Individuals' self-disclosure on social media reveals sentiment and mental well-being benefits of vaccination

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Abstract

Vaccination prevents not only the transmission of pathogens but also the adverse psychological effects of epidemics. Prior knowledge of the mental well-being benefits of vaccination relies on cross-sectional surveys, which are limited in scale, subject to self-report bias, and could be confounded by hidden differences across individuals. Here, we collected 154,348 Americans who self-declared receiving the COVID-19 vaccine on Twitter (now called X) and implemented a staggered quasi-experiment design to analyze their 160 million tweet activities, teasing out the causal effect of vaccination on changes in expressed sentiment and mental well-being. We found that being fully vaccinated is associated with an increase in sentiments of 0.055 (95% CI 0.037 to 0.072) standard deviations at the individual level. The effects are stronger among males, adolescents, Hispanic and Asian Americans, and individuals who have experienced severe local epidemics. Investigation of underlying mechanisms suggests that fully vaccinated individuals experience fewer negative emotions, engage in more leisure activities, and are less likely to grapple with conflicting thoughts. Additionally, a more relaxed social environment from lifted lockdowns and increasing herd immunity positively correlates with sentiment improvement. Our study provides a new approach to assessing the impact of medical treatment on mental health by mining large-scale self-reported social media data.

Introduction

Vaccination has long been the preferred way to contain infectious diseases[1]. Adequate vaccine delivery provides governments with the confidence to loosen public health interventions[2–4], and allows individuals to resume their normal lives. The societal benefits of the former can be largely attributed to the protection of physical health through established herd immunity, whereas the personal benefits of the latter can be attributed to the alleviation of mental distress caused by epidemics[5].

Two possible channels exist through which vaccination may improve mental well-being. First, individuals may experience a reduction in anxiety and fear related to infection. Second, a more robust mental status may be associated with an enhanced capacity for enjoyment of social and leisure activities, which is associated with the relaxation of lockdown orders. In accordance with early findings that disease prevalence significantly affects public psychological status[6,7], several studies have shown that vaccination is often associated with reduced distress, depression, and anxiety[8–11], particularly among the elderly and clinically vulnerable groups[12]. Additionally, scholars have documented a reduction in the perceived risks of infection, hospitalization, and death among vaccinated individuals[5], which partly explains the alleviation of psychological burdens.

Questionnaire-based surveys are the primary approaches through which scholars drew those findings. While these methods have been rigorously validated in psychiatric research, they are costly, have limited scalability for generalizing to the population, and hard to ensure survey frequency. One key challenge when using survey data is to overcome its limited temporal and spatial granularity to ensure the external validity of conclusions beyond the small survey sample, and the other key challenge is to transcend the clinical setting and assess the effects in real-world

contexts. For instance, some studies that analyze cross-sectional data have difficulty establishing causality when comparing across individuals[8–10,12,13]. Others have built cohorts for individual-level analysis, but still face challenges with discrete observations and self-report bias[5,11]. In the digital age, the rich text of social media platforms offers a promising alternative for understanding changes in mental well-being. Tracking individuals' social media activities, coupled with natural language processing (NLP), allows us to track the fluctuation of an individual's psychological state by revealing the linguistic cues in their self-disclosure content. Inference of psychological state from social media expressions has been shown to be relevant to mental well-being. For example, researchers have employed Twitter data to demonstrate higher levels of distorted thinking among individuals with depression[14]. Their online identification yielded results comparable to clinical psychological diagnoses based on cognitive behavioural therapy.

In this study, we collected 154,348 Americans who self-reported on Twitter that they had received the COVID-19 vaccine (see the experimental design in Fig. 1a-c). Individuals were divided into two cohorts based on whether they reported the first dose or a booster shot, and those who reported a second dose were grouped into the first cohort by inferring the timing of first dose. We retrieved each individual's historical tweets before and after vaccination and applied a set of NLP methods to measure the psychological state revealed by the text, with expressed sentiment as the primary indicator. The impact of vaccination was then assessed by integrating the established individual-level panel data with a staggered difference-in-differences (DiD) design (Fig. 1d-e). In each cohort, the design compares changes in psychological state before and after vaccination for early vaccinated individuals (treatment group) with changes at the same time for later vaccinated individuals (control group). Because the vaccines were

administered gradually, the control groups are dynamic and tailored to each group of individuals who received the vaccines at the same time. As our control group consists of people who eventually received the vaccines, just at a later time point, it is reasonable to assume that the treatment group individuals would have behaved similarly to individuals in the control group if they had not been vaccinated. This methodology offers a higher validity than selecting individuals who have never received a vaccine (e.g., vaccine deniers) as the control group.

To shed light on the driver of sentiment change, we explored its mechanisms with the hypotheses that receiving vaccines would induce fewer negative emotions (e.g., fear and anger) and encourage individuals to talk more about social and leisure life (see Fig. 1f-g). The latter dimension was assessed from two perspectives, linguistic shifts in life concerns and cognitive processes. We tested whether people would talk more about leisure activities after vaccination. Meanwhile, we examined changes in cognitive processes, specifically whether individuals changed their use of cognitive words representing differentiated (e.g., although, but), judgmental (e.g., always, never), or tentative (e.g., maybe, perhaps) ways of thinking that could be emotional taxing. Given that studies have documented that people's language showed more cognitive processes in the early days of the COVID-19 outbreak[7], it could be convincing evidence if an inversed trend could be found after people resumed free travel via vaccination. Finally, we linked sentiment dynamics to time-varying local lockdown stringency and vaccination rates, with the aim of exploring how individual sentiment was affected by what others in the surrounding social environment were thinking and doing.

Our methodological framework can be replicated to investigate the psychological effects of behaviors other than vaccination. Although it cannot replace clinical diagnoses, the identification of self-disclosure behaviors in online social media can serve as a signal of treatment uptake or

symptom onset[14]. By taking advantage of NLPs, we are able to cross-compare individuals while controlling for individual differences to estimate the effect of behaviors on mental well-being.

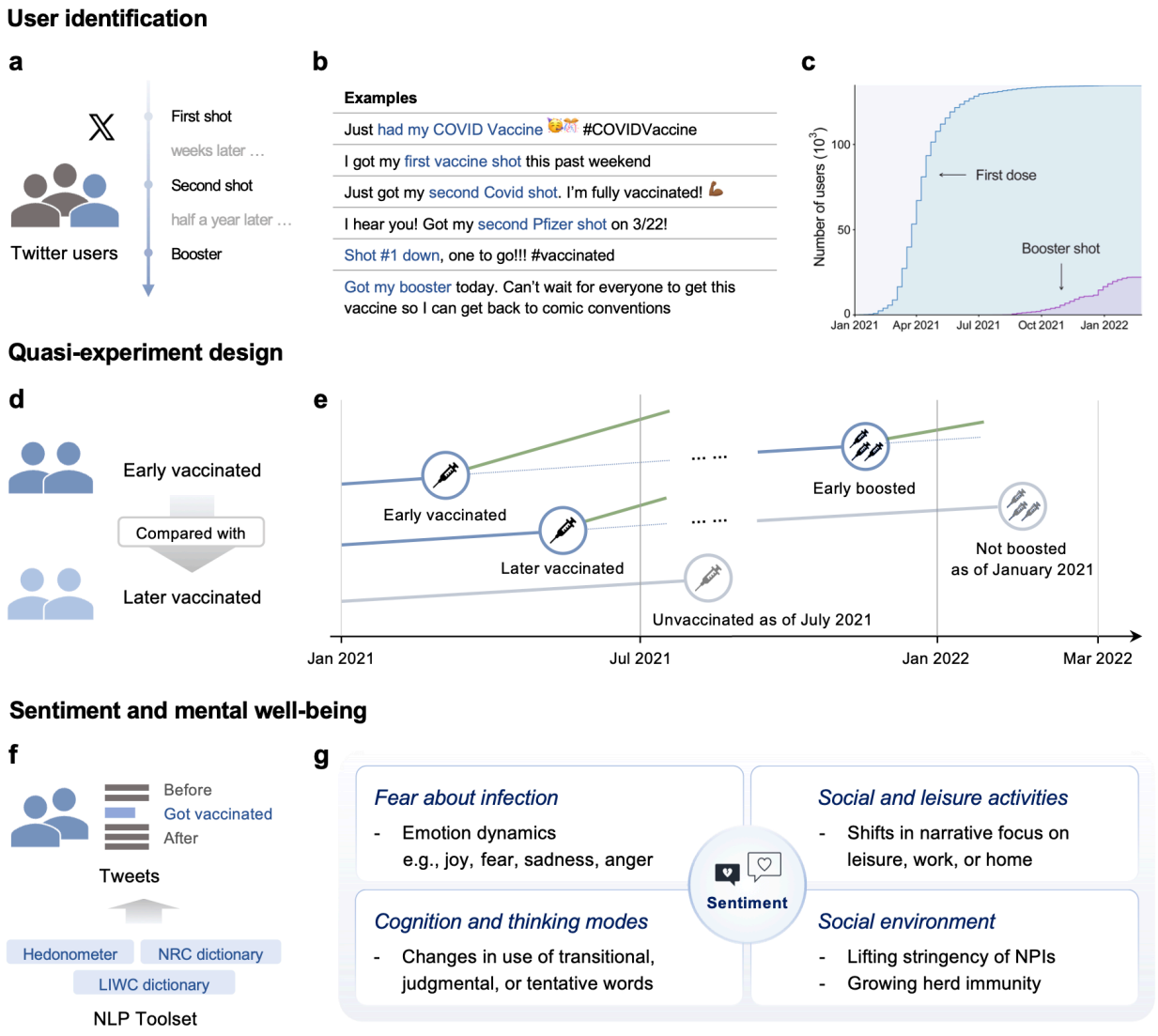


Figure 1. User identification, natural language processing, and empirical experiment design. a, d, f, schematic graphs of study design. **b,** rule of user selection and vaccination timing adjustment. **c,** distribution of users who received the first dose and booster shot of vaccination. For more details of subplots b and c please find Supplementary Note 1. **e,** schematic graph of staggered difference-in-differences model for the first and booster shots. **g**, personal and environmental factors that may contribute to vaccination-induced sentiment changes.

Results

Main results. The receipt of COVID-19 vaccines is associated with a significant increase in expressed sentiment. Fig. 2a illustrates the changes in individual's expressed sentiment as measured by the Hedonometer lexicon (see *Methods*). Prior to the first dose of vaccine, there are no systematic differences in sentiment between the treatment and control groups, suggesting that individuals who were vaccinated later can be considered legitimate counterfactuals for the early vaccination group. Individuals' sentiments begin to increase immediately after the first dose, reaching a plateau at around 8 weeks after vaccination. Because individuals typically received the second dose 3-4 weeks after the first dose (Supplementary Fig. 1), our results indicate that sentiment stabilizes approximately one month after individuals were fully vaccinated. Therefore, we interpreted the average effect of 8 to 15 weeks as the impact of full vaccination, which is an increase of 0.055 s.d. ($P < 0.001$, 95% CI 0.037 to 0.072). To provide a point of comparison, we also tracked the sentiment of individuals who received a booster in the second half of 2021. However, no significant changes were observed (see Supplementary Fig. 4 in Note 2), suggesting that a booster shot may not have the same affective benefits as the initial vaccination because people have already resumed their normal activities.

The magnitude of vaccination impact on sentiment is quite significant when putting into perspectives. First, the average range of weekly sentiment variations in our data is 0.016 (approximately 0.043 s.d.) between Tuesday (lowest) and Saturday (highest). The effect of vaccination is approximately 1.3 times the widest gap of affective swing between weekdays and weekends. Second, our estimated effect is quantitatively comparable to other studies that also implement individual-level analysis controlling for individual fixed effects. For example, Baylis

(2020)[15] demonstrated that an extremely cold (maximum temperature ≤5°C) or hot (maximum temperature >40°C) day would result in a decrease in sentiment changes of -0.08 s.d. and -0.10 s.d., respectively, compared to the most pleasant maximum temperatures of 21–24 °C. Third, our estimated effect was found to be qualitatively similar to the effects of other external factors on sentiment changes. Burke et al. (2022)[16] and Du et al. (2024)[17] reported a decline in sentiment of -0.2 s.d. and -0.14 s.d. caused by a heavy smoke day ($PM_{2.5}$ > 100 μg/m^3) on a weekly and daily basis, respectively. However, their analysis did not include individual fixed effects. The smaller magnitude in our estimate may be due to measurement error caused by sparser sources of within-individual variation[18].

To test the robustness of our model, we conducted a number of sensitivity analyses. First, we discarded part of the control group in two ways based on different model settings (see *Methods* and Supplementary Note 3 for details), which in fact shrinks the size of the control group and reduces the cross-comparison between early and later vaccinated individuals. Supplementary Figs. 5 and 6 show that the outcomes exhibit similar patterns to those in Fig. 2a, despite sometimes less satisfactory pre-treatment parallel trends and smaller effect sizes, suggesting that a staggered design with within-cohort comparison is essential to meet the identifying assumption for causal inference. Second, we tested whether the choice of time period for effect estimation affects our results. We ran models summarizing effects up to early June (week 23), early July (week 27), and early August (week 31) of 2021, respectively. Supplementary Fig. 7 shows a gradual, slight decrease in effect size as the time point moves backward. Finally, we ensured our results are robust across sentiment measurement algorithms (see *Methods*). The alternative methods confirm the conclusion of sentiment lifting, albeit with smaller effect sizes (Supplementary Fig. 8). The discrepancy between the results can be attributed to the fact that

158 Hedonometer had enriched with words related to the COVID-19 pandemic, which explains its
159 superior performance over the others and why we chose it.

160 We also performed a series of placebo tests to ensure that the effects we identified are due to
161 vaccination alone (see Supplementary Note 4). We adopted two approaches to set the dummy
162 timing of vaccination for later vaccinated individuals as a designated or arbitrary week prior to
163 the actual time, and found no notable changes in either (Supplementary Figs. 9 and 10). The
164 experiments suggest that our control groups are free of contamination and that our results are not
165 influenced by week-specific common shocks across states or by common long-term temporal
166 trends.

167 We further analyzed two affective dimensions associated with the expressed sentiment. First, we
168 decomposed the sentiment score into emotions of different polarities using the NRC emotion
169 lexicon (see *Methods*). We found that the increase in sentiment is dominated by a steady
170 decrease in negative emotions, the magnitude of which overwhelms the increase in positive
171 emotions (Fig. 2b). Specifically, we observed a decrease in the use of words associated with
172 sadness by -0.030 s.d. ($P < 0.001$, 95% CI -0.047 to -0.014), fear by -0.027 s.d. ($P < 0.001$, 95%
173 CI -0.042 to -0.011), disgust by -0.032 s.d. ($P < 0.001$, 95% CI -0.049 to -0.015), and anger by -
174 0.033 s.d. ($P < 0.001$, 95% CI -0.050 to -0.016) after full vaccination. Conversely, positive
175 emotions as exemplified by words denoting joy exhibit a comparatively less pronounced increase
176 in usage, with a value of 0.024 s.d. ($P = 0.003$, 95% CI 0.008 to 0.039).

177 Additionally, the improvement in expressed sentiment is accompanied by a decline in affective
178 fluctuation. As shown in Fig. 2c, we observed a gradual decline in the standard deviation of the
179 sentiment score after the first vaccine dose, which stabilizes after attaining -0.007 s.d. ($P <$

0.001, 95% CI -0.009 to -0.005) by the 8th week post-vaccination. However, this decline is followed by a gradual recovery till the 15th week. The inverse trend compared to what we observed in Fig. 2a indicates that individuals exhibited diminished sentiment fluctuations in their verbal expressions after full vaccination, which is a sign of greater affective stability and healthier mental status[19].

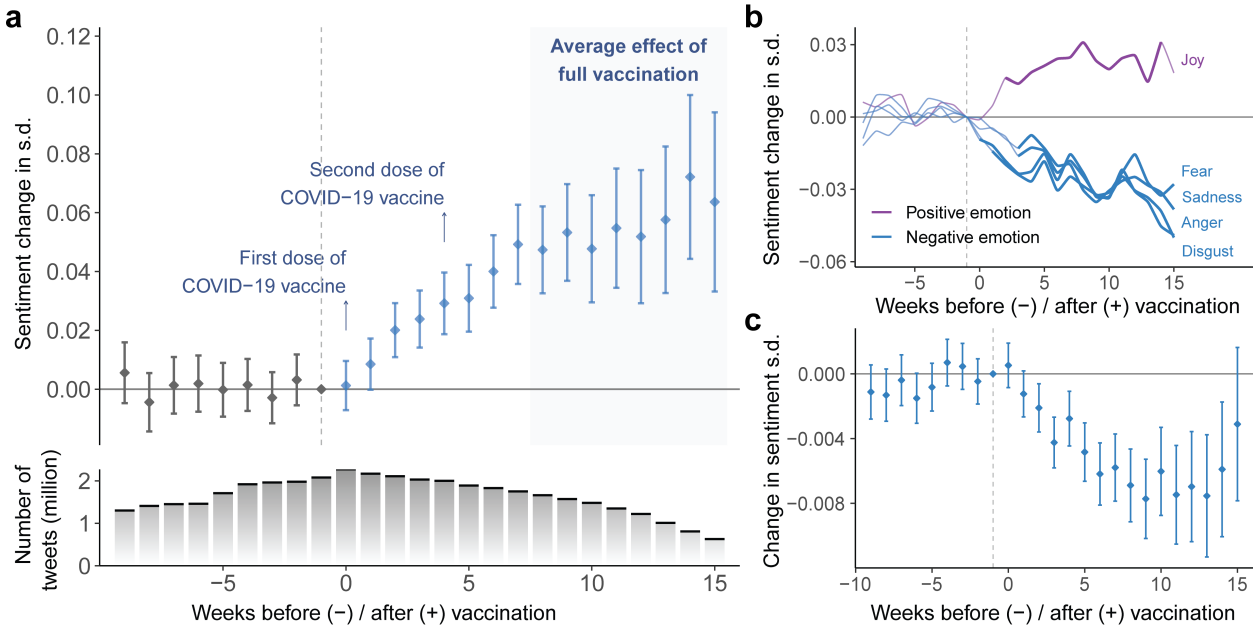


Figure 2. The effect of vaccination on expressed sentiment, standard deviations of sentiment and emotions dimensions. a, the effect of first-dose vaccination on expressed sentiment. The error bars represent the 95% confidence intervals. The bar plot below shows the number of tweets in our sample that fall into corresponding time bins. **b,** the effect of vaccination on positive and negative emotions. The bold lines indicate time periods when the change is significant at least at the 95% level. **c,** the effect of first-dose vaccination on standard deviation of expressed sentiment, which represents affective stability. Higher standard deviation indicates less stable sentiment. The error bars represent the 95% confidence intervals. For **a-c**, one week before vaccination was set as the baseline. Therefore, the other indicator variables show relative changes compared to the baseline.

Heterogeneity analysis. We investigated heterogeneous effects of vaccination across age, gender, and race, and found notable distinctions in sentiment variations. Fig. 3 shows the heterogeneity observed one month after full vaccination, which aligns with the main results. The short-term effect, spanning 4 to 7 weeks after the first-dose vaccination, is presented in Supplementary Fig. 11 in Note 5. The results reveal that the sentiment improvement observed following vaccination is primarily driven by males and adolescents. Male sentiment (0.061 s.d., $P = 0.002$, 95% CI 0.021 to 0.100) improves by approximately one-third more than female (0.047 s.d., $P = 0.003$, 95% CI 0.016 to 0.078). Additionally, the improvement observed in young individuals under the age of 18 (0.090 s.d., $P = 0.006$, 95% CI 0.026 to 0.155) is more than twice that observed in adults over the age of 40 (0.035 s.d., $P = 0.151$, 95% CI -0.013 to 0.083). As might be expected, adults between the ages of 19 and 39 comprising the majority of the study sample exhibit a sentiment change that is comparable to the main results (0.050 s.d., $P = 0.002$, 95% CI 0.018 to 0.082). With regard to racial disparity, the most positive sentiment response to vaccination is exhibited by Hispanic and Asian individuals. The expressed sentiments increase by 0.082 s.d. ($P = 0.030$, 95% CI 0.008 to 0.157) and 0.071 s.d. ($P = 0.033$, 95% CI 0.006 to 0.137), respectively, after individuals have been fully vaccinated. In contrast, the sentiment of African Americans shows an increase that is not statistically significant (0.045 s.d., $P = 0.078$, 95% CI -0.005 to 0.095).

In addition to demographic distinctions, people may respond differently to vaccination based on their local environment. For example, the Democratic Party typically advocated restrictive lockdown policies, while the Republican Party recommended economic reopening[20]. These different strategies may have different effects on human activities and the labor market. In

addition, regional economic development also affected people's accessibility and affordability of public services, thereby mediating the effect of vaccination on expressed sentiment. However, after grouping individuals by whether they belonged to Red states or Blue states, we observed almost identical changes in sentiment (Red states: 0.054 s.d., $P < 0.001$, 95% CI 0.025 to 0.082; Blue states: 0.053 s.d., $P < 0.001$, 95% CI 0.030 to 0.076). The same is true when individuals are separated by whether they lived in a state with a higher (0.054 s.d., $P < 0.001$, 95% CI 0.033 to 0.075) or lower (0.054 s.d., $P = 0.001$, 95% CI 0.022 to 0.087) GDP per capita. These results suggest that the post-vaccination increase in sentiment is not closely related to regional partisan discrepancy or economic status.

Finally, we examined the effects stratified by the severity of the local epidemic. The results indicate that a higher disease prevalence is generally associated with a more apparent sentiment improvement. When severity is defined based on the cumulative number of COVID-19 infections over the past quarter before mass vaccine rollout (October to December 2020), the sentiment improvement of people living in states with more infections above the median (0.057 s.d., $P < 0.001$, 95% CI 0.037 to 0.077) is nearly a third higher than people living in states with less infections (0.045 s.d., $P = 0.020$, 95% CI 0.007 to 0.083). Similar differences can be found when defining severity based on cumulative number of deaths over the same period (more deaths: 0.056 s.d., $P < 0.001$, 95% CI 0.036 to 0.076; less deaths: 0.047 s.d., $P = 0.017$, 95% CI 0.008 to 0.086). This discrepancy may be attributed to the fact that individuals experiencing more severe local epidemics were more eager to receive vaccines to protect themselves and resume their lives.

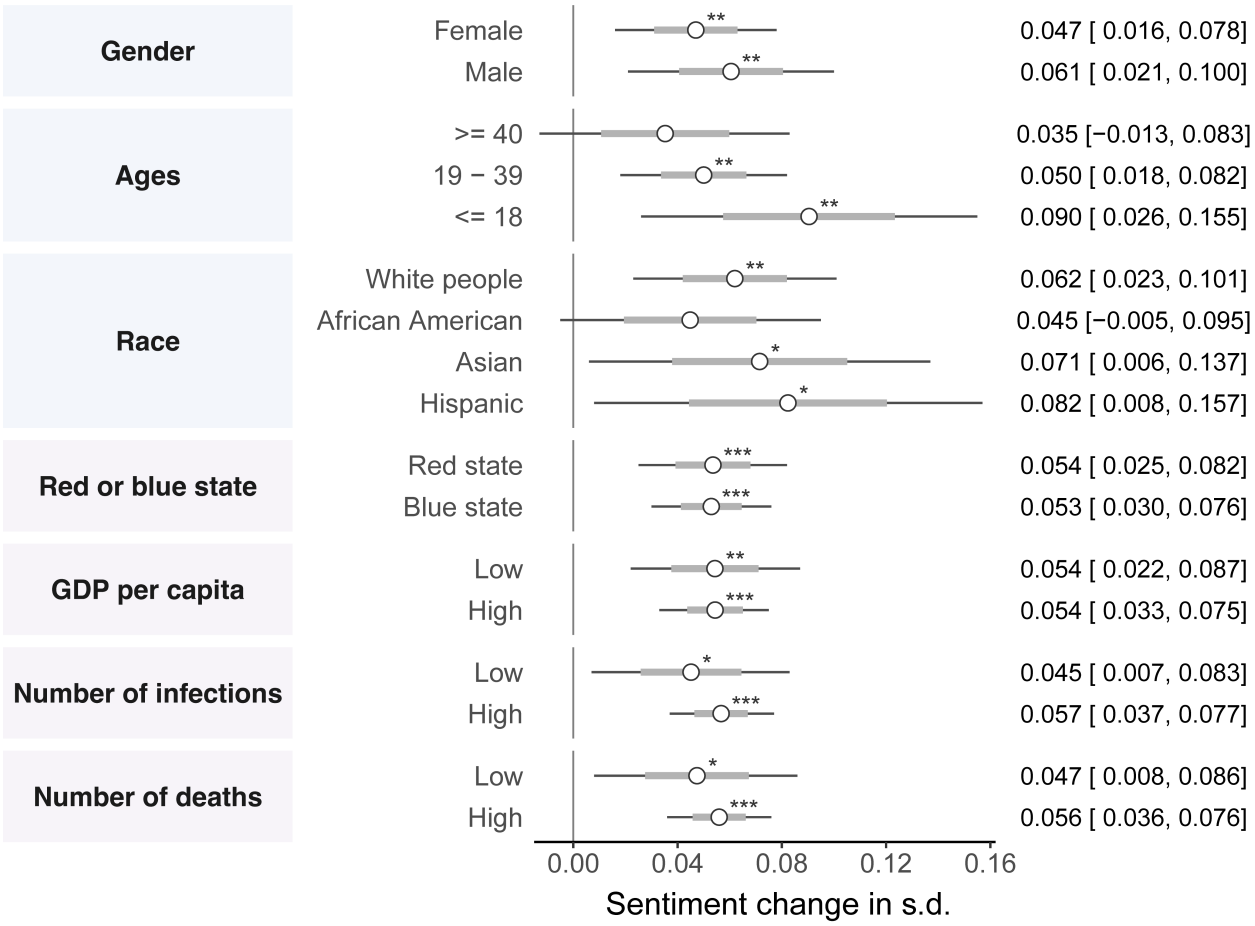


Figure 3. The heterogeneous effect of vaccination on expressed sentiment across demographics and geography. The categories with light blue backgrounds represent heterogeneities across demographics, where users were sub-grouped by individual characteristics. The categories with light purple backgrounds are heterogeneities across geography. Users were sub-grouped by the state in which they were located. The "high" and "low" in the last three groups were determined by whether the indicators of an individual's state were higher or lower than the median level. Error bars in bold, light grey show standard deviation. Error bars in black represent 95% confidence intervals, with * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Linguistic changes post-vaccination. Individuals' use of language can provide insight into shifts in narrative focus and way of thinking that are endogenously associated with the sentiments expressed. Using the LIWC dictionary (see *Methods*), we found that vaccination prompts individuals to talk more about their personal lives (Fig. 4a), particularly words related to leisure (0.032 s.d., $P < 0.001$, 95% CI 0.014 to 0.050) and financial concerns (the word category "money", 0.020 s.d., $P = 0.044$, 95% CI 0.001 to 0.039). In contrast, words related to work were observed to occur less frequently than before, although this is not statistically significant (-0.010 s.d., $P = 0.208$, 95% CI -0.027 to 0.006). We further investigated whether individuals paid more attention to acquaintances and family. However, no significant changes were observed (0.008 s.d., $P = 0.410$, 95% CI -0.011 to 0.027). These results suggest that vaccination, which increased engagement in leisure activities if local policies and the pandemic environment allow, could serve as an important mechanism for sentiment improvement.

The sentiment changes after vaccination may be associated not only with the changes in life focus, but also with one's thinking and cognitive processes. Referring to the word category "cognitive processes" in LIWC, we investigated individuals' linguistic changes with word usage representing differentiation thought (e.g., although, but), judgmental speaking (e.g., always, never), or tentative narrating (e.g., maybe, perhaps), etc. It is commonly found that individuals used those cognitive words more frequently when confronted with traumatic events[21,22], including during the early stage of the COVID-19 outbreak[7]. External shocks can force individuals to reflect on the reasons why the event occurred and to form their own understanding when trying to write down a coherent narrative[23].

Fig. 4a shows a generally lower usage of cognitive words when linking them with vaccine reception. In particular, the fully vaccinated group uses fewer differentiation words in writing

than before (-0.046 s.d., $P < 0.001$, 95% CI -0.064 to -0.028), which represents less conflicting thinking. Individuals may show conflicting thoughts when expressing something like "I'd like to go to a movie tomorrow, *but* I'm afraid of being infected". While people will need to make more of these balances and decisions during the pandemic, our results suggest that vaccinated individuals were likely to face easier decisions without these complex trade-offs. Comparatively, the use of insight (e.g., "think", "know"), tentative, and certainty words only see insignificantly decreases. The change in overall declines in emotional taxing cognitive processes could be one mechanism for the improved sentiment.

Social environment on expressed sentiment. Following the administration of a considerable number of vaccines, state governments gradually loosened non-pharmaceutical interventions (NPIs) in the first half of 2021. For instance, mask requirements in public spaces were less stringent, and outdoor gatherings were permitted with proof of vaccination. The improvement in sentiment may be partly explained by the benefits and freedoms associated with vaccination, rather than just medical protection.

Here, we focus on three NPIs that were widely implemented: stay-at-home restriction, gathering prohibition, and facemask requirement. Individuals were reclassified based on whether an NPI in their state was less stringent when they were fully vaccinated than it was in early 2021 (see *Methods*). We reconducted our analysis for each subgroup and found that policy easing generally induces greater sentiment improvement except for the facemask requirement (see Fig. 4b). Specifically, we observed no significant change in individual's expressed sentiment if the ban on gatherings was not lifted after being fully vaccinated. On the contrary, there is an increase of

0.064 s.d. ($P < 0.001$, 95% CI 0.044 to 0.085) when less restrictive requirements were introduced. Similarly, the lifting of restrictions on stay-at-home leads to an increase of 0.051 s.d. ($P < 0.001$, 95% CI 0.028 to 0.075) in sentiment, which would not have been significantly improved if the same intensity had been maintained (0.036 s.d., $P = 0.067$, 95% CI -0.003 to 0.075). However, we found no additional benefit from relaxing the facemask requirement, which poses fewer constraints on the freedom to participate in leisure and social activities.

Furthermore, we explored the role of local vaccination rates, a key indicator for establishing herd immunity and gaining insights into society's vaccine acceptance, on sentiment improvement. Instead of regressing by weeks, we linked users' tweets to the state-level daily vaccination rate and then aggregated them by 5% bins. We implemented a similar staggered DiD design, comparing individuals who were vaccinated when vaccine coverage was low to those who were vaccinated when coverage was high. We set those vaccinated after local coverage exceeded 50% as the literal never-treated group (see *Methods*). Fig. 4c shows a similar pattern to Fig. 2a, indicating that as the local vaccination rate increases, sentiment also rises. This suggests that growing herd immunity and being surrounded by vaccinated neighbors may be beneficial to sentiment. We provide further implications of this result for trust in science and vaccines in the Discussion.

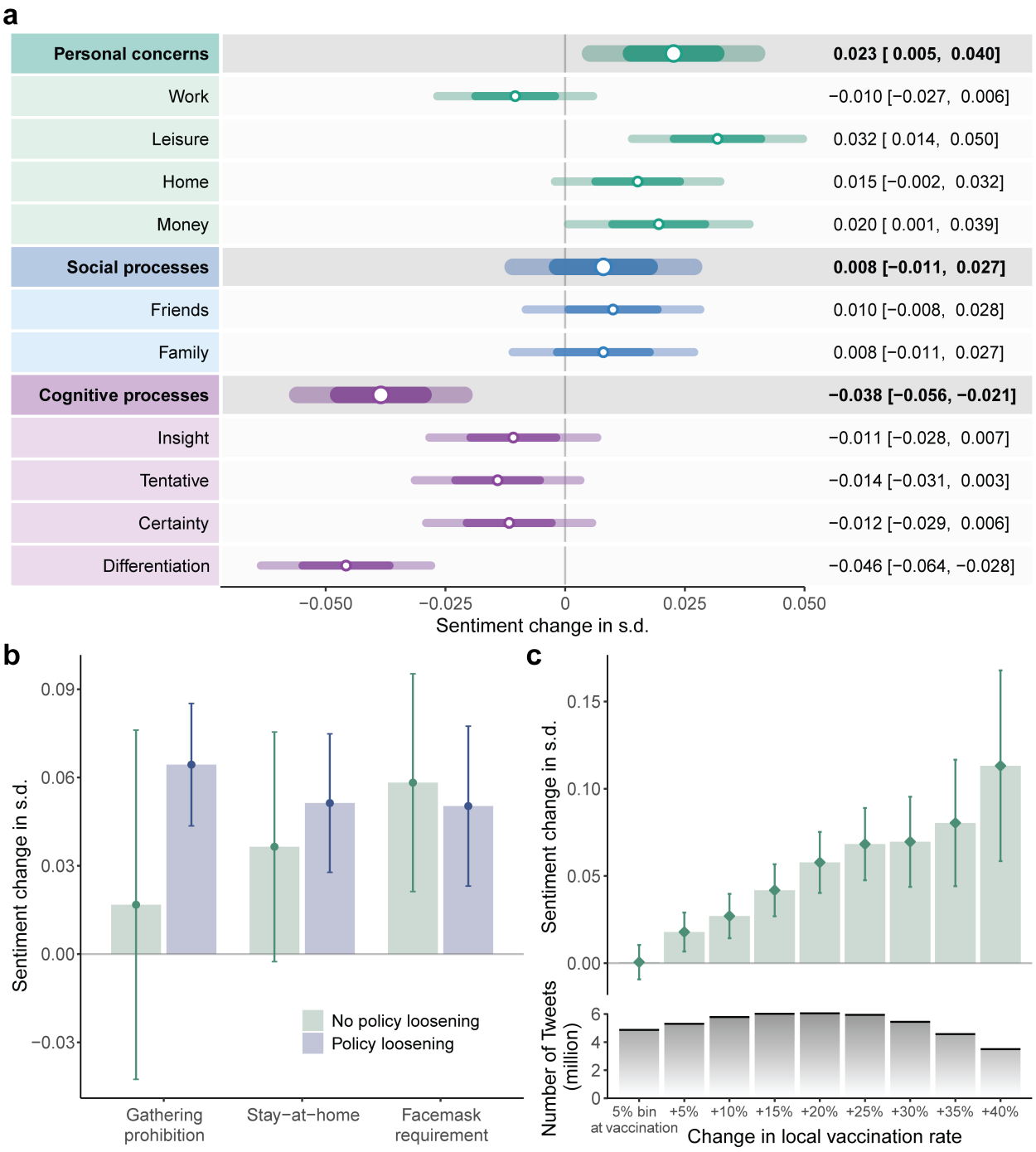


Figure 4. Driving factors for improved expressed sentiment from vaccination. a, the average treatment effect of (one month after) full vaccination on linguistic dimensions of personal concerns, social processes, and cognitive processes. The dark rows represent the above three major categories and are the aggregation of the corresponding minor dimensions in light

background. The dark error bar represents the standard deviation, and the light error bar represents the 95% confidence intervals. **b,** the effects of full vaccination on expressed sentiment stratified by whether people's living States loosened NPI policies (lower stringency) when they were fully vaccinated as compared to January 2021. The error bars represent the 95% confidence intervals. **c,** the change in expressed sentiment along with the local vaccination rate increases. The error bars represent the 95% confidence intervals. The bar plot below shows the number of tweets in total that fall in corresponding 5% bins referring to differences in vaccination rate between posting tweets and being vaccinated.

Discussion

This study uncovers short- and medium-term mental benefits of COVID-19 vaccination by analyzing tweets from over 154 thousand vaccinated Americans. Using a staggered DiD design, we found that individuals' expressed sentiment increases after the first dose, stabilizes one month after full vaccination, and shows no decline within our study period, i.e., at least 15 weeks after the first-dose vaccination. This conclusion of overall improvement in sentiment is consistent with existing questionnaire-based studies[5,11]. In particular, the proposed research framework differs from traditional cohort studies and excludes subjective influences of subjects due to the clinical environment. Instead, it identifies self-reporting behaviors, analyzes online postings in a natural setting, and compares individuals within a single cohort. These designs are more cost-effective to implement while ensuring robust conclusions.

The results of this study reflect the dynamics of individuals' mental well-being as they gradually recover from the initial shock of the pandemic. Early research suggests that exposure to such

global public health events causes negative impacts not only on physical health, but also on mental health. People tend to express lower sentiments[6], more sadness and anxiety, less analytical thinking, and more cognitive processing[7] during the first few months of the global pandemic. In contrast, we observed improvements in all of these dimensions after vaccination. Individuals show stable higher sentiment. The lower negative emotions and less conflicting thinking mode may contribute to that. These findings provide compelling support for the view that vaccination is a critical intervention in restoring people's lives.

Recent studies have shown that risk cognition[5] and actual infection risk[12] contribute to elevated mental well-being after vaccination. Although we did not uncover these individual-level drivers, this study disentangles the relationship between mental improvements and the social environment. Our observation that sentiment rises as local vaccination rates rise is consistent with the population-level study by Bari et al. in the United States[24]. This positive feedback can further promote vaccine uptake in local communities, thereby supporting the prediction of vaccination trends to guide tailored vaccination campaigns or delivery strategies. Our results also highlight striking improvements in sentiment as NPIs loosen. Combining with another finding that vaccinated people discuss more about leisure in their text with a more casual narrating style (less cognitive process), we conclude that leisure and social activities are positively associated with improved expressed sentiment. It offers potential explanations for the resumption of human physical activities observed in other research, while also warning governments to pay close attention to the risk of secondary outbreaks posed by the increase in mobility as a result of people's psychological recovery.

The above mechanistic explanations for sentiment variation extrapolate our findings to other knowledge about vaccine rollout, such as vaccine hesitancy. Researchers have documented that

misinformation[25], anti-intellectualism[26], and weak societal collectivism[27] can lead to vaccine hesitancy[28–30], and our results on lockdown stringency and vaccination rate shed light on similar areas. A rising vaccination rate of the entire society outlines the collective behaviors and consensus that promote vaccination. The subsequent loosened NPIs following adequate vaccine coverage further illustrate the science of vaccination. Higher sentiment improvement post-vaccination in a relaxed social environment could in turn alleviate people's concerns about vaccine hesitancy.

We acknowledge several limitations of our study. First, we did not perform matching between each treatment group and its corresponding control group[8,12]. Our staggered DiD design cross-compares people within the vaccinated cohort. This framework outperforms using another set of users without an established vaccination record because we can expect people to have similar pre-vaccination attitudes (e.g., no anti-vax) and behaviors. Nevertheless, the number of people in the treatment group and their demographic distribution cannot be identical to the control group in our model settings. Second, our estimated effect of vaccination cannot be extrapolated from its impact on mental health statues in the entire society. Existing studies have shown polarization of vaccine trust, hesitation, and sentiment and their high homophily in social networks[31]. However, our study did not take these elements into account. We had tried to collect a third batch of people who declared anti-vax on Twitter but were unable to collect sufficient samples. As a result, our results only show improvements in expressed sentiment and mental well-being among those who declared getting vaccinated, which is different from the entire vaccinated group. We should be cautious in interpreting the effects of vaccination when dealing with larger populations, paying particular attention to differences in people's education levels, scientific cognition, and political leanings. Finally, we did not bring our knowledge to alleviate vaccine inequality. Scholars have

found high vaccine hesitancy[32] and low vaccine uptake[33] among people with mental and psychiatric illnesses. However, identifying these individuals is beyond the scope of our study. It's valuable for future research to investigate whether vaccination can deliver its positive mental health effects to everyone equally, especially those who face psychological barriers.

In light of our findings, we recommend that governments maintain vaccination as the primary response to public health emergencies. Government campaigns to promote vaccination should emphasize the mental and hedonic benefits of vaccines in addition to their medical benefits, which could potentially increase willingness to get a vaccine[34]. Meanwhile, we should disseminate these conclusions to doctors, as numerous studies have shown that health care workers are the public's most trusted sources of vaccine guidance[35,36].

Methods

Vaccinated individuals. We searched users who explicitly stated they had gotten vaccinated in their tweets using keywords (or phrases) such as "vaccinated," "I got my first dose of vaccine," "I got the Pfizer," etc. (See Supplementary Table 1 for a complete list of keyword variants) through the Twitter application interface (API). To enrich our sample, we omitted exact phrase matching during the search but employed rigorous regular expression matching thereafter to clean them up (See matching patterns in Supplementary Table 2). Specifically, we excluded: 1) individuals who were not in the United States or countries that cannot be identified from their profile locations; 2) those who claimed they got a vaccine appointment (haven't got vaccinated actually); 3) who were unsure which dose they received; 4) who got other vaccines such as measles, shingles, and smallpox; 5) who said their family members had been vaccinated; 6) who

cannot be identified the exact week they got vaccinated; 7) double quoted statement that may come from others' words (See Supplementary Table 3 for rules of exclusion with examples). Correspondingly, we properly adjusted the timing of vaccination for those who mentioned phrases about time in their tweets, such as "yesterday," "two weeks ago," or "last Wednesday" (see list of examples in Supplementary Table 4). For people who reported their second shot, we backtracked four weeks for the first injection - this is a common time interval between doses in the United States, as evidenced by 4,813 users who reported both doses in our sample (see more details in Supplementary Fig. 1 in Note 1)

We subsequently restricted our sample to Americans who got the first dose of vaccines between January 1, 2021, and December 31, 2021, and those who got boosted between July 1, 2021, and March 31, 2022. We retrieved their historical tweets using the "get_timeline" API with non-English posts excluded, except that some people prohibit non-followings from tracking back their posting history. We kept original tweets, replies, and quotes but discarded retweets since they didn't intuitively reflect what people thought. To sum up, our data collection and screening led to a final sample set of 154,348 vaccinated individuals (134,498 for the first dose and 22,116 for the booster shot, Supplementary Fig. 2 and 3) and 160,511,041 original tweets, replies, and quotes. For future analysis, we further removed all data from users who fall into the highest and lowest 5% posting frequency.

Text analysis. We applied a suite of natural language processing (NLP) approaches to quantify the expressed sentiment, emotions, and signals of mental health statuses in tweets. For sentiment analysis, we adopted Hedonometer[37], an open-source lexicon constructed based on Twitter text analysis, to assign valence scores for each post ranging from 0 (totally negative) to 10 (totally positive). Its calculation depends on a timely updated corpus of 10187 words. The newly

emerged high-frequency words on Twitter during the pandemic, such as "covid," "ncov19," and "self-quarantine," have been included, which seldom appeared in other sentiment dictionaries. Still, we repeated our experiments using other commonly-used sentiment measures such as Valence Aware Dictionary and sEntiment Reasoner (VADER)[38], Linguistic Inquiry and Word Count (LIWC)[39], etc., which can be found in Supplementary Fig. 8.

Since Hedonometer could only generate a single sentiment valence, decomposing it to see which affective states shifted more when encountering vaccination fits in the strength of some other methods. In our study, we adopted the NRC dictionary[40] to recognize people's emotional dynamics, including "anger," "disgust," "fear," "sadness," and "joy." The extent to which people expressed those emotions was calculated as the proportion of words in the entire text that belong to each category.

For mental well-being implicit in numerous linguistic characteristics, we adopted the LIWC dictionary to uncover three major mental dimensions ranging from personal concerns, social processes, and cognitive processes. We determined them by the frequency of appearance in each tweet. Specifically, personal concerns consist of categories of words relative to work (e.g., job, majors), home (e.g., kitchen, landlord), leisure (e.g., cook, movie), and money (e.g., audit, cash); social processes concern family (e.g., daughter, dad) and friends (e.g., buddy, neighbor), and prepositions indicating differentiation (e.g., hasn't, but), insight (e.g., think, know), tentative (e.g., maybe, perhaps), and certainty (e.g., always, never) composite the cognitive processes.

Demographic information. While twitter never requires personal details to be disclosed in a canonical format for privacy concerns, users can opt to self-report what they are willing to share on their profile pages. Synthesizing multiple sources, such as biography and profile image, is a

promising framework for uncovering users' demographic information. Here, we adopted a three-step procedure to realize multidimensional demographic inferences: 1) First, we used the "face_locations" module in Face Recognition, a deep learning method with 99.38% reported accuracy (https://github.com/ageitgey/face_recognition), to detect face existences in profile images. 2) By selecting users whose image has only one face, we adopted the Deepface model (https://github.com/serengil/deepface) to classify their races into six categories ("white," "black," "Asian," "Indian," "Latino Hispanic," "middle eastern") based on complexions. 3) Finally, we adopted the M3 system (https://github.com/euagendas/m3inference) – a state-of-art deep learning model trained on a massive Twitter dataset by integrating profile images, screen name, and profiles descriptions – to recognize users' belonging age groups ("≤18," "19-29," "30-39," "≥40"), gender ("female," "male"), and account types ("individual," "organization"). In our study, we further merged age groups "19-29" and "30-39" into "19-39" since they both refer to young adults, an important circumscription in vaccine allocation in the United States.

Heterogeneity across geography. The severity of the pandemic for each state was determined by the cumulative number of cases and deaths three months before vaccine rollout (October to December 2020). The statistics on COVID-19 infection and mortality was obtained from the Johns Hopkins Coronavirus Resource Center (https://coronavirus.jhu.edu/map.html) and the residential population data was obtained from the Census Bureau of the United States.

We identified the Red and Blue states by who has won more times, Democrats or Republicans, over the past two decades. For the last five general elections, the state where a party won at least three times was identified as having the same partisan leaning.

The economic status of each state was determined by GDP per capita that divided the annual GDP in 2021 by the resident population.

Local vaccination rate. We collected the cumulative daily number of first-dose vaccines administered for each state from the New York Times (https://www.nytimes.com/interactive/2020/us/covid-19-vaccine-doses.html). With residential population data from official statistics, we calculated the vaccination rate for each state on each date and then assigned them to individual tweets for future analysis.

Lockdown policy. The Oxford Covid-19 Government Response Tracker (OxCGRT) database quantifies the dynamics of multi-dimensional governmental policy responses worldwide during the pandemic, ranging from containment and closure, to health and economy. We selected three dimensions: "C4_Restrictions on gatherings," "C6_Stay at home requirements," and "H6_Facial Coverings" from this dataset to investigate sentiment changes relative to loosening of gathering prohibition, mandatory stay-at-home, and facemask wearing requirement. For each state, we took the average level of policies in January 2021 (roughly before mass vaccination delivery) as baselines and determined whether policies had eased by comparing them with policy intensities when people were vaccinated.

Model specification. We estimate a model to investigate if people's expressed sentiment and other mental well-being dimensions are affected by getting COVID-19 vaccines. To account for variations in the timing of vaccination, we designed a staggered DiD model in which early vaccinated people (treated group) were cross-compared to later vaccinated people (control group). In this study, we took those who got vaccinated in the same week of the year as the same group. The control group is, therefore, dynamic for each treatment group depending on the

chronological order of vaccination. Moreover, we defined the control group vaccinated subsequent to effect estimating deadlines (July 2021 for the first dose and January 2022 for the booster, as illustrated in Fig. 1e) as the never-treated group, and those vaccinated previously as the not-yet-treated group. These individuals were incorporated into the model as separate categories. Finally, we kept balanced panel data with respect to calendar time for each cohort. For the first dose administration, we retained tweets before early July and discarded those thereafter; for the booster shot, we discarded those after January 2022.

Recently, literature has pointed out the pitfalls of standard two-way fixed effect (TWFE) models in conducting reliable causal inference[41], especially when treatment timing varies, and heterogeneous treatment effect dynamics exist. The resultant invalid DiD estimator could usually be attributed to the fact that the TWFE generates variance-weighted average of cross-group two-by-two treatment effects. The weight could be negative when treatment time varies, because the already-treated group will act as controls and a negative weight is therefore required to subtract its influence. To avoid these defects, Sun and Abraham (2020)[42] proposed a revised DiD estimator that is robust to staggered model settings. However, it still relies on the TWFE framework and can only additionally incorporate the last-treated group instead of all available not-yet-treated groups as controls. Alternatively, Callaway and Sant'Anna (2021)[43] developed a nonparametric DiD estimator that could more effectively avoid the inherent drawbacks of TWFE-based models.

In particular, Callaway and Sant'Anna define a causal parameter called *group-time treatment effect*, which refers to the average treatment effect for units who are members of a particular group g at a specific time period t, which could be represented by:

$$ATT(g,t) = E[Y_t(g) - Y_t(0)|G_g = 1]$$

where G represents the time period that a unit is first treated. The estimands of $ATT(g,t)$ can be realized by three methods: outcome regression (OR), inverse probability weighting (IPW), and doubly robust (DR). This study adopted the latter one. We can then summarize the overall treatment effect θ_O and dynamic treatment effects $\theta(e)$ varied with length of exposure to the treatment *e*:

$$\theta(g, e_1, e_2) = \frac{1}{e_2 - e_1 + 1} \sum_{t=e_1}^{e_2} \mathbf{1}\{g \le g + e_1 \le g + e_2 \le T\} ATT(g,t)$$

$$\theta_O = \sum_{g \in G} \theta(g) P(G = g | G \le T)$$

$$\theta(e) = \sum_{g \in G} \mathbf{1}\{g + e \le T\} P(G = g | G + e \le T) ATT(g, g + e)$$

where *T* is the maximum time period, $\theta(g, e_1, e_2)$ donates the average effect for units in group g across treatment period from $g + e_1$ to $g + e_2$. The overall treatment effect θ_O is a weighted summary of $\theta(g)$ for all groups *G*, with the weight proportional to the group sizes.

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Declarations

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Author contributions

J.W., Z.C., and Y.F. designed the project. Z.C. and J.W. collected and analyzed the data. Z.C., J.W., and Y.F. interpreted the results. Z.C. drafted the manuscript. Y.F. and J.W. edited the manuscript. S.L. and S.Z. supervised the project and reviewed the manuscript. All authors contributed to the development of the manuscript and approved the final version for publication.

Ethics declaration

This study received ethical approval from the Internal Review Board of the University of Southampton (ERGO II 79401). The social media data used were shared publicly by individuals and analyzed in an anonymous format; no personally identifiable information will be shared with this article. The study does not involve human subjects.

Human Ethics and Consent to Participate declarations

Not applicable

Competing interests

The authors declare no competing interests.

Data availability

Data associated with this study are freely available in deidentified and aggregated form in a public repository at https://github.com/CASGIS/VaccineSentiment. Twitter users cannot be shared publicly to protect privacy and prevent individuals from being identified. The users' historical tweets were aggregated into individual-level weekly panel data with encrypted user identifiers and shared publicly, maintaining the same level of granularity used in this study to ensure repeatability. Data on state-level infections and mortality, vaccination rates, and lockdown policy measures are publicly available online from the Johns Hopkins Coronavirus Resource Center at https://coronavirus.jhu.edu/map.html, the New York Times at https://www.nytimes.com/interactive/2020/us/covid-19-vaccine-doses.html, and the Oxford COVID-19 Government Response Tracker at https://github.com/OxCGRT.

Code availability

The code used in this paper is available at https://github.com/CASGIS/VaccineSentiment.

Supplementary Materials

Supplementary Note 1. Identification of user sample and its representativeness.

The user sample of this study was collected by first rough searching and then precise identification. We retrieved tweets through official Twitter APIs using a set of predefined keywords or phrases that widely occurred in related narratives such as “vaccine”, “I got vaccinated”, “I got/had/took/received my/the vaccine”, “I got the Pfizer/Moderna/Johnson”, etc. (Supplementary Table 1). The search dropped exact matches to obtain a sample as large as possible.

Supplementary Table 1. Keywords list for searching potentially vaccinated Twitter users

Keywords list
vaccine
vaccinate
vaccinated
I got vaccinated
I got/had/took/received my/the vaccine
I got/had/took/received my/the dose
I got/had/took/received my/the first shot
I got/had/took/received my/the second shot
I got the Pfizer
I got the Moderna
I got the Johnson

Next, we filtered out tweets that are irrelevant to self-vaccination through string matching, keeping only those that can clearly identify the date, dose, and type (if any) of vaccination. SI Table. 2 presents the rules of identification with some examples.

Supplementary Table 2. Matching strategy for identifying vaccinated Twitter users

Regex expression	Example
([.,!?]\\s|^)(?:\\w+\\s){0,3}(?i:We|We'v|We've|I|I'v|I've|We'v|We've|I'v|I've)(?:\\s\\w+){0,1}\\s(?i:got|had|took|received)\\s(?i:my|our|the)(?:\\s(#)?\\w+){0,5}\\s(#)?(?i:vaccine|vac|booster)	**I got my** 1st #COVID19 **#vaccine** today. The mass vax site was welcomingsefficient. **I got my** first dose of the **#vaccine** today, and it's such an amazing feeling I want to shout it to the world! 🙌🏻#onesteptowardfreedom
([.,!?]\\s|^)(?i:(Just\\s)?(Already\\s)?(Finally\\s)?Got|Had|Took|Received)\\s(?i:my|our|the)(?:\\s(#)?\\w+){0,5}\\s(#)?(?i:vaccine|vac|booster)	**Got our** 1st **vaccine** for covid today! #vaccine #science #thankful **Just had my** COVID **Vaccine** 🥳💏#COVIDVaccine #vaccinated
([.,!?]\\s|^)(?:\\w+\\s){0,3}(?i:We|We'v|We've|I|I'v|I've|We'v|We've|I'v|I've)(?:\\s\\w+){0,1}\\s(?i:got|had|took|received)\\s(?i:my|our|the)(?:\\s(#)?\\w+){0,3}\\s(#)?(?i:dose|doze|shot|jab|booster)	**I got my** second Pfizer **shot** last week.. s/o to us! ❤️ #Vaccinate **I had my** AstraZeneca **jab** yesterday. No reaction and could barely feel where it was all day yesterday.
([.,!?]\\s|^)(?i:(Just\\s)?(Already\\s)?(Finally\\s)?Got|Had|Took|Received)\\s(?i:my|our|the)(?:\\s(#)?\\w+){0,3}\\s(#)?(?i:dose|doze|shot|jab|booster)	**Just got my** second Covid **shot**. I'm fully vaccinated! 💪🏾 Go Billy! **Received my** first **dose** yesterday.
([.,!?]\\s|^)(?:\\w+\\s){0,3}(?i:We|We'v|We've|I|I'v|I've|We'v|We've|I'v|I've)(?:\\s\\w+){0,1}\\s(?i:got|had|took|received)(?:\\s(#)?\\w+){0,2}\\s(#)?(?i:vaccinated|boosted)	**I got vaccinated** today!!!!! 😁💪 #GetVaccinated Well **I** just **got vaccinated** lol. Let's hope I don't die
([.,!?]\\s|^)(?:\\w+\\s){0,3}(?i:I|I\\sam|I'm|I'v|I've|I\\sam|I'm|I'v|I've)(?:\\s\\w+){0,2}\\s(#)?(?i:vaccinated|boosted)	**I am** officially **vaccinated** against COVID19. Got the Johnson and Johnson shot this morning! **I'm** fully **vaccinated**, got my 2nd jab today! 😍
([.,!?]\\s|^)(?i:(Just\\s)?(Already\\s)?(Finally\\s)?Got|Had|Took|Received)(?:\\s(#)?\\w+){0,2}\\s(#)?(?i:vaccinated|boosted)	**Got** fully **vaccinated** yesterday and I feel like shit **Just got** fully **vaccinated** and I've never been hotter 🔥
([.,!?]\\s|^)(?i:Fully\\s)?(#)?(?i:vaccinated|booste	**Fully vaccinated**! Got my booster today. Can't

d)!	wait for everyone to get this vaccine so I can get back to comic conventions. **Fully #vaccinated**!!!! Got my 2nd Moderna shot today!!!! In 14 days I'll be 95% resistant!!!!
(?i:one\\sto\\sgo)	OUT Damn #Covid! / One☝Down, **One to GO**! / .💉 #vaccinated (CVS pharmacy in West Covina, CA) Shot #1 down, **one to go**!!! #vaccinated
([.,!?]\\s|^)(?:\\w+\\s){0,3}\\w+(!){1,10}\\s(?i:#vaccinated|boosted)	Did a thang today!!! **#vaccinated** Got it! **#vaccinated** #CovidVaccine This happened today! **#vaccinated**
([.,!?]\\s|^)(?:\\w+\\s){0,3}(?i:We|We'v|We've|I|I'v|I've|We'v|We've|I'v|I've)(?:\\s\\w+){0,1}\\s(?i:got|had|took|received)(?:\\s(#)?\\w+){0,5}\\s(#)?(?i:Pfizer|Moderna|Johnson|JsJ|J&J)	Yay! **I got** the **Pfizer** one yesterday! 💞 **I got** the **Moderna** on Monday. Six weeks to fully vaccinated!
([.,!?]\\s|^)(?i:(Just\\s)?(Already\\s)?(Finally\\s)?Got|Had|Took|Received)\\s(?i:my|our|the)(?:\\s(#)?\\w+){0,5}\\s(#)?(?i:Pfizer|Moderna|Johnson|JsJ|J&J)	**Got my Pfizer** yesterday. I had muscle aches all night in my sleep. Hope the second one is better **Got JohnsonsJohnson** vaccinated on Monday and was as sick Monday as I ever was.

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We further dropped tweets 1) pointing to an appointment, 2) saying other people got a vaccine, 3) referring to vaccines other than COVID-19, 4) cannot identify which dose people received, 5) cannot identify the exact week of vaccination, 6) double quoted that may come from others' words. SI Table. 3 lists the criteria of tweet exclusion with examples.

Supplementary Table 3. Rules of unqualified users exclusion

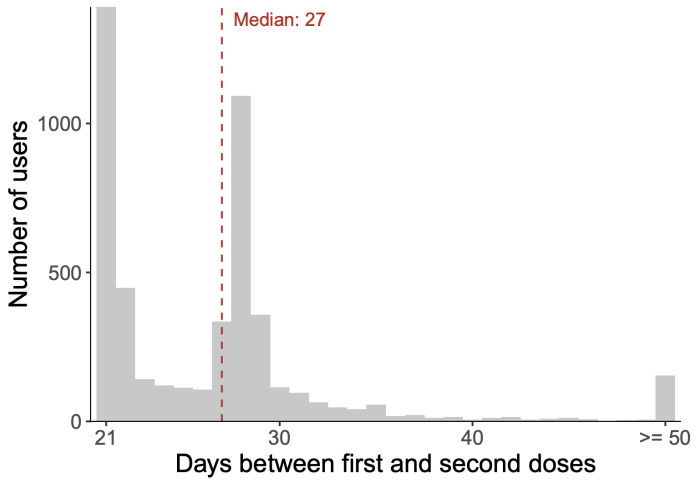
Rules of exclusion	Example
Vaccine appointment	Just got my 1st #COVID #vaccine **scheduled**! Thank god for science!
	Got my COVID vaccine **appt** for this Friday!!! I feel so much hope right now 😌💚
Family members or others got vaccinated	I got my **mom** a VACCINE!!!! 💉 💉
	I finally got my **parents** vaccine appointments! 🥰🥰🥰
Vaccine for other diseases	Got my **shingles** vaccine today. I'm officially old.
	I got my vaccine yesterday!***tetanus** shot
Cannot identify which dose they got	Glad I got vaccinated **before** this Johnson and Johnson vaccine came out! I don't trust it at all
	I **already** got my COVID vaccine soooo....
Cannot identify the exact week of vaccination	**When** I got my 1st vaccine I had headache and wicked arm pain.
	I got fully vaccinated **this month**.

People did not always tweet right after vaccination. We can usually see some phrases in the text representing the time interval between posting and being vaccinated, such as “yesterday”, “two days ago”, “this past Friday”, etc. We determined people’s actual date of vaccination prior to analysis. SI Table 4 presents typical cases of time adjustment.

Supplementary Table 4. Examples for adjusting vaccination timing of users

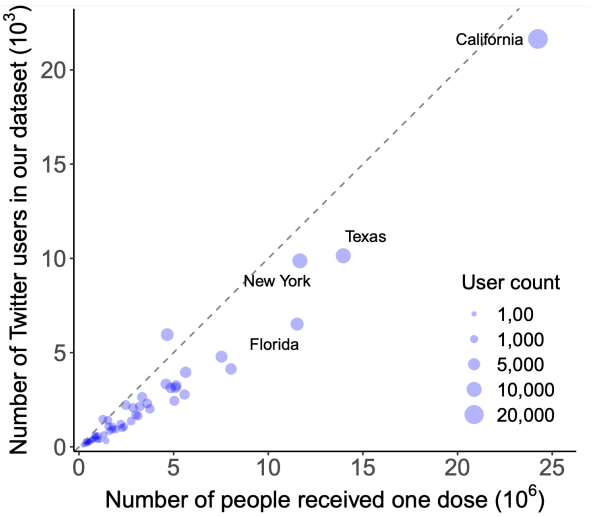
Example	Post date	Adjustment
Husband and I both got vaccinated **yesterday**! 😁		-1
Had my second Moderna shot **~23 hours ago**. Nurse told me the possible side effects.		-1
Just got my second dose of the Moderna vaccine **two hours ago**.		0
I literally got vaccinated **10 minutes ago** but I’m down!		0
I dunno. I got vaccinated **two days ago**		-2
I got Pfizer shot **10 days ago**. Only side effect was pain in the arm.		-10
I got my first Maderna vaccine **last week**! 👍💉		-7
I got my vaccine **two weeks ago**. Thanks BOP!!!		-14
That’s awesome! But how come I got prioritizes over Doyle. I got my second dose **over the weekend**.	2021-03-09, Tue	-3
I got my first vaccine shot **this past weekend** thanks to 😊💚 #grateful	2021-03-29, Mon	-2
I got my second Pfizer vaccine on **Friday** and my arm still sore 🙃	2021-02-22, Mon	-3
I got my first vaccine (pfizer) **this past Wednesday**	2021-02-26, Sat	-2
Be smart. Be safe. Get vaccinated! I got my 2nd vaccine **last Saturday**.	2021-03-01, Mon	-2
That's amazing!! YAY! I got my second shot of Moderna **3 Saturdays ago** because I am a caregiver. I had no side effects either. 👍😊	2021-03-24, Wed	-18
I hear you! Got my second Pfizer shot on **3/22**!	2021-04-03	-12
I got my 2nd dose of Moderna on **April 10th**!😊No side effects and feeling great.	2021-04-17	-7

For those who reported the second dose, we extrapolated the date of the first dose by going back four weeks before full vaccination. We tested the plausibility of this method. Taking advantage of 4,813 users who tweeted the exact dates of both shots, we summarized their actual date gaps between the two doses. SI Fig. 1 shows that most of them got the second dose three (21 days) or four (28 days) full weeks after their first-time injections, with a median date interval of 27 days, suggesting that our extrapolation method is reasonable.



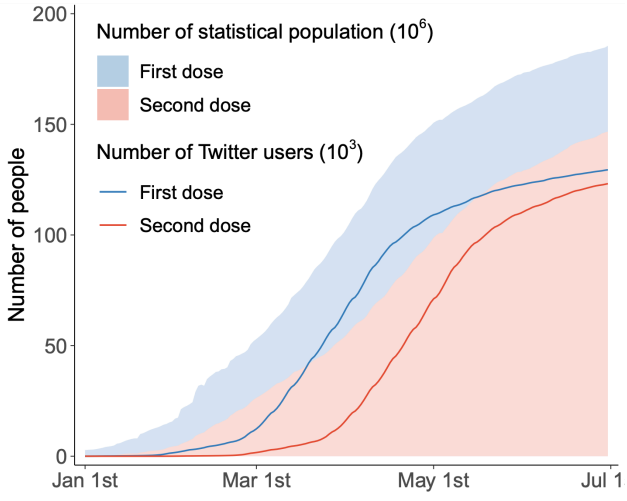
Supplementary Fig. 1 Distribution of day intervals between first and second doses. The histogram is drawn from 4,813 users who tweeted both shots in our sample. The red dashed line shows the median value.

Finally, we validated the representativeness of samples over space and time. In this study, we identified people's States from profile locations and discarded those who cannot be identified as living in America. From the spatial perspective, we gathered the official statistics of vaccination from *The New York Times* (https://www.nytimes.com/interactive/2020/us/covid-19-vaccine-doses.html). SI Fig. 2 shows that, by the end of June, the number of vaccinated Twitter users in our dataset is highly correlated with the statistical number of people who received at least one dose at the state level (*pearson corr.* = 0.97).



Supplementary Fig. 2 Representativeness of spatial distribution of users. The state-level comparison between the number of vaccinated Twitter users and the statistical number of populations received at least one dose by the end of June 2021.

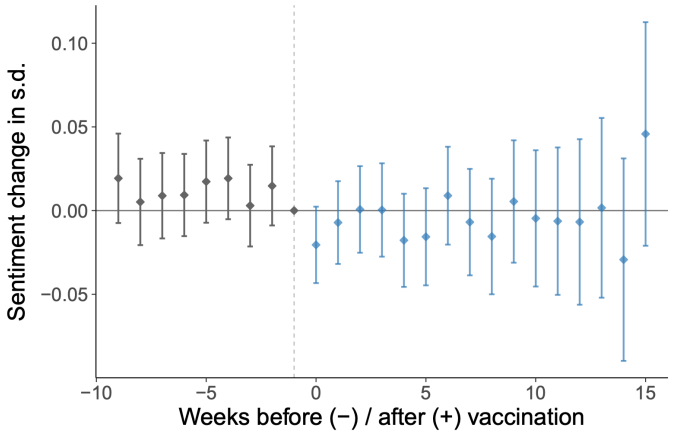
From a temporal perspective, we tracked the daily cumulative number of Twitter users who got one and two shots, respectively. We found our sample well correlated with the official statistics, especially since early March (*pearson corr.* = 0.99) when mass vaccination was rolled out to the general public and vaccines were not exclusively available to health workers (SI Fig. 3).



Supplementary Fig. 3 Representativeness of temporal distribution of users. The areal filled distributions in light blue and light red are overlapped, showing the statistical number of populations received one and two dose(s). The blue and red line show the number of Twitter users in this study.

Supplementary Note 2. The effect of booster shots on expressed sentiment.

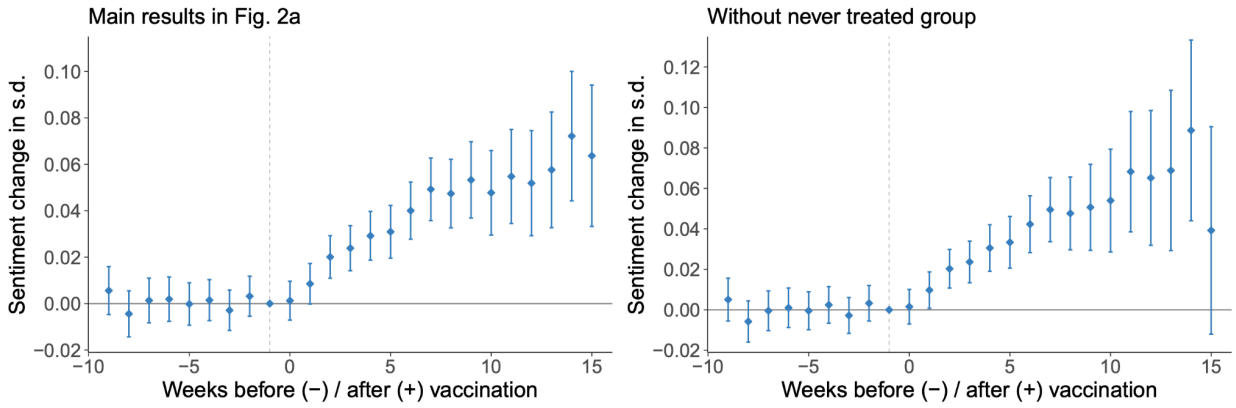
We investigated how people's expressed sentiment was affected by getting the booster shot of COVID-19 vaccine. Following the same modeling framework as Fig. 2a, we focused on 22,116 users who got boosted between 1st July, 2021 and 31th March, 2022, and set 5,326 of them in 2022 as the never-treated group. SI Fig. 4 shows that individuals' sentiments see no remarkable changes before and after the booster shots, indicating that a third dose of vaccine does not bring evident affective benefits as being vaccinated for the first time.



Supplementary Fig. 4. The effect of booster shot on expressed sentiment. The error bars represent the 95% confidence intervals.

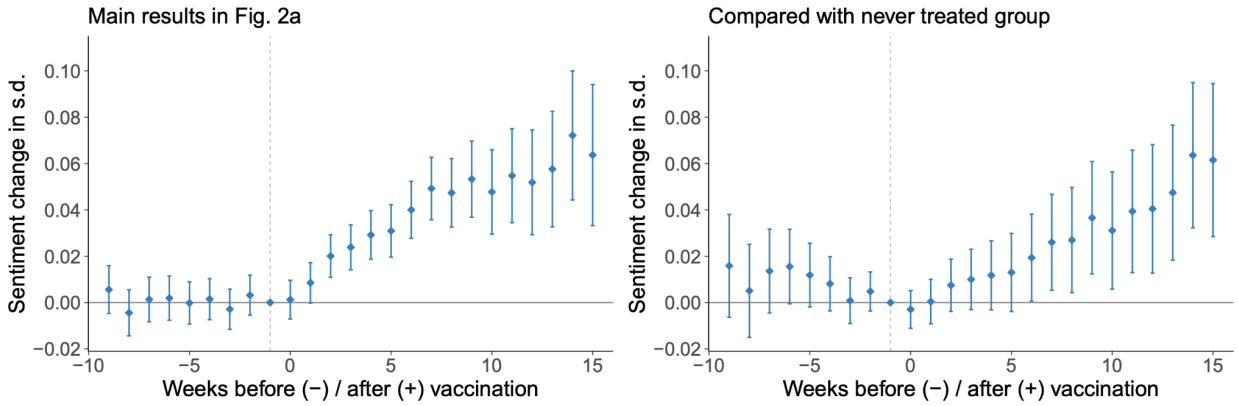
Supplementary Note 3. Robustness checks of staggered DiD model settings.

We tested our staggered DiD model settings from four aspects. First, we tried discarding those vaccinated after July 2021 (i.e., the never-treated group) to test what if early vaccinated individuals cross-compared only with later vaccinated individuals before July 2021 (i.e., the not-yet-treated group). Supplementary Fig. 5 shows a sentiment change similar to Fig. 2 except for an insignificant change in week 15. The aggregated effect size for full vaccination is 0.059 s.d. ($P < 0.001$, 95% CI 0.036 to 0.082), which is comparable to our main conclusion (0.055 s.d., $P < 0.001$, 95% CI 0.037 to 0.072), indicating that excluding the never-treated group has limited influence on our findings.



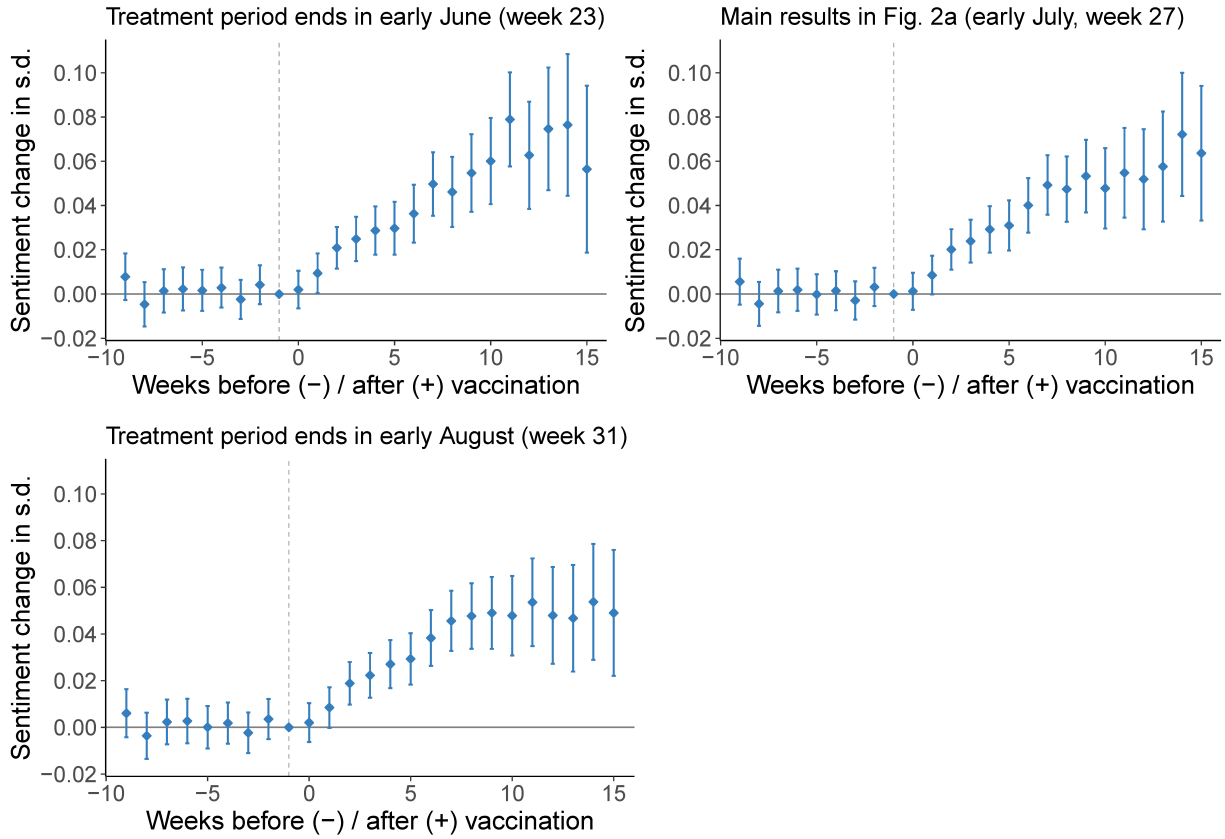
Supplementary Fig. 5. Sensitivity analysis for absence of never-treated group. The model setting is the same as Fig. 2a but excludes individuals vaccinated after early July, i.e., the never-treated group. The error bars represent the 95% confidence intervals.

We then alternatively deactivated the staggered setting by comparing early vaccinated individuals with only those who got vaccinated after July (i.e., the never-treated group). We found poorly followed parallel assumptions before vaccination with less significant post-vaccination sentiment changes (0.041 s.d., $P = 0.001$, 95% CI 0.016 to 0.065) (SI Fig. 6). These results underscore the importance of cross-comparison with the not-yet-treated group in investigating the impact of vaccination.



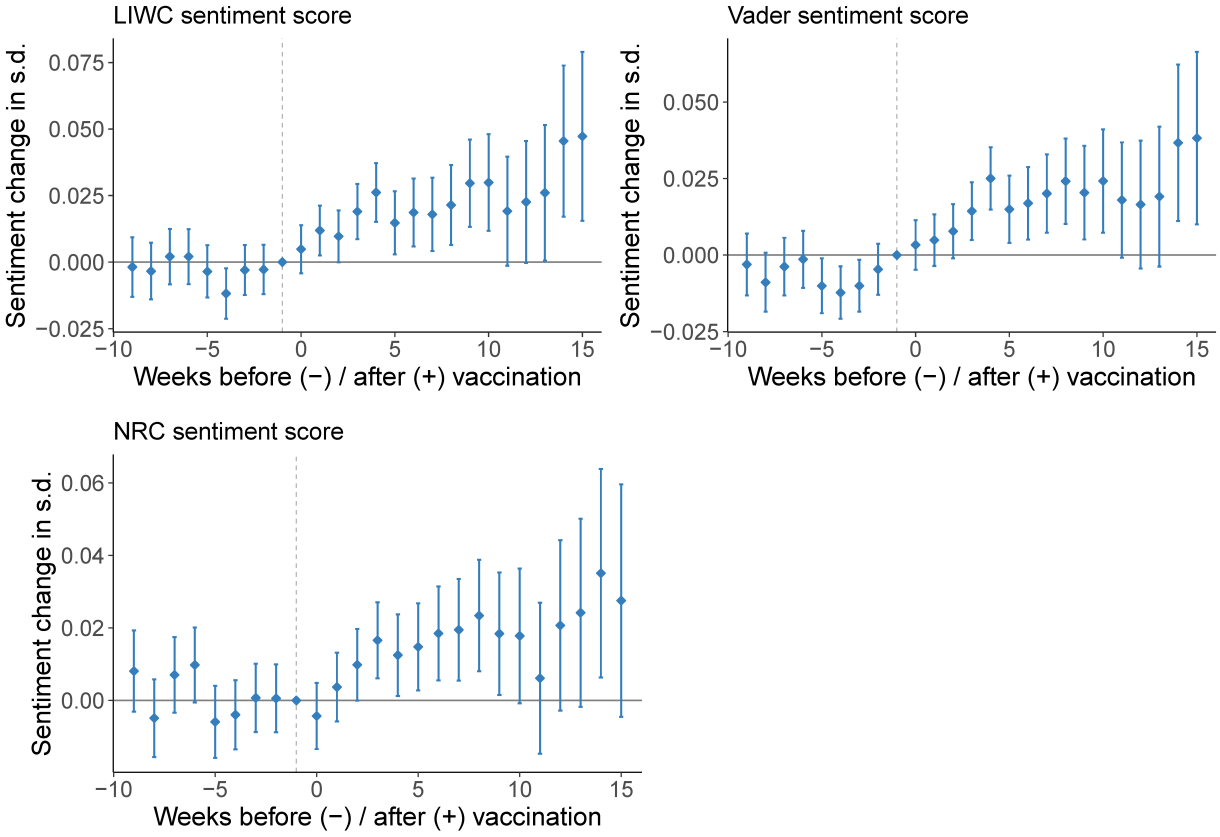
Supplementary Fig. 6. Sensitivity analysis for the absence of not-yet-treated group. The model setting is the same as Fig. 2a but removes later vaccinated individuals before early July, i.e., the not-yet-treated group, from the control group. The error bars represent the 95% confidence intervals.

The concluded impact of vaccination on expressed sentiment may be also associated with the time point separating out the never-treated group. We tested different model settings by defining individuals who got vaccinated after early June (week 23), early July (week 27, the same as Fig. 2), and early August (week 31) as the never-treated group, respectively. We found average treatment effects gradually decline from 0.060 s.d. ($P < 0.001$, 95% CI 0.044 to 0.076) in week 23 to 0.049 s.d. ($P < 0.001$, 95% CI 0.032 to 0.067) in week 31 (SI Fig. 7), indicating that the effect of vaccination on expressed sentiment is more pronounced in earlier stages.



Supplementary Fig. 7. Sensitivity analysis for different length of effect estimate. The model setting is the same as Fig. 2a but sets early June, early July, and early August as the end point of effect estimate (the time point separating out never-treated group), respectively. The error bars represent the 95% confidence intervals.

Finally, we validated our results by applying the same model as Fig. 2a to sentiment valence calculated from LIWC, VADER, and NRC, three other commonly used dictionaries. We found smaller medium-term effects for LIWC (0.028 s.d., $P = 0.002$, 95% CI 0.011 to 0.046), VADER (0.023 s.d., $P = 0.005$, 95% CI 0.007 to 0.040), and NRC (0.021 s.d., $P = 0.027$, 95% CI 0.002 to 0.039). We attributed their difference with our main results to the fact that they did not include high-frequency terms newly emerged during the pandemic.

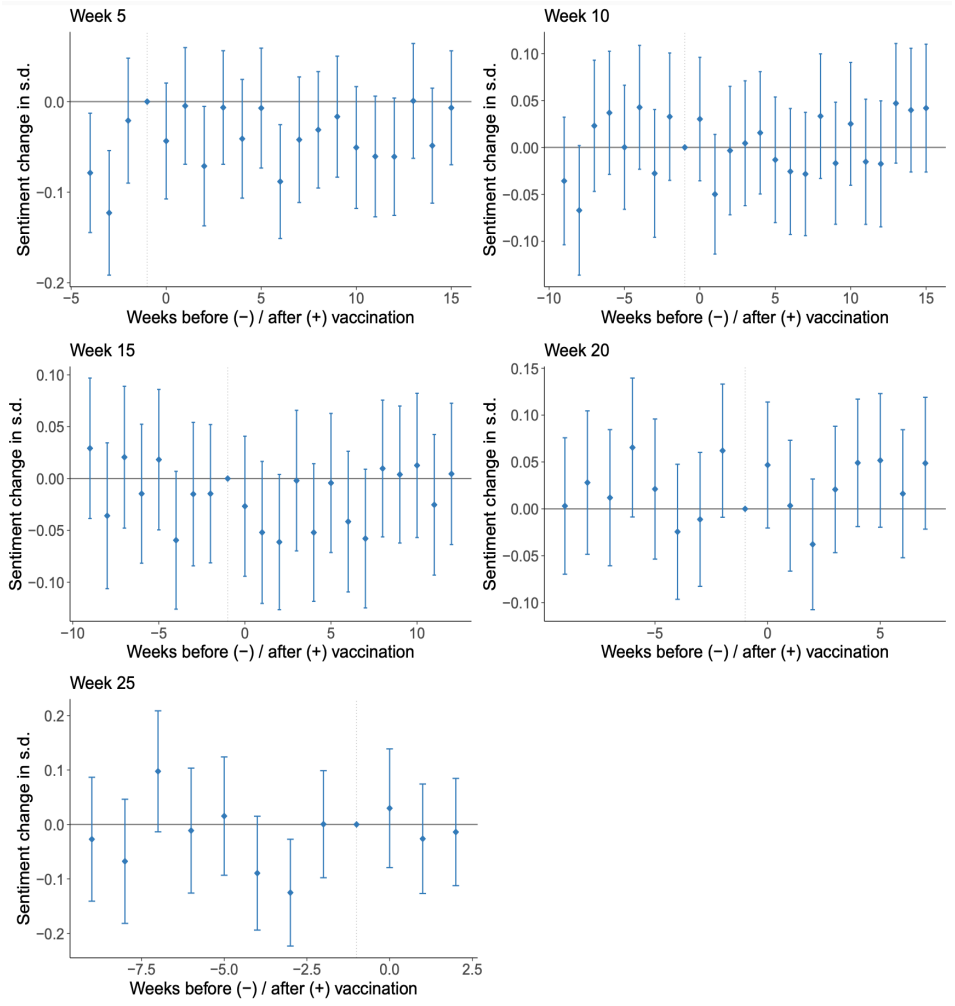


Supplementary Fig. 8. Sensitivity analysis for alternative sentiment measures. The model setting is the same as Fig. 2a, with expressed sentiment measured by alternative dictionaries including LIWC, VADER, and NRC. The error bars represent the 95% confidence intervals.

Supplementary Note 4. Parallel assumption test

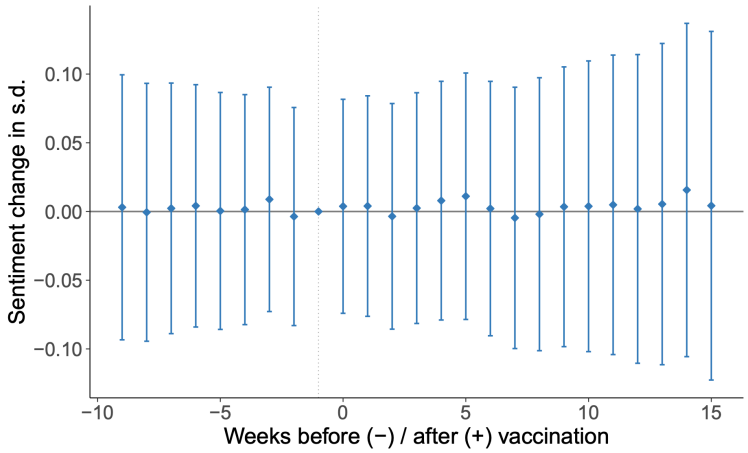
Under the staggered DiD model setting, we examined the parallel assumption by designing Placebo tests for the never-treated group and the not-yet-treated group separately.

First, we focus on the not-yet-treated group. For each group of people vaccinated in the same week, we selected the corresponding not-yet-treated group (i.e., individuals who got later vaccinated after that week but before early July), assigned that week as their dummy week of vaccination, and then reperformed staggered DiD. SI Fig. 9 shows the selected cases for week 5, 10, 15, 20, and 25. We see no remarkable changes in different time slots, suggesting that the not-yet-treated group of later vaccinated individuals are a reasonable control group for the early vaccinated.



Supplementary Fig. 9. Placebo test for not-yet-treated group. The error bars represent the 95% confidence intervals.

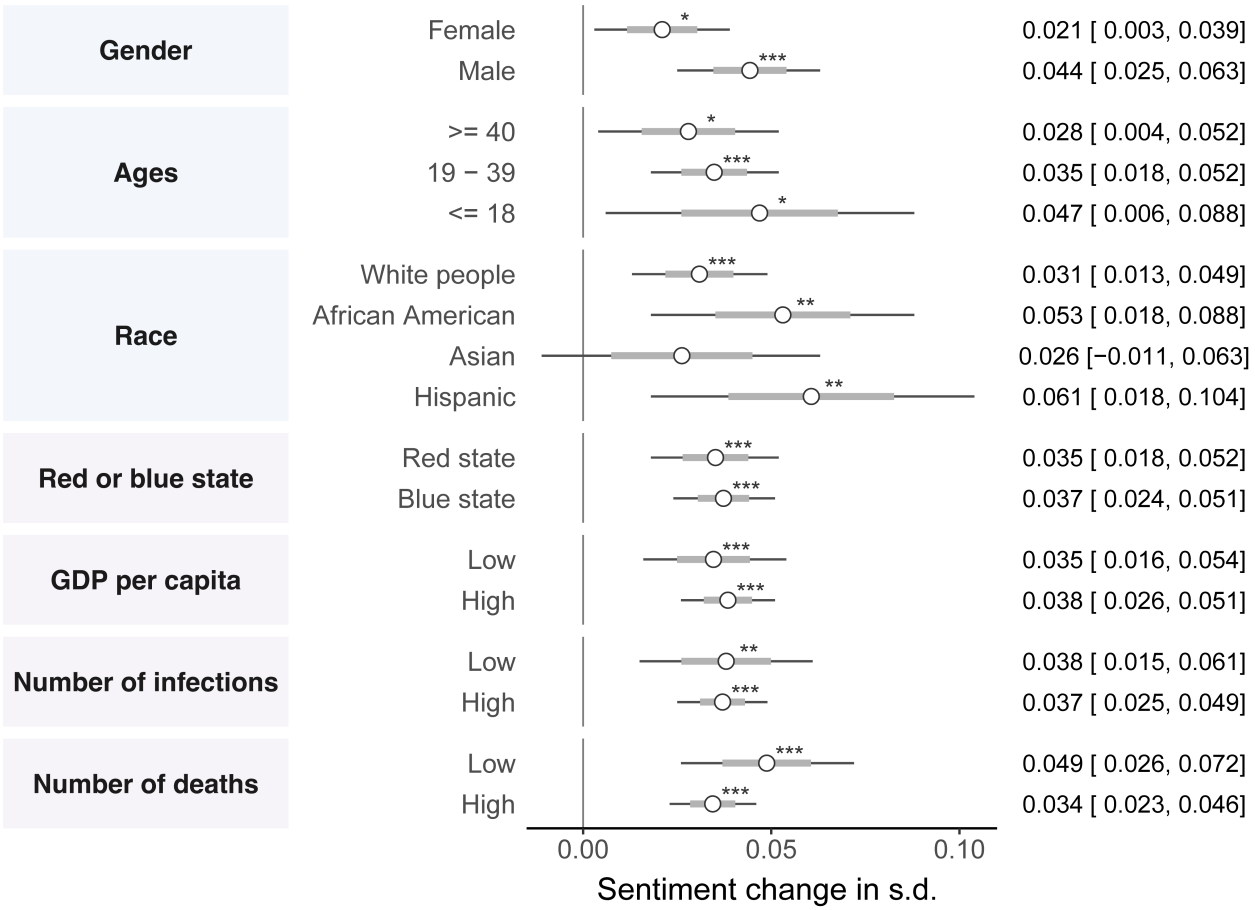
Next, we isolated the never-treated group, i.e., individuals who got their first dose after early July, from our sample. We assigned them a random week before their first dose as the dummy week of vaccination, reperformed staggered DiD on dummy vaccination weeks with the same model setting as our main results, and then iterated 1,000 times. The averaged effects in SI Fig 10 shows no significant changes over time, implying that our defined never-treated group is a legitimate control for early vaccinated individuals.



Supplementary Fig. 10. Placebo test for never-treated group. The error bars represent the 95% confidence intervals.

Supplementary Note 5. Short-term heterogeneity effect sizes

SI Fig. 11 reports the short-term effect sizes of vaccination (4-7 weeks post first dose) on the expressed sentiment. We found that the relative effect sizes for most heterogeneous dimensions are identical across short- and medium-term periods. Males (0.044 s.d., $P < 0.001$, 95% CI 0.025 to 0.063), younger generation (0.047 s.d., $P = 0.024$, 95% CI 0.006 to 0.088), and Hispanic American (0.061 s.d., $P = 0.006$, 95% CI 0.018 to 0.104) see higher sentiment improvement. The sentiment changes between people living in states with different party leaning and economic development show insignificant differences or a gap at the lowest significant level ($P < 0.05$). However, some ethnic minorities see diverging changes. Asian people show no significant changes during the short-term period (0.026 s.d., $P = 0.162$, 95% CI -0.011 to 0.063) but 0.071 s.d. ($P = 0.033$, 95% CI 0.006 to 0.137) sentiment increase one month after full vaccination. On the contrary, African Americans show significant sentiment improvement during the short-term period (0.053 s.d., $P = 0.003$, 95% CI 0.018 to 0.088) but back to insignificant thereafter (0.045 s.d., $P = 0.078$, 95% CI -0.005 to 0.095), indicating that the mental bonus from vaccination is transitionally evident to African Americans rather than long-lasting.



Supplementary Fig. 11. Short-term heterogeneous effects of vaccination on expressed sentiment. The average treatment effect across 4-7 weeks after first dose vaccination. The heterogeneous dimensions are defined in the same way as Fig. 3. Error bars in bold, light grey show standard deviation. Error bars in black represent 95% confidence intervals, with * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.