President Trump Stress Disorder: Partisanship, Ethnicity, and Expressive Reporting of Mental Distress After the 2016 Election

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Abstract
In the aftermath of the 2016 election, many Democrats reported significant increases in stress, depression, and anxiety. Were these increases real, or the product of expressive reporting? Using a unique data set of searches by more than 1 million Bing users before and after the election, we examine the changes in mental-health-related searches among Democrats and Republicans. We then compare these changes to shifts in searches among Spanish-speaking Latinos in the United States. We find that while Democrats may report greater increases in post-election mental distress, their mental health search behavior did not change after the election. On the other hand, Spanish-speaking Latinos had clear, significant, and sustained increases in searches for “depression,” “anxiety,” “therapy,” and antidepressant medications. This suggests that for many Democrats, expressing mental distress after the election was a form of partisan cheerleading.

Keywords
partisanship, partisan cheerleading, expressive reporting, race, ethnicity, mental health, search

Introduction
In the fall of 2016, many therapists and mental health professionals in the United States noticed an alarming trend in their patients. One therapist, Inger Burnett-Zeigler, wrote in *Time*, “In the weeks since the election, many of my patients have come to therapy with anxiety, fear, and worry . . . It’s obvious to me that this highly contested election is already having real mental health consequences” (Burnett-Zeigler, 2016). Burnett-Ziegler was not alone—during this period, a variety of publications, including Slate, the Washington Post, Politico, and the New York Times, reported that Democrats were suffering from an array of Trump-related ailments.¹ A full 72% of Democrats reported that the presidential election outcome was “a significant source of stress,” as compared to 26% of Republicans.²

The idea that President Trump might make some Democrats physically ill is not surprising. Over the past 30 years, both Democrats and Republicans have become dramatically more negative in their evaluations of the opposing party (Iyengar, Sood, & Lelkes, 2012). These negative assessments correspond to real behavioral outcomes—Partisans are more likely to discriminate against the opposing party in settings as diverse as the allocation of scholarship funds (Iyengar & Westwood, 2015), mate selection (Huber & Malhotra, 2017; Iyengar, Konitzer, & Tedin, 2017), evaluations of physical attractiveness (Nicholson, Coe, Emory, & Song, 2016), and employment decisions (Gift & Gift, 2015).

Furthermore, some scholars have found that partisan gaps in responses to surveys about policy attitudes correspond to actual behavioral differences. For example, Krupenkin, Hill, and Rothschild (2018) found that in the aftermath of the 2016 election, Democrats were less likely to search for terms related to car and house purchases, which suggests that Democrats’ pessimistic survey responses to economic questions reflected their actual expectations of the economy. These consequences are not limited to economic decisions.

Republicans, who tend to register significant opposition to the Affordable Care Act in responses to surveys, were indeed less likely to enroll in health care exchanges (Lerman, 2018).

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Sadin, & Trachtman, 2017), and individuals identifying as members of the party not in the presidency were both less likely to report vaccinating their children and to actually vaccinate them (Krupenkin, 2018).

Still, survey respondents may over-report their negative emotions about presidential elections. Scholars have found that people often engage in “expressive reporting,” which means they provide inaccurate information as a means of expressing support for a party or candidate. Expressive reporting is distinct from genuinely held misperceptions based on motivated reasoning. In the first case, respondents know that they are providing an answer that does not reflect their true opinion, while in the second, respondents are unknowingly giving a truly held but incorrect response.

For example, while people are more likely to report perceptions of past performance of the economy that are complimentary to presidents of their own party and critical to the opposing party, these gaps diminish when respondents are given financial incentives for providing accurate answers (Bullock, Gerber, Hill, & Huber, 2013; Prior, Sood, & Khanna, 2015). However, Flynn, Nyhan, and Reifler (2017) noted that financial incentives for correct answers have an inconsistent effect in reducing incorrect responses, suggesting that in some cases, the psychological rents of providing an incorrect answer outweigh financial considerations. The relative crowd size during presidential inaugurations provides an even more striking case. Republicans were more likely to say that a photograph of the crowd at Trump’s inauguration had more people in it than a photograph of the crowd at Obama’s first inauguration, even though the second photograph was visibly more populated than the first (Schaffner & Luks, 2018).

Partisanship is closely identified with various observable demographics: Education, gender, religion, age, and race have all, at various times, been heavily correlated with party identification and voting decisions. Because Latino immigration was a preeminent issue in the 2016 election, we consider ethnicity as an interesting and important contrast with general partisanship. Roughly 28% of Latinos voted for President Trump, which is much higher than the percentage of Democrats who voted for him (roughly 8%).

However, Latinos were directly targeted by President Trump, who sought to repeal Deferred Action for Childhood Arrivals (DACA) protections for about 800,000 individuals, primarily Latinos, brought to the United States as children. Furthermore, he referred to Mexican Americans as als, primarily Latinos, brought to the United States as children (DACA) protections for about 800,000 individuals, primarily Latinos, brought to the United States as children, and made building a wall between the United States and Mexico (and having Mexico pay for it) a major campaign focus. And, we focus on a subset of Latinos, people who: use Spanish first, may or may not be voters, may or may not even be documented immigrants, which is reasonable to assume strongly opposed Trump’s proposed immigration policies and would almost uniformly have voted against Trump.

In this article, we seek to answer the following question:

Research Question 1: Was the reported increase in negative mental health outcomes among Democrats and Spanish-speaking Latinos reported comparable and statistically significant increases in daily levels of worry in the months after Donald Trump’s election (Davis, 2017; Ritter & Tsabutashvili, 2017), and even a year later, Democrats and Latinos reported similar decreases in well-being (Witters, 2017), do these reports correspond to actual increases in mental distress? To test this hypothesis, we compare mental health searches among Democrats to those of several other groups, including Republicans and Spanish speakers in America (which is a good proxy for Spanish-speaking American Latinos).

Our approach, which combines the individual search records of over 1 million Bing users with survey responses, language, and geographic data, has several advantages over both traditional survey approaches and analyses of aggregate mental health data. First, the use of search data allows us to eliminate social desirability effects. Mental illness still carries a serious stigma that prevents people from seeking necessary care (Wahl, 1999). This stigma may even influence respondents’ willingness to report mental health outcomes on a survey (Van de Mortel, 2008). However, in this specific context, there may be some groups who experience social desirability bias to report negative mental health outcomes as a result of the election. Trump was so reviled among liberal Democrats that not reporting negative emotions after his victory might be taken as a sign of moral failure. Search data are significantly less prone to social desirability bias than survey data (Stephens-Davidowitz, 2017), reducing these concerns.

Second, search patterns have proven to have deep connections with real-world behaviors. Searches have been shown to be significantly correlated with suicide attempts (McCarthy, 2010), disease outbreaks (Yom-Tov, Borsa, Cox, McKendry, 2014), and health care use (White & Horvitz, 2013a, 2013b). Outside the arena of public health, Internet searches have been shown to be predictive of consumption (Vosen & Schmidt, 2011), housing prices (Wu & Brynjolfsson, 2015), ballot rolloff (Reilly, Richey, & Taylor, 2012), and even foreign tourist volume (Yang, Pan, Evans, & Lv, 2015).

Finally, using search data allows us to examine negative mental health outcomes that, while not severe enough to warrant medical intervention, still significantly affect people’s lives. Even if someone does not feel sufficiently depressed or anxious to meet the clinical symptoms of mental illness, an increase in these negative emotions is nonetheless important. Furthermore, many people in the United States do not have sufficient access to mental health treatment, and searches for mental health issues are an indicator of mental distress in these medically underserved populations.
We find that while Democrats expressed serious mental distress about the election result on surveys, on average, the Democrats in our sample did not show an increase in mental-health-related searches after the election. However, Spanish-speaking Latinos showed a significant increase in searches for depression, anxiety, therapy, and antidepressant drugs. This finding suggests that while Democrats’ descriptions of mental distress after the election had an element of expressive reporting, the mental consequences of Trump’s ascendance were very real for Latinos.

Theory

Scholars have long noted the power of expressive motivations on political participation. The desire to express their political beliefs motivates voter turnout (Fiorina, 1976), campaign contributions (Shieh & Pan, 2010), and online blogging (de Zuniga, Bachmann, Hsu, & Brundidge, 2013; for a review, see Hamlin & Jennings, 2011). One especially salient category of expressive behavior is partisan cheerleading, or expressive reporting on surveys of factually inaccurate statements to communicate support for a respondent’s political party (Bullock et al., 2013). For example, when respondents are asked about the country’s recent economic performance, co-partisans of the president may respond with evaluations that are more optimistic than their true beliefs.

We propose a theory of “reverse cheerleading,” where partisans misreport or exaggerate their negative evaluations of an out-partisan president’s tenure to signal dislike of the opposing party. This can take the form of misreporting of objective facts about policy areas like the economy, or the form of over-reporting of other negative consequences of the presidency, including negative effects on mental health.

Reverse cheerleading can be a powerful motivator of partisans’ behavior for three reasons. First, negative emotions have a much stronger effect on peoples’ political behavior than positive emotions (Rozin & Royzman, 2001; Soroka, 2014). Given this well-documented negativity bias, partisans may have a stronger impulse to derogate the opposing party than to support their own.

Second, expressing negativity about the other party yields significant psychological rents. Derogation of a disliked out-group increases self-esteem (Branscombe & Wann, 1994; Fein & Spencer, 1997), especially if the outgroup is perceived as threatening. Given the intense fear and negativity that partisans feel about the opposing party (Iyengar & Westwood, 2015), derogating Trump would be a powerful method of boosting Democrats’ self-image. Expressing that a Trump presidency has precipitated or exacerbated a mood disorder is an extreme form of derogation—“This presidency is so terrible, it’s literally driving me crazy!”

Finally, expressing extreme negativity about Trump is an effective form of signalling to fellow Democrats that you are a co-partisan. In situations where partisans are less able to express in-group membership signals, they turn to out-group derogation to better communicate their partisanship (Matherly & Ghosh, 2017). The 2016 election provides an especially strong motivation for White Democrats to distance themselves from Trump specifically, as Trump expressed a number of statements denigrating various non-White racial and ethnic groups. Given the efforts by many White liberals to not appear as “racist” (Condor, Figgou, Abell, Gibson, & Stevenson, 2006), derogating Trump is a useful signalling method.

The 2016 election presents an especially useful test case for our theory for two reasons. First, partisans are even more negative toward the opposing party in 2016 than in prior years (Iyengar & Krupenkin, 2018). This has significant consequences for reporting of election-related stress. According to Gallup, in 2016, Democrats but not Republicans reported a significant increase of 8.5 percentage points in stress after the election. There was no similar associated increase in stress among Republicans after the 2008 election (Davis, 2017).

Second, focusing on Trump allows for the comparison of mental health effects among Democrats and groups that have been materially negatively affected by his policies. One group particularly negatively affected is immigrants from Mexico and other Spanish-speaking countries, especially people who still use Spanish as their primary language. While undocumented immigrants have suffered the greatest consequences of the increase in deportations under Trump, deportations severely disrupt immigrant family and community structures (Hagan, Castro, & Rodriguez, 2009, 2011), and thereby negatively affect both undocumented immigrants and the people closest to them, regardless of documentation status. And many legal residents and citizens are also directly caught up in aggressive anti-immigrant round-ups. The deleterious psychological effects of fear of deportation among Latino immigrants are well documented (Arbona et al., 2010) and have only grown worse since Trump became president (Viser, 2017).

Furthermore, increased anti-Latino discrimination during the Trump era (Chen, 2017) has significant mental health consequences (Torres, Driscoll, & Voell, 2012). Even among documented Latino immigrants, permanent residents, and citizens, the Trump presidency is likely associated with negative mental health outcomes.

Democrats, as partisans, are reporting Trump-related mental distress as a form of reverse cheerleading, while Latinos are reporting genuine mental distress. In a situation where partisans are engaging in reverse cheerleading, they will be vocal about their mental distress about the presidency in a public forum but will not engage in behaviors associated with that distress in private. On the other hand, individuals who are not engaging in reverse cheerleading may or may not share their mental distress publicly but will engage in private behaviors associated with mental health issues.
**Method**

To examine the effects of partisanship and ethnicity on mental health searches, we compiled a list of searches from over 1 million Bing users who had searched both before and after the 2016 presidential election. Bing is the second largest search engine in the United States, accounting for 21% of the search market share (comScore 2016).

To label partisan web searchers, we identified a subgroup of 300,000 Bing users who had also answered a question on MSN.com between 31/07/2016 and 08/11/2016 about their 2016 vote preference or party identification (in addition to questions about gender and age). Of these users, 67% were Republican and/or Trump voters, and 33% were Democratic and/or Clinton voters. On average, the respondents in our dataset were 65% male. Of our respondents, 37% had a bachelor’s degree. While race was not a perfect proxy for Latino ethnicity because not all Latinos are Spanish speakers, many U.S. searchers who are searching in Spanish are Latino. We examined these users’ searches in both Spanish and English.

To identify Spanish-speaking Latino searchers, we compiled a list of U.S. Bing searchers who had searched in Spanish at least once between 19/05/2016 and 15/12/2017, which amounted to a total of 16 million users. When we subsetted these to include users who searched both before and after the election, the number fell to around 700,000 users. While searching in Spanish is not a perfect proxy for Latino ethnicity because not all Latinos are Spanish speakers, many U.S. searchers who are searching in Spanish are Latino. We examined these users’ searches in both Spanish and English.

To compare Spanish speaking and English-only Bing searchers, we randomly sampled 15 million user ids from the total number of unique U.S. users who had searched in English between 19/05/2016 and 15/12/2017. Again, we subsetted to limit our sample only to users who had searched both before and after the 2016 presidential election, yielding about 200,000 unique English users.

While search data have many advantages over survey data, there are several drawbacks. First, search data in general are nonrepresentative. Even in the United States, lower income people struggle to achieve consistent access to the Internet (Gonzales, 2016). Furthermore, different demographic groups use the Internet differently, suggesting that some types of users may be overrepresented in search logs (Van Deursen & Van Dijk, 2014). Thus, Bing users are not perfectly representative of the population in general: gender is balanced, but it is slightly more educated than the general population with 50% having bachelor’s degrees or more. Age is pretty good with 29% 18 to 34, 18% 35 to 44, 20% 45 to 54, 17% 55 to 64, and 17% 65+ year olds.

To account for the nonrepresentativeness of our sample, we both controlled for demographics and used an over-time design that measured changes in the same respondent pool over time. We restricted searchers to those who had searched at least once both before and after the election, to prevent new influxes of searchers from unduly influencing results.

To identify mental health issues, we examined searches between 19/05/2016 and 15/12/2017 for six sets of mental-health-related keywords and their Spanish translations—“depression,” “anxiety,” “stress,” “suicide”/“suicidal,” “therapy,” as well as searches for general and specific antidepressants and anti-anxiety medications (see Appendix for details of medication list). For users identified as Spanish-speaking, we looked at mental health searches in both English and Spanish on the English and the Spanish Bing websites, since many users searched on both.

These six terms encompass mental distress and illness to varying degree and severity. “Stress,” the least severe term, could be searched by someone looking for stress relief, and does not indicate mental illness. On the contrary, terms such as depression and anxiety may be searched by people who have identified in themselves some of the symptoms of these conditions, and are wondering whether they have an illness. Finally, terms such as therapy and specific medications are likely searched by people who have already decided that they are in need of mental health treatment. In general, mental-health-related searches were relatively rare, which is not surprising, given that the stigma against mental illness may significantly influence whether people will even seriously consider treatment.

To analyze the data, we used a binomial logit regression with controls for day of the week, seasonality, and age and gender (when available). Searchers who had searched for a mental-health-related term on a specific day were coded as “1” for the day on which they searched, and “0” otherwise. Standard errors were clustered by user ID.

**Measure Validation**

To ensure that our Bing search measures were valid and were correlated with real rates of mental health problems, we relied on two tests. First, we measured seasonality in Bing searches for “depression.” Google searches for depression are highly seasonal, with significant declines in searches during the summer months (Ayers, Althouse, Allem, Rosenquist, & Ford, 2013; Yang, Huang, Peng, & Tsai, 2010). These seasonal patterns are correlated with real-world indicators of depression (Harmatz et al., 2000). If our data are a valid indicator of mental health, we should see a decrease in searches for depression during the summer months. Figure 1 shows that our data confirm these expectations—people are least likely to search for “depression” in the summer.

Our second test relates to the relative incidence of depression and anxiety among men and women. Women tend to be about twice as likely as men to be diagnosed with depression (Kessler et al., 2003) and anxiety (Hettema, Prescott, & Kendler, 2001). While some of this variation in diagnosis may be due to gendered differences in seeking help for mental illness (Kilmartin, 2005), women should still be more likely to search for both depression and anxiety. Figure 2 corroborates this prediction—Women are about twice as likely as men to search for depression. The results of these two tests...
confirm the validity of Bing searches for mental-health-related terms as an indicator of real-world mental illness.

To test the validity of our partisanship measure, we relied on two tests. First, for respondents who answered survey
questions about both party identification and prospective 2016 vote choice, we looked at the consistency between these two items. In our sample, 90% of Republicans responded that they were going to vote for Trump, and 90% of Democrats responded that they would vote for Clinton. This is comparable with the rate among the general population, where 89% of Democrats and 88% of Republicans voted for their party’s nominee in 2016.

Our second test is a positive placebo test for the effect of partisanship on searches. We examined search rates for the term impeach among both Democrats and Republicans between 19/05/2016 and 15/12/2017. Given the fervor for impeaching Trump among Democrats, searches for the term impeach ought to increase significantly among Democrats after the election. On the contrary, few Republicans have an interest in impeaching Trump, so the election should have no effect on their searches for the term impeach. Figure 3 shows that the percentage of Democrats who searched for “impeach” dramatically increased after the election, while the percentage of Republicans stayed the same. This is consistent with our expectations and further confirms the validity of our measure of partisanship.

**Results**

Consistent with our theory of reverse cheerleading, we find no significant partisan election effect for mental-health-related searches (Figure 4). Democrats did not experience a greater increase in searches for any of the six sets of terms than Republicans. While Republicans were less likely overall than Democrats to search for all six mental-health-related terms, there was no significance on the interaction between party and the post-election dummy variable (Table 1). Even the least severe of these terms, stress, had no partisan effect. Furthermore, while none of the interaction coefficients were significant, four of the six were in the opposite direction than expected, further suggesting that there was no increase in mental health searches among the Democrats in our sample after the election.

As expected, gender and age had a significant effect on searches for mental-health-related terms—Women and younger searchers were more likely to search for mental-health-related terms. Women are significantly more likely to be diagnosed with both anxiety and depression, and as such should be more likely to search for these terms. There was also no consistent postelection pattern among searchers in general—While searches for “stress” and “therapy” had a statistically significant increase, searches for “suicide” had a decrease, and searches for “anxiety,” “depression,” and antidepressant drugs showed no statistically significant changes.

On the contrary, we find a very clear difference between the search behaviors of English- and Spanish-speaking searchers (Figures 5 and 6). English-speaking searchers showed very little difference between their mental health search behaviors before and after the election. Spanish-speaking searchers, however, showed a clear and sustained
**Figure 4.** Frequency of searches for mental health term—Democrat versus Republican.

**Table 1.** Regressions on Frequency of Searches for Mental Health Term—Democrat Versus Republican.

| Dependent variable | Depression | Anxiety | Stress |
|--------------------|------------|---------|--------|
| Republican         | −0.307*** (0.043) | −0.290*** (0.058) | −0.156*** (0.045) |
| Post-Election      | 0.014 (0.035) | −0.061 (0.048) | 0.131*** (0.042) |
| Republican × Post  | −0.016 (0.047) | 0.090 (0.065) | −0.067 (0.053) |
| Age                | −0.168*** (0.015) | −0.131*** (0.022) | −0.118*** (0.015) |
| Female             | 0.266*** (0.020) | 0.432*** (0.030) | 0.235*** (0.018) |
| Day of Week        | X           | X         | X      |
| Seasonality        | X           | X         | X      |
| Constant           | −7.703*** (0.085) | −8.000*** (0.125) | −7.684*** (0.080) |

| Dependent variable | Therapy | Drugs | Suicide |
|--------------------|---------|-------|---------|
| Republican         | −0.207*** (0.034) | −0.166*** (0.037) | −0.225*** (0.032) |
| Post-Election      | 0.057*** (0.028) | −0.008 (0.027) | −0.318*** (0.027) |
| Republican × Post  | 0.011 (0.036) | 0.003 (0.036) | 0.037 (0.041) |
| Age                | −0.019 (0.012) | 0.018 (0.018) | −0.214*** (0.013) |
| Female             | 0.362*** (0.016) | 0.403*** (0.021) | 0.025 (0.019) |
| Day of Week        | X           | X         | X      |
| Seasonality        | X           | X         | X      |
| Constant           | −7.045*** (0.065) | −7.141*** (0.102) | −5.527*** (0.068) |

*p < .1, **p < .05, ***p < .01.
Figure 5. Frequency of searches for mental health term—English speaking.

Figure 6. Frequency of searches for mental health term—Spanish speaking.
increase in searches for “therapy,” “depression,” “anxiety,” and mental-health-related drugs. While there was a spike in searches for suicide-related terms for both Spanish and English speakers in August 2016, this spike was largely associated with searches for the movie “Suicide Squad.”

The differences between Spanish- and English-speaking searchers were statistically significant for five of the six terms: “therapy,” “depression,” “anxiety,” “suicide”/“suicidal,” and antidepressant/anti-anxiety medications (Table 2). This clear and consistent result shows that Spanish-speaking searchers, and by proxy, Latinos, were indeed more likely to search for mental-health-related terms after the election than before, while English-only searchers showed no consistent change.

In summary, only Spanish-speaking searchers had a real increase in mental-health-related searches after the election. Neither Democrats nor English speakers at large changed their search rate for these terms after Trump’s election.

### Conclusion

Search engine data provide an unparalleled look into people’s inner thoughts and feelings. Under a shroud of anonymity, stripped of the need to appear respectable to survey researchers or to their peers, people search for the information they genuinely want and need. Mental health remains a stigmatized topic for many, and looking at search data provides a useful metric for understanding how current events may influence the well being of various communities.

Democrats and Latinos provided similar mental health survey responses, and therapists and mental health workers reported significant mental distress among both Latinos and Democrats in the aftermath of the 2016 election. Despite these similarities, their search behaviors have been dramatically different. It is important to note that while many Democrats are Latino and many Latinos are Democratic, the Democratic party remain majority-White.

While Spanish speakers both reported significant stress after Donald Trump’s election, and showed an increase in searches for mental-health-related terms, the same was not true for Democrats: Democrats showed no statistically significant change in searches. Democrats were no more likely to search for stress relief, nor mental illness, nor treatment for mental illness before or after the election. This suggests that some Democrats reported mental health declines after Trump’s election as a form of reverse cheerleading, where partisans report evaluations that are more negative than their true beliefs to reflect badly on a president of the opposing party.

These differences highlight the importance of supplementing survey data with behavioral data. While in some instances, partisan behavior matches their survey responses (e.g., Krupenkin et al., 2018; Lerman et al., 2017; Gerber and Huber, 2009), in others, it does not (e.g., Bullock et al., 2013; Prior et al., 2015).

Clearly, many Democrats were, and are, upset about the Republican victory in 2016; these findings do not invalidate those feelings but put their depth and related actions into perspective. We do not see a widespread, sustained push for mental-health-related help from the Internet from Democrats. While, at the margin, some Democrats may have been influenced to search for these terms, it was not enough to make a statistical significant jump in Democratic searchers. At the same time, with similarly sized dataset, there was enough of
an increase in Latinos to register a statistically significant jump. Democrats with increased mental distress that just turned to friends and family (or did not address or addressed their distress without any help) would not be reflected in our results, nor would Democrats who turned their distress into activism. Democrats already seeking treatment who may have increased their treatment, that would not be reflected in our results.

While these results are provocative, several important questions remain. First, on which topics are partisan respondents more likely to engage in cheerleading? Do topics for which objective facts are easily accessible (the economy) prompt less cheerleading than questions whose truth is known only to the respondent (the respondent’s level of mental distress)? Second, how do the incentives for reverse cheerleading differ from those for regular partisan cheerleading? Given many partisans’ intense dislike of the opposing party, reverse cheerleading may actually be a more common occurrence than regular cheerleading, as partisans clamor to tear down the opposition rather than build up their party. Finally, under what conditions are partisans most likely to cheerlead? Would partisans engage in more cheerleading if they believe that they are being surveyed by an organization affiliated with their own party, or with the opposing party?

Appendix

Antidepressant and Anti-Anxiety Medication
Search Terms

English

Antidepressant*
St. Johns Wort
Selective serotonin reuptake inhibitor*
SSRI
Serotonin and norepinephrine reuptake inhibitor*
SNRI
Monoamine oxidase inhibitor*
MAOI
fluoxetine
citalopram
escitalopram
paroxetine
fluvoxamine
desvenlafaxine
duloxetine
levomilnacipran
venlafaxine
amitriptyline
amoxapine
clomipramine
desipramine
doxepin
imipramine
nortriptyline
protriptyline
trimipramine
Maprotiline
Bupropion
vilazodone
nefazodone
trazodone
vortioxetine
isocarboxazid
phenelzine
selegiline
tramiprosamine
Mirtazapine
olanzapine
alprazolam
clonazepam
diazepam
lorazepam
oxazepam
chloridiazepoxide
propranolol
atenolol
oxalate
buspirone
Valproate
Pregabalin
Gabapentin
Zoloft
Prozac
Celexa
Lexapro
Paxil
Luvix
Pristiq
Cymbalta
Fetzima
Effexor
Anafranil
Norpramin
Tofranil
Pamelor
Surmontil
Wellbutrin
Viibryd
Oleptro
Brintellix
Marplan
Nardil
Emsam
Parnate
Remeron
Symbyax
Xanax
Klonopin
| English | Spanish |
|---------|---------|
| Valium  | Bupropion |
| Ativan  | vilazodone |
| Serax   | nefazodona |
| Librium | trazodona |
| Inderal | vortioxetina |
| Tenormin| isocarboxazid |
| Aventyl | phenelzine |
| Elavil  | selegilina |
| Sinequan| tranlylcypromine |
| Desyrel | Mirtazapina |
| BuSpar  | olanzapina |
| Depakote| alprazolam |
| Lyrica  | clonazepam |
| Neurontin| diazepam |
| Sarafem | lorazepam |
| Pexeva  | oxazepam |
| Khedezla| Clordiazepóxido |
| Forfivo | propranolol |
| Pertosfrane| atenolol |
| Adapin  | oxalato |
| Brisdelle| buspirona |
| Aplenzin| Valproate |
|         | Pregabalina |
|         | Gabapentina |
|         | Zoloft |
|         | Prozac |
|         | Celexa |
|         | Lexapro |
|         | Paxil |
|         | Luvox |
|         | Pristiq |
|         | Cymbalta |
|         | Fetzima |
|         | Effexor |
|         | Anafranil |
|         | Norpramin |
|         | Tofranil |
|         | Pameler |
|         | Surmontil |
|         | Wellbutrin |
|         | Viibryd |
|         | Oleptro |
|         | Brintellix |
|         | Marplan |
|         | Nardil |
|         | Emsam |
|         | Parnate |
|         | Remeron |
|         | Symbax |
|         | Xanax |
|         | Klonopin |
|         | Valium |
|         | Ativan |
|         | Serax |
|         | Librium |
Inderal
Tenormin
Aventyl
Elavil
Sinequan
Desyrel
BuSpar
Depakote
Lyrica
Neurontin
Sarafem
Pexeva
Khedezla
Forfivo
Pertofrane
Adapin
Brisdelle
Lyrica
Depakote
BuSpar
Desyrel
Sinequan
Aventyl
Tenormin
Elavil

Authors’ Note
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Notes
1. Dana Milbank, a columnist for the Washington Post, summarized Democrats’ complaints thusly: “From the left came a flood of responses from people experiencing all manner of symptoms, real or imagined, of what I called Trump Hypertensive Unexplained Disorder: Disturbed sleep. Anger. Dread. Weight loss. Overeating. Headaches. Fainting. Irregular heartbeat. Chronic neck pain. Depression. Irritable bowel syndrome. Tightness in the chest. Shortness of breath. Teeth grinding. Stomach ulcer. Indigestion. Shingles. Eye twitching. Nausea. Irritability. High blood sugar. Tinnitus. Reduced immunity. Racing pulse. Shaking limbs. Hair loss. Acid reflux. Deteriorating vision. Stroke. Heart attack.”
2. http://www.apa.org/news/press/releases/2017/02/stressed-nation.aspx
3. http://edition.cnn.com/election/results/exit-polls
4. http://www.pewresearch.org/fact-tank/2017/09/25/key-facts-about-unauthorized-immigrants-enrolled-in-daca/
5. Republicans showed no change
6. For respondents whose vote choice and party ID were known, 90% of partisans responded they would vote for their party’s candidate.
7. Searched in Spanish means that they searched using Spanish Bing, accessible at: https://www.bing.com/?cc=es
8. https://www.prri.org/research/american-values-survey-2017/
9. The authors did a similar analysis, comparing women with men, and found that neither women nor men changed their mental-health-search-related behaviors after the election.

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