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Political Depression? A Big-Data, Multimethod Investigation of Americans' Emotional Response to the Trump Presidency

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Previous studies suggested that the 2016 presidential elections gave rise to pathological levels of election-related distress in liberal Americans; however, it has also been suggested that the public discourse and the professional discourse have increasingly overgeneralized concepts of trauma and psychopathology. In light of this, in the current research, we utilized an array of big data measures and asked whether a political loss in a participatory democracy can indeed lead to psychopathology. We observed that liberals report being more depressed when asked directly about the effects of the election; however, more indirect measures show a short-lived or nonexistent effect. We examined self-report measures of clinical depression with and without a reference to the election (Studies 1A & 1B), analyzed Twitter discourse and measured users' levels of depression using a machine-learning-based model (Study 2), conducted time-series analysis of depression-related search behavior on Google (Study 3), examined the proportion of antidepressants consumption in Medicaid data (Study 4), and analyzed daily surveys of hundreds of thousands of Americans (Study 5), and saw that at the aggregate level, empirical data reject the accounts of "Trump Depression." We discuss possible interpretations of the discrepancies between the direct and indirect measures. The current investigation demonstrates how big-data sources can provide an unprecedented view of the psychological consequences of political events and sheds light on the complex relationship between the political and the personal spheres.

Keywords: emotion, politics, big data, social media, social cognition

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In what now feels like a memory from a distant era, on November 8th, 2016, the United States seemed to be on the eve of the election of its first female president. However, the morning after, millions of Liberal Americans awoke to a very different reality—the election of a president who they believed to represent some of the worst aspects of their country. Many reported feeling severe distress following this major event in U.S. history, and numerous media reports of "political depression" appeared (Brooks, 2017; Goldberg, 2016; Khazan, 2017; Maltby, 2018; Milbank, 2017; Zaharna & Miller, 2017).

Supporting this public perception, recent empirical evidence suggests that Liberal Americans suffered a long-lasting decrease in their well-being following the election. For example, Lench et al. (2019) asked participants to predict the effects of the election on

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their happiness and to complete measures of affect and satisfaction with life at various time points before and after the election. The results showed that Liberal participants reported reduced levels of happiness that lasted for at least six months after the election.

Alongside with these reports of decreased happiness, further studies provide evidence for the phenomenon of "election-related distress" among Liberal Americans. Specifically, in a study by Pitcho-Prelorentzos et al. (2018), Americans who reported voting for the democratic candidate had increased levels of anxiety and depression as indicated by their answers on a questionnaire designed to screen for clinical levels of depression and anxiety (PHQ-4; Kroenke, Spitzer, Williams, & Löwe, 2009).

Moreover, in a recent study (Tashjian & Galván, 2018), nearly a quarter of the participants who saw themselves as being personally affected by the election (e.g., identified with marginalized groups such as women, African Americans, Homosexuals, Muslims) reported experiencing depression symptomology that was above the clinical cut-off on a standard depression questionnaire (CES-D; Radloff, 1977). This increase in depression levels in members of marginalized groups was fully mediated by participants' levels of distress over the results of the election.

To some, it may be surprising if a political event in a participatory democracy can be so consequential for citizens' personal emotional lives and result in psychopathology. It is well known that personal losses (e.g., loss of loved ones; Wijngaards-de Meij et al., 2005; loss of relationships; Bruce & Kim, 1992; loss of employment; Dooley, Catalano, & Wilson, 1994) can trigger depression. However, the loss sustained by the Liberal Americans was a political rather than a personal loss. While the election of Trump was a staggering defeat in an abstract battleground of values and ideologies, in terms of real-world consequences, the immediate repercussions of the election did not involve traditional depressionogenic factors such as the loss of loved ones, the loss of a relationship, or loss of employment.

Nonetheless, it is likely that even such a symbolic loss should not be underestimated. Individuals' political ideologies and their national identification play a central role in people's self-narratives (Atran, 2006) and provide them with a sense of meaning and purpose (Rovenpor et al., 2019). To many Liberal Americans, the rhetoric of Donald Trump seemed to reflect a departure from long-standing Enlightenment-era ideals that they believed to be at the core of the American project; as such, the election of Trump may have symbolized a major loss in the "battle for the soul of the country" (Meacham, 2018) with which they strongly identified. Given that past research suggests that a personal loss of meaning may be associated with depression (e.g., Debats, 1996), it indeed may be warranted to consider the possibility that consequential political events such as the election of Donald Trump could indeed be reflected in actual psychopathology.

Moreover, many Americans saw the rhetoric of Donald Trump, promising to "Make America Great Again", as a promise to reestablish a White male hegemony that has persisted for years and that disenfranchised minorities. The election of Barack Obama, the first black president, and the anticipated election of Hilary Clinton, who would have been the first female president, symbolized that the United States has finally become a more inclusive place for diverse populations. Against this backdrop, the victory of Donald Trump may have suggested to many Americans that their fellow citizens have again turned their backs on them, excluding them from the table of political influence (e.g., Abu-Ras, Suárez, & Abu-Bader, 2018). Given past research showing that depression preponderance is associated with a sense of social exclusion (e.g., Williams, 2007) and with the subjective experience of discrimination (Kessler, Mickelson, & Williams, 1999), the possibility that the 2016 elections had an effect on rates of depression indeed seems plausible.

In light of such considerations, it has been argued that the election was experienced by many Americans as a truly psychologically traumatizing event—and as such as being potentially depressionogenic (Tashjian & Galván, 2018). Consistent with this view, a survey we have conducted on a group of 65 professional psychologists (see Figure 1; see online supplemental materials for full details) showed that most professionals believe that the election of Trump was traumatic to the extent that it could cause a significant increase in Liberal Americans' average levels of depression; moreover, this rise in depression symptomatology was predicted to remain for at least a year.

Despite these perceptions of "Trump Depression"—reflected in public discourse and by the psychological community—it has been recently argued that the psychological discourse has overgeneralized the terminology of trauma and mental illness, a phenomenon referred to as *concept creep* (Haslam, 2016). While it is clear that Liberal Americans experienced anger, sadness, and dismay in response to the election results, it could be the case that such a collective affective reaction should not be confused with actual depressive psychopathology. According to Haslam (2016), such a potential muddling of clinical–psychological discourse and social–political processes runs the risk of obfuscating scientists' understanding of real psychological trauma and illness.

Arbitrating questions regarding the "realness" of individuals' subjective affective states entails challenging philosophical and empirical difficulties of so-called "hedonometry" (Kahneman, 2011). Therefore, in the current article, we attempted to address this challenge by gauging individuals' levels of depression using an array of measures (for a similar approach see Wojcik, Hovasapian, Graham, Motyl, & Ditto, 2015). We examined the effect of the election by directly asking participants to report their emotional well-being as well as by using indirect methods that rely on big data (using a machine learning-based model predicting mood from social media language, analyzing millions of Google searches, medication use, and periodic surveys of the well-being of hundreds of thousands of Americans). Each of the methods we employed provides a partial view of the American psyche; hopefully, together, they provide a relatively comprehensive picture of the affective reaction to the elections and will allow us to examine the existence of a purported phenomenon of "Political Depression."

Study 1A

As the first step in our investigation, we examined whether we could replicate findings from previous studies that used clinical questionnaires to assess whether Liberal Americans indeed report greater levels of depression in response to the election.

Method

We ran a https://aspredicted.org/pn74u.pdf online study using 1,007 participants recruited through Amazon Mechanical Turk

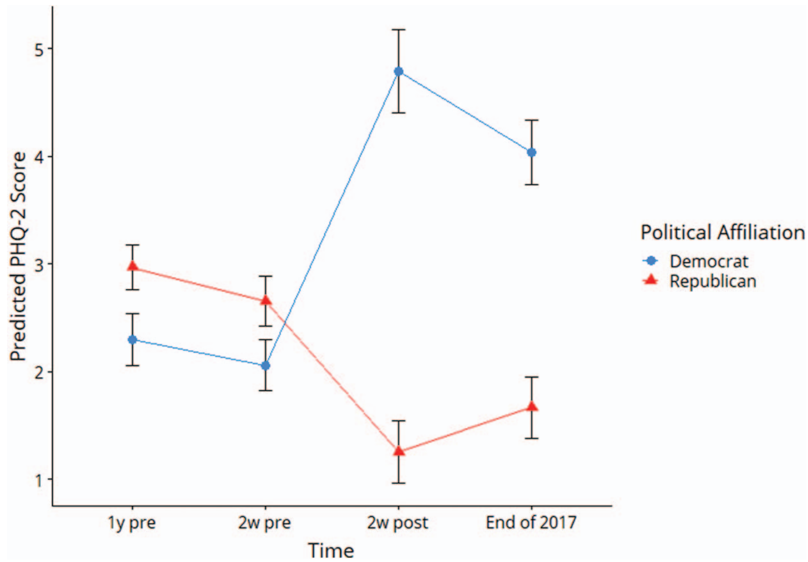

Figure 1. Depression scores of Republican (red/light gray) and Democrat (blue/dark gray) individuals, predicted by professional psychologists. The results show that in the year before the elections and during the two weeks before the elections, psychologists predicted Republicans to exhibit higher levels of depression. However, two weeks after the elections and in the year after the election, psychologists predicted much higher levels of depression for Democrat individuals. Error bars denote Cousineau-Morey within-subjects 95% confidence intervals. See the online article for the color version of this figure.

(MTurk) who received a compensation of $0.6. Participants were all residents of the United States. The following exclusion criteria were determined a priori and applied to the data: 98 participants were excluded based on duplicate GPS coordinates or IP addresses. Another 287 participants were excluded for not identifying as either Democrats or Republicans. One hundred and fifty-one subjects were excluded from the analysis for providing invariant responses to the main parts of the study (8 questions) or for not completing the questionnaire. The final analysis included 507 participants (299 women; 348 Democrats). Participants ranged in age from 18 to 84 ($M = 40.55$; $SD = 12.46$).

We constructed a mean depression score using a modified version of the Patient Health Questionnaire (PHQ-2; Löwe, Kroenke, & Gräfe, 2005). The participants were asked to state on a 0–7 Likert scale how much have they felt down, depressed, or hopeless and how much have they felt little interest or pleasure in doing things for the year before the election, the two weeks before the election, two weeks after the election, and from the election until the day of the survey (May, 2018). The modified PHQ-2 shows a range of Cronbach's alpha of 0.78–0.83 (one alpha for every time point); these are consistent with the alpha reported in the literature (0.83; Löwe et al., 2005). In addition, participants were asked about the political party they felt the greatest identification with ("Do you consider yourself: Democrat/Republican/Independent or other") and which candidate they voted for.

For the current and all subsequent studies, ethical approval was granted by the ethics committee of Ben-Gurion University of the Negev.

Results

In the current and following studies, analyses were conducted with R (R Core Team, 2013) and RStudio (Rstudio Team, 2015) using the packages tidyverse (Wickham et al., 2019), BayesFactor (Morey & Rouder, 2018), and bayestestR (Makowski, Ben-Shachar, & Lüdecke, 2019).

As predicted, political affiliation moderated self-reported levels of depression following the 2016 election [$F(3, 1515) = 137.98$, $p < .001$, $\eta^2_G = 0.07$, $BF_{Inclusion} > 3^*10^{76}$] such that Democratic participants reported feeling more depressed after than before the election, whereas Republicans exhibited an opposite pattern of results (see Figure 2.), demonstrated by an interaction contrast between the first point in time and the last point in time [$t(1515) = 12.47$, $p < .001$, $\eta^2_p = 0.093$, $BF_{10} = 9.22^*10^{27}$].

Study 1B

The results of Study 1A provided strong evidence for the occurrence of "Trump Depression." However, a skeptical interpretation of these results is still possible. Much research has shown that people do not have direct access to their internal experiences and often interpret their emotions based on lay causal psychological theories of how they "should" feel (e.g., Nisbett & Wilson, 1977; Schachter & Singer, 1962). Another possible explanation of the results is that this study (as well as previous studies that examined election-related distress) may have had an element of experimental demand; namely, the reference to the election may have signaled to the participants the expected pattern of results, and influenced their answers.

Therefore, in order to diminish the possible effects of individuals' lay theories and demand characteristics, in Study 1B we repeated Study 1A but omitted the reference to the election as a temporal anchor and instead asked participants to answer the depression questionnaire as it relates to the years 2015, 2016, 2017, and 2018.

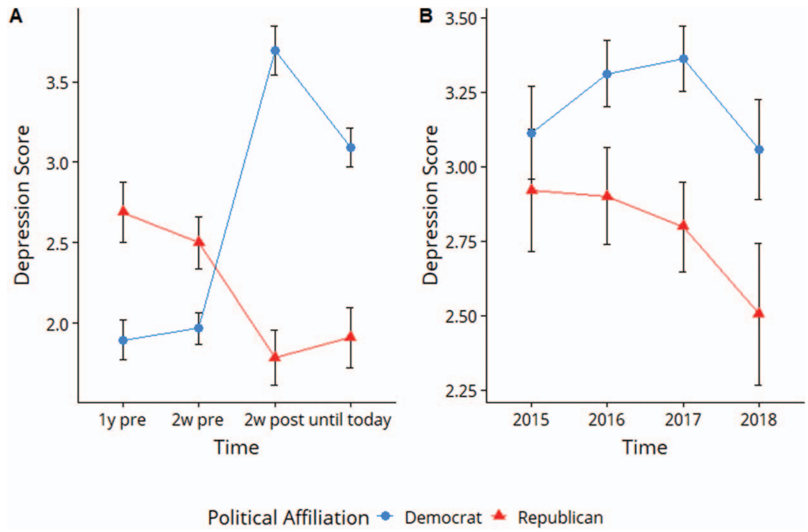

Figure 2. Self-reported depression score by political affiliation. Error bars denote Cousineau-Morey within-subjects 95% confidence intervals. Panel A describes the results of Study 1A in which participants reported their levels of depression using the date of the 2016 election as a reference point. Panel B describes the results when the reference to the election as a temporal anchor was omitted. See the online article for the color version of this figure.

Method

We ran a slightly modified version of Study 1A. We recruited 1,001 participants through MTurk and compensated $0.3 for their participation. The compensation for this study was slightly lower than that of Study 1A due to the fact that in the prior study, participants answered a few additional questions, which were included for exploratory purposes. Participants were all residents of the United States. One hundred and fifty-nine were excluded based on duplicate GPS coordinates or IP addresses. Another 273 participants were excluded for not identifying as either Democrats or Republicans. Eighty-eight subjects were excluded from the analysis for providing invariant responses or for not completing the questionnaire. The final analysis included 481 participants (273 women; 306 Democrats). Participants ranged in age from 18 to 71 (M = 35.79; SD = 11.15). Participants were asked to report their depression levels in 2015, 2016, 2017, and 2018 until the date of the survey (August, 2018).

Results

When the reference to the election as a temporal anchor was omitted, political affiliation did not moderate the perceived depression over time [$F(3, 1437) = 2.12$, $p = .095$, $\eta^2_G = 0.001$, $BF_{Inclusion} = 0.20$], namely, the pattern of depression across the 4-year period did not differ between Democrats and Republicans. In the previous study (Study 1A), an interaction contrast looking at the difference in differences between the first and last time point yielded a meaningful effect ($\eta^2_p = 0.093$) and compelling evidence for a differential increase in liberals' level of depression following the election; in Study 1B the corresponding analysis also reached statistical significance, $t(1437) = 2.16$, $p = .03$, however, the effect size in this analysis was trivial ($\eta^2_p = 0.009$), and the findings did not provide any evidence in favor of H1 (BF_{10} = 1.01). Thus, as can be readily observed in Figure 2, the pattern of results from Study 1B markedly differs from that of Study 1A. Most notably, in Study 1A, Democrats' levels of depression dramatically increased from 2015 and 2018; in Study 1B this increase in depression was no longer evident, if anything, nominal levels of depression slightly decreased between 2015 and 2018.

Discussion

In Study 1A, wherein participants' responses were anchored to the 2016 presidential election, we saw that politically liberal Americans reported experiencing significant depressive symptomatology following the election. However, in Study 1B, wherein participants answered the same question, encompassing the same time period—but without any mention of the election—the effect of the election of Democrats' levels of depression decreased by an order of magnitude, and the findings did not support the hypothesis of election-related depression. This conflicting pattern of results between Study 1A and 1B highlights the complexity of retrospective reports of emotional experience.

Much research into the distinction between the so-called "experiencing vs. remembering self" (Kahneman, 2011; Robinson & Clore, 2002) suggests that the emotional life of individuals is composed of an online, experiential component and a more retrospective, interpretive component whereby individuals build a "story" of their lives. Importantly, this retrospective, narrative component is often uncorrelated with the impressions of the online, experiencing self (Redelmeier, Katz, & Kahneman, 2003). For example, in the context of the 2000 presidential election, Wilson and colleagues (Wilson, Meyers, & Gilbert, 2003) found that Bush supporters reported higher levels of remembered (vs. experienced) positive emotion. Furthermore, the same pattern was observed in Gore supporters for negative affect.

It could be the case that Liberal Americans told themselves a story according to which their mental health must be affected by the election—where in fact it had little impact on their day-to-day emotional well-being. Such a personal and collective narrative of “Trump Depression” would be in line with Liberal Americans’ value system and could also potentially serve important communicative purposes in affirming the liberal/humanistic ideology in a time where it is under siege.

Alternatively, it could be that the omission of the temporal reference to the election in Study 1B made it more difficult for participants to accurately recollect depressive symptomatology. Disentangling such questions requires the use of unobtrusive measures that gauged Liberal Americans’ mood in real-time. Thus in, subsequent studies we utilized several ecological, big data measures of affective experience.

Study 2

Recent work has shown the utility of analyzing Twitter data as a way to gauge the collective psyche unobtrusively and in real-time. For example, studies have shown that analysis of Twitter data can be used to measure changes in mood and rhetoric following events such as school shootings (Doré, Ort, Braverman, & Ochsner, 2015) and violent protests (Mooijman, Hoover, Lin, Ji, & Dehghani, 2018). Moreover, studies have shown that language use on social media can be predictive of individuals’ levels of depression (Eichstaedt et al., 2018; Guntuku, Yaden, Kern, Ungar, & Eichstaedt, 2017). Therefore, in Study 2, we turned to conduct a large-scale discourse analysis on the social network Twitter in order to investigate the extent and duration to which the election results affected Liberal Americans’ mood. In order to examine Americans’ mood, we used a machine learning-based algorithm that was previously shown to detect depressed individuals based on their social media language (Schwartz et al., 2014).

Method

We collected 10,584,997 tweets gathered in the five weeks between October 24, 2016, and November 27, 2016. The sample consisted of Twitter users from all 50 states in the United States, including the District of Columbia. Tweets were sampled on an hourly basis from two regions in each state. One region was centered at the most populated city in the state, and the other region was centered at the state’s approximate geographic center. The radii of each of the two regions were determined such that they covered the maximal area without crossing state borders, minimizing overlap with each other. Five hundred tweets were sampled from each region every hour, starting at two weeks prior to the election. After the exclusion of retweets and duplicates, all tweets containing links were removed in order not to incorporate commercials and reduce the chances of sampling bots. Due to technical issues, the rate of data collection somewhat varied between days ($Mdn_{\text{Daily Tweets}}$ = 339,508; tweet range: 90,159–387,029).

In order to get a large-scale estimate of election-related changes in the mood of Liberal Americans, we used a state-of-the-art language model developed in order to detect individuals’ depression from social media language (Schwartz et al., 2014). The model was trained on a sample of 28,749 users who had taken psychological self-report questionnaires and provided access to their social media accounts. In the original validation, the model was able to predict participants’ propensity for depression and anxiety reasonably well (a Pearson correlation of r = .38 predictive performance, which is considered a high correlation in these domains; Meyer et al., 2001). From each post in our dataset, the frequency of single words was extracted using an open-source language analysis toolkit (Schwartz et al., 2017). Words were tokenized (using an emoticon-aware tokenizer) from the messages, and the frequency of words falling into each category of linguistic inquiry and word count (LIWC; Pennebaker, Boyd, Jordan, & Blackburn, 2015) was calculated. LIWC has 73 categories, of which over 40 are psychologically relevant categories such as affective processes (positive and negative emotions), and is shown to predict multiple user traits such as stress, health, personality, and so forth (Pennebaker, 1993; Tausczik & Pennebaker, 2010). The extracted linguistic features are input to the text-regression model, which then predicts depression and anxiety scores for each post.

The original model was trained on Facebook data, and here we use Twitter data. Facebook and Twitter are different social media platforms used in potentially different ways (Jaidka, Guntuku, & Ungar, 2018), but research shows generalizability of language-based predictive models trained on Facebook and tested on Twitter both on individuals and across regions (Guntuku, Buffone, Jaidka, Eichstaedt, & Ungar, 2018). Furthermore, in a separate line of research within our lab, we have examined the applicability of this specific depression model to Twitter data. We applied the model to a cohort of 601 participants who responded to the CESD-R scale (Eaton, Smith, Ybarra, Muntaner, & Tien, 2004) and shared their Twitter data and saw that the model does generalize to the Twitter data (AUC = .65).

Results

The results showed that the effects of the election on the mood of predominantly Democratic versus predominantly Republican states were only observable in the first few days after the election as can be seen in Figure 3. Namely, whereas democratic states showed a spike in negative mood in the days after the election, this response was ephemeral, and by November 13, mood estimates in Democratic states did not differ from the preelection baseline.

These results shown in Figure 3 provide a coarse, state-level (rather than individual-level) view of the response to the election. We thus conducted a finer-grained subsequent analysis on individual-level observations. Barberá, Jost, Nagler, Tucker, and Bonneau (2015) used machine learning methods to estimate the ideological views for 3.8 million Twitter users. By using their data, we were able to estimate political ideology for 1,610,792 observations in our own sample. The estimated political ideology measure ranged between −4.25 (most left-leaning) and 3.49 (most right-leaning), $M = -0.04$, $SD = 1.15$ (see Supplementary Figure 1 for details). We aggregated the depression measure by date and users, and for each day we correlated the estimated ideology with our measure of depressed mood. Consistent with the view of short-lived response, a stronger association of political affiliation with depressive mood was evident right after the elections but faded away in a little over a week. Specifically, by November 15, it returned to preelection levels, and by November 20, the outputs

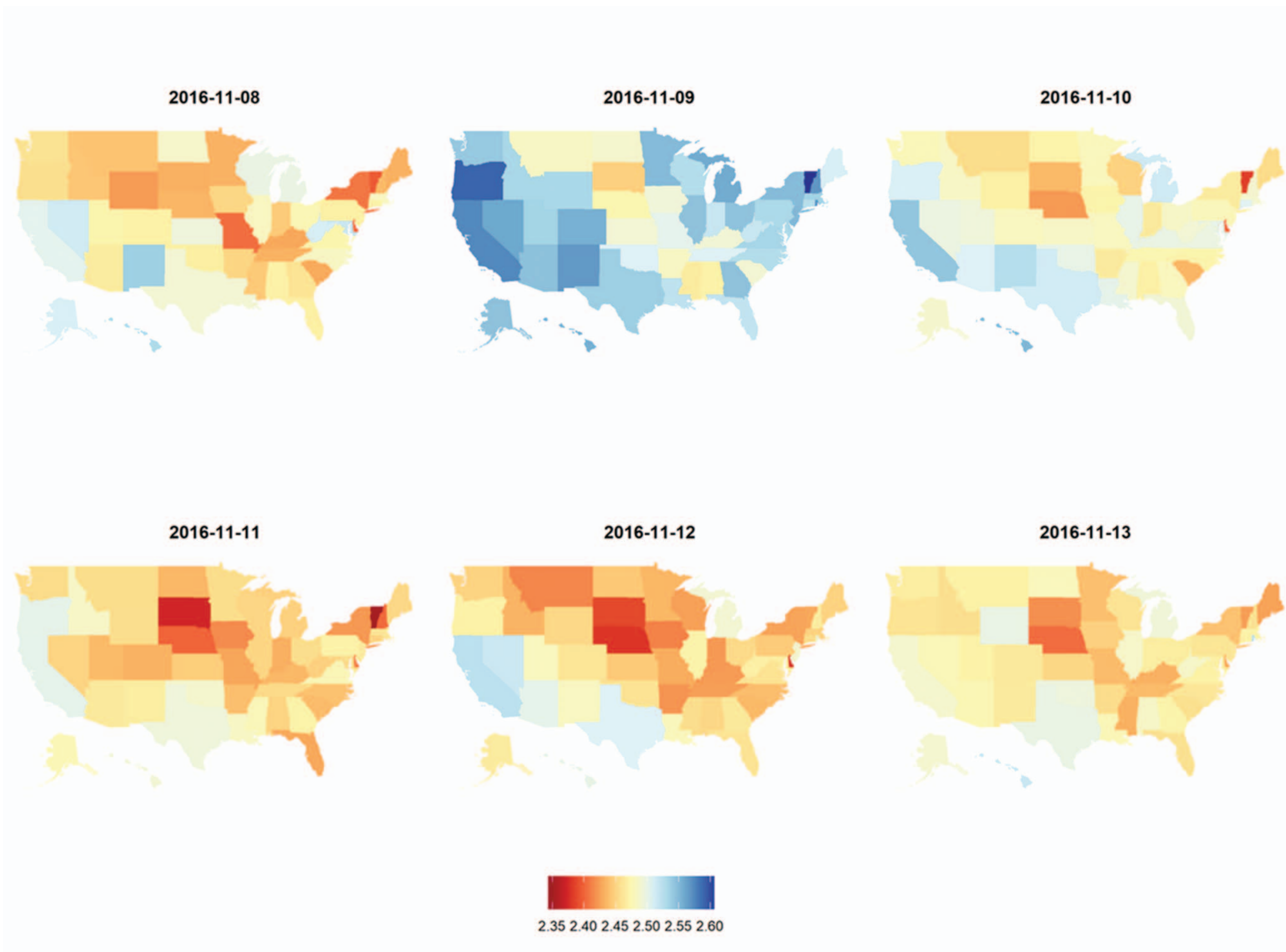

Figure 3. Geographic representation of depressed mood score on Twitter per state. Cold colors represent a more negative mood. The result of the election was revealed at the night between November 8th and 9th. See the online article for the color version of this figure.

of the depression model did not show a significant association between mood and political affiliation (see Figure 4).

Discussion

The results of Study 2 provide evidence for a decline in Democrats' mood followed by a relatively rapid return to affective baseline following the 2016 election. The results from this study join those of Study 1B and suggest that individuals may have overestimated the effect of the election on their well-being.

The limits of humans' insights into their own well-being are exemplified in the research into the so-called "impact bias" (for a comprehensive review see Wilson & Gilbert, 2005). This line of work demonstrates that individuals often overestimate the effect dramatic events will have on their life. More broadly, much research on individuals' affective reactions to personal life events has highlighted that people tend to quickly "bounce back" and return to their affective baseline after both positive and negative experiences—a phenomenon referred to as the "hedonic treadmill" or "hedonic adaptation" (Frederick & Loewenstein, 1999; Silver, 1983). The current findings are consistent with this literature and provide additional, large-scale support for humans' rapid adaptation to negative events.

However, it is possible that social media behavior can only capture short-lived reactions to contemporary events and cannot be used to gauge individuals' private, longer-term affective reactions. Therefore, in Study 3, we relied on a different big-data source, namely, aggregated Google search behavior.

Study 3

When facing various challenges in their lives, people in today's digital world heavily rely on private, online information-seeking behavior (Stephens-Davidowitz, 2017). In light of this, individuals who experience depression will often attempt to understand their predicament and seek remedy by searching the Internet for depression-related information and treatment. As such, depression-related searches can provide invaluable information concerning the well-being of residents of specific geographic areas. This was previously done on public health issues such as flu outbreaks

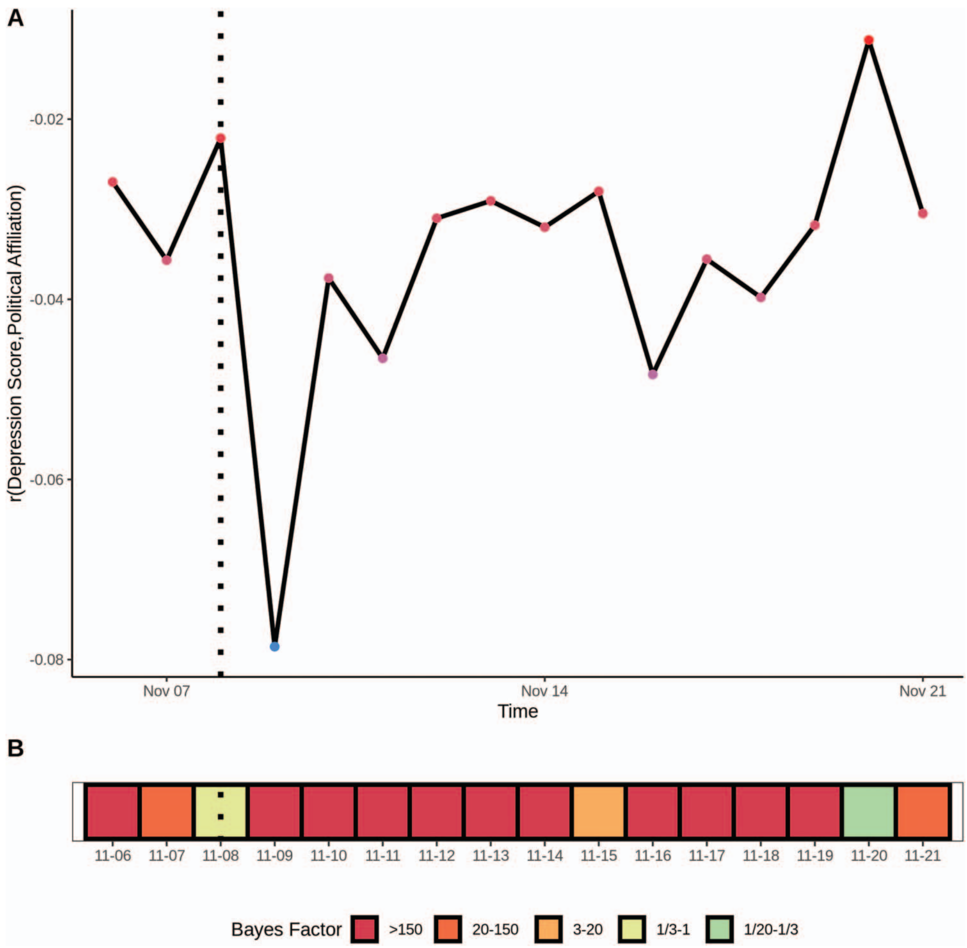

Figure 4. A. trajectory of correlation coefficients between depression score and political affiliation in Twitter users. The estimated political ideology measure ranged between −4.25 (most left-leaning) and 3.49 (most right-leaning). B. the corresponding Bayes-Factor. The dashed line represents election day. See the online article for the color version of this figure.

(Dugas et al., 2013) and suicide rates (Gunn & Lester, 2013). Therefore, in Study 3, we utilized a similar approach by gauging state-level depression-related searches in the time period before and after the election.

Method

To estimate state-level depression-related search behavior, we extracted weekly data from Google Extended Trends API for Health (GETAH). Queries from this tool result in values that represent the search volume of a specific term bound in time and location. The output is adjusted to all Google searches at the same time and location, so the final number stands for a proportion of searches, multiplied by 10 million. These numbers are based on a uniformly distributed random sample of 10%-15% of Google web searches since 2004 and updated once a day.

We used Google's Adwords interface to find search terms that are targeted by advertisers that seek to promote their services to individuals who suffer from depression. We constructed a composite depression score as a sum of the top search terms related to depression. The terms were *depression*, *therapy*, *anxiety*, *panic attack*, *psychologist,* and *OCD*.

Since the Google Trends algorithm considers search volume of any word *X* as the sum of all searches containing that word, it means that by looking at the search volume of, for example, *depression*, it accounts for any search that is comprised of the word *depression*, including *depression symptoms, how to treat depression, depression test,* and so forth.

To validate that this composite score can be argued to reflect state-level variations in depression, we correlated the composite score of depression related search volume to antidepressants consumption. The data were collected from Medicaid for the years 2013–2017 (Centers for Medicare & Medicaid, 2019a, 2019b, 2019c, 2019d, 2019e). Our analysis shows that the proportion of antidepressants consumption correlates well with state-level google search behavior (2013: $r(49) = .38$, $p = .006$; 2014: $r(49) = .43$, $p = .001$; 2015: $r(49) = .41$, $p = .003$; 2016: $r(49) = .45$, $p < .001$; 2017: $r(49) = .41$, $p = .002$; see Supplementary Figure 2), providing evidence for the convergent validity of the method.

Spatial dependence. When dealing with spatially represented data, it is important to account for the effects of neighboring geographical units. Failing to do so may result in violating the assumption of independent residuals or error terms (Anselin, 2001). To account for spatial dependence, we calculated a spatial lag score for every data point, which is the average of the dependent variable among neighboring geographical units (e.g., Gebauer et al., 2017; Webster & Duffy, 2016). For example, the t-1 spatial lag score in California would be the average of the search volume in Arizona, Nevada, and Oregon in t-1. Since spatial lag can only be accounted for the 48 contiguous states (+ DC), we excluded Alaska and Hawaii from the current analysis.

Political affiliation. We gauged the political affiliation of each state as the Democratic margin of victory in the 2016 election (Federal Election Commission, 2017).

Results

To understand the nature of the response to the elections, we conducted an interrupted time series (ITS) analysis following methods suggested by Jebb, Tay, Wang, and Huang (2015). ITS procedure allows setting a point a priori in which an interruption in a time series is assumed. As a first step, we removed the seasonal components both the dependent variable (i.e. Google search volume) and the spatial lag. We then performed a multilevel interrupted time-series analysis (MLITS) using the lme4 package in R (Bates, Mächler, Bolker, & Walker, 2015), estimating the fixed-effects of the seasonally adjusted spatial lag, time, event, time-by-event interaction, and political affiliation. To account for between-states variation, we included a random intercept by state and random slopes of the time, event, and time-by-event interaction by state. The models were estimated using the maximum likelihood method to allow for proper model comparison of different fixed effects (Zuur, Ieno, Walker, Saveliev, & Smith, 2009). The variables time, time-by-event and political affiliation underwent grand-mean centering before entering the model.

The MLITS analysis did not show a significant interaction of political affiliation with the event or the time by event interaction, interpreted as lack of support for either a short-lived or long-lived difference in depression searches as a result of the 2016 elections (see Table 1 and Figure 5). When the models are compared, the model that estimates the event by political affiliation parameter (intercept change) is not preferred over the model that does not account for the interaction $BF_{D1\backslash D2} = 69.71$, and the addition of the three-way interaction of time by event by political affiliation (slope change) overcomplicated the model $BF_{D2\backslash D3} = 159.45$.

To make sure the method itself is sensitive to interactions with political affiliation, we conducted the same analysis on the search term *protest*, given that Democrats were more likely to seek out ways to protest against the new administration. The model yielded significant interactions both with the event (suggesting protest-related searches were more pronounced in Democratic states after the election) and with the time by event interaction, which is interpreted as Democrats gradually returning to baseline after the sharp increase in protest-related searches. When comparing the model with the political affiliation interactions and without, we found that the addition of the event by political affiliation parameter by itself was not favorable ($BF_{P1\backslash P2} = 9.05$); however, the full model that also accounts for the change in slope was preferred ($BF_{P3\backslash P2} = 2774.99$; $BF_{P3\backslash P1} = 306.60$). For full results see Supplementary Table 1.

Discussion

Similarly to Studies 1B and 2, the results of Study 3 provided evidence for a null effect for depression-related increases in Liberal Americans. The analysis of Google data can provide unobtrusive measures of large-scale phenomena (e.g., Gunn & Lester, 2013; Ma-Kellams, Bishop, Zhang, & Villagrana, 2018). However, the use of Google search behavior is an indirect measure of depression, and it may be the case that many individuals who sought help due to election-related distress did not use Google as their way to find assistance (e.g., were referred to mental health practitioners through friends and family). Furthermore, another limitation of this analysis is that it relied on a quasi-experimental method, namely, interrupted time-series analysis. In such analyses, it is always possible that some unknown third variable gave rise to an effect (or, in the context of the current findings, such a third variable may have suppressed the effect of the election on google searches). In light of these concerns, in Study 4 we sought to attain converging evidence from a more direct outcome measure, namely, antidepressant consumption.

Study 4

As noted, our measures of Google search correlated with antidepressant consumption. It could be argued that a more direct measure of state-level depression comes from the medical health data itself. In light of this, in Study 4 we examined changes in state-level antidepressant consumption on Medicaid between 2016 and 2017 in order to see whether we would again observe a null effect of political affiliation.

Method

We gathered the Medicaid's State Drug Utilization records (Centers for Medicare & Medicaid, 2019d, 2019e) for the years 2016–2017 and calculated the percentage of antidepressant consumption for each state (Iowa Medicaid P&T Committee, 2008). The states' political affiliation was calculated in the same fashion as in Studies 2 and 3 (Democrats margin of victory). Like in Study 3, a spatial lag was calculated to account for spatial dependence, narrowing the analysis to the 48 contiguous states (+ DC).

Results

We conducted a multiple regression analysis, predicting the difference of antidepressant consumption between 2016 and 2017 (d = antidepressants$_{2017}$ – antidepressants$_{2016}$) by the variables political affiliation and spatial lag. The results of the regression [$R^2 = .024$, $F(2, 46) = 0.57$, $p = .57$] indicated that neither political affiliation ($\beta = 0.12$, $p = .41$, $BF_{Inclusion} = 0.18$) nor spatial lag ($\beta = -0.10$, $p = .50$, $BF_{Inclusion} = 0.18$) were found to be significant predictors. These results provide further evidence for a null effect of political affiliation on time—suggesting that Trump's election did not modulate the differences between Democratic states and Republican states in proportion of antidepressant consumption.

Table 1
Multilevel Interrupted Time-Series Analysis for the Search Terms Depression (Composite Term)

	D1		D2		D3	
Predictors	Estimates	Partial r	Estimates	Partial r	Estimates	Partial r
(Intercept)	5789.63*** (195.11)	0.158 [0.15, 0.17]	5789.63*** (190.66)	0.155 [0.14, 0.17]	5789.63*** (190.66)	0.185 [0.17, 0.2]
Spatial lag	0.73*** (0.01)	0.323 [0.31, 0.33]	0.73*** (0.01)	0.323 [0.31, 0.33]	0.73*** (0.01)	0.323 [0.31, 0.33]
Time	2.31*** (0.32)	0.046 [0.03, 0.06]	2.31*** (0.32)	0.045 [0.03, 0.06]	2.31*** (0.32)	0.044 [0.03, 0.06]
Event	318.42 (187.37)	0.007 [−0.01, 0.02]	318.42 (184.96)	0.007 [−0.01, 0.02]	318.42 (184.96)	0.01 [0, 0.02]
Time: event	1.09 (241)	0.005 [−0.01, 0.02]	1.09 (243.28)	0.005 [−0.01, 0.02]	1.09 (243.29)	0 [−0.01, 0.01]
Dem margin	−2628.74 (1383.9)	−0.01 [−0.02, 0]	−2617.86 (1339.9)	−0.01 [−0.02, 0]	−2617.86 (1339.94)	−0.012 [−0.02, 0]
Time: Dem margin	6.43* (2.65)	0.015 [0, 0.03]	6.47* (2.66)	0.015 [0, 0.03]	6.47* (2.65)	0.015 [0, 0.03]
Event: Dem margin			−1348.26 (1545.96)	−0.002 [−0.01, 0.01]	−1348.27 (1545.95)	−0.005 [−0.02, 0.01]
Time: event: Dem margin					15.88 (2034.07)	0 [−0.01, 0.01]
				Random effects		
σ^2		1497398.47		1497500.63		1497517.4
τ_{00}		$1338092.09_{\mathrm{State}}$		$1253962.99_{\mathrm{State}}$		$1254044.35_{\mathrm{State}}$
$4.76_{\mathrm{State.Time}}$		$4.77_{\mathrm{State.Time}}$		$4.74_{\mathrm{State.Time}}$		
$1600192.04_{\mathrm{State.Event}}$		$1556380.29_{\mathrm{State.Event}}$		$1556361.93_{\mathrm{State.Event}}$		
$2845772.82_{\mathrm{State.Time.Event}}$		$2900053.53_{\mathrm{State.Time.Event}}$		$2900118.65_{\mathrm{State.Time.Event}}$		
N		49_{State}		49_{State}		49_{State}
Observations		25480		25480		25480
AIC		435808.594		435808.937		435810.935
BIC		435906.3		435914.8		435925
log-Likelihood		−217892.297		−217891.469		−217891.468

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion. Affiliation stands for political affiliation and signifies Democrats' margin of victory. Values in parentheses denote standard errors; values in brackets denote 95% CIs.
* $p < .05$. ** $p < .01$. *** $p < .001$.

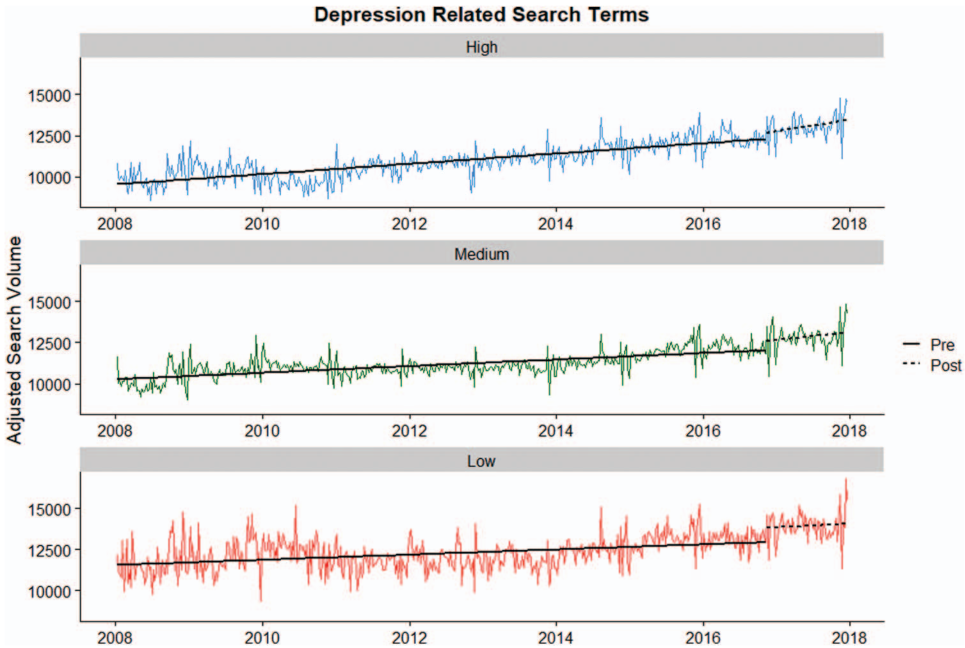

Figure 5. Interrupted time-series analysis of seasonally adjusted composite depression score. Pre- and post-regression lines denote the trend before and after the election. The upper panel shows time-series in states of high democratic support (+1 *SD* of democratic victory margin), the middle panel shows medium democratic support, and the lower panel shows the time-series in states of low democratic support (−1 *SD* of democratic victory margin). Values on the Y-axis represent Google Extended Trends API for Health (GETAH) search volume. See the online article for the color version of this figure.

Discussion

The results of Study 4 join those of Studies 1B, 2, and 3 in suggesting that the 2016 election did not increase aggregate levels of depression among Liberal Americans. However, whereas Studies 1 and 2 provide individual-level analysis of the affective reaction to the election, in Studies 3 and 4, levels of depression were only assessed at the state level, which entails a loss of granularly. Another limitation of Study 4 is that it is possible that many individuals are diagnosed with depression but avoid pharmacological treatment for various reasons. Finally, it is possible that the findings of Study 4 (which relied on Medicaid data) do not generalize to wealthier individuals that do not use the Medicaid program (which provides insurance for low-income individuals). In light of these limitations, in Study 5 we examined levels of depression in a representative sample of individuals.

Study 5

In Study 5, we analyzed whether Liberal and Conservative Americans received treatment for depression before and after the election, using survey data from the Gallup U.S. Daily microdata in which a large representative sample of the U.S. population is surveyed each day and answers questions about political affiliation and depression status.

Method

We analyzed depression proportions starting from 2013 (the year Gallup started to survey depression treatment) until 2017. We analyzed the results of a single question that asked: "Do you currently have, or are you currently being treated for depression?" After excluding participants who did not identify as Democrats or Republicans, we were left with 360,864 participants. The data were binned into 60 bins, representing a 5-year month-level time-series.

Results

Like in Study 3, we fitted an interrupted time-series analysis and positioned the interruption in November 2016. We fitted a multiple regression model, estimating the parameters time, event, and time by event interaction on the seasonally adjusted data, with the inclusion of gender as a covariate. The variables time and time-by-event were grand-mean centered.

Again, we did not find evidence for an election effect either on the intercept or the slope. Model comparison favored a time series model without an interrupting event $BF_{M1\backslash M2} = 93.02$, $BF_{M1\backslash M3} = 92{,}730.41$ (see Figure 6, Supplementary Table 2).

Discussion

Study 5 joins the results of Studies 1B, 2, 3, and 4 in providing evidence for a null effect of the 2016 election on depression levels of Liberal Americans. A possible limitation of this study is that the participants who were willing to take part in the Gallup survey and disclose personal information are not completely representative of the American population. However, these concerns can be quelled by considering the high rates of depression revealed in this data (approximately 10% of the sample) that are consistent with previous estimates

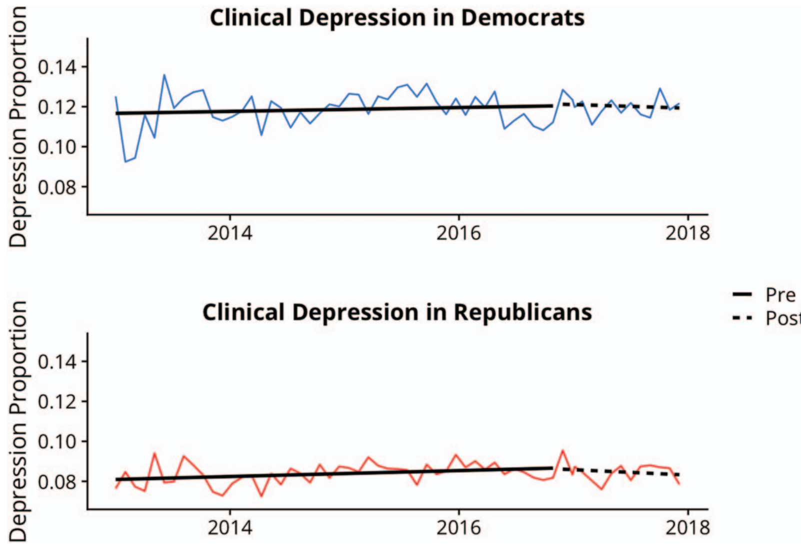

Figure 6. Interrupted time-series analysis of clinical depression based on Gallup surveys. Pre and Post regression lines denote the trend before and after the election. The upper panel shows time-series in Democratic individuals and the lower panel shows Republican individuals. Values on the Y-axis represent the proportion of respondents who are currently treated for depression. See the online article for the color version of this figure.

of depression prevalence in the adult population in the United States (Lim et al., 2018). Furthermore, the conclusions of this study converge with those derived from unobtrusive, ecological measures of depression prevalence (i.e. Studies 3 and 4).

General Discussion

In the current research, we examined the nature of the relation between the political and personal/psychological spheres by testing whether the loss experienced by the Democrats in the 2016 election led to an increase in their levels of depression. Consistent with previous studies (e.g., Lench et al., 2019; Roche & Jacobson, 2019), in Study 1A we found that when participants were asked to retrospectively assess their mood, Liberals reported considerably higher levels of depression following the election (while Republicans' level of depression decreased). However, importantly, in Study 1B we saw that when participants retrospectively reported on their mood in the same time period without reference to the election, Liberals' levels of reported depression were much lower and were similar to those reported for the Obama years.

In light of the conflicting results of Studies 1A and 1B, we reasoned that it is possible that discussions of "Trump Depression" reflect an expanded use of mental health terminology (i.e. "concept creep") rather than a large-scale, election-related increase in levels of severe psychological distress. Therefore, in Studies 2–5 we gauged depression using measures using more indirect measures that bypass participants' lay-theories (e.g., Nisbett & Wilson, 1977) of the likely effects of the election and that eliminate concerns of motivated responding. In Study 2, we analyzed real-time Twitter discourse of hundreds of thousands of Americans and gauged participants' mood using a machine learning-based model that was trained to predict levels of depression. We found that in both the state-level and the individual-level of political affiliation, an increase in Liberals' level of depression was only observable in the first few days after the election, suggesting quick hedonic adaptation. In Study 3 we conducted a time-series analysis of billions of Google search queries and did not find any evidence for an election-related increase in depression-related searches in Democratic (vs. Republican) states. In Study 4 we replicated the main finding of Study 3 by showing that the proportion of antidepressant consumption did not change between 2016 and 2017 as a function of the political affiliation of the state. Finally, in Study 5, we analyzed daily survey data of hundreds of thousands of Americans and found evidence for a null effect of the election on depression rates.

Together, these analyses provide a comprehensive view of the American affective reaction to the 2016 election and show that although Liberals report a large effect of increased depression when asked directly about the effects of the election on their well-being, measures that do bring the political events to mind do not show any such effect of the election. The findings can be interpreted as reflecting a disconnect between the actual day-to-day feelings of Liberal Americans, (i.e. their "experiencing self") and the ideologically informed narrative created by their "remembering self" (Kahneman, 2011).

Why then do Liberal Americans speak of experiencing a "Trump depression?" It is possible that such self-reports (and supposedly self-perceptions) of emotional suffering serve a value-expressive function (Katz, 1960), namely, as a way to signal one's group identity and ideological beliefs. Similarly, this effect could reflect some degree of "cognitive dissonance" (Festinger, 1962) in that it may be difficult for Liberal Americans to reconcile a lack of distress in their daily lives with a perceived crisis of American democracy. The current results may also suggest that the application of clinical terminology to political outcomes in a participatory democracy can be best regarded as a "concept creep" (Haslam, 2016).

Our findings are limited to a specific test-case—the 2016 American election. Nonetheless, it is worth noting that this test-case is especially informative, given that the election of Donald Trump probably reflects an upper bound on the levels of emotional turmoil that citizens may experience in a modern democracy, and as such, may be generalizable to less extreme contexts.

These findings should not be taken as evidence that Liberal Americans' self-reported distress with regards to the election is inauthentic. Rather, they provide further evidence that the affective lives of people are complex and multifaceted (Kahneman, 2011; Robinson & Clore, 2002) and that these different aspects can be context-specific and affected by temporary availability of information (Strack, Martin, & Schwarz, 1988). Furthermore, the results do not suggest that specific individuals did not experience episodes of depression attributed to Trump's election—only that there is no such effect at the aggregate level. Finally, the findings do not mean that Liberals did not experience election-related perturbations that occurred within the normative range; what our findings suggest is that such fluctuations did not amount to psychopathology—and thus it may be inadvisable to construe such phenomena in terms of trauma and illness (Haslam, 2016).

The current findings join previous work on emotional resilience and provide compelling, large-scale evidence that individuals' affective reactions to important events could be short-lived (i.e. the literature on "hedonic adaptation"; Luhmann, Hofmann, Eid, & Lucas, 2012). Much research has shown that people often underestimate the capacity of the so-called "psychological immune system" that helps them cope with distressing events (Gilbert, Pinel, Wilson, Blumberg, & Wheatley, 1998). Along these lines, it is possible that in response to the election, many Liberal Americans found new meaning in their life in the goal to resist the new administration (Rovenpor et al., 2019)—a possibility reflected, for example, in the finding of increased "protest" related searches in Democratic states.

Another possible limitation of the current research is that our analysis only pertains to the first year following the election of Trump. Future studies could continue to examine longer-lasting changes in Americans' well-being and examine whether election-related differences in Republicans' and Democrats' level of depression begin to emerge. However, such longer-lasting effects may no longer be attributable to the symbolic/ideological loss experienced by Democrats and may begin to reflect the outcomes of the policies implemented by the new administration (e.g., separation of families of immigrants, changes in health insurance coverage)—and as such, will represent a different phenomenon from the one investigated herein.

The current research also sheds light on the ongoing debate concerning the relationship between well-being and political ideology. In the political psychology literature, differences between Liberals and Conservatives in well-being is a robust finding (Napier & Jost, 2008; Schlenker, Chambers, & Le, 2012). However, in a recent study (Wojcik et al., 2015), it was claimed that this effect is caused by Conservatives' greater reluctance to expose (or acknowledge) their weaknesses. Our findings provide further support for this claim, as we see differences in measures of depression in Studies 1, 2 and 5 that measure individuals overt behavior (i.e. public Twitter posts, self-report questionnaire, surveys), but find no main effect in Study 3, which is based on covert behavior (private Google searches).

More generally, the current study presents the first attempt to examine the effects of a large-scale political event on the well-being of entire populations by integrating information across various, newly available big data sources: Google search behavior, large-scale surveys, drug prescription data, and natural language use on social media. The complex, multifaceted nature of human well-being means that measurement of happiness and misery ("hedonometry") presents difficult methodological and philosophical challenges; nonetheless, given the centrality of pain and pleasure in human existence, the importance of advancements in hedonometry cannot be overstated. Our results suggest that future research in economics, public policy, and epidemiology of psychiatric illness could benefit from applying a multimethod, big data approach to the study of well-being. Such investigations can shed further light on the complex relationship between large-scale social/political events and the psychological reactions of the individual.

Context of the Research

The current research is part of broader research conducted in our lab regarding the socially constructed nature of affective phenomena. Emotion research often construes emotion as a primarily intrapsychic phenomenon, dependent on people's biology and their prior history of appetitive and aversive experiences. In our work on the topic, we examine when and how socially derived ideas (e.g., norms, social identities, narratives, values) shape one's emotional experience and mood. In light of this, we were interested in examining the possibility that an ideological/political loss can have profound and protracted effects on individuals' emotional well-being. The current findings inform our thinking on these topics by highlighting some boundaries of the effects of social contexts on people's emotional lives.

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