total words in each account's tweets. This table estimates the effects of non-CR imprints on pro-Trump and anti-democratic stances. The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Table A9: Heterogeneous Effects

Panel A. Heterogeneous Effects by Age				
	Supporting Trump	Denying the result	Overthrowing the result	Anti-Democracy
	(1)	(2)	(3)	(4)
CR Imprints	0.090	0.094	0.027*	0.121*
	(0.104)	(0.069)	(0.015)	(0.072)
Age (>1960)	-0.001	-0.005	0.002	0.003
	(0.012)	(0.007)	(0.001)	(0.008)
CR Imprints × Age	-0.000	0.045	-0.017	0.029
	(0.118)	(0.085)	(0.018)	(0.090)
Observations	24,118	24,118	24,118	24,118
Controls	YES	YES	YES	YES
Date FE	YES	YES	YES	YES

Panel B. Heterogeneous Effects by Education				
	Supporting Trump	Denying the result	Overthrowing the result	Anti-Democracy
	(1)	(2)	(3)	(4)
CR Imprints	0.081	0.120***	0.013*	0.133***
	(0.051)	(0.041)	(0.008)	(0.045)
Education (1= Ph.D. Degree)	-0.011	-0.007	-0.001	-0.008
	(0.008)	(0.009)	(0.001)	(0.009)
CR Imprints × Education	0.140	0.168	0.004	0.171
	(0.102)	(0.127)	(0.016)	(0.133)
Observations	24,118	24,118	24,118	24,118
Controls	YES	YES	YES	YES
Date FE	YES	YES	YES	YES

Notes: The table displays heterogeneous effects by age and education levels. The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Table A10: Performance Comparison of Supervised Learning Algorithms for Classifying Anti-CCP Tweets

	Logistic Regression	K-nearest Neighbor	Multinomial Naive Bayes	Support Vector Machine	Random Forest
F1-score	0.86	0.83	0.83	**0.89**	0.83
Balanced Accuracy	0.56	0.50	0.50	**0.64**	0.50

Notes: We randomly selected 3,200 tweets from January 2020 to January 2021 as our training sample. A research assistant was trained to manually code the tweets as "1" if their content involves denouncing the CCP, Chinese government, or China's top leadership, and "0" otherwise. Examples are listed in Section G of the Online Appendix. We cross-checked the coding results before applying supervised learning algorithms to train a classifier. The metric results from k-fold cross-validation based on the manually coded tweets. The table shows that the SVM outperforms the other four commonly used algorithms.

Table A11: Results Controlling for Anti-CCP Stances

	Supporting Trump (1)	Denying the result (2)	Overthrowing the result (3)	Anti-Democracy (4)
CR Imprints	0.094*	0.135***	0.015*	0.150***
	(0.051)	(0.042)	(0.008)	(0.046)
Anti-CCP	-0.005	-0.007	-0.002	-0.009
	(0.008)	(0.007)	(0.002)	(0.009)
Observations	24,118	24,118	24,118	24,118
Controls	YES	YES	YES	YES
Date FE	YES	YES	YES	YES

Notes: The table shows the association between CR imprints and pro-Trump and anti-democratic stances when controlling for anti-CCP stances. The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Table A12: The Spillover Effects of CR Imprints

	Dependent Variable					
	Retweets		Replies		Likes	
	(1)	(2)	(3)	(4)	(5)	(6)
CR Imprints	4.944***	3.647***	1.517***	1.330***	15.735***	12.065***
	(1.228)	(0.736)	(0.300)	(0.274)	(3.556)	(2.416)
Sentiment	-0.013	-0.014	0.023	0.021	0.462	0.370
	(0.133)	(0.124)	(0.043)	(0.038)	(0.369)	(0.351)
Observations	817,216	804,548	817,216	804,548	817,216	804,548
Controls	YES	YES	YES	YES	YES	YES
Date FE	YES	NO	YES	NO	YES	NO
Account FE	YES	NO	YES	NO	YES	NO
Date × Account FE	NO	YES	NO	YES	NO	YES

Notes: The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

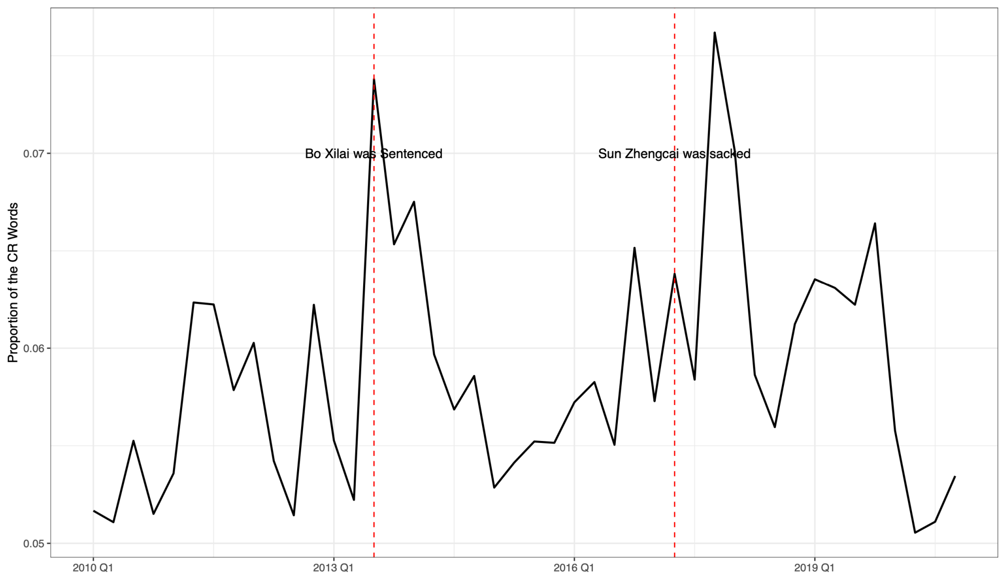
C The Use of CR Words during Anti-Corruption Campaigns

Our focus is on the cases of Bo Xilai and Sun Zhengcai, two prominent figures involved in high-profile corruption cases, to provide insight into the use of CR words during anti-corruption campaigns. Bo Xilai and Sun Zhengcai both held the position of party secretary of Chongqing and were considered contenders for top leadership within the CCP. Following their downfall, the official newspaper of the Chongqing Party Committee, *Chongqing Daily*, employed CR words in its coverage of their corruption cases. During this time, the official newspaper of the Chongqing Party Committee, *Chongqing Daily*, employed CR words in its coverage of their corruption cases. Figure C1 illustrates that the usage of CR words in *Chongqing Daily* reached its peak after the purging of Bo Xilai and Sun Zhengcai.

When reporting Bo Xilai's case, *Chongqing Daily* used such terms as "struggle" (*douzheng*), "thought" (*sixiang*), "firmly" (*jianding*), "determined" (*jianjue*), and "political line" (*luxian*) to denounce Bo Xilai and signal loyalty to the central authorities. For instance, in an article entitled "The Four Consciousnesses Must Be Further Enhanced," Chongqing Daily stated, "At present, our country's reform and development is in a critical period, and the struggle in the ideological field is sharp and complex. If we do not have a correct political awareness and cannot look at problems politically, we may lose our political direction and lose our political stance. Emphasizing the enhancement of political awareness is to guide party members and cadres to unswervingly maintain a high degree of unity with the party Central Committee with Comrade Hu Jintao as the general secretary, and to firmly adhere to the socialist pathway, theoretical system, and institutions with Chinese characteristics."[1]

In addition, Chongqing Daily adopted similar propaganda strategies when framing the Sun Zhengcai case. The newspaper employed terms such as "leader" (*lingxiu*), "loyal" (*zhongcheng*), "eradicate" (*suqing*), and "pernicious influence" (*liudu*) in its narrative to condemn Sun Zhengcai and demonstrate loyalty to the central leadership. In an article dated October 1, 2017, Chongqing Daily strongly criticized Sun Zhengcai for being a "fair-weather official" (*taiping guan*) and a "two-faced man" (*liang mian ren*). The newspaper

Figure C1: The Proportion of CR Words in Chongqing Daily



Notes: Drawing on all news articles published on Chongqing Daily between 2005 and 2020, the figure plots the proportion of CR words to the total words each quarter.

concluded that Sun Zhencai's case "has had a great impact on Chongqing's reform and development and its external image. It is necessary to link the eradication of Sun Zhengcai's negative influence with the actual implementation of various ongoing tasks."[2] In another article published on February 3, 2018, this newspaper stressed that "(everyone has) a deep understanding of the true colors and serious harms of Sun Zhengcai, as well as Bo Xilai and Wang Lijun, a deep reflection and analysis of the existing problems, and a deep thinking of the direction and measures of rectification. Everyone believes that Sun Zhengcai and Bo Xilai exemplify a combination of political degeneration, economic greed, and life corruption. The most prominent problem is political corruption. The reasons for Sun Zhengcai and Bo Xilai's violations of discipline and law vary, while the most fundamental one lies in ideological and political problems. Sun Zhengcai and Bo Xilai have caused significant losses to Chongqing, and the most serious consequence is that they have polluted Chongqing's political ecology. There are many things to be done in the eradication work. The most important task is to always maintain a high degree of consistency with the Party Central Committee with Comrade Xi Jinping as the core, ideologically, politically, and in action."[3]

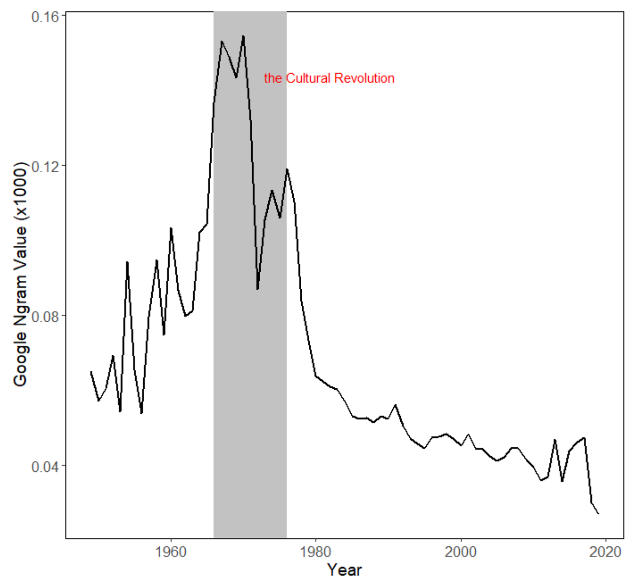
D Validation Exercises

To validate the CR dictionary, we employ two major approaches. First, we leverage Google Books, a digital database containing over 40 million titles of books in various languages, including Chinese. This database allows us to check whether the words in our CR dictionary were frequently used in Chinese publications during the CR period. Using the Google Ngram Viewer, an online search engine built on the Google Books,[4] we retrieve the usage frequency of each CR word by year. Specifically, we calculate the percentage of each word's instances in a specific year relative to the total number of words contained in Chinese publications of Google Books for that year. We then plot the mean usage frequency of all CR words over time, as shown in Figure D1. Clearly, the trend in Figure D1 mirrors that in Figure A5 of the Online Appendix, which is derived from the *People's Daily* corpus. The usage of CR words peaks between 1966 and 1976, corresponding to the Cultural Revolution period. Therefore, it can be concluded that the words in the CR dictionary we developed were indeed used more frequently in Chinese publications during the Cultural Revolution period than in other periods.

As an alternative validation approach, we use a dataset of Weibo — considered China's equivalent to Twitter — with geographic information to examine whether people living in areas with a greater degree of exposure to political violence during the Cultural Revolution are more likely to use CR words. Prior research suggests that exposure to violence and conflict has long-lasting, intergenerational impacts on individuals' political behavior and attitudes.[5] Given the varying levels of violence during the Cultural Revolution in different regions, we propose that the frequency of CR word usage on Weibo varies by region and is correlated with the degree of violence during the Cultural Revolution period. This Weibo dataset, sourced from Weiboscope Open Data—one of the largest known freely available Weibo datasets—includes over 100 million posts from nearly 350,000 Weibo accounts in 2012.[6] We filtered out posts without geographical coordinates and identified the locations of Weibo accounts at the county level. Drawing on political violence data compiled by,[7] we investigate the association between the death toll during the Cultural Revolution as a proxy for political violence (see Figure D2) and the usage of CR words on Weibo across Chinese counties. The results in Table D1 demonstrate that individuals residing in counties with higher death tolls during the Cultural Revolution tend to use CR words more frequently in their Weibo posts. These validation exercises lend credibility to the CR dictionary we developed for further analysis.

Figure D1: Validation Exercise Using the Google Books Database

Panel A: The Top 1000 CR Words in Chinese Books



Panel B: The Top 500 CR Words in Chinese Books

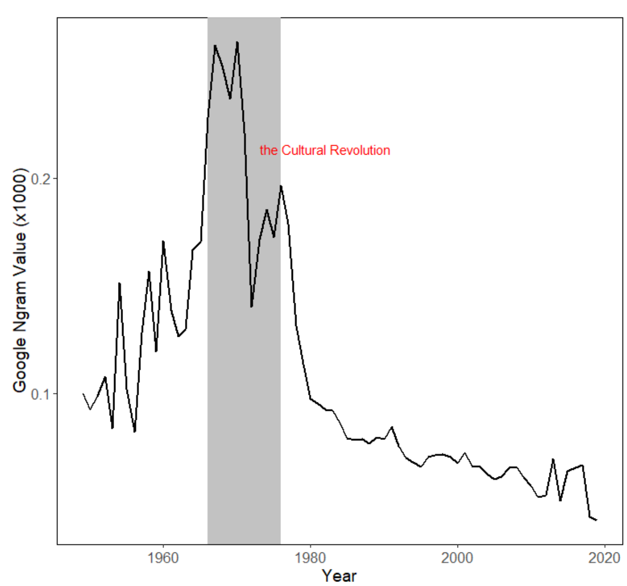
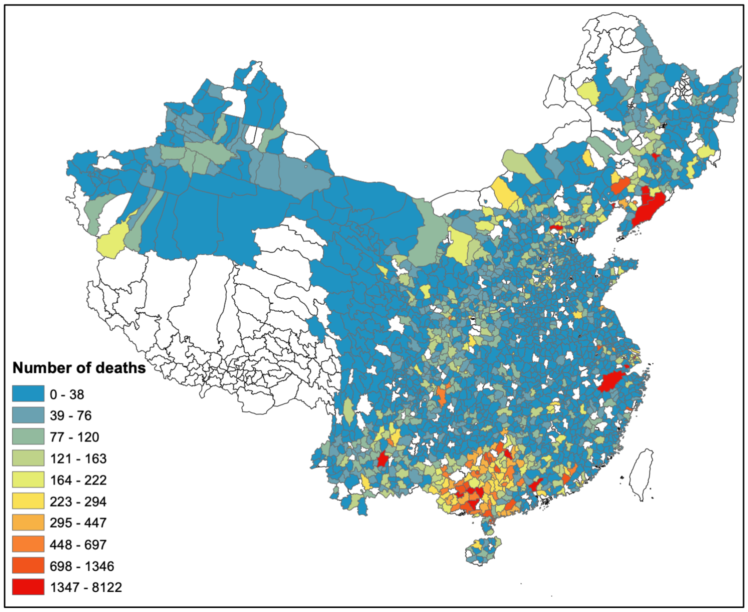


Figure D2: Geographical Distribution of Death Toll by County during the Cultural Revolution



Data source:[8]

Table D1: The Cultural Revolution Deaths and Weibo's CR Word Usage

Panel A. Summary Statistics			
	Observations	Mean	Std. Dev.
CR Imprints	447357	0.031	0.072
Death (in 1,000)	447357	0.200	0.419
Panel B. Deaths during Cultural Revolution and CR Words on Weibo			
	(1)	(2)	(3)
		CR Imprints	
Death (in 1,000)	0.00104**	0.00101**	0.000975**
	(0.000415)	(0.000406)	(0.000404)
Observations	447,357	447,357	447,050
Province FE	YES	YES	NO
Date FE	NO	YES	NO
Province × Date FE	NO	NO	YES

Notes: The sample is at the Weibo post level. The sample consists of 447,357 Weibo posts with geographical information and non-missing information on deaths in a county during Cultural Revolution. We include province fixed effects, date fixed effects, or province by date fixed effects. The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Notes

1. *Chongqing Daily*, April 15, 2012. “The Four Consciousnesses Must be Further Enhanced”(Bixu Jinyibu Zengqiang Sizhong Yishi).

2. *Chongqing Daily*, October 1, 2017. “Resolutely Safeguarding a Favorable Situation of Reform, Development, and Stability” (Jianjue Weihu Gaige Fazhan Wending Lianghao Jumian).

3. *Chongqing Daily*, February 3, 2018. “Chen Min’er: Resolutely Eradicate Sun Zhengcai’s Bad Influence and the Toxic Ideological Remnants of ’Bo and Wang”’(Chen Min’er: Jianjue Suqing Sun Zhengcai E’lie Yingxiang he Bo Wang Sixiang Yidu).

4. Jean-Baptiste Michel et al., “Quantitative Analysis of Culture Using Millions of Digitized Books,” *Science*, 331 (December 2011), 176–182.

5. Charnysh and Finkel, “The Death Camp Eldorado: Political and Economic Effects of Mass Violence”; Lupu and Peisakhin, “The Legacy of Political Violence across Generations.”

6. King-wa Fu, Chung-hong Chan, and Michael Chau, “Assessing Censorship on Microblogs in China: Discriminatory Keyword Analysis and the Real-Name Registration Policy,” *IEEE Internet Computing*, 17 (May 2013–June 2013), 42–50.

7. Andrew G Walder, “Rebellion and Repression in China, 1966–1971,” *Social Science History*, 38 (2014), 513–539; Walder, *Agents of Disorder: Inside China’s Cultural Revolution.*

8. Walder, “Rebellion and Repression in China, 1966–1971”; Walder, *Agents of Disorder: Inside China’s Cultural Revolution.*

E CR Imprints and the BLM Movement

One potential concern is that Trump's defeat might have fueled his supporters' political extremism and their use of radical language, resulting in the observed association between our measure of CR imprints and the radical political attitudes expressed through specific CR words. In other words, if Trump had won the election, we might not have been able to identify the robust correlation between CR imprints and support for Trump. To mitigate this concern, we investigate how opinion leaders reacted to the 2020 Black Lives Matter (BLM) movement.

To measure opinion leaders' attitudes toward the BLM movement, we focus on the tweet corpus between May and June 2020, approximately one month before and one month after the death of George Floyd. We randomly selected 800 tweets (approximately 1% of the total tweets) during this period and trained a research assistant to label them as "1" if the tweet involves criticizing or attacking the BLM movement and "0" otherwise. We cross-checked the coding results and employed supervised learning algorithms to train a classifier. Once again, SVMs delivered the best performance in terms of accuracy for the training dataset (see Table E1).

Table E1: Performance Comparison of Supervised Learning Algorithms for Classifying Anti-BLM Tweets

	Logistic Regression	K-nearest Neighbor	Multinomial Naive Bayes	Support Vector Machine	Random Forest
F1-score	0.77	0.77	0.77	**0.77**	0.77

Notes: We focus on the tweet corpus between May and June 2020, approximately one month before and one month after the death of George Floyd. Five popular supervised learning methods are employed to train a classifier, and the performance is comparable. The metric results from k-fold cross-validation based on the manually coded tweets. To make consistency with the previous classification throughout the paper, we use the SVM to process the data.

Table E2: The Cultural Revolution Imprints and the Anti-BLM Stances

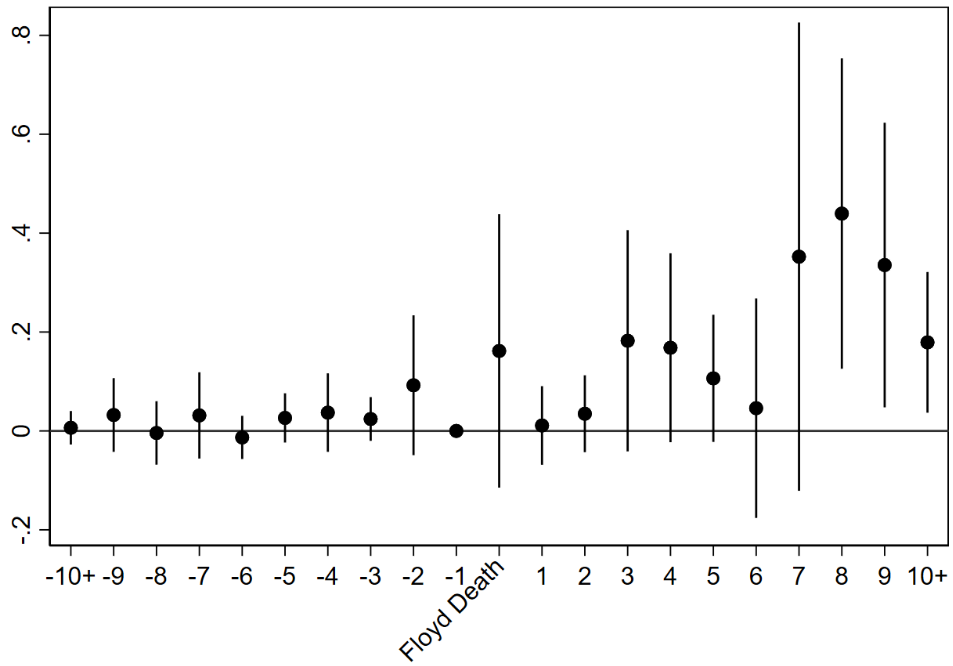
Panel A. Summary Statistics				
Variables	Observations	Mean	Median	Std. Dev.
Anti-BLM	7,470	0.006	0	0.046
CR Imprints	7,121	0.081	0.082	0.023
Age	7,470	0.855	1	0.352
Education	7,470	0.076	0	0.265
Wiki	7,470	0.251	0	0.433
Sentiment	7,470	-0.049	0	1.511

Panel B. CR Imprints and Anti-BLM Stances				
	Proportion of Tweets on Anti-BLM			
	(1)	(2)	(3)	(4)
CR Imprints	0.102***	0.099***		
	(0.034)	(0.032)		
CR Imprints × Post-Floyd Event			0.170***	0.170***
			(0.051)	(0.051)
Observations	7,121	7,121	7,120	7,120
Controls	NO	YES	NO	YES
Account FE	NO	NO	YES	YES
Date FE	YES	YES	YES	YES

Notes: Panel A shows the summary statistics of the sample. At the tweet-by-day level, Panel B of the table reveals the relationship between opinion leaders' CR imprints and the percentage of tweets they posted expressing opposition to the BLM movement between May and June 2020. The dependent variable is a continuous variable indicating the daily percentage of anti-BLM tweets posted by accounts. The standard errors clustered at the account level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, or 10% level, respectively.

Column (1) of Table E2 presents evidence that opinion leaders' CR imprints are significantly associated with their anti-BLM inclination at the 1% level without adding control variables. One standard deviation increase in CR imprints is associated with an approximate 44% increase in the likelihood of anti-BLM stance, relative to the mean. Column (2) shows that the positive relationship remains significant when we add several control variables. In columns (3) and (4), we leverage the death of George Floyd as an exogenous shock and employ a generalized DID design to estimate the effect of CR imprints on anti-BLM inclinations. The results suggest that the opinion leaders with stronger CR imprints are more likely to oppose the BLM. Given the polarization of this issue, the vast majority of people who attacked the BLM are also Trump supporters. We also estimate the dynamic treatment effects of the CR imprint on anti-BLM stances and plot the results in Figure E1. Clearly, we see that the opinion leaders with deeper CR imprints took stronger anti-BLM stances after the outbreak of the BLM movement.

Figure E1: Dynamic Effects of CR Imprints on Anti-BLM Stances



Notes: The coefficients of the interaction terms between CR imprints and day dummies are plotted. The treatment period begins on May 25th, 2020, the day when George Floyd was murdered by a police officer in Minnesota. Standard errors are clustered at the account level.

F Selected Tweets with English Translations

The Original Texts of the Cited Tweets

1. December 3, 2020: We must dare to struggle and at the same time be good at fighting. At this time, we should strive to gain as many allies as possible. Venting anger is a secondary matter. (勇于斗争的同时，还要善于斗争。此时，要争取尽可能多的同盟军，泄愤是次要之事。)

2. December 16, 2020: The lawsuit has just entered its peak, how can one speak of victory or defeat? Even if Trump is no longer the president, his influence endures. The struggle against evil forces must never cease. The darker the society, the more force we need to resist. (诉讼刚进入高峰，何言胜败？即使川不当总统了，影响力依然存在。与邪恶势力的斗争更不能停止。社会越黑暗，越需要投入更多的力量去抗争。)

3. November 13, 2020: The rally in DC will begin tomorrow. The American people will come in a torrential force, striking fear into all the big and small cow demons and snake spirits involved in this election coup.(明天的 DC，集会正式开始，美国人民将以排山倒海之势，让所有参与这次选举政变的大小牛鬼蛇神恐惧。)

4. December 6, 2020: When the video of the Georgia State election fraud was released, some Biden supporters have turned silent, while others keep insisting that everyone should respect the election results. This isn't an election, it's outright theft. I have to admire the executive order on foreign interference in the election issued by Trump two years ago, which paved the way for sweeping out all the cow demons and snake spirits through a legal framework.(当乔治亚州舞弊录像放出来之后，一部分白粉变哑巴了，另一部份还在喋喋不休要求众人尊重选举结果。这哪是选举，明明是盗窃。我不得不佩服两年前创普发布的外🄵干涉大选的行政令，从法理上为横扫一切牛鬼蛇神铺平了道路。)

The 10 Most Widely Circulated Tweets with CR Words (Sep 2020–Jan 2021)

1. September 1, 2020 (1,101 retweets): The craziness of Pelosi and Big Tech shows their fear. They know that at this point, public opinion will swallow them up at any time. They have no confidence in their control of the situation and know exactly what will happen next. This war, to some extent, is just beginning. It's about completely eliminating the cancer of communism from the earth. (佩洛西和大科技公司的疯狂展示的是他们的恐惧。他们知道走到现在这步，随时民意会把他们吞噬。他们对局势的控制毫无信心，且很清楚接下来会发生什么。这场战争从某种程度上来说才刚刚开始。彻底在地球上清除共产主义毒瘤。)

2. December 12, 2020 (1,018 retweets): Trump is a president who has been hollowed out by the shadow government. He chose to stand against evil, to stand with the American people, to save the faltering America, and to choose the difficult and lonely path of Don Quixote. Since his presidency, he has endured too many traps and betrayals, and with his own tolerance and burden, he has truly moved public opinion, letting the white ethnic group, who have been living comfortably for many years, understand the crisis in America. The election curtain has not fallen yet, Trump's resistance is just beginning. (川普是个被影子政府架空的总统，他选择对抗邪恶，和美国人民站在一起，选择挽救摇摇欲坠的美利坚，选择堂吉柯德式的艰难孤独的路，他任职总统以来，承受太多的陷害和背叛，而他用自己的忍辱负重，真真实实的撬动了民意，让安逸度日多年的白人族群明白了美国危机。选举大幕还没落，川普的反抗才真正开始。)

3. November 6, 2020 (889 retweets): The darkest time is just before dawn. Using the CCP's own words against them, the American public have awakened and are not to be trifled with. Once they are provoked to anger, things can get very tough. Xi and the CCP will soon know how difficult this will be to deal with. (黎明前的至暗时刻。用中共的话送回给他们，美国民意已经觉醒了，是不好惹的，如果惹翻了，是不好办的。习和中共很快就会知道这个不好办将会是多不好办。)

4. December 19, 2020 (878 retweets): Someone asked me about my motivation for supporting Trump, and I gave three reasons: 1. I know what hell looks like, I don't want the US to turn into hell; 2. When I was most helpless, the US took me in; today the US is in trouble, if I don't stand up to support this country, when looking back in the future, I will blame myself for the rest of my life, and I will be ashamed to death! 3. My children are in America, I hope to leave them a bright country, not a Sodom city. (一人问我挺川的动机我讲三点：1、我知道地狱什么样，我不想让美国变成地狱; 2、在我最无助的时候，美国收留了我；今天美国有难，我若不站出来支持美国，回首往事，我会自责一生，惭愧至死！3、我的孩子在美国，我希望交给他们一个光明之国，而不是一个索多玛城。)

5. November 14, 2020 (478 retweets): Starting at 12 noon on Saturday, a million people will hold a parade in support of Trump in Washington DC, with people from all over the country pouring into the capital. The event organizers said millions of patriots will protest election fraud to defend the Constitution, protect the President, protect

the homeland, defend traditional American values, and defend freedom. Participants said that the people have the right to an open, fair, and transparent general election. There is news that President Trump will address millions of people, vowing never to give up. (周六中午 12 点开始，华盛顿将举行百万人挺川大游行，来自全国各地的民众正在涌入华府。活动组织者称，百万爱国者将抗议选举舞弊捍卫宪法，保护总统，保护家园，捍卫美国传统价值，捍卫自由。与会者称人民有权利要一个公开公正公平透明的大选。有消息称川普总统将对百万民众发表讲话，誓言绝不放弃。)

6. December 28, 2020 (384 retweets): On January 6th, it is expected that Washington will be “overwhelmed” by millions of Trump supporters. Everyone should make adequate preparations in advance, especially friends who come from afar. However, no matter how difficult it is, try to come, because this is the final struggle, no one can stay out of it. Everyone who participates in this movement, everyone who supports this movement, and everyone who cares about this movement is a warrior, following their heart, choosing justice. (1 月 6 日，预计华盛顿会被几百万挺川大军所“淹没”大家还是要提前做号充足准备，尤其是远道而来的朋友但是，即便是再困难，都尽量要来，因为这是最后的斗争，没有一个人能置身其外每一个参与这场运动的，每一个支持这场运动的，每一个关心这场运动的都是勇士，都遵从了内心，都选择了正义。)

7. November 14, 2020 (339 retweets): A torrent of people flocked to Capitol Hill. They use actions to defend the votes in their hands and defend the value and dignity of the US!(滚滚人流涌向国会山。他们用行动捍卫手中的选票，捍卫美国的价值和尊严！)

8. November 14, 2020 (218 retweets): The voice of the American people defending freedom will become louder and louder, and the voice of the people of the world defending freedom will become louder and louder. The act of stealing the general election will not be allowed by the people of the world, otherwise, the world will fall into the abyss of eternal doom. (美国人民捍卫自由的声音，将会越来越大，世界人民捍卫自由的声音，将会越来越响亮。窃取大选的行为，不会被世界人民所允许，不然，世界将堕入万劫不复的深渊。)

9. November 14, 2020 (210 retweets): Thousands of Trump supporters are marching towards DC, refusing election fraud and protesting in a peaceful manner to express the will of the people. The 80 million Trump supporters are flesh and blood, protecting the constitution, guarding America, and defending freedom. Are Biden’s 80 million supporters the walking dead or Satan’s shadow army? (成千上万的挺川大军正在向 DC 方向进发，拒绝偷票抗议游行，将以和平方式表达民意。8 千万川普支持者有血有肉，保护宪法守护美国捍卫自由。败登的 8 千万支持者是行尸走肉还是阴军撒旦?)

10. January 6, 2021 (148 retweets): At this point, if you still view the support of Trump’s supporters as support for him as a person, then you are not looking at the overall trend of the world and are obsessed with fragmented information. What Trump’s supporters defend is a set of values, a way of life. After globalization entered the 2000s, they lost a lot, and Trump’s campaign voiced their concerns. Now, globalization is not working, and a great reset is needed. The biggest difference between the two is the reverse

replacement of systems.(事到如今，你仍然将川普支持者的支持看作对这个人的支持，那是你不看世界大势，沉迷于信息碎片。川普支持者捍卫的是一种价值观、一种生活方式。在全球化进入 2000 年代之后，他们失去了很多，川普的竞选主张喊出了他们的声音。如今是全球化不行了，要大重置。二者最大的不同是制度的反向置换。)

G Examples of Manually Coded Tweets

Examples of Manually Coded Tweets

1. **Supporting Trump**: I have always believed that Trump will be re-elected, never wavered, God's script will not change! Recently, various media outlets have been cheering against Trump, while those who support Trump feel sad and desperate. Let friends with a sense of justice and conscience remain steadfast in their faith. The drama of the century is not over yet, and the true winners are those who laugh last! (我一直坚信川普会连任，从没动摇，上帝的剧本不会改! 近日各种传媒反川的一片欢呼，挺川的伤心绝望，请有正义良知的朋友们坚定信心，世纪大戏还没有结束，笑到最后的才是真正的赢家。)

2. **Supporting Trump**: In fact, during Trump's presidency, all Americans enjoyed unprecedented freedom of speech. Especially for those against Trump, no matter how they attacked and vilified him, they didn't have to worry about personal safety and freedom. Their WeChat, Twitter, and Facebook accounts were not occasionally blocked like those of pro-Trump individuals. How will the next four years be? —Kind-hearted people, learn to be grateful and discerning! (其实川普执政的这四年所有的美国人都享有了前所未有的言论自由。尤其是反川人士，无论如何攻击诋毁川普，把他当成棒槌打，不会担心个人安全和自由，微信，推特，脸书账户也不会像挺川人士那样偶尔被封锁。下面的四年怎么样呢？——善良的人们，要学会感恩与分辨！)

3. **Denying the Result**: From the comparison between President Trump's and Biden's campaign rallies, we can see who the public truly supports. The reality is that Trump won in all 50 states in the U.S.! Therefore, American democracy is not only not in decline but also very healthy. It is the top echelons of the Democratic Party who have fallen, resorting to apocalyptic and insane fraudulent means to steal the election in order to cover up their crimes! （从川普总统与拜登竞选集会对比可以看出，民意到底支持谁？真实的情况应该是美国 50 个州都是川普胜出！所以美国民主不仅没有堕落，而且非常健康。堕落的是民主党高层，他们为了掩盖犯罪的事实，采用末世疯狂的舞弊手段来窃取大选!）

4. **Denying the Result**: My elementary school son told me that the U.S. election was manipulated. I asked him, "Where did you hear that from, kid?" He said he spent hours looking at the voting results from all counties in the U.S. and found that even in states that voted for the Democratic Party, the vast majority were won by the Republican Party. Only a few counties had a very concentrated Democratic vote, which doesn't make mathematical sense... When I checked, it was indeed true. The Democratic Party went overboard this time.(我上小学的儿子告诉我，美国的选举被操纵了，我说你小孩子从哪听说的？他说他花了几个小时看了所有美国各县的投票情况，发现即使在投了民主党的州，也绝大部分是共和党赢了，只有几个县非常集中票投给了民主党，这不符合数学... 我一看，果然是的，民主党这回真的演过头了。)

5. **Overturning the Result**: In American democratic society, the main body of citizens values integrity and contracts. They not only have votes in their hands but also have guns to overthrow a blatantly fraudulent and illegal scamming president and his corrupt party government.(美国民主社会主体公民讲究诚信和契约，他们手里不仅有选票，更有枪去推翻一个公然造假违法的骗子总统及其腐败政党政府。)

6. **Overturning the Result**: The geographic areas supporting President Trump are vast! The majority of the poor and lower-middle-class farmers all support President Trump! The areas supporting Biden are only concentrated in a few major cities, comprising capitalists, reactionary academic authorities, petite bourgeoisie intellectuals, and small-town citizens! President Trump is truly close to the hearts of the poor and lower-middle-class farmers! If the reactionary group behind Biden dares to seize power and usurp the party, we, the poor and lower-middle-class farmers, will absolutely not agree! Inheriting Chairman Mao's will, we will surround the cities from the rural areas and once again seize power!(支持川总的地域有多大面积！广大贫下中农都支持川总！支持拜登的地域只是集中在少数大城市，都是些资本家、反动学术权威、小资产阶级知识分子和小市民！川总才是贫下中农的贴心人！如果拜登反动集团胆敢篡党夺权，我们贫下中农坚决不答应！继承毛主席遗志，农村包围城市，再次夺取政权！)

Examples of Manually Coded Anti-CCP Tweets

1. **Attacking the CCP**: The CCP is not the son of the Chinese people, it is the son of Stalin, the grandson of Lenin, and the great-grandson of Marx! (中共不是中国人的儿子，是斯大林的儿子，列宁的孙子，马克思的曾孙!)

2. **Attacking China's political system**: Only a system like yours is capable of solving disasters that other countries are unable to create. It' s a classic Soviet joke. (只有您国这样的体制才有能力解决别国没有能力制造的灾难，简直经典的苏联笑话。)

3. **Attacking China's top leadership**: When Ying Yong was transferred, everyone in Shanghai was overjoyed and even hoped to send Secretary Li Qiang away in a package without returning! Xi's faction gives the impression of a ruffian who is uneducated, sycophantic, imbecile, and low-grade. Chen Min'er, Cai Qi, Ying Yong, Xia Baolong, etc. are this type! (应勇调离，上海人都欢天喜地，希望连市委书记李强一起打包送走，不退貨！习家军给人的印象是不学无术，阿谀奉承、低智低档的痞子流氓形象。陈敏尔、蔡奇、应勇、夏宝龙等基本都是这种类型的！)