Economics and Human Biology 40 (2021) 100963

Contents lists available at ScienceDirect

Economics and Human Biology

journal homepage: www.elsevier.com/locate/ehb

Insights on the implications of COVID-19 mitigation measures for mental health☆

Bita Fayaz Farkhad*, Dolores Albarracín

University of Illinois at Urbana-Champaign, United States

ARTICLE INFO

Article history:
Received 6 July 2020
Received in revised form 20 November 2020
Accepted 24 November 2020
Available online 2 December 2020

JEL classification:
I12
I31
I1

Keywords:
Mental health
COVID-19 policies
Social distancing

ABSTRACT

Given the unprecedented level and duration of mitigation policies during the 2020 COVID-19 pandemic, it is not surprising that the public and the media have raised important questions about the potential for negative mental health consequences of the measures. To answer them, natural variability in policy implementation across US states and over time was analyzed to determine if mitigation policies correlated with Google searches for terms associated with symptoms of depression and anxiety. Findings indicated that restaurant/bar limits and stay-at-home orders correlated with immediate increases in searches for *isolation* and *worry* but the effects tapered off two to four weeks after their respective peaks. Moreover, the policies correlated with a reduction in searches for *antidepressants* and *suicide*, thus revealing no evidence of increases in severe symptomatology. The policy implications of these findings are discussed.

1. Introduction

In the absence of a vaccine, mitigation measures such as stay-at-home orders (also known as lockdowns or shelter in place mandates) have been the major device to slow down the staggering death and morbidity of the COVID-19 pandemic (Anderson et al., 2020; Lasry et al., 2020; Friedson et al., 2020; Allcott et al., 2020; Greenstone and Nigam, 2020; Fowler et al., 2020; Courtemanche et al., 2020; Chen et al., 2020; Devaraj and Patel, 2020; Dave et al., 2020a, 2020b). However, questions about the negative mental health impact of mitigation measures have been raised (New York Times, 2020b, a) and the World Health Organization (WHO) recommends that governments put mental health "front and center" when planning their responses (New York Times, 2020b).

Although recent evidence suggests that the number of visits for depression and anxiety during the pandemic has not increased relative to the pre-pandemic levels (Trinkl and del Río, 2020), correlational, often uncontrolled, studies of the psychological impact of lockdowns during other disease outbreaks have indicated that quarantines are associated with increased mental health symptoms (Brooks et al., 2020). Furthermore, two recent studies attempted to estimate the mental health effects of stay-at-home orders. First, a simulation using data on time spent alone from the 2012–2013 American Time Use Survey forecasted likely negative effects of the imposed isolation on happiness (Hamermesh, 2020). Second, an important study investigated the effects of stay-at-home orders on mental health symptom related searches on Google and reported increases in searches on boredom, sadness, loneliness, and worry (Brodeur et al., 2020). However, how serious is the mental health impact of the mitigation policies? Does the mental health impact go beyond feeling anxious or depressed? Is it long lasting, and does it increase suicide ideation and the need for medical treatment for depression?

The question of whether the mitigation measures elicit temporary anxious and depressed feelings, or more permanent or severe effects is important from a mental health perspective. According to the DSM-5, major depression involves a change towards a depressed mood or a loss of interest or pleasure in daily activities that lasts for more than two weeks, impairs social, occupational, and/or educational functioning, and involves at least 5 of the following 9 symptoms present nearly every day: (1)

☆ Researchers own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

* Corresponding author at: University of Illinois at Urbana Champaign, College of Liberal Arts and Sciences, 603 East Daniel Street, Champaign, IL, 61820, United States.

E-mail address: bitaf@illinois.edu (B. Fayaz Farkhad).

http://dx.doi.org/10.1016/j.ehb.2020.100963
1570-677X/

depressed or irritable mood most of the day, nearly every day, (2) decreased interest or pleasure in most activities, most of each day, (3) significant weight change (5%) or change in appetite, (4) insomnia or hypersomnia, (5) psychomotor agitation or retardation, (6) fatigue or loss of energy, (7) feelings of worthlessness or excessive or inappropriate guilt, (8) diminished ability to think or concentrate, or greater indecisiveness, and (9) thoughts of death or suicide, or having a suicide plan (Diagnostic and Statistical Manual of Mental Disorders (DSM-5®), 2013). Importantly, anxiety symptoms can co-occur with depression and entail preoccupation with past mistakes or failure (i.e., rumination), as well as thoughts and fears about the future (i.e., anxious thoughts). Both depressive and anxious thoughts can be treated with psychotherapy and medication, and thoughts of suicide are considered severe and require immediate intervention.

One challenge in quantifying the mental health consequences of the mitigation measures is that it requires a longitudinal analysis that can track the relatively rapid changes that mitigation policies could produce and the duration of the changes. Although longitudinal studies can be carefully planned for anticipated events, to the best of our knowledge, no direct, daily measures of anxiety and depression are available to study the impact of the policies. Google Trends, however, can index daily population concerns by recording internet searches for a particular term, relying on Google being the leading search engine and retaining a dominant market share of all search traffic within the United States. Google Trends are normalized over time, can validly gauge the salience of specific concerns within a region, such as a state, and have been found to predict influenza trends (Pelat et al., 2009; Valdivia and Monge-Corella, 2010), HIV (Young and Zhang, 2018; Zhang et al., 2018), suicide (Parker et al., 2017), and economic activity (Choi and Varian, 2012; Choi and Varian, 2009).

A substantial proportion of internet users perform online searches for health information, including information related to depression and mental disorders (Baker et al., 2003; Lam-Po-Tang and McKay, 2010). Moreover, searches for health information are more frequent when people have less (vs. more) positive health assessments, indicating that searches self-report being concerned with health as opposed to feeling healthy (Weaver et al., 2010). Consistent with associations between these searches and mental health symptoms, the impact of negative economic conditions on anxiety and depression has been detected through Google searches for *anxiety* and *depression* (Tefft, 2011). Even more relevant to our problem, a recent study of searches for *boredom*, *sadness*, *loneliness*, and *worry* suggested that the stay-at-home orders increased these negative feelings (Brodeur et al., 2020), lending credence to the hypothesis that this mitigation measure may have affected mental health outcomes. Our study began by including similar searches for depression and worry, with the expectation that they may become stronger in states with stay-at-home and other policies during the days when the policy was in effect. But our study departed from past work by distinguishing searches for depressive and anxious feelings from searches suggestive of more severe clinical symptoms. We additionally examined whether any effect on searches for depression and anxiety symptoms is long-lasting or temporary.[1]

Although depressive and anxious feelings may arise during stay-at-home periods, more significant symptoms may not. In economic models, health is produced by lifestyle behaviors, human capital investments of time, material, and human resources into healthy activities, and stochastic shocks (Grossman, 1972). This model then suggests that greater flexibility in time and production decisions within the family could lead to improvements in health and thus may counteract any potential negative health effect of the mitigation policies (e.g., massive layoffs).[2] Indeed, recession-induced declines in work hours increased the amount of time spent on home production activities, leisure, child care, education, and health (Aguiar et al., 2013; Page et al., 2019; Lindo et al., 2018). Stay-at-home policies could additionally decrease the frequency of suicide ideation as well as the need to use of antidepressants by increasing the time spent with family.[3] All in all, taking up a hobby, regular physical activity, and social support traditionally are associated with better physical health and enhanced psychological well-being (Stansfeld, 2006; Taliaferro et al., 2009; Paluska and Schwenk, 2000).

The introduction and lifting of the mitigation measures naturally varied over time and across states. The directives for stay-at-home orders began in California in mid-March, with 29 additional states passing the orders by the end of March and followed by 12 states elected to pass during the April. States implemented five mitigation measures (i.e., stay-at-home orders, restaurant/bar limits, non-essential business closures, large gathering bans, and school closures). Of these policies, stay-at-home orders are likely to have important mental health implications because of the increase in isolation and decrease in social support. We additionally included state of emergency declarations, school closures, restaurant/bar limits, and non-essential business closures in our models.

Not all the changes in mental health can be attributed to the mitigation policies. Historically, infectious diseases have been responsible for the greatest human death tolls and function as a major stressor for the population at large. For example, although as mentioned above, visits to mental health services during the week of July 12, 2020 did not increase relative to pre-pandemic levels (Trinkl and del Río, 2020), nearly half of adults reported that worry and stress over the SARS-CoV-2 virus have negatively impacted their mental health (KFF, 2020b; Czeisler et al., 2020). This finding suggests that the epidemic itself can increase mental health symptoms, which is consistent with the well-known effects of stress on mental health (Aneshensel et al., 1991; Marin et al., 2011; Bovier et al., 2004; Creamer et al., 2001; Langner and Michael Stanley, 1963). Thus, we analyzed the effects of the mitigation policies using queries between January 1, 2020, and June 30, 2020, while controlling for the course of the epidemic. In so doing, we first verified that the policies correlated with searches directly related to the policies. For example, we investigated how mitigation policies affected search intensity for locations such as *park*, *restaurant*, or *bar*. We then correlated the policies with searches for *anxiety*, *depression*, *antidepressant*, *suicide*, and various substances including *liquor* and *cigarette*.[4]

Our research yielded three major results. First, consistent with prior reports, social distancing policies correlated with an increase in searches for *isolation* and *worry*. However, our second finding was that the effects on searches for *isolation* and *worry* were temporary and decreased gradually after peaking. Finally, the stay-at-home order and restaurant/bar limits decreased searches for *antidepressants* and *suicide*. A potential explanation of this finding

[1] Brodeur et al. (2020) studied Google searches with a timeframe up to April 10th, 2020, thus preventing investigation of the duration of the effects.

[2] However, perhaps counter-intuitively, an extensive literature documents that negative shocks to labor market were associated with reductions in mortality and improvements in adult health (Ruhm, 2000, 2003; 2005). Ruhm (2015) showed that the relation between recessions and adult mortality weakened during the Great Recession but remained pro-cyclical, particularly for deaths due to cardiovascular disease and transport accidents.

[3] We note that this does not apply to single member households. Based on the 2019 Current Population Survey only 28% of households report living alone, so on average stay-at-home orders should increase the time spent with families.

[4] We used *liquor* instead of *alcohol* to exclude the possibility of searches related to disinfection during the pandemic.

is that even though social isolation increased risk factors for mental health, the stay-at-home order also increased within-home hours which might promote new routines and greater social support within the family. Accordingly, we found that searches for activities such as *exercise* and *cooking* were positively associated with the stay-at-home policy, suggesting that individuals spent more time with their family.

2. Data

2.1. Mitigation measures

We gathered data on state-by-day COVID-19 mitigation policies via a systematic policy review.[5,6] We used the original documents issued by the state governments, collected by the Kaiser Family Foundation to determine the date of implementation and lifting (when applicable) of stay-at-home policies, restaurant/bar limits, non-essential business closures, K-12 school closures, and state of emergency declaration (KFF, 2020a). These data appear in Fig. A1.

2.2. Google trends

We measured mental health concerns by obtaining an indication of daily, state-located search queries on Google ("Google Trends", 2020). Google Trends is an unbiased sample of Google search data and allows users to download information about searches for a particular term normalized per search location (in this case, per state). The normalization controls for the total volume of internet usage across time and involves: (1) each data point being divided by the total search volume of the geography and time range, and (2) scaling the results on a range from 0 to 100 based on a topic's proportion over all searches on all topics. An increase for a given search term indicates more searches for those terms over the time being considered.

We used search queries between January 1, 2020, and June 30, 2020, and followed a procedure used by Tefft (2011) and Kahn and Kotchen (2010) to standardize the exported Google search indexes for each state across time such that the normalized distribution for each state across time has a mean of zero and a variance of one.

We first used a set of terms related to the mitigation policies, because any impact of the mitigation measures on mental health is assumed to operate through changes in social activities. The set involved terms associated with public activities that the policies are designed to curtail. Specifically, we obtained data on searches for the terms *park*, *restaurant*, *bar*, *pharmacy*, and *grocery*. The set also included in-home activities that the orders are designed to promote, such as using *Amazon*, *delivery,* and *takeout* instead of leaving home to make unnecessary purchases.

The key set of search terms concerned mental health. Specifically, we obtained trends for *isolation*, *anxiety*, *worry*, *angry*, *concentration*, *insomnia*, *depression*, *antidepressant*, *SSRI*, *Sertraline*, *Prozac*, *Zoloft*, and *suicide*. We also gathered trends for the terms associated with substance use, specifically *liquor*, *wine*, *beer*, *cigarette*, *marijuana*, and *naloxone*.[7]

2.3. Validation datasets

The validity of using Google searches for depression and anxiety has been established previously (Tefft, 2011; Parker et al., 2017). However, we were interested in understanding whether Google searches are a valid representation of users' needs or behaviors studied more frequently than annually (i.e., daily or weekly). Our second goal was using Google searches to verify the impact of the policies on (1) social activities, (2) medications, and (3) substance use. Therefore, we analyzed the correlation between Google indexes for several topics with daily/weekly measures from two supplementary data sources, Google-released data on community mobility ("COVID-19 Community Mobility Reports", 2020) and the Nielsen Retailer Scanner data ("Nielsen Dataset - Kilts Center | Chicago Booth", 2020), as follows:

1 Google-released aggregated, anonymized daily location data on movement trends aim to provide insights into changes following the COVID-19 policies. The data were gathered by Google from users who have enabled the Location History setting on their accounts and are used by Google Maps to track human traffic at various locations. The reports chart movement trends over time by geographic location, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. The mobility data allowed us to examine the extent to which Google searches for social activities correlate with specific daily mobility measures. Finding that the search index for *grocery* in the state of New York correlates the mobility measure for grocery stores would indicate the validity of the Google search index.

2 Our second validation dataset came from the Nielsen Retailer Scanner data which comprises a sample of approximately 30,000–35,000 retailers, including grocery stores, drug stores, mass merchandise retailers, and other types of stores. The volume of each product sold at each store is recorded weekly. Using the 2018 Nielsen Retailer Scanner data, we constructed weekly sales of over-the-counter painkillers as well as weekly sales of substances.[8] In particular, we calculated weekly units of over-the-counter painkillers, liquor, beer, and wine sold in a state and correlated them with the 2018 weekly indexes of Google searches for *headache*, *liquor*, *beer*, and *wine* respectively. Finding positive associations would indicate that searches for *headache*, *liquor*, *beer*, and *wine* can be used as a proxy for the volume of painkillers, liquor, beer, and wine sold, respectively.

2.4. COVID-19 cases

We used publicly available data on confirmed COVID-19 cases from Johns Hopkins University (Dong et al., 2020). The dataset is a panel at the day-by-state level, with data from a variety of agencies, including the World Health Organization, the Centers for Disease Control, state health departments,and local media reports. Our analyses relied on the logarithm of one plus the cumulative number of cases and deaths, both to correct for outliers with a large number of cases and because of the exponential nature by which the SARS-CoV-2 virus spreads make the logarithm normalization optimal.

[5] A systematic review was necessary because there were discrepancies in policy start dates among datasets available in third-party sources (Raifman et al., 2020; KFF, 2020a).

[6] We considered the effective date as the first day on which the policy was in full effect.

[7] We used *liquor* instead of *alcohol* to exclude the possibility of searches related to disinfection during the pandemic.

[8] Drugs for treating mental illnesses require prescriptions and thus data on their sales are not available in the Nielsen Retailer Scanner database.

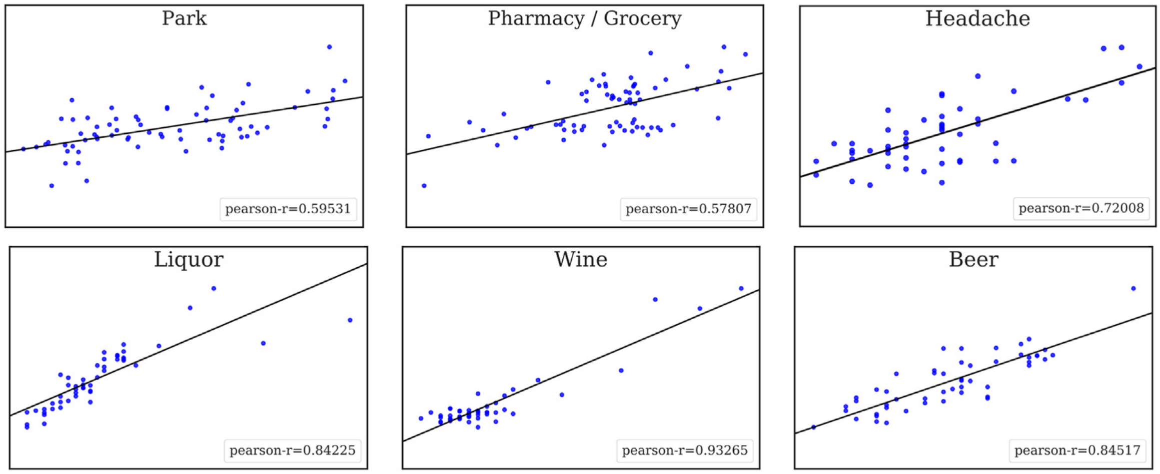

Fig. 1. Association between Google search activity and community behavior.
Notes: The first two figures in the first row (Park and Pharmacy/Grocery) display the correlation between state-by-day Google Trends data and Google released community mobility. The third figure in the first row (Headache) displays the correlation between state-by-week Google Trends data and sales of painkillers as calculated from the Nielsen Retailer Scanner data. The last three figures in the second row display the correlation between state-by-week Google Trends data and alcohol-units sold as calculated from the Nielsen Retailer Scanner data.

3. Empirical framework

To estimate the effects of mitigation measures on search indexes, we implemented a difference-in-differences (DiD) strategy that capitalizes on the staggered rollout of policies across states. Our approach leveraged variation in the timing of lifting the polices to investigate how the effects changed once the policies were lifted. In particular, we estimated the following regression as our main equation:

$$Y_{sd} = \alpha + \sum_{j} \beta_j \, mandate_{jsd} + \sum_{j} \gamma_j \, lift_{jsd} + \delta_s + \delta_d + \varepsilon_{sd}, \quad (1)$$

Where Y_{sd} is the Google search index in a given state s and day d, $mandate_{jsd}$ indicates whether state-wide mandate j (i.e., stay-at-home orders, restaurant/bar limits, and non-essential business closures) is active on a given day and $lift_{jsd}$ indicates whether policy j has been lifted. We additionally include state-by-day school closures and state of emergency declaration. Finally, δ_s and δ_d are state and day fixed effects, respectively, and ε_{sd} is a random error term. Standard errors are clustered at the state to correct for within-state correlation in outcomes (Bertrand et al., 2004). State fixed effects were included to control for time-invariant unobservable state characteristics that may affect outcomes, whereas day fixed effects were included to absorb unobservable shocks that are common across states. In this model, β_j is the effect of introducing mitigating policy j and γ_j is the effect of lifting it.

As is standard in DiD models, identification relies on the "common trend assumption" that, in the absence of the policy, outcomes in the "treated" states would have evolved as in the "untreated" states. We assessed the plausibility of this identifying assumption using an event study type model specifying a full set of policy leads to determine whether the policies were endogenously implemented in response to previous trends. We replaced each single policy indicator variable with a series of indicator variables representing the number of periods relative to policy implementation. To estimate the dynamic effect of a policy around the timing of its implementation, we estimated the following model:

$$Y_{sd} = \alpha + \sum_{k} \beta_m^k mandate_{msd}^k + \sum_{j \neq m} \beta_j \, mandate_{jsd} + \sum_{j} \gamma_j \, lift_{jsd} + \delta_s + \delta_d + \varepsilon_{sd}, \quad (2)$$

in which $mandate_{msd}^k$ is a dummy variable equal to 1 if the mandate m has been implemented for k periods, $k = \{< -10, -10, \cdots, 0, 1, \cdots, 10, > 10\}$, or is zero otherwise, with the day before the implementation of the mandate ($k = -1$) as the omitted category. Also, we present event study figures for lifting each of the mitigation measures on the sample of states that mandated the policy. In the event study for each policy (either mandate or lift), we included all control variables as defined in Eq. (1) including binary variables on the implementation and lifting policy j in the regression model.

Finally, we estimated a distributed lag model to examine the dynamic effects of the mitigation policies. As seen in Fig. A1, because of the gradual implementation of the measures, we are unable to disentangle the dynamic effect of each of the policies. For this reason, we limited the main effects of interest to the mandate of the first major mitigation policy in a state (i.e., either stay-at-home order, restaurant/bar limits, or non-essential business closure), the last mandate, and the first lift. Because the median difference between the last mitigation policy and the first lift across states was 42 days, we included two 2-week lagged effects of the last mandate (i.e., a 2-week lagged, and a 4-week lagged). We additionally included a 2-week lagged effect of the first lift.

4. Results

4.1. Validation of google trends data

First, to understand whether daily Google searches represent the intention to visit a given place (e.g., a grocery store) or perform a given behavior on the day of a search, we correlated daily Google searches and Google-released mobility data. Visual representations of trends in Google searches for *park* and *pharmacy/grocery* along with community mobility are depicted in Figs. A2 and A3 respectively. As seen in both graphs, the Google Trends data strongly resembled community mobility. Importantly, the correlation between state-by-day mobility data and Google searches for *park* and *pharmacy/grocery* in Fig. 1 led to the conclusion that Google Trends, which provide a broad spectrum of keywords beyond mobility data, had convergent validity.

Second, we were interested in validating the degree to which Google searches for health symptoms are meaningful

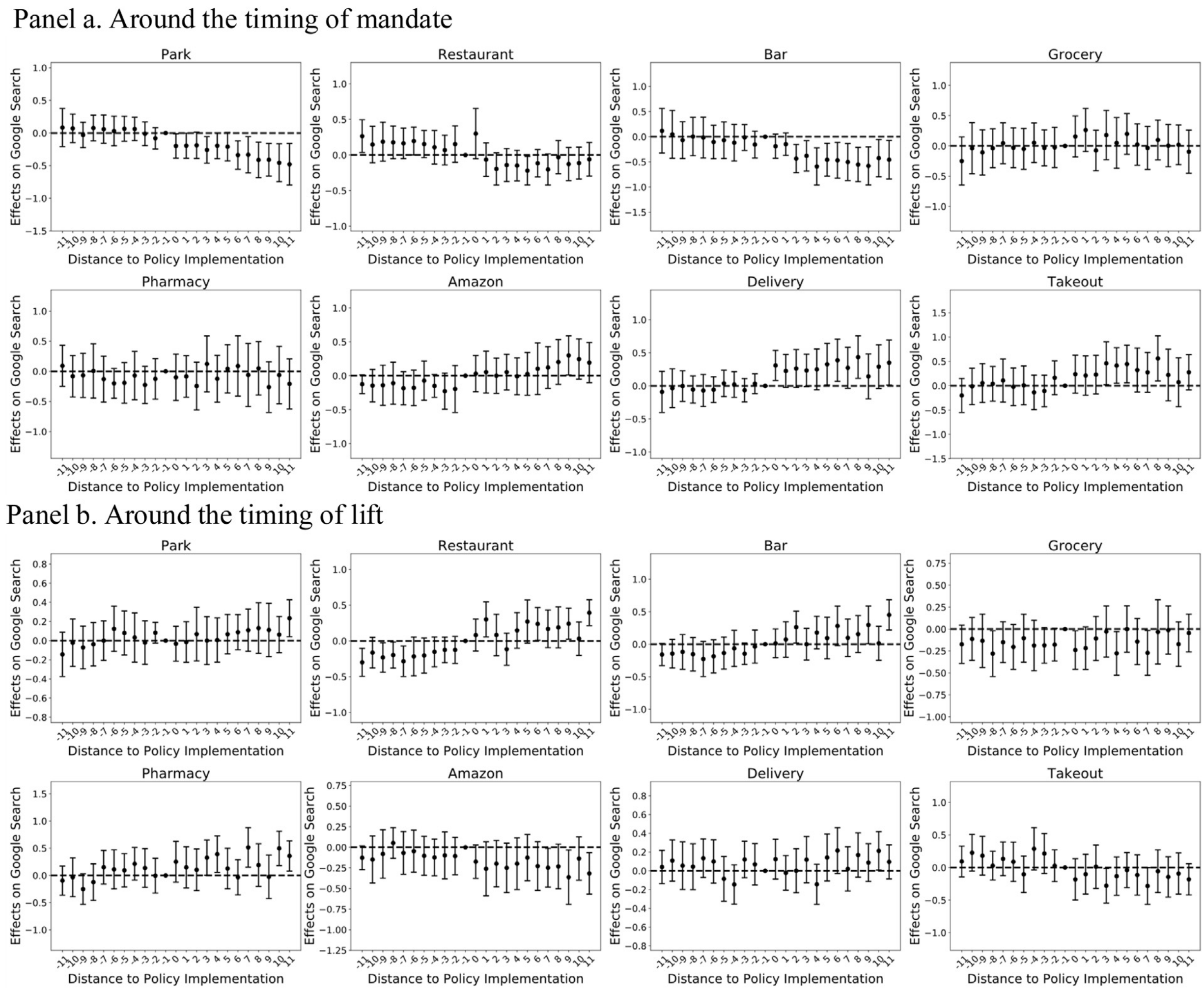

Fig. 2. Event study of restaurant/bar limits and reopening on searches for public locations.
Panel a. Around the timing of mandate.
Panel b. Around the timing of lift.
Notes: Standard errors are clustered at the state level and coefficients are shown with 95 % confidence intervals.

representations of users' health conditions. Fig. A4 suggests that weekly searches for *headache* and weekly sales of painkillers calculated from the 2018 Nielsen Retailer Scanner data had similar trends. As with the searches for *park* and *pharmacy/grocery*, the correlation between state-by-week Google searches for *headache* and painkillers' sales in Fig. 1 confirms the validity of Google Trends as a measure of specific health concerns within a region.

Finally, Figs. A5 through A7 depict the similar weekly trends of Google searches for *liquor*, *beer*, and *wine* and weekly data on the sold units of liquor, beer, and wine. Importantly, the correlation between Google searches and sales data on three types of alcoholic beverages presented in Fig. 1 suggests that keyword searches for substances correlated with alcoholic-beverage sales.

4.2. Effects on searches for public locations

Before presenting our estimated effects of the mitigation policies on Google searches for mental health, we first examined whether the mitigation policies affected Google searches for public places.

Fig. A8 presents trends in state-level Google searches for various public locations. In Panel (a), the horizontal axis represents weeks relative to the first major mitigation policy in a state (i.e., either stay-at-home order, restaurant/bar limits, or non-essential business closure), whereas in Panel (b) the horizontal axis represents weeks relative to the date each state began to lift mitigation policies. These graphs suggest that Google searches for public places such as *park*, *restaurant*, *bar*, and *pharmacy* dropped immediately after the introduction of mitigation policies. At the same time, searches for *Amazon*, *delivery*, and *takeout* rose. These effects tapered off gradually, but most indexes did not cross zero until a few weeks past the order's lift.

Before we begin the discussion of the regression testing the relations between mitigation policies and the daily search indexes for various locations, we tested for the equality of pre-policy trends using the event study method in Eq. (2). In Fig. 2, we plot the day-by-day coefficients from the models for restaurant/bar limits (both mandate and lift) and the corresponding 95 % confidence intervals.[9] Fig. 2a suggests that the coefficients on the pre-policy dummies were generally non-significant for the majority of outcomes (except *restaurant*). Likewise, Fig. 2b suggests that we cannot reject the null hypothesis of equal trends for the majority of our indexes (except *restaurant* and *grocery*). These results thus

[9] The analogous event study figures for stay-at-home orders and non-essential business closures are presented in Figs. A9 and A10.

Table 1
Effects of the mitigation measures on Google searches for public locations.

	Stay-at-home		Restaurant limit		Business closure		
	Implement	Lift	Implement	Lift	Implement	Lift	N
Park	−0.304***	0.169**	−0.352***	0.171**	0.059	0.042	9282
	(0.10)	(0.07)	(0.09)	(0.08)	(0.10)	(0.07)	
Restaurant	−0.227**	−0.025	−0.148	0.460***	0.033	0.140***	9282
	(0.10)	(0.05)	(0.09)	(0.06)	(0.10)	(0.05)	
Bar	−0.277**	0.034	−0.368***	0.375***	0.075	0.104*	9282
	(0.13)	(0.06)	(0.12)	(0.06)	(0.11)	(0.06)	
Pharmacy	−0.099	−0.043	−0.041	0.186**	0.066	0.148***	9282
	(0.11)	(0.06)	(0.11)	(0.08)	(0.12)	(0.06)	
Grocery	−0.015	−0.012	0.145	0.079*	−0.016	0.025	9282
	(0.07)	(0.04)	(0.09)	(0.04)	(0.08)	(0.03)	
Amazon	0.216	−0.081	0.271***	−0.102	0.111	−0.079	9282
	(0.13)	(0.06)	(0.08)	(0.07)	(0.12)	(0.06)	
Delivery	0.244***	−0.080**	0.331***	0.055	−0.075	0.061	9282
	(0.07)	(0.03)	(0.07)	(0.03)	(0.08)	(0.04)	
Takeout	0.095	−0.108***	0.360***	−0.267***	0.012	−0.027	9282
	(0.08)	(0.04)	(0.10)	(0.05)	(0.09)	(0.05)	

Notes: Each row reports regression coefficients from a linear regression model, weighted by state population in 2019. In addition to the listed variables, we control for indicators for school closures and state of emergency, state and day fixed effects. Standard errors in parentheses are clustered at the state level.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

provide reassuring evidence that the key assumption of the DiD study design was generally satisfied.

In Table 1, we present our DiD estimates based on Eq. (1). Three sets of results are important. First, as shown in the first and third columns of Table 1, stay-at-home orders and restaurant/bar limits were significantly associated with decreased searches for *park*, *restaurant*, and *bar*. Second, restaurant/bar limits and to some extent stay-at-home orders were significantly associated with increased searches for *Amazon*, *delivery*, and *takeout*. Third, relaxing stay-at-home, restaurant/bar limits, and, to some extent, non-essential business closures, had offsetting effects on the search indexes for public locations.

Taken together, these results are consistent with documented evidence that mitigation measures were effective at reducing physical activities by reducing mobility and shifting consumer patterns from person shopping to delivery and online platforms (Dave et al., 2020a, 2020b; Sears et al., 2020; Abouk and Heydari, 2020). As a result, the mitigation measures increased the amount of time Americans spent at home.

4.3. Effects of mitigation policies on searches for terms associated with mental health

In this section, we turn our attention to the searches for terms concerning mental health, which were the focus of our study. We start our analysis by presenting trends in Google searches for mental health in Fig. A11. Notably, Google searches for mental health symptoms such as *isolation* and *worry* spiked after the implementation of the first major mitigation policy. This finding is consistent with a recent survey in early April, which concluded that depression symptoms increased during the pandemic (Ettman et al., 2020). However, the trends in Google searches also indicate that these increases were temporary and fell after their respective peaks. This short duration is consistent with evidence suggesting that the number of visits for depression and anxiety in July was not higher than the corresponding number a year before the pandemic (Trinkl and del Río, 2020). Furthermore, despite increasing trends for Google searches for mental health symptoms in the weeks following the policy implementation, Google searches for more severe psychopathology keywords such as *antidepressant*, *Sertraline, Prozac, Zoloft,* and *suicide* dropped as a result of the mitigation policies.

Event study figures for search indexes for mental health from the models for restaurant/bar limits are presented in Fig. 3.[10] Fig. 3a presents the day-by-day coefficients from the models for restaurant/bar limits and the corresponding 95 % confidence intervals, whereas Fig. 3b presents the analogous coefficients and the corresponding confidence intervals from the models for relaxing restaurant/bar limits. Although limited precision in the estimated effects makes it difficult to identify the extent to which the effects vary over time, the point estimates of the policy leads for both the mental health and substance use indexes in the models for restaurant/bar limits were not significant (except *angry*). Likewise, as seen in Fig. 3b, there is not any divergence in trends prior to the date when the policies were lifted (except *concentration* and *anxiety*). These results thus confirmed the validity of our DiD framework.

Table 2 presents DiD estimates for Google searches for mental health. The first column of Table 2 indicates that stay-at-home orders were associated with an increase in the *isolation* and *worry* indexes but with a decrease in searches for *antidepressant*, *Sertraline*, and *Zoloft*. Similarly, restaurant/bar limits were positively associated with searches for *isolation* and *worry*, but negatively associated with searches for *Sertraline*, *Prozac*, and *suicide*. Surprisingly, non-essential business closures seem to have a limited effect. Presumably, because many private businesses began their response to the pandemic prior by closing or limiting activity prior to state-wide non-essential business closures (Aaronson et al., 2020). Finally, there were generally no adverse effects of any of the policies on the substance use indexes.[11] The one exception was that restaurant/bar limits significantly increased searches for *liquor*. However, this finding is consistent with

[10] The analogous event study figures from the models for stay-at-home orders and non-essential business closures are presented in Figs. A12 and A13.

[11] Likewise, we found no associations of any of the policies with the search indexes associated with illegal drugs (i.e., *Cocaine*, *Heroin*, and *Crack*). However, we do not report these results because we lack evidence that the search indexes for illegal drugs are a meaningful representation of drug use. These results are available upon request.

a shift from purchasing alcohol at bars and restaurants to purchasing alcohol from stores.

Next, to examine the dynamic effect of the mitigation policies, we present the results from a distributed lag model. As discussed in the Methods Section, we restricted our attention to the first major mitigation policy, the last major policy, and the first lift. These results are reported in Table 3. Consistent with the graphical evidence in Fig. A11, mitigation policies produced an immediate increase in Google searches for mental health symptoms such as *isolation* and *worry*. Also, the estimated coefficient on the first 2-week lag and the second 2-week lag of the mandate suggest that the increases fell after 2–4 weeks after their spike. Importantly, the sum of coefficients on the contemporaneous and lagged terms resulted in a statistically imprecise positive effect suggesting that the negative-feeling increases were transitory, and after 2–4 weeks were statistically indistinguishable from their pre-mandate levels. In contrast, the effects of the mitigation policies on searches for *suicide* in the lagged models reproduced our prior findings (see Table 2).

We next investigated whether the effects differed across states with longer versus shorter time of mitigation policy (i.e., the first lift minus the first major mandate). Fig. A14 presents weekly trends in Google searches by the duration of the policy (short and long holders) and suggests similar trends for the two sets of states prior to the implementation of the policy. Likewise, both groups of states experienced similar upticks in the growth of mental health symptoms, as well as similar declines in searches for *antidepressant* and *suicide*. This result is consistent with the observation that any

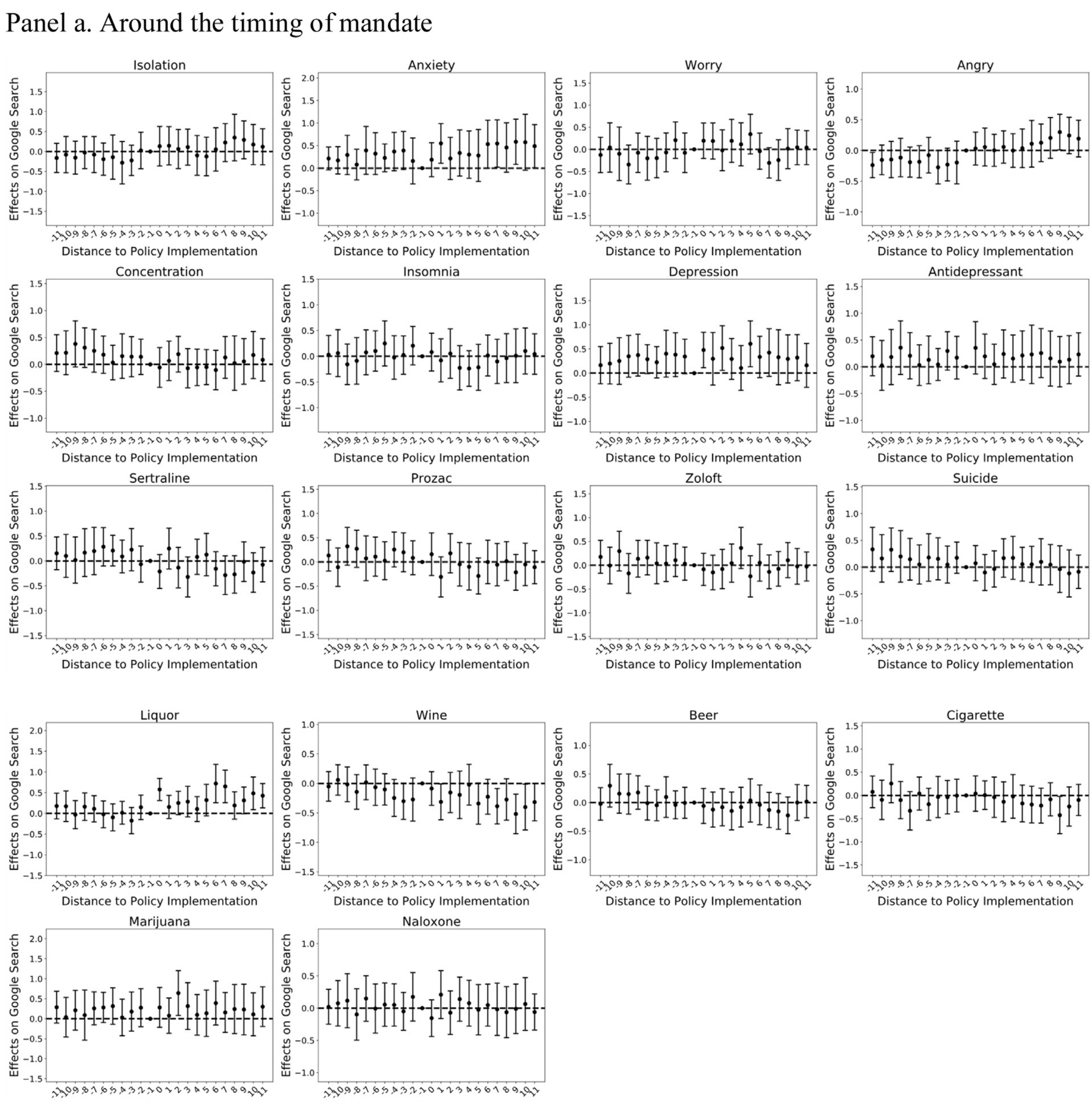

Fig. 3. Event study of restaurant/bar limits and reopening on searches for mental health.
Panel a. Around the timing of mandate.
Panel b. Around the timing of lift.
Notes: Standard errors are clustered at the state level and coefficients are shown with 95 % confidence intervals.

Panel b. Around the timing of lift

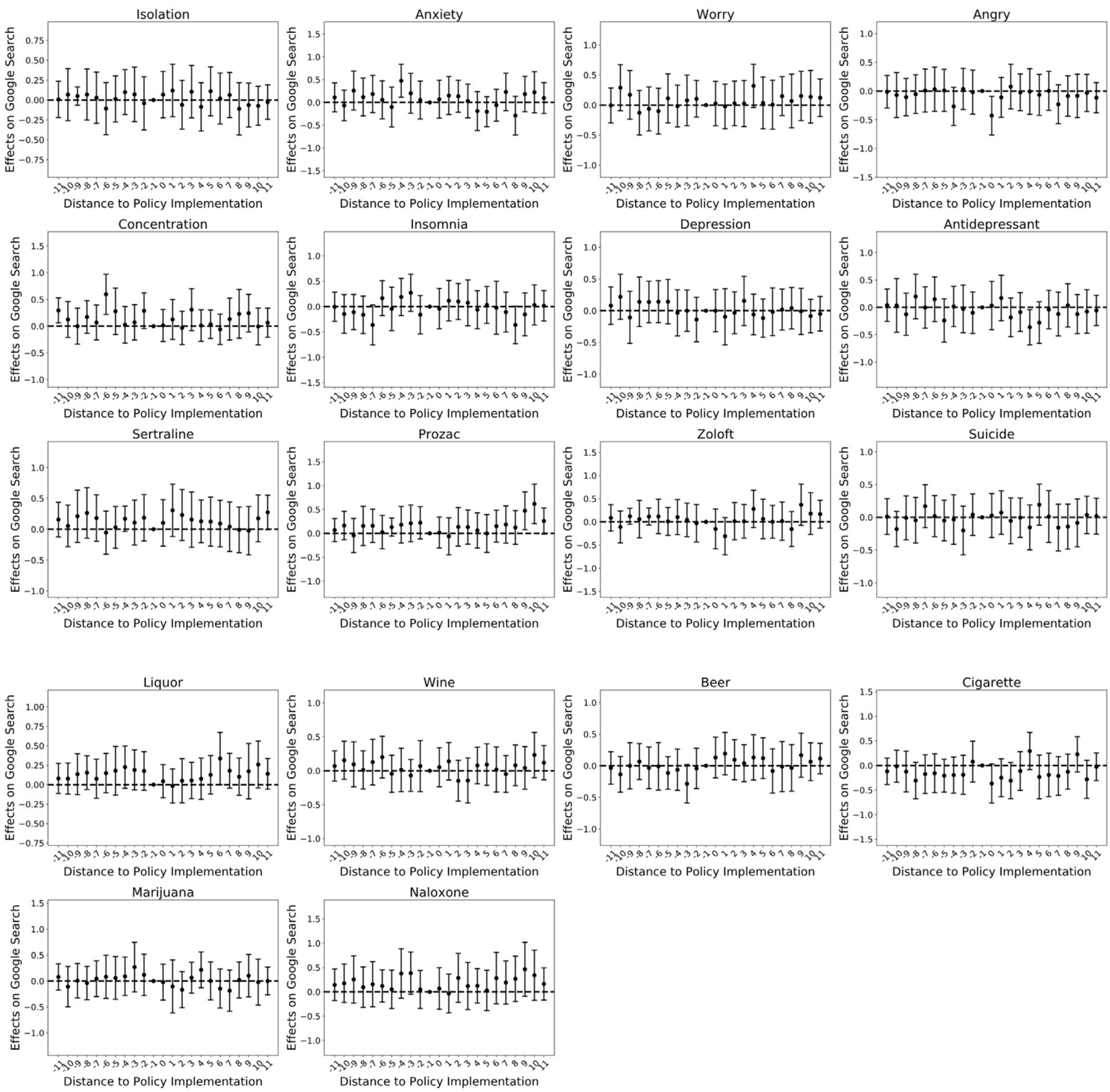

Fig. 3. (Continued)

effects of mitigation policies were temporary and fell after 2–4 weeks. As a result, the length of the duration of the mitigation policies, which varied between 29 and 81 days did not matter.

We next examined the sensitivity of our DiD results to modifications of the model by sequentially adding controls to the benchmark specification. First, the results were robust to the inclusion of state-specific weekly trends (Table A1). Second, even though the onset and duration of mitigation measures might be driven by the incidence of the COVID-19 cases (for example, see, (Dave et al., 2020a) adding the number of COVID-19 cases to the benchmark model did not alter our findings (Table A2).

Finally, our analysis may be compromised if the errors of each equation were correlated, which would make our t-tests not statistically independent from each other. To account for multiple hypothesis bias, we used two approaches. First, we estimated a Seemingly Unrelated Regression (SUR) and evaluated the compound null hypothesis that the effects are jointly equal to zero (Simon et al., 2017; Dave and Kaestner, 2009). In Table A3, we report p-values representing the probability of rejecting the null hypothesis of at least one type I error across the outcomes. We rejected the hypothesis that the effects of either stay-at-home orders or restaurant/bar limits on different search indexes were jointly equal to zero. Second, we calculated p-values using the "wyoung" Stata command developed by Jones et al. (2020), which calculates Westfall-Young step-down adjusted p-values to allow for dependence amongst outcomes. The adjusted p-values using this conservative approach are reported in Table A4. Although some estimates were not statistically significant when adjusting the p-values to account for multiple hypothesis testing, the qualitative conclusions remained robust.

4.4. Effects of mitigation policies on searches for other drugs

In the above section, we presented evidence that the mitigation policies correlated with reduced searches for antidepressants. Although we cannot fully understand the

Table 2
Effects of the mitigation measures on Google searches for mental health and substance use.

	Stay-at-home		Restaurant limit		Business closure		N
	Implement	Lift	Implement	Lift	Implement	Lift	
Isolation	0.120*	−0.02	0.218**	0.003	0.129	0.060	9282
	(0.07)	(0.05)	(0.11)	(0.05)	(0.11)	(0.04)	
Worry	0.096*	0.012	0.167**	0.029	0.045	0	9282
	(0.06)	(0.06)	(0.07)	(0.07)	(0.09)	(0.06)	
Anxiety	0.023	0.021	0.066	0.011	0.044	0.002	9282
	(0.07)	(0.06)	(0.09)	(0.06)	(0.09)	(0.06)	
Concentration	−0.089	−0.041	−0.098	−0.131	0.089	0.064	9282
	(0.10)	(0.07)	(0.08)	(0.08)	(0.10)	(0.06)	
Fatigue	0.034	−0.135***	0.086	−0.031	−0.05	0.016	9282
	(0.06)	(0.04)	(0.05)	(0.07)	(0.07)	(0.06)	
Angry	0.071	−0.113**	−0.101	0.007	−0.09	0.03	9282
	(0.06)	(0.05)	(0.07)	(0.06)	(0.08)	(0.05)	
Insomnia	−0.031	−0.013	−0.035	−0.021	−0.079	−0.049	9282
	(0.05)	(0.05)	(0.07)	(0.05)	(0.07)	(0.04)	
Depression	0.012	−0.083	0.079	−0.140**	0.11	0.111*	9282
	(0.09)	(0.06)	(0.09)	(0.06)	(0.10)	(0.06)	
SSRI	−0.096*	−0.005	−0.134	−0.008	−0.057	0.06	9282
	(0.06)	(0.06)	(0.09)	(0.05)	(0.07)	(0.05)	
Antidepressant	−0.083*	0.008	0.029	−0.036	−0.019	−0.06	9282
	(0.05)	(0.05)	(0.07)	(0.05)	(0.07)	(0.05)	
Sertraline	−0.116**	−0.02	−0.160**	0.057	−0.007	0.019	9282
	(0.06)	(0.05)	(0.07)	(0.06)	(0.08)	(0.05)	
Prozac	0.07	−0.048	−0.188*	0.055	−0.095	−0.017	9282
	(0.06)	(0.05)	(0.10)	(0.05)	(0.07)	(0.05)	
Zoloft	−0.115*	0.046	−0.125	−0.03	0.126	0.067	9282
	(0.07)	(0.06)	(0.08)	(0.06)	(0.08)	(0.06)	
Suicide	−0.096*	−0.02	−0.233***	0.054	−0.052	0.055	9282
	(0.06)	(0.05)	(0.09)	(0.05)	(0.08)	(0.06)	
Liquor	0.085	−0.005	0.369***	0.001	−0.215**	−0.025	9282
	(0.07)	(0.05)	(0.09)	(0.05)	(0.09)	(0.05)	
Wine	0.174*	−0.072	0.023	−0.032	−0.094	−0.111**	9282
	(0.09)	(0.05)	(0.06)	(0.06)	(0.09)	(0.04)	
Beer	−0.087	0.02	−0.146**	0.110**	0.071	−0.110**	9282
	(0.07)	(0.04)	(0.06)	(0.05)	(0.07)	(0.04)	
Cigarette	−0.114*	0.08	−0.046	0.038	0.056	−0.048	9282
	(0.07)	(0.05)	(0.06)	(0.05)	(0.07)	(0.05)	
Marijuana	−0.076	0.018	0.039	−0.046	−0.004	0.089	9282
	(0.10)	(0.05)	(0.10)	(0.06)	(0.11)	(0.06)	
Naloxone	−0.033	0.039	0.016	−0.049	0.012	−0.043	9282
	(0.06)	(0.05)	(0.08)	(0.06)	(0.07)	(0.04)	

Notes: Each row reports regression coefficients from a linear regression model, weighted by state population in 2019. In addition to the listed variables, we control for indicators for school closures and state of emergency, state and day fixed effects. Standard errors in parentheses are clustered at the state level.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

causal mechanisms underlying this pattern, we were interested in determining whether these effects were unique to antidepressants or represented a more general trend of decreased searches for medications in general. For example, the pandemic might have led to fewer prescriptions due to physician office closures or to reduced affordability affecting all drugs. In this context, Fig. A15 presents weekly trends in Google searches for prescription drugs in other classes. These drugs were selected from a list of top-selling drugs in the US. As shown, the searches for the majority of these other drugs appear to not change as a result of the mitigation policies.

Table 4 shows the average effects of the mitigation policies on searches for other prescription drugs using our baseline DiD model in Eq. (1). As suggested by the trends in Fig. A19, the mitigation policies had no effect on the searches for the majority of the drugs and actually increased searches for *Zestril*, *Losartan*, and *Flonase* (except marginally significant negative effect on *Amoxicillin*). We concluded that the decreases in searches for antidepressants were unlikely due to either physician office closures or reduced affordability. In fact, medications that require a prescription, like *Losartan*, increased in use, and generally any changes in medication use after the mitigation policies involved increases.

4.5. Effects of mitigation policies on home activities

We last tested whether changes in leisure and home production activities help to combat negative feelings and plausibly explain the reduction in searches for antidepressants and suicide. To test this hypothesis, we analyzed changes in search indexes for home activities assuming that the mitigation measures increased within-home hours and individuals had greater flexibility in time allocation for socially supportive and health producing activities. Specifically, we obtained search indexes for *Netflix*, *recipe*, *sex*, *game*, *exercise*, and *gardening* and estimated our baseline DiD model in Eq. (1). These results are reported in Table 5 and suggest that restaurant/bar limits and stay-at-home orders increased searches on *recipe*, *exercise*, *Netflix*, and *gardening*.[12] In the context

[12] To assess multiple inferences while accounting for correlations among the outcomes, we estimated models using SUR. This model evaluated the null hypothesis that the effects are jointly equal to zero. We rejected the hypothesis that the effects of either stay-at-home orders or restaurant/bar limits were jointly equal to zero (p<0.001). In addition, Table A5 reports adjusted p-values to account for multiple hypothesis testing using “wyoung” Stata command.

Table 3
Distributed lagged effects of mitigation measures on Google searches for mental health.

	First mandate	Last mandate	Mandate lag 1	Mandate lag2	Lift	Lift lag 1	N
Isolation	0.264*	0.111	0.068	−0.136*	0.019	−0.003	7752
	(0.16)	(0.13)	(0.07)	(0.08)	(0.04)	(0.06)	
Worry	0.136*	0.114	−0.142**	−0.02	0.018	0.087	7752
	(0.08)	(0.09)	(0.07)	(0.09)	(0.05)	(0.06)	
Anxiety	0.023	0.112	−0.021	0.029	0.003	0.005	7752
	(0.10)	(0.10)	(0.07)	(0.07)	(0.06)	(0.06)	
Concentration	−0.190*	0.061	0.091	0.121	−0.114**	−0.039	7752
	(0.11)	(0.09)	(0.09)	(0.10)	(0.06)	(0.08)	
Fatigue	0.073	0.046	0.015	−0.021	−0.178***	0.06	7752
	(0.08)	(0.08)	(0.06)	(0.07)	(0.05)	(0.05)	
Angry	0.019	−0.111*	−0.133*	0.092	−0.058	0.002	7752
	(0.10)	(0.06)	(0.09)	(0.10)	(0.06)	(0.05)	
Insomnia	−0.073	−0.043	0.112*	−0.003	−0.024	0.033	7752
	(0.10)	(0.08)	(0.07)	(0.08)	(0.06)	(0.05)	
Depression	0.088	0.145*	−0.114*	0.087	−0.091	−0.014	7752
	(0.12)	(0.09)	(0.08)	(0.08)	(0.06)	(0.08)	
SSRI	−0.157	−0.045	0.029	0.074	0.01	−0.028	7752
	(0.11)	(0.07)	(0.06)	(0.08)	(0.06)	(0.05)	
Antidepressant	0.123	−0.159**	0.085	−0.057	−0.079	−0.018	7752
	(0.09)	(0.08)	(0.07)	(0.08)	(0.06)	(0.06)	
Sertraline	−0.014	−0.129*	0.033	−0.013	−0.024	0.099*	7752
	(0.09)	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	
Prozac	−0.082	−0.017	−0.08	−0.032	−0.038	0.024	7752
	(0.12)	(0.10)	(0.08)	(0.08)	(0.04)	(0.05)	
Zoloft	−0.004	−0.068	0.097	0.034	0.002	−0.008	7752
	(0.08)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	
Suicide	−0.083	−0.132*	−0.132**	−0.103	0.042	0.008	7752
	(0.11)	(0.08)	(0.07)	(0.07)	(0.06)	(0.06)	
Liquor	0.394***	−0.054	−0.046	−0.128**	0.026	0.008	7752
	(0.11)	(0.10)	(0.10)	(0.06)	(0.05)	(0.04)	
Wine	0.064	0.042	−0.011	−0.095	−0.155**	0.153***	7752
	(0.08)	(0.07)	(0.09)	(0.06)	(0.06)	(0.05)	
Beer	−0.182**	−0.115	−0.037	−0.095*	0.077**	0.123**	7752
	(0.08)	(0.07)	(0.06)	(0.05)	(0.04)	(0.05)	
Cigarette	−0.047	0.059	−0.065	0.021	0.097*	0.082	7752
	(0.08)	(0.09)	(0.07)	(0.07)	(0.05)	(0.06)	
Marijuana	0.129	−0.041	0.088	−0.023	−0.012	0.007	7752
	(0.14)	(0.11)	(0.07)	(0.07)	(0.05)	(0.05)	
Naloxone	0.055	−0.033	0.024	−0.015	0.026	−0.001	7752
	(0.10)	(0.08)	(0.09)	(0.08)	(0.06)	(0.05)	

Notes: Each row reports regression coefficients from a linear regression model, weighted by state population in 2019. In addition to the listed variables, we control for state and day fixed effects for each regression. Standard errors in parentheses are clustered at the state level.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

of the previous findings, these results provide suggestive evidence that the temporary increase in within home hours following mitigation policies allowed individuals to undertake activities such as exercise, to spend time relaxing, or to spend time with family. These activities helped to adapt behaviorally to new circumstances and potentially offset any negative effects of the isolation, and perhaps also decreased searches for antidepressants and suicide.

5. Discussion and conclusion

The US response to the current COVID-19 pandemic has entailed a number of mitigation measures to reduce the transmission of the SARS-CoV-2 virus. Early evidence suggested that the measures were effective in reducing population mobility and consequently reducing the number of COVID-19 cases (Abouk and Heydari, 2020; Friedson et al., 2020; Sears et al., 2020; Lasry et al., 2020). However, prior research has not fully ascertained the impact of these policies on the mental health of the population. Although some evidence suggested an increase in mental health symptoms such as depression and anxiety (New York Times, 2020b, a; Brodeur et al., 2020), the severity of the effect has not been studied. Hence, our study investigated the impact of mitigation policies on mental health, distinguishing depressive and anxious feelings from more severe symptoms such as the need for medications or thoughts of suicide. We additionally characterized the temporal trajectory of the symptoms to understand the effects' duration.

Results from our DiD model indicated that mitigation measures, in particular state-wide stay-at-home orders and bar/restaurant limits, were positively associated with the search indexes for mental health symptoms but do not suggest durable effects. We also found that searches for *suicide* and mental medications such as *Prozac* and *Zoloft* decreased as a function of the mitigation measures. A potential explanation of the reduction in the searches for mental medications is that during temporary lockdowns increases in within-home hours and greater flexibility in time allocation (e.g., remote-work) made it more feasible to undertake within-home activities, exercise, or consume a healthy diet. For example, we found evidence that stay-at-home orders increased searches on *recipe*, *exercise*, and *movie*, all activities that can improve mood and sustain health.

Our study has limitations. First, notably, our data sources did not allow us to investigate effect heterogeneity with respect to population characteristics such as age, education, income, or health status. This limitation is important because certain subpopulations, including children and young people isolated

Table 4
Effects of mitigation measures on Google searches for other drugs.

	Stay-at-home		Restaurant limit		Business closure		N
	Implement	Lift	Implement	Lift	Implement	Lift	
Acetaminophen	0.031	−0.048	0.029	0.041	−0.024	0.076	9282
	(0.09)	(0.05)	(0.12)	(0.08)	(0.12)	(0.05)	
Vicodin	−0.074	−0.007	−0.114	0.03	0.045	0.100**	9282
	(0.05)	(0.05)	(0.07)	(0.05)	(0.07)	(0.04)	
Synthroid	0.042	−0.044	0.013	0.100*	−0.007	0.007	9282
	(0.07)	(0.05)	(0.05)	(0.06)	(0.08)	(0.05)	
Amoxicillin	−0.042	−0.008	−0.165*	0.082	−0.055	0.098	9282
	(0.13)	(0.06)	(0.09)	(0.07)	(0.13)	(0.06)	
Zestril	0.136**	0.015	0.108	0.073	−0.004	0.041	6370
	(0.06)	(0.05)	(0.13)	(0.06)	(0.07)	(0.05)	
Atorvastatin	−0.038	−0.001	−0.121	0.045	−0.011	0.028	9282
	(0.08)	(0.05)	(0.09)	(0.05)	(0.08)	(0.05)	
Prinivil	−0.012	0.069	0.206	−0.013	−0.073	−0.007	4732
	(0.09)	(0.05)	(0.12)	(0.06)	(0.09)	(0.06)	
Norvasc	−0.03	−0.049	−0.117	0.114*	−0.105	0.034	8918
	(0.04)	(0.04)	(0.09)	(0.06)	(0.07)	(0.05)	
Omeprazole	0.031	−0.061*	−0.035	0.061	0.01	0.027	9282
	(0.04)	(0.03)	(0.08)	(0.06)	(0.06)	(0.04)	
Prilosec	0.071	0.011	−0.107	−0.059	−0.028	0.005	9282
	(0.06)	(0.06)	(0.07)	(0.06)	(0.07)	(0.05)	
Zocor	0.049	−0.039	−0.063	−0.018	−0.01	−0.006	8554
	(0.07)	(0.05)	(0.09)	(0.05)	(0.09)	(0.05)	
Losartan	0.055	−0.056	0.234**	0.106*	−0.006	0.011	9282
	(0.07)	(0.04)	(0.09)	(0.06)	(0.09)	(0.05)	
Proair	0.005	0.018	−0.035	−0.009	0.006	0.064	8736
	(0.08)	(0.05)	(0.10)	(0.05)	(0.08)	(0.05)	
Ventolin	0.104	−0.028	0.001	0.08	−0.005	0.001	9282
	(0.07)	(0.05)	(0.09)	(0.05)	(0.09)	(0.04)	
Flonase	0.065	0.047	0.229***	−0.117*	−0.094	0.007	9282
	(0.09)	(0.06)	(0.08)	(0.07)	(0.09)	(0.06)	
Tenormin	0.096	0.015	0.144	0.023	−0.043	−0.008	5642
	(0.09)	(0.05)	(0.14)	(0.07)	(0.12)	(0.05)	
Atenolol	−0.053	0.097*	−0.07	−0.046	0.026	−0.006	9282
	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	

Notes: Each row reports regression coefficients from a linear regression model, weighted by state population in 2019. In addition to the listed variables, we control for indicators for school closures and state of emergency, state and day fixed effects for each regression. Standard errors in parentheses are clustered at the state level.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 5
Effects of mitigation measures on Google searches related to home activities.

	Stay-at-home		Restaurant limit		Business closure		N
	Implement	Lift	Implement	Lift	Implement	Lift	
Netflix	0.122*	−0.062*	0.180***	−0.044	0.033	−0.047	9282
	(0.07)	(0.04)	(0.07)	(0.04)	(0.06)	(0.03)	
Recipe	0.167**	−0.102**	0.193***	−0.107**	0.072	−0.070*	9282
	(0.07)	(0.04)	(0.06)	(0.05)	(0.08)	(0.04)	
Exercise	0.184***	−0.164***	0.255**	−0.061	0.079	−0.012	9282
	(0.06)	(0.06)	(0.10)	(0.07)	(0.15)	(0.06)	
Game	0.155	−0.065*	0.048	0.034	0.157*	0.047	9282
	(0.11)	(0.04)	(0.06)	(0.04)	(0.09)	(0.04)	
Sex	0.034	0.002	0.169*	0.068	0.022	−0.045	9282
	(0.06)	(0.05)	(0.11)	(0.05)	(0.07)	(0.05)	
Gardening	0.066	−0.043	0.219***	−0.202**	0.040	−0.058	9282
	(0.1)	(0.07)	(0.06)	(0.07)	(0.08)	(0.07)	

Notes: Each row reports regression coefficients from a linear regression model, weighted by state population in 2019. In addition to the listed variables, we control for indicators for school closures and state of emergency, state and day fixed effects for each regression. Standard errors in parentheses are clustered at the state level.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

from friends and school, are more vulnerable to mental distress (New York Times, 2020b, a; KFF, 2020b). As another example, the prevalence of depression may increase for older adults who are more likely to live alone or to require home health care at a time when the mitigation policies limit their interactions with caregivers and family. Likewise, existing mental illness may be exacerbated by the pandemic, as populations suffering from a mental illness may not have the same access to mental health services. Second, our findings are based on the Google Trends data rather than direct measures of symptoms or population behavior.

However, our results were robust to the inclusion of both COVID-19 cases and state-specific linear time trends, and were not present for physical health keywords unrelated to COVID-19 (Appendix Table A6), thus providing evidence that our findings are not driven by unobserved state population characteristics that might have increased all health-related Google searches.

Despite these limitations, the findings in this study have important policy implications. Our findings showed that even though the mitigation measures increased negative feelings of isolation or worry, the effects were mostly transient and did not involve increases in more severe psychopathology, such as clinical depression, or suicide ideation/plans. We thus concluded that the psychological distress following the COVID-19 policies is likely to be low compared to the health benefits of mitigating the COVID-19 pandemic. We hope that these mental health toll estimates can be useful in planning optimal policy responses to the pandemic. One possible response is to segment policy and allow exemptions for populations whose mental health risks are higher, while allowing the general population to shelter in place. Implementing interventions aimed at increasing social connection and social support such as tele-mental health services might be an important mechanism for addressing the potential negative psychological consequences of the pandemic (Reger et al., 2020).

CRediT authorship contribution statement

Bita Fayaz Farkhad: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft. **Dolores Albarracín:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgements

Research reported in this publication was supported by the National Institute of Mental Health under Award Number R01MH114847, the National Institute on Drug Abuse under Award Number DP1 DA048570, and the National Institute of Allergy and Infectious Diseases under Award Number R01AI147487. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ehb.2020.100963.

References

Aaronson, Daniel, Brave, Scott A., Andrew Butters, R., Fogarty, Michael, 2020. The stay-at-Home labor market: google searches, unemployment insurance, and public health orders. Chicago Fed Lett. doi:http://dx.doi.org/10.21033/cfl-2020-436.

Abouk, Rahi, Heydari, Babak, 2020. The immediate effect of COVID-19 policies on social distancing behavior in the United States. SRN Electronic J. doi:http://dx.doi.org/10.1101/2020.04.07.20057356 April, 2020.04.07.20057356.

Aguiar, Mark, Hurst, Erik, Karabarbounis, Loukas, 2013. Time use during the great recession. Am. Econ. Rev. 103 (5), 1664–1696. doi:http://dx.doi.org/10.1257/aer.103.5.1664.

Allcott, Hunt, New York University, Microsoft Research, Conway, Jacob, Ferguson, Billy, Gentzkow, Matthew, Goldman, Benny, 2020. Economic and Health Impacts of Social Distancing Policies during the Coronavirus Pandemic. .

Anderson, Roy M., Heesterbeek, Hans, Klinkenberg, Don, Déirdre Hollingsworth, T., 2020. How will country-based mitigation measures influence the course of the COVID-19 epidemic? Lancet doi:http://dx.doi.org/10.1016/S0140-6736(20)30567-5 Lancet Publishing Group.

Aneshensel, Carol S., Rutter, Carolyn M., Lachenbruch, Peter A., 1991. Social structure, stress, and mental health: competing conceptual and analytic models. Am. Sociol. Rev. 56 (2), 166–178.

Baker, Laurence, Wagner, Todd H., Singer, Sara, Kate Bundorf, M., 2003. Use of the internet and E-Mail for health care information: results from a national survey. J. Am. Med. Assoc. 289 (18), 2400–2406. doi:http://dx.doi.org/10.1001/jama.289.18.2400.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Q. J. Econ. 119 (1), 249–275. doi:http://dx.doi.org/10.1162/003355304772839588.

Bovier, Patrick A., Chamot, Eric, Perneger, Thomas V., 2004. Perceived stress, internal resources, and social support as determinants of mental health among young adults. Qual. Life Res. doi:http://dx.doi.org/10.1023/B:QURE.0000015288.43768.e4 Springer.

Brodeur, Abel, Clark, Andrew E., Flèche, Sarah, Powdthavee, Nattavudh, 2020. COVID-19, Lockdowns and Well-being: Evidence from Google Trends. .

Brooks, Samantha K., Webster, Rebecca K., Smith, Louise E., Woodland, Lisa, Wessely, Simon, Greenberg, Neil, James Rubin, Gideon, 2020. The psychological impact of quarantine and how to reduce it: rapid review of the evidence. Lancet doi:http://dx.doi.org/10.1016/S0140-6736(20)30460-8 Lancet Publishing Group.

Chen, M.Keith, Zhuo, Yilin, de la Fuente, Malena, Rohla, Ryne, Long, Elisa F., 2020. Causal Estimation of Stay-at-Home Orders on SARS-CoV-2 Transmission May. . http://arxiv.org/abs/2005.05469.

Choi, Hyunyoung, Varian, Hal, 2009. Predicting the Present with Google Trends. . http://cran.r-project.org.

Choi, Hyunyolung, Varian, Hal, 2012. Predicting the present with google trends. Econ. Rec. 88 (SUPPL.1), 2–9. doi:http://dx.doi.org/10.1111/j.1475-4932.2012.00809.x.

Courtemanche, Charles, Garuccio, Joseph, Le, Anh, Pinkston, Joshua, Yelowitz, Aaron, 2020. Strong social distancing measures in the United States reduced the COVID-19 growth rate. Health Aff. 39 (7), 1237–1246. doi:http://dx.doi.org/10.1377/hlthaff.2020.00608.

COVID-19 Community Mobility Reports. . 2020 https://www.google.com/covid19/mobility/.

Creamer, M., Burgess, P., Mcfarlane, A.C., 2001. Post-traumatic stress disorder: findings from the Australian national survey of mental health and well-being. Psychol. Med. 31 (7), 1237–1247. doi:http://dx.doi.org/10.1017/S0033291701004287.

Czeisler, MarkÉ., Lane, Rashon I., Petrosky, Emiko, Wiley, Joshua F., Christensen, Aleta, Njai, Rashid, Weaver, Matthew D., et al., 2020. Mental health, substance use, and suicidal ideation during the COVID-19 pandemic — united States, June 24–30, 2020. MMWR Morb. Mortal. Wkly. Rep. 69 (32), 1049–1057. doi:http://dx.doi.org/10.15585/mmwr.mm6932a1.

Dave, Dhaval, Kaestner, Robert, 2009. Health insurance and ex ante moral hazard: evidence from medicare. Int. J. Health Care Finance Econ. 9 (4), 367–390. doi:http://dx.doi.org/10.1007/s10754-009-9056-4.

Dave, Dhaval, Friedson, Andrew, Matsuzawa, Kyutaro, Mcnichols, Drew, Sabia, Joseph, 2020a. Did the Wisconsin Supreme Court Restart a COVID-19 Epidemic? Evidence from a Natural Experiment. .

Dave, Dhaval, Friedson, Andrew, Matsuzawa, Kyutaro, Sabia, Joseph, 2020b. When do shelter-in-place orders fight COVID-19 best? Policy heterogeneity across states and adoption time. Econ. Inq. doi:http://dx.doi.org/10.1111/ecin.12944.

Devaraj, Srikant, Patel, Pankaj, 2020. Effectiveness of stay-in-place-orders during COVID-19 pandemic: evidence from US border counties. SSRN Electron. J.(June) doi:http://dx.doi.org/10.2139/ssrn.3614187.

Diagnostic and Statistical Manual of Mental Disorders (DSM-5®). American Psychiatric Association.

Dong, Ensheng, Du, Hongru, Gardner, Lauren, 2020. An interactive web-based dashboard to track COVID-19 in real time. Lancet Infect. Dis. doi:http://dx.doi.org/10.1016/S1473-3099(20)30120-1 Lancet Publishing Group.

Ettman, Catherine K., Abdalla, Salma M., Cohen, Gregory H., Sampson, Laura, Vivier, Patrick M., Galea, Sandro, 2020. Prevalence of depression symptoms in US adults before and during the COVID-19 pandemic. JAMA Network Open 3 (9) e2019686 doi:http://dx.doi.org/10.1001/jamanetworkopen.2020.19686.

Fowler, James H., Hill, Seth J., Obradovich, Nick, Levin, Remy, 2020. The effect of stay-at-home orders on COVID-19 cases and fatalities in the United States. edRxiv (May) doi:http://dx.doi.org/10.1101/2020.04.13.20063628 2020.04.13.20063628.

Friedson, Andrew, McNichols, Drew, Sabia, Joseph, Dave, Dhaval, 2020. Did California's Shelter-in-Place Order Work? Early Coronavirus-Related Public Health Effects. Cambridge, MA. doi:http://dx.doi.org/10.3386/w26992.

Google Trends." 2020. Accessed October 4, 2020. https://trends.google.com/trends/?geo=US.

Greenstone, Michael, Nigam, Vishan, 2020. Does social distancing matter? SSRN Electron. J.(March) doi:http://dx.doi.org/10.2139/ssrn.3561244.

Grossman, Michael, 1972. On the concept of health capital and the demand for health. J. Polit. Econ. 80 (2), 223–255. doi:http://dx.doi.org/10.1086/259880.

Hamermesh, Daniel S., 2020. Lockdowns, Loneliness and Life Satisfaction. .

Jones, Damon, Molitor, David, Reif, Julian, Bhattacharya, Jay, Deryugina, Tatyana, Doyle, Joseph, Finkelstein, Amy, et al., 2020. Advance access publication on August 16. Q. J. Econ. 1747–1791. doi:http://dx.doi.org/10.1093/qje/qjz023.

Kahn, Matthew E., Kotchen, Matthew J., 2010. Environmental Concern and the Business Cycle: The Chilling Effect of Recession. . http://www.nber.org/papers/w16241.

KFF, 2020a. State Data and Policy Actions to Address Coronavirus 2020. Kaiser Family Foundation. https://www.kff.org/coronavirus-covid-19/issue-brief/state-data-and-policy-actions-to-address-coronavirus/.

KFF, 2020b. The Implications of COVID-19 for Mental Health and Substance Use 2020. Kaiser Family Foundation. https://www.kff.org/coronavirus-covid-19/issue-brief/the-implications-of-covid-19-for-mental-health-and-substance-use/.

Lam-Po-Tang, John, McKay, Diana, 2010. Dr Google, MD: a survey of mental health-related internet use in a private practice sample. Australas. Psychiatry 18 (2), 130–133. doi:http://dx.doi.org/10.3109/10398560903473645.

Langner, Thomas S., Michael Stanley, T., 1963. Life Stress and Mental Health: II. The Midtown Manhattan Study. Free Press, Glencoe Free Press Glencoe.

Lasry, Arielle, Kidder, Daniel, Hast, Marisa, Jason Poovey, Sunshine, Gregory, Winglee, Kathryn, Zviedrite, Nicole, Ahmed, Faruque, Ethier, Kathleen A., 2020. Timing of Community Mitigation and Changes in Reported COVID-19 and Community Mobility — Four U.S. Metropolitan Areas, February 26–April 1, 2020. . https://www.cdc.gov/mmwr/volumes/69/wr/pdfs/mm6915e2-H.pdf.

Lindo, Jason M., Schaller, Jessamyn, Hansen, Benjamin, 2018. Caution! Men not at work: gender-specific labor market conditions and child maltreatment. J. Public Econ. 163 (July), 77–98. doi:http://dx.doi.org/10.1016/j.jpubeco.2018.04.007.

Marin, Marie France, Lord, Catherine, Andrews, Julie, Juster, Robert Paul, Sindi, Shireen, Arsenault-Lapierre, Geneviève, Fiocco, Alexandra J., Lupien, Sonia J., 2011. Chronic stress, cognitive functioning and mental health. Neurobiol. Learn. Mem. 96 (4), 583–595. doi:http://dx.doi.org/10.1016/j.nlm.2011.02.016.

New York Times, 2020a. The Coronavirus Mental Health Crisis Hits Home May 20, 2020. . https://www.nytimes.com/2020/05/12/opinion/coronavirus-mental-health.html.

New York Times, 2020b. U. N. Warns of Global Mental Health Crisis Due to COVID-19 Pandemic May 22, 2020. . https://www.nytimes.com/reuters/2020/05/13/world/europe/13reuters-health-coronavirus-mentalhealth.html.

Nielsen Dataset - Kilts Center | Chicago Booth." 2020. Accessed October 4, 2020. https://www.chicagobooth.edu/research/kilts/datasets/nielsen#simple2.

Page, Marianne, Schaller, Jessamyn, Simon, David, 2019. The effects of aggregate and gender-specific labor demand shocks on child health. J. Hum. Resour. 54 (1), 37–78. doi:http://dx.doi.org/10.3368/JHR.54.1.0716.8045R.

Paluska, Scott A., Schwenk, Thomas L., 2000. Physical Activity and Mental Health: Current Concepts. Sports Medicine doi:http://dx.doi.org/10.2165/00007256-200029030-00003.

Parker, Jason, Cuthbertson, Courtney, Loveridge, Scott, Skidmore, Mark, Dyar, Will, 2017. Forecasting state-level premature deaths from alcohol, drugs, and suicides using google trends data. J. Affect. Disord. 213 (April), 9–15. doi:http://dx.doi.org/10.1016/j.jad.2016.10.038.

Pelat, Camille, Turbelin, Clément, Bar-Hen, Avner, Flahault, Antoine, Jacques Valleron, Alain, 2009. More diseases tracked by using google trends. Emerging Infect. Dis. 15 (8), 1327–1328. doi:http://dx.doi.org/10.3201/eid1508.090299.

Raifman, J., Nocka, K., Jones, D., Bor, J., Lipson, S., Jay, J., Chan, P., 2020. COVID-19 US State Policy Database." 2020. . https://docs.google.com/spreadsheets/d/1zu9qEWI8PsOI_i8nI_S29HDGHlIp2lfVMsGxpQ5tvAQ/edit#gid=0.

Reger, Mark A., Stanley, Ian H., Joiner, Thomas E., 2020. Suicide mortality and coronavirus disease 2019—a perfect storm? JAMA Psychiatry (April) doi:http://dx.doi.org/10.1001/jamapsychiatry.2020.1060.

Ruhm, Christopher J., 2000. Are recessions good for your health? Q. J. Econ. 115 (2), 617–650. doi:http://dx.doi.org/10.1162/003355300554872.

Ruhm, Christopher J., 2003. Good times make you sick. J. Health Econ. 22 (4), 637–658. doi:http://dx.doi.org/10.1016/S0167-6296(03)00041-9.

Ruhm, Christopher J., 2005. Healthy living in hard times. J. Health Econ. 24 (2), 341–363. doi:http://dx.doi.org/10.1016/j.jhealeco.2004.09.007.

Ruhm, Christopher J., 2015. Recessions, healthy no more? J. Health Econ. 42 (June), 17–28. doi:http://dx.doi.org/10.1016/j.jhealeco.2015.03.004.

Sears, James, Miguel Villas-Boas, J., Villas-Boas, Sofia, Villas-Boas, Vasco, 2020. Are we #StayingHome to flatten the curve? SSRN Electron. J. doi:http://dx.doi.org/10.2139/ssrn.3569791 Elsevier BV.

Simon, Kosali, Soni, Aparna, Cawley, John, 2017. The impact of health insurance on preventive care and health behaviors: evidence from the first two years of the ACA medicaid expansions. J. Policy Anal. Manag. 36 (2), 390–417. doi:http://dx.doi.org/10.1002/pam.21972.

Stansfeld, Stephen., 2006. Social support and social cohesion. Social Determinants of Health, , pp. 148–171 2.

Taliaferro, Lindsay A., Rienzo, Barbara A., Morgan Pigg, R., David Miller, M., Dodd, Virginia J., 2009. Associations between physical activity and reduced rates of hopelessness, depression, and suicidal behavior among college students. J. Am. Coll. Health 57 (4), 427–436. doi:http://dx.doi.org/10.3200/JACH.57.4.427-436.

Tefft, Nathan., 2011. Insights on unemployment, unemployment insurance, and mental health. J. Health Econ. 30 (2), 258–264. doi:http://dx.doi.org/10.1016/j.jhealeco.2011.01.006.

Trinkl, Jeff, del Río, AlejandroMuñoz, 2020. Effect of COVID-19 Pandemic on Visit Patterns for Anxiety and Depression – Epic Health Research Network. . https://ehrn.org/effect-of-covid-19-pandemic-on-visit-patterns-for-anxiety-and-depression/.

Valdivia, Antonio, Monge-Corella, Susana, 2010. Diseases tracked by using google trends, Spain. Emerging Infect. Dis. 16 (1), 168. doi:http://dx.doi.org/10.3201/eid1601.091308.

Weaver, James B., Mays, Darren, Weaver, Stephanie Sargent, Hopkins, Gary L., Eroglu, Dogan, Bernhardt, Jay M., 2010. Health information-seeking behaviors, health indicators, and health risks. Am. J. Public Health 100 (8), 1520–1525. doi:http://dx.doi.org/10.2105/AJPH.2009.180521.

Young, Sean D., Zhang, Qingpeng, 2018. Using search engine big data for predicting new HIV diagnoses. Edited by Hiroshi Nishiura. PLoS One 13 (7) e0199527 doi:http://dx.doi.org/10.1371/journal.pone.0199527.

Zhang, Qingpeng, Chai, Yi, Li, Xiaoming, Young, Sean D., Zhou, Jiaqi, 2018. Using internet search data to predict new HIV diagnoses in China: a modelling study. BMJ Open 8 (10) doi:http://dx.doi.org/10.1136/bmjopen-2017-018335.