The impact of stay-at-home orders on mental health: Evidence from search-based symptoms

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Abstract

I investigate the impact of the implementation of stay-at-home orders on the incidence of mental health conditions in the US during the first year of the coronavirus pandemic. I use a novel dataset that maps search queries to thirty mental health symptoms. Exploiting the staggered implementation of lockdowns, I document that the enaction of the stay-at-home orders increased mental health searches related to various anxiety disorders, severe forms of depression, sleep disorders, attention deficit, and epilepsy. Treated states are estimated to have experienced two mental distress waves in April-May and November-December.

JEL classification: I10, I14, I18, I30.

Keywords. mental health, coronavirus pandemic, COVID-19 Search Trends symptoms dataset, US, stay-at-home orders.

1 Introduction

The outbreak of the COVID-19 pandemic has profoundly disrupted people's lives. Since the virus can easily spread unnoticed, many governments early introduced lockdowns in an attempt to 'flatten the curve'. How these social isolation measures have affected people's mental health is a major public health concern. With that concern in mind, I study the effect of the implementation of stay-at-home orders on the incidence of mental health conditions in the US. Using a novel high-quality dataset of search-based symptoms, I exploit the roll-out of these orders through an event study design that leverages the generated large temporal variation across states in the adoption of lockdowns. My results suggest that the implementation of lockdowns increased search-based mental distress.

People can experience mental distress in different forms, including anxiety, mood, sleep, personality, eating, or psychotic disorders, all of which might affect people's feelings, thinking, and behavior. Poor mental health is a severe problem in many developed countries. In the US, mental illnesses are among the most common health conditions, affecting one in five Americans (CBHSQ, 2020). Mental health is a key dimension of overall well-being at every stage of life (Chisholm et al., 2016; Patel et al., 2018), as well as a predictor of future overall health and longevity (Chida and Steptoe, 2008; Keyes and Simoes, 2012). Exposure to the risk factors that trigger lasting mental health distress is thus particularly problematic, leading to sustained suffering for people affected and their families.

The lasting nature of mental distress makes its associated costs high. The US devotes more than $200 billion per year to mental disorders, which has been estimated to be the largest source of health care spending (Roehrig, 2016). Notwithstanding these direct costs, most of the economic burden of poor mental health conditions develops from indirect sources (Gustavsson et al., 2011; Hewlett and Moran, 2014). These include higher care costs in other areas of health, lower employment rates, lower earnings and tax revenues, and increased crime rates.[1] For the EU, Gustavsson et al. (2011) estimate aggregated costs of about €798 billion per year, and another study predicts that the direct and indirect costs of mental will double by 2030 (Bloom et al., 2012). These figures illustrate that it is in society's best interest to eliminate — or at least reduce — the incidence of mental distress.

[1] See Naylor et al. (2012) for evidence on cost spillovers on physical health care. In terms of unemployment costs, Hoedeman (2012) for instance estimates that were people with mental health conditions ready to work full-time, total employment would rise by 4 p.p. For crime-related costs, conduct disorders has been associated with increasing the risk of offending (Mordre et al., 2011; Mohr-Jensen et al., 2019; Gottfried and Christopher, 2017). See OECD (2018) and Trautmann et al. (2016) for a review of the direct and indirect costs of mental distress.

Cost-effective interventions that focus on preventing mental illness have been called to be one key area of policy action to tackle this burden, as they can help to reduce exposure to the risk factors associated with severe mental disorders (McDaid et al., 2019). Existing evidence suggests that certain targeted, intensive, promotion-focused interventions such as evidence-based cognitive behavioral therapy can be particularly successful (Karyotaki et al., 2017; Rakovshik and McManus, 2010).

While effective in containing the spread of coronavirus in the US (Fowler et al., 2020), lockdown measures implemented throughout 2020 might have however been counter-productive from a mental health prevention standpoint. In addition to the mental distress associated with the evolution of the pandemic itself, the literature suggests that social distancing and reduced mobility are stressors that can severely hamper mental health (Holt-Lunstad et al., 2015; Taliaferro et al., 2009; Paluska and Schwenk, 2000). For example, studies from previous pandemics estimate that imposing lockdowns points to a greater prevalence of symptoms of anxiety, depression, insomnia, stress, avoidance behavior, and detachment from others (Bai et al., 2004; Marjanovic et al., 2007). Part of this literature has even found pervasive mental health effects even three years after quarantine, in the form of major depressive and post-traumatic stress disorders (Liu et al., 2012; Wu et al., 2009). Accordingly, several studies have called for rapid and effective policy interventions to deal with the expected mental health effects of the implementation of this and previous lockdowns (Rubin and Wessely, 2020; Caleo et al., 2018; Bai et al., 2004) as well as to take into account the evolution of mental health for managing lockdown lifts (Layard et al., 2020).

This study investigates the effects of the implementation of lockdowns on the evolution throughout 2020 of a wide range of search-based mental health symptoms. Such indicators come from a novel high-quality dataset from Google that maps search queries to the medical symptom at hand. For identification, I use the staggered implementation of lockdowns, which generated temporal variation across states. I then apply an event study design to explore mental distress dynamics up to December, when the COVID-19 vaccination campaign started in the US. The identifying assumption is that conditional on fixed-effects and the set of epidemiological controls included, in the absence of treatment, the evolution of mental health symptoms in lockdown adopters would have evolved as the one from non-treated states. To properly estimate the causal effect of interest, I use Borusyak et al. (2021)'s estimator, dealing with problems present at the traditional difference-in-differences estimation procedure that would otherwise bias the results.

Results from this paper show that lockdowns fostered search-based mental distress in treated states in the form of various anxiety disorders, severe forms of depres-

sion, sleep disorders, attention deficit, and epilepsy. Such mental health deterioration generally evolved following a two-wave pattern. First, many conditions worsened in April-May, suggesting a mental health burden during the lockdown. Mental health conditions then improved during the summer — in the context of many states lifting their lockdown orders in May and July. A second mental health wave reached treated states in November-December. This would imply that the effects of stay-at-home orders on mental health conditions went beyond their length and had a more permanent effect that materialized by the end of 2020. I report that countries with different lockdown adoption trajectories follow parallel trends in mental symptom searches before the policy change. These findings suggest that real-time data can help to detect the immediate and long-term implications of policy interventions for mental health.

This paper contributes to three strands of the literature. First, it expands previous findings on the effect of economic downturns on mental disorders (Chang et al., 2013; Frasquilho et al., 2015). Second, it enriches the growing research on the effect of the pandemic on mental health and overall well-being (Adams-Prassl et al., 2021; Armbruster and Klotzbücher, 2020; Brodeur et al., 2021; Brulhart and Lalive, 2021; Silverio-Murillo et al., 2021). This paper is the first to document how stay-at-home orders have both short and long-term effects on specific areas of mental health. Finally, this paper also contributes to a recent body of research that has applied recent advances in difference-in-differences estimation to overcome the problems of the traditional OLS-based two-way fixed effect estimator — see for instance Ang (2021), Bartik et al. (2020), Bismarck-Osten et al. (2021), and Karaivanov et al. (2021).

Because this investigation includes also the analysis of long-term effects, it might help to better understand what can we learn from the management of the pandemic. My findings suggest that the implementation of lockdowns may exacerbate mental health distress while they are in place, as well as trigger mental deterioration even months after the lift of stay-at-home orders. Still, there is much uncertainty surrounding how social distancing measures affected the second mental health wave. Further empirical evidence in this direction is needed to validate the overall mental health costs of lockdown measures, so that future cost-benefit analysis can help to guide better policy.

The rest of this paper is organized as follows. Section 2 reviews the literature on the impact of stay-at-home on mental health, covering both descriptive and quasi-experimental work. Section 3 presents the data used, its strengths, and limitations. Section 4 discusses in detail the identification strategy. Section 5 presents the main findings of the study. Section 6 discusses how results relate to prior evidence. Finally, section 7 concludes.

2 Literature review

This section gives an overview of the literature on the effects of lockdowns on mental health, discussing in the first place some relevant general findings from descriptive studies. I then review empirical evidence from quasi-experimental studies. For both bodies of research, I combine insights from surveys and search data.

For the US, several descriptive studies have estimated the prevalence of mental distress among US adults during the coronavirus outbreak. One worth mentioning is the Household Pulse Survey (HPS) from the US National Center for Health Statistics and the US Census Bureau. This project makes use of clinically validated instruments to weekly track the prevalence of anxiety and depression symptoms from April 23, 2020 to July 5, 2021.[2] Prevalence estimates from HPS during the weeks at which stay-at-home orders were in place for anxiety and depression are around 30% and 25%, respectively. By contrast, estimated prevalence rates among US adults in 2019 were 8.1% and 6.5%, respectively (Terlizzi and Schiller, 2021). HPS data thus suggests a huge increase in mental distress during the lockdown.[3] Finally, in the long run, the HPS study estimates that the prevalence of anxiety and depression raised again by the end of 2020 up to 36.5% and 29.6%, respectively.

Part of the descriptive literature has employed Google Trends to explore search patterns in mental health topics as a proxy for mental distress. US studies point to an increase in mental health search topics related to mental health during the stay-at-home period. Knipe et al. (2020) find that "anxiety" and "suicide" raised during March. By contrast, "depression", "fear", and "loneliness", either remained stable or went down. Similarly, Hoerger et al. (2020) find sudden changes in searches related to "anxiety" that eventually converged to pre-lockdown levels at the end of the analysis period (mid-April). They find no systematic changes in "depression", "loneliness", "suicide", or "abuse".

While informative, descriptive before-and-after comparisons of the evolution of mental distress do not offer a proper counterfactual of how mental health levels would have evolved had the stay-at-home orders not been implemented. Another strand of the literature has hence exploited quasi-experimental evidence in the social distancing response to the pandemic to identify the causal effect of interest. The most relevant of these studies is Adams-Prassl et al. (2021), which examines the impact of lockdowns on mental health for the US economically active population exploiting variation in

[2]Data is available at https://www.cdc.gov/nchs/covid19/pulse/mental-health.html. See also (Vahratian et al., 2021).

[3]Studies using other surveys with validated scales find similar short-term patterns as well (Czeisler et al., 2020; Ettman et al., 2020)

treatment timing across states. They make use of three waves of survey data collected on March, April, and May, and estimate through a difference-in-differences (DiD) design that the clinically validated mental health scores of individuals living in states that had implemented stay-at-home orders were 0.083 standard deviations lower. In a similar vein, Yamamura and Tsutsui (2020) explore the effect of stay-at-home orders across prefectures in Japan. The orders were issued during the sampling period, which allows them to use DiD to estimate changes in a (non-validated) self-reported measure for anxiety. They find a deterioration in their proxy for anxiety symptoms in the weeks that immediately followed the lockdown. Armbruster and Klotzbücher (2020) use helpline data from Germany and find that calls increased by around 20% one week after the stay-at-home order was issued. An analysis of the content of the calls reveals that this increase was driven by loneliness, anxiety, and suicidal ideation. They also report larger effects in those states that imposed stricter social distancing orders. In Switzerland, which issued only social distancing recommendations, Brulhart and Lalive (2021) find no effect on mental health worry from helpline data. The former is suggestive of the effect of mandatory stay-at-home orders.

Finally, two quasi-experimental studies have relied on Google Trends data to estimate the causal effect of stay-at-home orders on mental health. Looking at the three weeks after the lockdown in Europe and the US, Brodeur et al. (2021) provide significant event study estimates for the evolution of "sadness", "worry", and "loneliness" in treated regions. No (short-term) effect is found in terms of "sleep problems", "stress", and "suicide". Finally, Silverio-Murillo et al. (2021) pool data from 11 Latin American countries from January to June 2020 to estimate the relationship between the implementation of the lockdown and search patterns in mental health. Exploiting cross-country differences in treatment timing, their event study results suggest that searches related to "anxiety" and "stress" remained high in treated regions for the lockdown period. For "insomnia", they document a sharp increase during the first five weeks after the introduction of the orders, which then declined and converged to the non-significance region in the weeks that followed. Finally, they do not find supportive evidence of changes in "depression" or "suicide" searches among treated countries.

Overall, despite differences in sample design, data source, and empirical strategy, the deterioration of mental health conditions during the weeks that followed the implementation of lockdowns is a consistent finding. Existing studies suggest that this burden is mainly materialized in terms of anxiety, insomnia, and stress. Greater uncertainty exists for long-term effects, as all the evidence comes from descriptive studies.

3 Data

I use weekly data from the novel COVID-19 Search Trends symptoms dataset (hereinafter, the symptoms dataset).[4] Released on Sept. 2, 2020, this dataset was launched to help researchers better understand the impact of COVID-19 on health. The project shows the volume of Google searches for more than 400 health symptoms, signs, and conditions, such as anxiety, fever, or iron deficiency.[5] The resulting dataset is a daily or weekly real-time panel that tracks the evolution of the covered health symptoms for several countries since January 2017. In what follows, I first introduce surveys as the main alternative data source to search engine data, reviewing their own limitations. I then comment on search data, putting special emphasis on discussing how the symptoms dataset departs from its main alternative, Google Trends data. I close this section by explaining some details of the symptoms dataset.

Scholars have repeatedly relied on surveys for studying how the coronavirus outbreak has affected the prevalence of mental distress. Data from surveys promise to bring a more in-depth understanding of mental distress, and it is also more easily adapted into more systematic and internationally comparable metrics (Kessler et al., 2004; Pez et al., 2010). However, survey instruments have been shown to face various problems, such as selection, recall, survivor, and non-response biases. For instance, there is an ongoing concern about long-run trends in non-response rates in traditional surveys.[6] The pandemic seems to have exacerbated this issue (Rothbaum and Bee, 2021). One final aspect that puts the validity of survey data into question is stigma, which might make the respondent reluctant to report her symptoms or her use of mental health services. In a recent systematic review for serious mental health conditions, Dubreucq et al. (2021) find strong evidence of self-stigma across all geographical areas at all stages of such conditions. Stuart (2008) and Stuart et al. (2014) provide evidence on fear of stigma from health professionals and society.[7]

Search engine data has emerged as a powerful alternative to track changes in health and health behaviors in real-time. In ten years, its use in health research has experienced an about 25-fold increase — see Figure S1 in the Supplementary

[4] Google LLC "Google COVID-19 Search Trends symptoms dataset". http://goo.gle/covid19symptomdataset. Accessed: May 18, 2021.

[5] Following Google's approach, I will refer to all of these collectively as symptoms.

[6] Luiten et al. (2020) present trend data for the 1998–2015 period and finds systematic response declines across an array of instruments of 25 National Statistical Institutes from developed countries (see also Leeuw et al. (2018)). In the US, a similar picture emerges over different surveys from recent studies (Heffetz and Reeves, 2019; Gummer, 2019; Rosenberg et al., 2019).

[7] Studies using health administrative data to tackle the question at hand are much scarce. The strengths and limitations of this source are hence not reviewed here. See Davis et al. (2016) for a systematic review exploring the accuracy of this data tool.

Material; see Arora et al. (2019) for a systematic review of studies using Google Trends in health and health policy research. While having its own issues, search data promise to tackle some of the limitations of surveys. In what follows, I first review the main methodological characteristics of search data sources. I then discuss how Google Trends and the symptoms dataset differ.

Google Trends data has several advantages that make it valuable for doing empirical work. In my application, one main advantage is that it might help to provide insights into a topic that is difficult to capture through surveys, as stressed earlier. Search data is not affected by stigma and more easily reaches groups underrepresented in surveys e.g. the youth. Google Trends data also has its caveats, in terms of representativeness (excluding those with no internet access or more difficulties on accessing e.g. the elderly, or those living in areas with low search intensities) and context, as it is difficult to know from raw queries why a specific term was searched. In addition, efforts to made search data anonymous prevent exploring heterogeneity.

While still having some of these shortcomings, Google's new symptoms dataset is superior to Google Trends data in some crucial aspects. First and foremost, it does not use raw search queries but maps instead search queries to the medical symptom at hand. A given search query can be thus linked to several symptoms. For instance, Google states that they "mapped the search query 'acid reflux and coughing up mucus' to three symptoms: 'cough', 'gastroesophageal reflux disease', and 'heartburn'" (Google Health, 2021)[p.1]. Moreover, the symptoms dataset allows the researcher to discern between related yet distinct symptoms. For example, using this data one can separately evaluate the evolution of insomnia, sleep deprivation, sleep disorder, or hypersomnia, a task which would have been quite challenging if implemented with Google Trends. Another strength of the employed dataset is that all symptoms are handled as search topics, rather than search queries. This implies that the volume of searches of all symptoms of the dataset accounts for the relevant related queries, including, for example, searches in other languages. For the US, for instance, for a given symptom, both searches in Spanish and English are included. Overall, while limitations on representativeness and heterogeneity analysis posed earlier remain, the employed dataset is much richer than raw search queries from Google Trends data. The examination of search-based symptoms is thus expected to better enlighten how lockdowns have affected mental health conditions.

One noticeable difference between Google Trends and the symptoms dataset is how search intensity is operationalized in each source. In Google Trends, search intensity is a measure that ranges from 0 to 100, where 0 denotes the smallest proportion of searches in a given area and time frame and 100 represents the highest proportion. By

contrast, in the symptoms dataset, the search intensity of each symptom is expressed relative to that of other symptoms. In particular, for a given geographical area, Google first counts for the volume of each symptom's searches in that day or week. Google then expresses this count as a ratio, over the volume of searches in that area. The symptom that then reaches the highest relative ratio of volume searches over the five-year time window is scaled to 100.[8] For that area, the remaining week-values of that and the rest of the symptoms are assigned a proportional value between 0 and 100.[9]

For this study, I use weekly symptoms data for all the states in the US for the period Jan. 7, 2019 to Dec. 28, 2020. Using this time window, I explore mental distress dynamics up to the beginning of the COVID-19 vaccination campaign in the US, using 2019 data to test for pre-trends. In terms of outcomes covered, I focus on thirty symptoms related to different dimensions of mental health distress. The first dimension encompasses anxiety disorders and covers "anxiety", "generalized anxiety disorder (GAD)", "panic attack", "hyperventilation", "palpitations", "tachycardia", and "tachypnea". One second set of symptoms clusters mood disorders in terms of "mood-swing", "mood disorder", "depression", "major depressive disorder (MDD)", "self-harm", and "suicidal ideation". The symptoms dataset also makes it possible to explore dynamics of sleep disorders, which are captured based on symptoms of "insomnia", "sleep deprivation", "sleep disorder", "hypersomnia", and "excessive daytime sleepiness", which conforms the third dimension considered in this study. The fourth encompasses personality and dissociative disorders. For the former, the dataset allows me to track patterns in internet searches related to four conditions: "avoidant personality disorder", "paranoia", "compulsive hoarding", and "compulsive behavior". Disruptions in dissociative disorders are captured by "depersonalization". Finally, I group one last set of symptoms in a residual cluster that considers sexual disorders ("sexual dysfunction", and "erectile dysfunction"), eating disorders ("binge eating"), neurodevelopmental disorders ("attention deficit hyperactivity disorder"), psychotic disorders ("psychosis" and "auditory hallucination"), and neurological disorders ("epilepsy").

Table 1 lists each symptom and its summary statistics, grouped by dimension. The mean value of a given symptom is taken as a rough summary of the popularity of each symptom vis-á-vis others. Notice that there is considerable variation in this regard: within each dimension, it is usually the case that one or two symptoms present

[8]For example, for the state of Maryland, the symptom "infection" reaches the value 100 on March 9, 2020. In Oregon, the value 100 is also reached for "infection" but on March 16, 2020.

[9]For instance, for the state of Maryland, the value of the relative popularity of "infection" the following week (March 16, 2020) is 81.46. In that same week, "depression" for instance reached a 4.74 value.

Table 1: Summary statistics

	Mean	S.D.	Min.	Max.
Anxiety disorders				
"Anxiety"	9.72	1.01	6.15	17.66
"Generalized Anxiety Disorder (GAD)"	1.36	0.17	0.74	2.08
"Panic attack"	1.93	0.21	1.20	2.73
"Hyperventilation"	0.13	0.03	0.04	0.72
"Palpitations"	0.54	0.08	0.26	0.90
"Tachycardia"	1.04	0.15	0.55	1.64
"Tachypnea"	0.13	0.03	0.04	0.31
Mood disorders				
"Mood swing"	0.29	0.04	0.13	0.62
"Mood disorder"	1.37	0.19	0.78	2.22
"Depression"	5.95	0.76	3.29	12.05
"Major depressive disorder (MDD)"	4.98	0.65	2.80	6.95
"Self-harm"	0.36	0.06	0.12	0.75
"Suicidal ideation"	0.59	0.11	0.32	1.34
Sleep disorders				
"Insomnia"	3.83	0.45	2.28	5.67
"Sleep deprivation"	0.47	0.08	0.22	1.00
"Sleep disorder"	2.88	0.34	1.64	4.53
"Hypersomnia"	0.12	0.02	0.04	0.23
"Excessive daytime sleepiness"	0.38	0.07	0.13	0.73
Personality and dissociative disorders				
"Avoidant personality disorder"	0.23	0.06	0.06	0.55
"Paranoia"	0.20	0.03	0.06	0.43
"Compulsive hoarding"	0.17	0.05	0.06	1.05
"Compulsive behavior"	0.81	0.12	0.47	2.46
"Depersonalization"	0.11	0.03	0.03	0.25
Other: sexual, eating, neurodevelopmental, and psychotic disorders				
"Sexual dysfunction"	0.77	0.10	0.41	1.26
"Erectile dysfunction"	3.13	0.47	1.74	4.44
"Binge eating"	0.32	0.06	0.17	0.68
"Attention deficit/hyperactivity disorder"	4.00	0.65	2.15	5.97
"Psychosis"	2.09	0.26	1.26	3.78
"Auditory hallucination"	0.12	0.02	0.04	0.23
"Epilepsy"	2.84	0.70	1.42	8.82

Source: Google's symptoms dataset.

the largest relative popularity, on average. For instance, "depression", and "MDD" emerge as the two most common mood disorders. At this exploratory stage, another interesting pattern comes from the maximum value of each symptoms. Large positive

departures from the mean might be suggestive of the worsening of the mental health condition at hand during the weeks that followed the enaction of stay-at-home orders. This is for instance the case for "anxiety" or "epilepsy". Of course, any conclusions at this point are very tentative. In the next section, I review the empirical strategy employed to estimate the causal effect of lockdowns on the different areas of mental health.

4 Empirical approach

For identification, I exploit temporal variation across US states on the adoption of stay-at-home orders. I then apply an event study design, regressing mental health search-based symptoms on a treatment indicator, controlling for week, month, and state fixed-effects. Since this specification controls for state fixed-effects, the roll-out of stay-at-home orders does not need to be orthogonal to time-invariant state characteristics. I however include a set of time-variant state controls that track the evolution of the pandemic, which might correlate with both the adoption of stay-at-home orders and the evolution of mental health outcomes. The identifying assumption is that conditional on fixed-effects and the set of time-varying state factors, in the absence of treatment, the evolution of mental health symptoms in lockdown adopters would have mimic the one from non-treated states. To properly estimate the causal effect of interest, I will use Borusyak et al. (2021)'s estimator, which will allow me to account for problems present at the traditional estimation procedure of DiD models that would otherwise bias the results.[10] In what follows, I discuss in detail the implemented empirical strategy.

Let i denote each of the states in our panel and t each of its time periods. We observe some outcomes $Y_{t,i}$, denoting each of the 30 search-based mental health symptoms. Let $D_{t,i}$ be a binary treatment indicator, which is one if in a given period a given state issues the stay-at-home order. Under the canonical 2*2 DiD model, one would compare the evolution of potential outcomes in the treated units versus never treated units to obtain the estimated effect of receiving treatment, $\hat{\tau}$:

$$\begin{aligned} \hat{\tau} \equiv E\left[(Y_1^1 - Y_0^1 \mid D=1) - (Y_1^0 - Y_0^0 \mid D=1)\right] = \\ E\left[(Y_1^1 - Y_0^1 \mid D=1) - (Y_1^0 - Y_0^0 \mid D=0)\right] \end{aligned} \tag{1}$$

where $(Y_1^0 - Y_0^0 \mid D=1)$ is the missing counterfactual: among treated units, one never observes the difference in untreated outcomes. In the canonical setup, one recovers the later component by invoking the parallel trend assumption $(Y_1^0 - Y_0^0 \mid D=0)$,

[10] See Bismarck-Osten et al. (2021) for an example of recent empirical work using this estimator.

which states that, in the absence of treatment, treatment units $D = 1$ would have experienced the evolution of the outcome of not treated units $D = 0$. If the parallel trend assumption holds, $\hat{\tau}$ is an unbiased estimate of the ATT. In practice, researchers often estimate this ATT from the two-way fixed effect (2WFE) regression:

$$Y_{it} = \alpha_i + \beta_t + \tau D_{it} + \varepsilon_{it} \tag{2}$$

where Y_{it} is regressed on units and time fixed-effects and the effect of the treatment indicator on the outcome, τ. Until quite recently, common practice has been to deal with situations with staggered treatment adoption by extending the 2WFE model to an event study specification:

$$Y_{it} = \tilde{\alpha}_i + \tilde{\beta}_t + \sum_{\substack{h=-a \\ h\neq -1}}^{b-1} \tau_h 1\left[t = E_i + h\right] + \tau_{b+} 1\left[t \geq E_i + b\right] + \varepsilon_{it} \tag{3}$$

where the outcome is now regressed on the fixed-effects and then some leads (pre-treatment) and lags (post-treatment) event indicators to allow for dynamics. However, traditional estimation practice through OLS has been shown to be subject to bias under treatment effect heterogeneity (Goodman-Bacon, 2021). As Borusyak et al. (2021) show, such problems can be intuitively illustrated by considering a static version of the event study design:

$$Y_{it} = \tilde{\alpha}_i + \tilde{\beta}_t + D_{it}\tau + \varepsilon_{it} \tag{4}$$

where τ is meant to summarize overall treatment effects — without worrying about exact dynamics. This static specification will help us to detect the three implicit assumptions of the event study model. First, notice that τ implies homogeneous treatment effects. Under heterogeneous treatment effects, the OLS-based traditional estimation approach to 2WFE will be biased. For instance, this would include bias in situations such as dynamic treatment effects that are either constant or unequal across states (Baker et al., 2021), which are reasonable scenarios for the evolution of the effect of lockdowns on mental health symptoms.[11] Second, the authors also notice that $\tilde{\alpha}_i + \tilde{\beta}_t$ imply how parallel trends is imposed: differences in outcomes of different units that can be attributed to differences across units and periods, are, in expectation, equal across units. This is the main assumption of the model. One last

[11] For example, the prevalence of symptoms might grow from the introduction of the stay-at-home orders (dynamic treatment effects that are constant across states). Alternatively, it might be the case that early adopters experience different outcome trajectories than late adopters (dynamic treatment effects that are unequal across states) — because of time-to-adjust mechanisms, or social unrest, for instance.

implicit assumption of the OLS 2WFE estimator is the lack of anticipation effects. For the former, notice that by imposing that only when a given unit is treated there is some treatment effect the researcher is implicitly assuming no anticipation — when $D_{it} = 0$ τ is zero as well.

Borusyak et al. (2021) propose an alternative estimator, built in the following fashion. Let Ω_1 denote the set of treated observations. Conversely, let Ω_0 denote the set of untreated observations, encompassing both not-yet-treated and never-treated observations. The estimation parameter of interest is $\tau_w = \sum_{it \in \Omega_1} w_{it}\tau_{it}$, which just generalizes the estimator to allow for weighing treatment effects in some sensical way e.g. dynamic treatment effects weighted by state population. τ_{it} denotes for treated observations the group of outcome differences between the observed outcome Y_{it}^1 and the potential outcome Y_{it}^0. To identify the parameter of interest, Borusyak et al. (2021) impose the following assumptions on the model below, which will slightly modify those of the traditional OLS-based 2WFE estimator:

$$Y_{it} = \alpha_i + \beta_t + D_{it}\tau_{it} + \varepsilon_{it} \tag{5}$$

First, their estimator allows for heterogeneous treatment effects — notice that in τ_{it} that now τ varies across units and time. Second, they also impose parallel trends, where the untreated potential outcome for all units has again a unit and time fixed-effects structure. This assumption can be then relaxed to invoke a more flexible parallel trend assumption i.e. to allow for unit-specific trends or time-varying controls. Finally, they impose a no-anticipation type of assumption, which follows the same logic explained above for Equation 4. Their estimator nonetheless also allows to relax the former, where the researcher would then redefine treatment from the period where anticipation effects started e.g. if one thinks there could be anticipation effects for two periods before treatment she will redefine treatment as two periods early.

For estimation, Borusyak et al. (2021) show that the model in Equation 5 can be obtained as an imputation estimator, in three steps. First, for *each* untreated observation, the state and week fixed-effects α_i and β_t are estimated using OLS. Second, an unbiased estimate $\hat{Y}_{it}^0$ is then obtained for each treated observation by extrapolating from untreated units. The estimator of interest is then obtained as the evolution of outcomes for each treated observation vis-á-vis its imputed counterfactual: $Y_{it} - \hat{Y}_{it}^0$. Borusyak et al. (2021) warn that treatment effects for each week and state cannot be consistently estimated. The last step is thus to aggregate the individual effects into a more general parameter that better helps to answer the research question of interest. For my application, the presented aggregated dynamic parameter is the weekly average treatment effect across states, weighted by state population. That is, I estimate the

impact of implementing the lockdown on the weekly evolution of a given web-based symptom. This approach allows me to explore treatment effect dynamics.

As Borusyak et al. (2021) show, providing empirical support for the parallel trends assumption requires to regress, on the set of untreated observations, the following specification:

$$Y_{it} = \alpha_i + \beta_t + \sum_{p=-P}^{-1} \gamma_p 1\left[t = E_i + p\right] + \varepsilon_{it} \tag{6}$$

where $1\left[t = E_i + p\right]$ is a set of dummies for the pre-intervention periods. From the test, it is expected that conditional on the parallel trend structure invoked e.g. $\alpha_i + \beta_t$, there should be no pre-intervention difference in outcomes between treated and non-treated units–and thus the group of the pre-intervention dummies should be non-significant. As Borusyak et al. (2021) recommend, I perform this test on the pool of untreated states as a pre-imputation step, hence separating testing from estimation. The validity of this test can then be visually examined via an event study plot.

5 Results

In this section, I provide the most important findings of this study. I begin by discussing a heatmap that will allow me to explore in a concise manner the dynamic effects of stay-at-home orders in the large set of mental health outcomes covered. Using this tool, we will learn at a glance which conditions were mostly affected by the intervention of interest and whether any common pattern across symptoms emerges. Afterwards, I focus on a selection of those symptoms that either present the largest or the most sustained effects. All results presented control for the evolution of the pandemic i.e. the evolution of confirmed cases and deaths and include time (week and month) and state fixed-effects.[12] Results are also clustered at the state level and are weighted by population. For all symptoms, there is no evidence of major violations of the common trend assumption through pre-trends and hence the former is not discussed for the shake of brevity — see Tables S1-S5 of the Supplementary Material.

Figure 1 provides the results of the event study estimations for the intervention of interest, the declaration of the stay-at-home orders. Dynamics are explored up until December 2020, when the vaccination campaign started in the US. Each row shows the event study results from one specific mental health symptom. Time is represented in the horizontal axis, and thus each cell is the dynamic ATT of one given symptom

[12]Month fixed-effects help the researcher to get rid of seasonality in mental health instruments and symptoms — see Banks and Xu (2020) for evidence on the former.

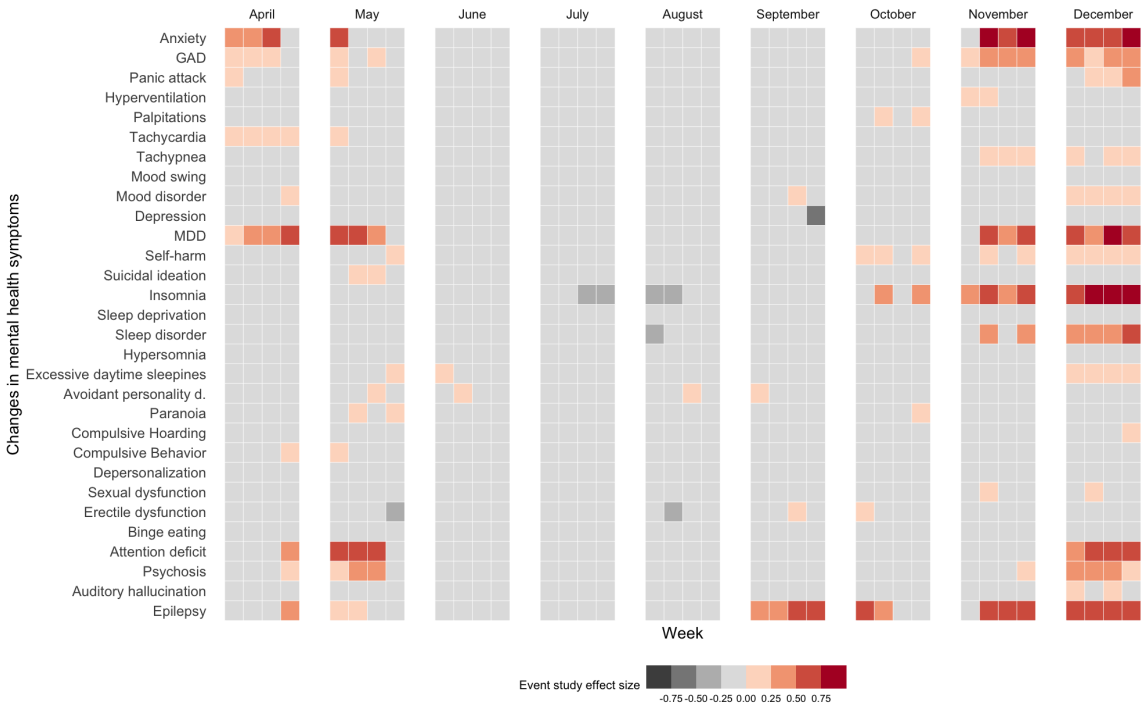


Figure 1: Event study results summary. Source: Google's symptoms dataset.

in any given week. For instance, the first cell provides the effect of the lockdown on "anxiety" the first week after the stay-at-home order is passed. The intensity of the effect is represented by a diverging color palette centered at zero. In the palette, the red hue represents positive effects and the dark grey negative effects, while the light grey in the middle of the palette indicates no statistically significant effect. Accordingly, the weeks at which one specific symptom peaked high in treated states relative to not-yet-treated states are shown in darker shades of red.

At the top of the figure, I first provide results from symptoms related to **anxiety disorders**. One clearly sees that, in treated states, searches related to "anxiety" and "GAD" first peaked in April-May. Treated states then experienced a second peak in those conditions in November-December. For "anxiety", immediate effects and long-term effects are quite large, while searches related to "GAD" experience relatively smaller peaks in treated states. Notice however that "GAD" symptoms deteriorate over time, showing larger effects in November-December. Other symptoms related to anxiety disorders match this two-wave pattern. Smaller effects are found for "panic attack" and "tachycardia" in the weeks that followed the implementation of the lockdowns. Treated states also experienced higher search-based prevalence of "panic attack", "hyperventilation", "palpitations", and "tachypnea" during the second wave.

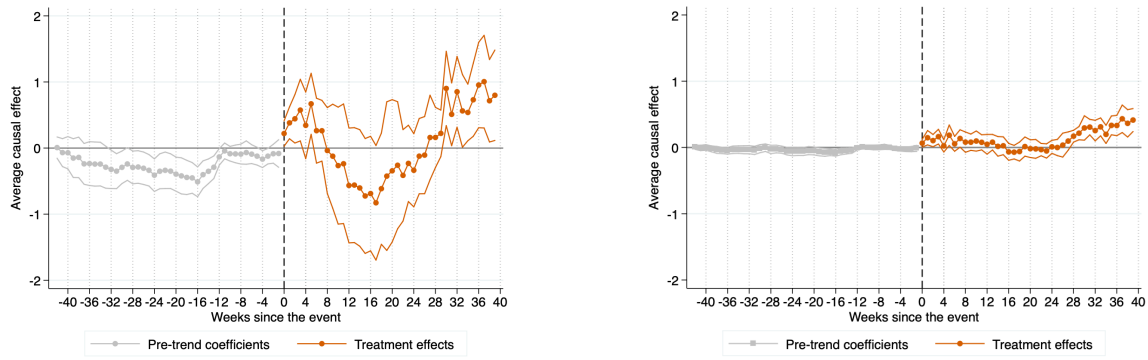
The results for **mood disorders** are then provided. For "depression", no immediate or long-term effect is found. Instead, the symptoms dataset reveals a substantial

worsening in terms of "major depressive disorders", thus suggesting a severe deterioration in mood disorders during and after the lockdown. For "self-harm" and "suicidal ideation", effects are quite small, although generally match the two wave pattern. I estimate small immediate effects for both conditions. While searches related to "self-harm" remained slightly higher in treated states than in non-treated states during the second wave, no long-term effect is found for "suicidal ideation".

Event study estimates of **sleep disorders** are then reported. Except for some small effects in terms of "excessive daytime sleepiness" in May-June, effects on sleep disorders mostly appeared in the long run. Figure 1 reveals a quite strong disruption in terms of "insomnia" and "sleep disorder" in the last three months of 2020. The next dimension shown is **personality and dissociative disorders**. For personality disorders, relatively small effects are found in later April and May — in terms of searches related to "avoidant personality disorder", "paranoia", and "compulsive behavior". None of these conditions does however show a long-term effect. In terms of "depersonalization", I do not find evidence of any disruption in states that implemented stay-at-home orders. Finally, the figure shows the results for a residual cluster of **other disorders**. I report strong effects in terms of "attention deficit" in both waves. Non-negligible effects are found for "psychosis" in both waves. Searches related to "epilepsy" in treated states also increase to some extent in late April-May, and then followed a distinct path, showing a much prolonged second wave that started in September with quite sustained strong effects. I do not find any evidence of deterioration in terms of sexual disorders and eating disorders.

All together, event study estimates for this large set of symptoms reveal that the stay-at-home orders fostered mental distress in treated states in the form of various anxiety disorders, severe forms of depression, sleep disorders, attention deficit, and epilepsy. Treated states experienced two mental distress waves, occurring in April-May and November-December, respectively. As stressed, the former implies that the lockdowns had both immediate and long-term costs for the US population.

Once overall changes have been explored through the heatmap, I take a closer look at the evolution of those symptoms showing more significant patterns through event plots. Figure 2 shows the event study results for the main anxiety and mood disorder symptoms. In Panel a), for "anxiety", one clearly sees the two found waves. During the five weeks after the implementation of the stay-at-home orders, treated states reported search-based anxiety symptoms around 0.5 higher. Thirty weeks after the implementation of the stay-at-home order, that is, around the first weeks of October up until December, treated states show anxiety levels that are about 0.72 higher — for some weeks, "anxiety" levels rose up to around 1 search intensity point. The event



(a) Anxiety

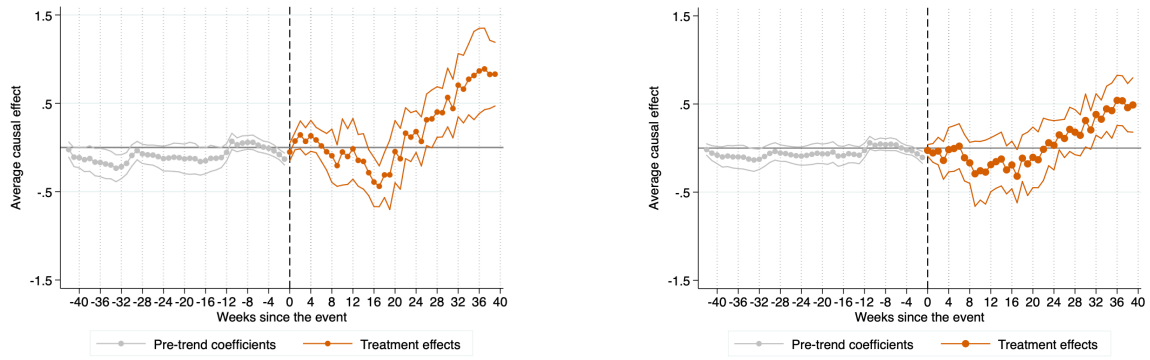
(b) Generalized anxiety disorder

(c) Depression

(d) Major depressive disorder

Figure 2: Event study results from anxiety and depression.
Source: Google's symptoms dataset.

study results for "anxiety" thus show relatively large effects during the weeks that immediately followed the onset of the lockdown and more severe permanent effects at the beginning of the period. In Panel b), I explore the dynamics of "GAD". In treated states, searches associated with "GAD" show relatively smaller increments during the first eight weeks of about 0.10 points. From around late October to December, search-based GAD slightly increased to about 0.25 points, still below anxiety levels. With regards to mood disorders, no effect is found for "depression". Noticeable effects are however found for "MDD" during both the first and second waves. Specifically, search-based MDD remained around 0.43 points higher in treated states during the 7 weeks that followed the intervention. During November and December, "MDD" searches were around 0.55 points higher in treated states. Overall, this suggests that lockdown measures affected the whole spectrum of anxiety disorders, especially in the long run, although more clearly to less severe forms of such disorders. Lockdown measures only affected more severe forms of depression, while the latter was less prevalent than



(a) Insomnia

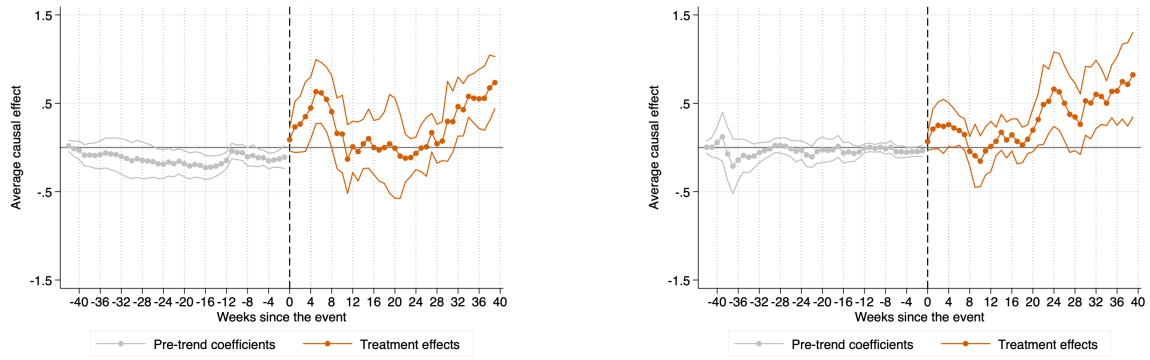
(b) Sleep disorder

Figure 3: Event study results from sleep disorders.
Source: Google's symptoms dataset.

anxiety, though.

Figure 3 shows the event study results for the selected sleep disorders. In general, effects found for this cluster of symptoms tend to be in the form of long-run permanent effects. The strongest deterioration is found for "insomnia", as shown in Panel a): from October until December treated US states had systematically higher search-based insomnia symptoms. This is one of the most sustained effects on mental health from this study. Effects are not only quite permanent but substantive in magnitude. From October to the beginning of November, the average event study effect for "insomnia" in treated regions is about 0.4 points. From late November to December, "insomnia" becomes even more prevalent, rising by about 0.75 points on average. "Sleep disorder" also remained relatively high since late November — around 0.4 points. These findings suggest a quite sustained long term impact in terms of sleep disorders, where "insomnia" plays a more central role.

Finally, Figure 4 shows the event study results for two selected symptoms of the residual category. In Panel a), I provide the event study estimates for "attention deficit", while Panel b) brings the estimates for "epilepsy". Both conditions show a more-delayed first wave, which coincides with late April-May. In terms of long-term dynamics, "attention deficit" is found to have been deteriorated during December, where those states that implemented stay-at-home orders experienced "attention" deficit levels that were, on average, around 0.5 points higher. By contrast, "epilepsy" shows the largest second wave of all symptoms explored, with effects already materializing by the beginning of September. During this more spread second wave, "epilepsy" in treated states remained about 0.5 points higher relative to non-treated states.



(a) Attention-deficit

(b) Epilepsy

Figure 4: Event study results from attention deficit and epilepsy.
Source: Google's symptoms dataset.

6 Discussion

This section provides a discussion of the main findings of this study, exploring whether results confirm previous evidence from other studies. This exercise has its own limitations, as for some dimensions the evolution of mental health conditions is better documented than for others. Importantly, I have not found any empirical studies that have explored the mental health implications of stay-at-home orders during the end of 2020. For this purpose, I leverage descriptive evidence, whenever possible. These shorts of evidence gaps nonetheless help me to evaluate the uncertainty around estimates.

For forms of anxiety and depression, results seem to be relatively safely validated by other sources of evidence, at least in terms of their dynamics. Estimated effect sizes are admittedly harder to evaluate because of differences in the operationalization of outcomes. As the present study, prior empirical work has also found evidence of very immediate effects on anxiety in treated regions (Yamamura and Tsutsui, 2020; Armbruster and Klotzbücher, 2020), that in some settings remained high up to the beginning of summer (Silverio-Murillo et al., 2021). Existing evidence on depression is also in line with this study, reporting no supportive evidence of (immediate) changes in the former (Hoerger et al., 2020; Silverio-Murillo et al., 2021). These studies are nonetheless silent about more severe forms of depression, for which this study estimates a non-negligible deterioration in treated regions. For the dynamics experienced during the second wave, one must necessarily rely on descriptive sources. Those studies that make use of validated scales generally map the evolution reported here for search-based anxiety and depression, showing two waves of increasing intensity as well (Fisher et al., 2020; Garcia-Priego et al., 2020; González-Sanguino et al., 2020; Jenkins et al.,

2021; Lee et al., 2021; Marmot, 2021; McCracken et al., 2020; National Statistics, 2020; Parlapani et al., 2020; Pieh et al., 2020; Rossi et al., 2020; Ueda et al., 2020; Vahratian et al., 2021; Winkler et al., 2020). It should be however stressed that these studies while having their own flaws because of their reliance on pre- and post- comparisons that are not empirically linked to the effect of the implementation of stay-at-home orders point to much more substantive deterioration of anxiety and depression.[13]

The validity of the rest of the findings is arguably less clear, as prior evidence for these symptoms is based on descriptive studies or inconclusive empirical work. For insomnia and other sleep disorders, a blurred picture emerges when comparing obtained results with existing evidence. On the one hand, one study with a quasi-experimental design has found no immediate effect of lockdown on search-based insomnia in treated US states (Brodeur et al., 2021). Other study has however pointed to the opposite picture (Silverio-Murillo et al., 2021). In terms of second wave dynamics, Dale et al. (2021) descriptively document further deterioration in terms of a clinically validated instrument for sleep quality. For attention-deficit hyperactivity disorder, Daly and Robinson (2021) also finds that distress increased on average at the onset of the state-at-home orders–for US people diagnosed with such condition. Other studies have confirmed the worsening of such symptoms on children during the lockdown (Zhang et al., 2020). For epilepsy, existing evidence relies on pre- and post- comparisons around the implementation of the stay-at-home orders. For patients with epilepsy, descriptive studies have associated the former with an increase in seizures (Conde Blanco et al., 2021; Zeng et al., 2021). To the best of my knowledge, no prior evidence exists on the effect of stay-at-home orders on epilepsy in the general population.

7 Conclusion

The present study provides evidence on the role of stay-at-home orders on the development of a mental health crisis in the US during the first year of the COVID-19 pandemic. Event study estimates based on high-quality search data reveal that this policy provoked a surge in anxiety disorders, severe forms of depression, sleep disorders, attention deficit, and epilepsy. The effect of the lockdowns goes beyond its duration, as most of these conditions deteriorated in treated states at the end of 2020. Given evidence gaps, the latter finding is an important contribution of this study. Because of these gaps, the results of this study should nonetheless be taken with caution,

[13]The HPS project for instance estimates that anxiety disorders experience an about 20 p.p. increase during the first mental health wave. During the second wave, they estimate that these disorders experience an about 26 p.p. increase. For depression disorders, HPS data suggests an about 17 p.p. (22 p.p.) increase for the first (second) wave.

especially for symptoms other than anxiety and depression.

It should be acknowledge that measuring mental distress is a difficult task. Survey instruments face worrying non-response rates that might even worsen in the future as a result of the pandemic. Different forms of stigma also challenge their validity. Because of these shortcomings, surveys might offer a distorted, lower bound picture of the problem. Real-time search data comes as a complementary tool that is less severely affected by these two gaps. By using a recently developed search data source that maps search queries to medical symptoms, I also tackle some of the own limitations of traditional search data sources. Caveats on representativeness and the ability to explore heterogeneity still apply. Moreover, despite its richness, the first version of the symptoms dataset better tracks certain mental health areas than others (eating disorders is one prominent area not sufficiently well captured).

Significant uncertainty remains on the impact of stay-at-home orders on mental distress, especially for long-term dynamics. Accordingly, further research is needed to properly guide the policy response to the pandemic. Indeed, this is the sole urgent recommendation of the 2020 report of the Lancet's COVID-19 Commission Mental Health Task Force (Aknin et al., 2021). Other areas of promising research include the re-assessment of the societal cost per patient of the different dimensions of mental distress so that it better reflects the current scenario or the more ambitious evaluation of the psychological costs of these policies by considering mental health as a facet of the broader more complex phenomena of well-being. It is also still unclear how the roll-out of the vaccination campaign might have alleviated the mental health burden of social distancing policies.

In the meanwhile, several institutions have already called for emergency policy action. The Lancet's COVID-19 Commission Mental Health Task Force has first stressed the importance of a more systematic screening protocol of mental health conditions at health care centers, so that distress conditions are early-detected, monitor appropriately, and treated when necessary. It also calls for making of safe access to childcare and schooling a priority, so that kids' learning and socialization do not suffer further disruptions and parents (especially young women) improve their altered family responsibilities and reduce their psychological distress. The OECD has proposed a plan of action based on three pillars that complements some of the recommendations already raised (OECD, 2021). The first of these pillars is governments' need to provide quality mental health services, ensuring that the increasing demand for mental health care is sufficiently covered. Secondly, the OECD calls for safeguarding mental health at work, taking an integrated, more ambitious approach than mere health care interventions — through unemployment plans and better protection schemes, for example.

Finally, the OECD recommends developing better governance of teleworking so that characteristics traditionally attributed to the former such as longer workloads or more irregular work shifts do not become the new norm.

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Master thesis
Supplementary material

Pablo Brugarolas

Additional figures

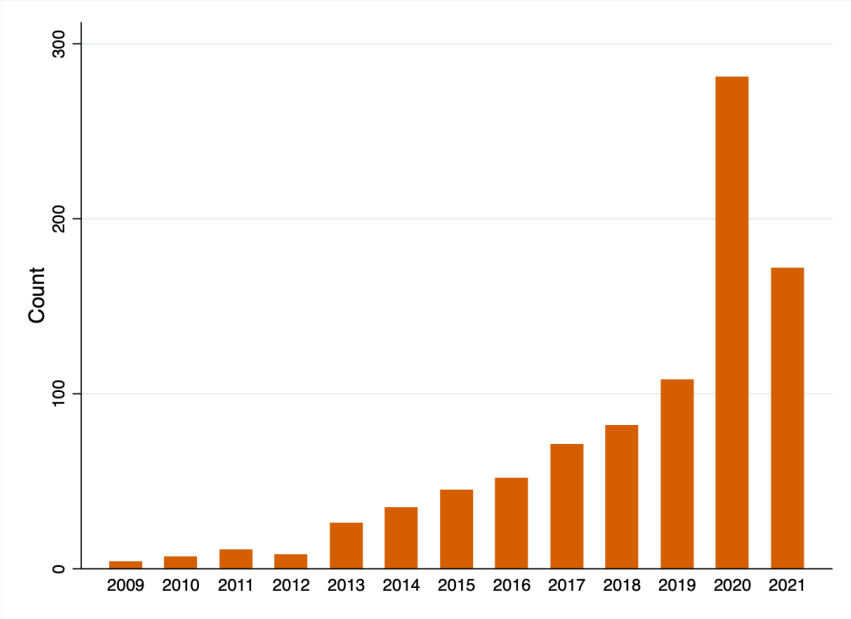

Figure S1. Research articles mentioning “Google Trends” or “Google Insights” in their titles or abstracts in PubMed

Event study results: pre-trend tests

Table S1. Anxiety disorders

	Anxiety	GAD	Panic attack	Hyperventilation	Palpitations	Tachycardia	Tachypnea
pre1	-0.082	-0.014	0.035	0.015**	-0.020*	-0.019	0.000
	(0.107)	(0.023)	(0.034)	(0.005)	(0.008)	(0.017)	(0.007)
pre2	-0.086	-0.025	0.019	0.005	-0.021*	-0.034*	-0.001
	(0.073)	(0.020)	(0.028)	(0.005)	(0.010)	(0.016)	(0.007)
pre3	-0.122*	-0.028	-0.023	-0.002	-0.013	-0.046**	0.000
	(0.060)	(0.018)	(0.022)	(0.006)	(0.009)	(0.017)	(0.007)
pre4	-0.167**	-0.025	-0.042*	0.004	-0.008	-0.034*	-0.002
	(0.065)	(0.015)	(0.020)	(0.005)	(0.008)	(0.014)	(0.006)
pre5	-0.123	-0.017	-0.018	0.002	-0.002	-0.016	-0.001
	(0.069)	(0.015)	(0.020)	(0.004)	(0.008)	(0.016)	(0.006)
pre6	-0.092	0.001	-0.005	-0.000	-0.001	-0.019	0.001
	(0.073)	(0.016)	(0.019)	(0.004)	(0.006)	(0.016)	(0.005)
pre7	-0.068	0.009	0.011	-0.002	-0.010	-0.011	0.002
	(0.090)	(0.020)	(0.019)	(0.004)	(0.008)	(0.017)	(0.005)
pre8	-0.091	0.001	-0.011	-0.003	-0.010	-0.019	-0.008
	(0.076)	(0.018)	(0.019)	(0.005)	(0.006)	(0.019)	(0.005)
pre9	-0.089	0.000	-0.016	0.007	-0.019*	-0.014	-0.008
	(0.068)	(0.018)	(0.017)	(0.007)	(0.009)	(0.018)	(0.004)
pre10	-0.086	0.000	-0.008	0.010	-0.021	-0.007	-0.005
	(0.057)	(0.014)	(0.015)	(0.006)	(0.013)	(0.017)	(0.006)
pre11	-0.043	0.008	0.021	0.012**	-0.020	-0.005	-0.012
	(0.061)	(0.015)	(0.016)	(0.005)	(0.012)	(0.018)	(0.007)
pre12	-0.134*	-0.008	0.013	0.010*	-0.023	-0.017	-0.011
	(0.064)	(0.015)	(0.015)	(0.004)	(0.012)	(0.018)	(0.009)
pre13	-0.290***	-0.046*	-0.016	0.003	-0.035**	-0.022	-0.019*
	(0.087)	(0.021)	(0.021)	(0.004)	(0.013)	(0.020)	(0.009)
pre14	-0.352***	-0.053*	-0.028	0.001	-0.032*	-0.049*	-0.009
	(0.095)	(0.023)	(0.025)	(0.004)	(0.014)	(0.019)	(0.009)
pre15	-0.402***	-0.059*	-0.021	-0.006	-0.033*	-0.039*	-0.013
	(0.107)	(0.026)	(0.027)	(0.005)	(0.013)	(0.018)	(0.009)
pre16	-0.511***	-0.080**	-0.042	-0.009	-0.032*	-0.024	-0.008
	(0.115)	(0.026)	(0.029)	(0.006)	(0.013)	(0.020)	(0.008)
pre17	-0.451***	-0.072**	-0.022	-0.002	-0.024	-0.004	0.000
	(0.119)	(0.026)	(0.035)	(0.006)	(0.014)	(0.021)	(0.009)
pre18	-0.444***	-0.073*	-0.025	-0.003	-0.022	-0.012	0.003
	(0.132)	(0.031)	(0.039)	(0.007)	(0.013)	(0.021)	(0.008)
pre19	-0.421**	-0.067*	-0.012	-0.001	-0.028	-0.018	-0.001
	(0.139)	(0.031)	(0.042)	(0.008)	(0.015)	(0.021)	(0.007)
pre20	-0.395**	-0.052	-0.026	-0.001	-0.027*	-0.007	0.002
	(0.131)	(0.031)	(0.037)	(0.008)	(0.014)	(0.021)	(0.007)
pre21	-0.350**	-0.047	-0.031	0.002	-0.021	0.008	0.006
	(0.134)	(0.031)	(0.036)	(0.009)	(0.013)	(0.024)	(0.007)
pre22	-0.337*	-0.060	-0.027	-0.000	-0.025*	-0.015	-0.001
	(0.141)	(0.031)	(0.036)	(0.009)	(0.012)	(0.021)	(0.007)
pre23	-0.351**	-0.060	-0.003	-0.002	-0.025	-0.020	0.008
	(0.135)	(0.031)	(0.040)	(0.009)	(0.014)	(0.021)	(0.007)

Table S1. Anxiety disorders

	Anxiety	GAD	Panic attack	Hyperventilation	Palpitations	Tachycardia	Tachypnea
pre24	-0.410**	-0.062	-0.027	-0.002	-0.022	-0.019	0.006
	(0.126)	(0.032)	(0.038)	(0.007)	(0.012)	(0.019)	(0.007)
pre25	-0.336**	-0.055	-0.003	-0.001	-0.012	-0.018	0.005
	(0.121)	(0.029)	(0.038)	(0.007)	(0.017)	(0.018)	(0.006)
pre26	-0.305*	-0.033	0.009	-0.001	-0.006	0.003	0.003
	(0.125)	(0.027)	(0.037)	(0.007)	(0.015)	(0.016)	(0.007)
pre27	-0.287*	-0.024	0.027	-0.002	-0.009	0.013	0.000
	(0.126)	(0.030)	(0.036)	(0.006)	(0.015)	(0.019)	(0.007)
pre28	-0.293*	-0.030	0.024	-0.001	-0.010	0.002	-0.003
	(0.126)	(0.032)	(0.039)	(0.006)	(0.012)	(0.019)	(0.005)
pre29	-0.240	-0.003	0.030	-0.004	-0.016	-0.012	0.001
	(0.126)	(0.029)	(0.037)	(0.006)	(0.011)	(0.019)	(0.005)
pre30	-0.291*	-0.018	0.017	-0.000	-0.019	-0.008	0.006
	(0.126)	(0.031)	(0.038)	(0.006)	(0.011)	(0.018)	(0.005)
pre31	-0.350**	-0.043	0.018	0.004	-0.012	0.000	0.006
	(0.135)	(0.032)	(0.038)	(0.007)	(0.012)	(0.020)	(0.005)
pre32	-0.322*	-0.034	0.016	0.004	-0.018	-0.017	0.005
	(0.148)	(0.032)	(0.039)	(0.008)	(0.012)	(0.020)	(0.004)
pre33	-0.289	-0.034	0.011	0.001	-0.025	-0.008	0.006
	(0.162)	(0.031)	(0.044)	(0.007)	(0.014)	(0.021)	(0.005)
pre34	-0.242	-0.032	0.020	0.002	-0.022	-0.021	0.002
	(0.169)	(0.029)	(0.046)	(0.006)	(0.014)	(0.020)	(0.005)
pre35	-0.242	-0.034	0.001	0.004	-0.022	-0.018	0.008
	(0.170)	(0.028)	(0.041)	(0.005)	(0.016)	(0.021)	(0.004)
pre36	-0.235	-0.050	-0.001	0.004	-0.021	-0.022	0.004
	(0.169)	(0.026)	(0.039)	(0.006)	(0.017)	(0.021)	(0.004)
pre37	-0.239	-0.045	-0.003	0.006	-0.008	-0.019	0.003
	(0.158)	(0.024)	(0.034)	(0.006)	(0.024)	(0.022)	(0.004)
pre38	-0.141	-0.036	-0.011	0.010	-0.003	-0.001	0.009*
	(0.156)	(0.026)	(0.031)	(0.007)	(0.022)	(0.022)	(0.004)
pre39	-0.152	-0.021	-0.006	0.009	-0.008	0.001	0.007
	(0.150)	(0.023)	(0.029)	(0.007)	(0.019)	(0.020)	(0.004)
pre40	-0.071	-0.000	0.011	0.010	-0.000	-0.004	0.001
	(0.124)	(0.022)	(0.026)	(0.006)	(0.017)	(0.020)	(0.005)
Observations	5199	5199	5199	5154	5199	5151 5199	

Table S2. Mood disorders, self-harm, and sucidial ideation

	Mood swing	Mood disorder	Depression	Major dep. disorder	Self-harm	Suicidal ideation
pre1	-0.013*	0.004	-0.138	-0.090	-0.002	-0.024*
	(0.007)	(0.023)	(0.077)	(0.065)	(0.011)	(0.012)
pre2	-0.011	-0.015	-0.117*	-0.071	0.005	-0.032***
	(0.006)	(0.021)	(0.055)	(0.048)	(0.010)	(0.008)
pre3	-0.007	-0.010	-0.125**	-0.056	0.002	-0.038***
	(0.005)	(0.021)	(0.047)	(0.041)	(0.008)	(0.008)
pre4	-0.008	-0.018	-0.132**	-0.076	-0.004	-0.033**
	(0.006)	(0.018)	(0.049)	(0.044)	(0.007)	(0.011)
pre5	-0.015*	0.003	-0.050	-0.053	-0.010	-0.027**
	(0.006)	(0.015)	(0.051)	(0.040)	(0.007)	(0.010)
pre6	-0.009	0.021	-0.051	-0.024	0.002	-0.017
	(0.007)	(0.019)	(0.050)	(0.042)	(0.007)	(0.009)
pre7	-0.003	0.020	-0.026	0.005	0.004	-0.010
	(0.008)	(0.018)	(0.056)	(0.044)	(0.006)	(0.009)
pre8	0.006	0.005	-0.032	-0.025	0.011	-0.007
	(0.007)	(0.019)	(0.049)	(0.042)	(0.008)	(0.012)
pre9	0.009	0.022	-0.035	0.006	0.003	-0.008
	(0.006)	(0.019)	(0.045)	(0.045)	(0.009)	(0.013)
pre10	0.007	0.010	0.008	0.017	0.004	0.004
	(0.005)	(0.022)	(0.044)	(0.033)	(0.007)	(0.012)
pre11	0.013*	0.002	0.009	0.028	0.017*	0.015
	(0.006)	(0.020)	(0.044)	(0.036)	(0.008)	(0.013)
pre12	0.007	-0.032	-0.095*	-0.064	0.002	0.004
	(0.006)	(0.023)	(0.041)	(0.038)	(0.009)	(0.011)
pre13	-0.001	-0.053*	-0.192***	-0.140**	-0.003	-0.001
	(0.008)	(0.023)	(0.055)	(0.044)	(0.008)	(0.014)
pre14	0.001	-0.061*	-0.215***	-0.167***	-0.010	-0.006
	(0.010)	(0.027)	(0.064)	(0.049)	(0.009)	(0.015)
pre15	0.007	-0.087**	-0.294***	-0.210***	-0.019	-0.018
	(0.013)	(0.031)	(0.070)	(0.056)	(0.014)	(0.016)
pre16	0.004	-0.097**	-0.299***	-0.200***	-0.023	-0.033*
	(0.014)	(0.033)	(0.072)	(0.061)	(0.016)	(0.015)
pre17	0.000	-0.079**	-0.279***	-0.200***	-0.020	-0.035*
	(0.016)	(0.029)	(0.073)	(0.051)	(0.014)	(0.015)
pre18	0.004	-0.066*	-0.266***	-0.187**	-0.021	-0.031
	(0.016)	(0.032)	(0.076)	(0.061)	(0.012)	(0.016)
pre19	0.001	-0.065*	-0.278***	-0.184**	-0.021	-0.039**
	(0.015)	(0.030)	(0.075)	(0.060)	(0.012)	(0.014)
pre20	0.001	-0.049	-0.272***	-0.166**	-0.022	-0.044**
	(0.014)	(0.030)	(0.068)	(0.058)	(0.012)	(0.015)
pre21	0.002	-0.044	-0.238***	-0.138*	-0.016	-0.041**
	(0.014)	(0.028)	(0.068)	(0.058)	(0.012)	(0.014)
pre22	-0.003	-0.053	-0.237**	-0.135*	-0.022*	-0.045**
	(0.013)	(0.028)	(0.079)	(0.063)	(0.009)	(0.015)
pre23	-0.012	-0.054*	-0.290***	-0.160**	-0.020**	-0.049**
	(0.011)	(0.027)	(0.073)	(0.058)	(0.007)	(0.016)
pre24	-0.016	-0.065**	-0.306***	-0.161**	-0.013	-0.045**
	(0.009)	(0.023)	(0.072)	(0.059)	(0.008)	(0.017)

Table S2. Mood disorders, self-harm, and sucidial ideation

	Mood swing	Mood disorder	Depression	Major dep. disorder	Self-harm	Suicidal ideation
pre25	-0.009	-0.043	-0.234**	-0.141*	-0.003	-0.049*
	(0.009)	(0.024)	(0.076)	(0.057)	(0.008)	(0.020)
pre26	-0.001	-0.052**	-0.214**	-0.122*	-0.000	-0.032
	(0.008)	(0.019)	(0.075)	(0.059)	(0.010)	(0.021)
pre27	0.001	-0.040	-0.193*	-0.110	0.004	-0.041*
	(0.007)	(0.021)	(0.082)	(0.066)	(0.012)	(0.020)
pre28	0.002	-0.045	-0.208*	-0.138*	-0.013	-0.057**
	(0.007)	(0.026)	(0.085)	(0.068)	(0.010)	(0.022)
pre29	0.002	-0.018	-0.112	-0.081	-0.019*	-0.035
	(0.006)	(0.027)	(0.085)	(0.067)	(0.008)	(0.022)
pre30	0.009	-0.017	-0.090	-0.108	-0.016*	-0.017
	(0.008)	(0.029)	(0.088)	(0.068)	(0.007)	(0.018)
pre31	0.005	-0.012	-0.129	-0.138*	-0.009	-0.025
	(0.008)	(0.029)	(0.086)	(0.066)	(0.009)	(0.018)
pre32	0.007	-0.021	-0.109	-0.102	-0.018	-0.019
	(0.008)	(0.030)	(0.090)	(0.070)	(0.010)	(0.017)
pre33	0.010	-0.009	-0.156	-0.133	-0.025**	-0.017
	(0.011)	(0.030)	(0.098)	(0.076)	(0.009)	(0.017)
pre34	-0.002	-0.027	-0.157	-0.127	-0.022**	-0.017
	(0.011)	(0.030)	(0.107)	(0.080)	(0.008)	(0.019)
pre35	0.001	-0.026	-0.168	-0.145	-0.012	-0.012
	(0.012)	(0.033)	(0.111)	(0.086)	(0.008)	(0.020)
pre36	0.001	-0.018	-0.141	-0.149	-0.009	-0.012
	(0.011)	(0.034)	(0.114)	(0.092)	(0.011)	(0.018)
pre37	-0.002	-0.026	-0.148	-0.128	-0.004	-0.013
	(0.011)	(0.033)	(0.108)	(0.090)	(0.009)	(0.017)
pre38	-0.013	-0.024	-0.126	-0.117	-0.003	-0.010
	(0.009)	(0.033)	(0.105)	(0.090)	(0.008)	(0.016)
pre39	-0.004	-0.015	-0.096	-0.092	-0.002	0.001
	(0.008)	(0.027)	(0.099)	(0.082)	(0.010)	(0.015)
pre40	-0.010	-0.003	-0.046	-0.048	-0.001	0.019
	(0.008)	(0.024)	(0.086)	(0.071)	(0.010)	(0.015)
Observations	5196	5199	5199	5199	5199	5199

Table S3. Sleep disorders

	Insomnia	Sleep deprivation	Sleep disorder	Hypersomnia	Excessive daytime sleepiness
pre1	-0.131***	-0.024*	-0.106**	-0.006	0.007
	(0.034)	(0.009)	(0.035)	(0.004)	(0.015)
pre2	-0.080**	-0.015	-0.065*	-0.002	0.001
	(0.029)	(0.009)	(0.027)	(0.004)	(0.015)
pre3	-0.038	-0.015	-0.030	-0.002	0.010
	(0.034)	(0.010)	(0.025)	(0.004)	(0.014)
pre4	-0.009	-0.007	-0.021	0.001	0.005
	(0.036)	(0.012)	(0.026)	(0.004)	(0.013)
pre5	0.005	-0.011	0.002	0.005	0.003
	(0.035)	(0.013)	(0.028)	(0.004)	(0.015)
pre6	0.027	-0.003	0.036	0.008*	-0.016
	(0.039)	(0.012)	(0.033)	(0.004)	(0.017)
pre7	0.058	-0.000	0.044	0.007	-0.006
	(0.042)	(0.016)	(0.037)	(0.004)	(0.015)
pre8	0.058	0.003	0.039	0.011***	0.009
	(0.040)	(0.009)	(0.034)	(0.003)	(0.012)
pre9	0.050	0.004	0.046	0.013***	0.021
	(0.042)	(0.012)	(0.035)	(0.004)	(0.012)
pre10	0.031	0.004	0.032	0.012***	0.026*
	(0.040)	(0.013)	(0.032)	(0.004)	(0.012)
pre11	0.069	-0.008	0.059	0.012**	0.025
	(0.047)	(0.012)	(0.037)	(0.004)	(0.013)
pre12	-0.055	-0.021	-0.027	0.009**	0.015
	(0.050)	(0.012)	(0.041)	(0.003)	(0.010)
pre13	-0.114*	-0.028*	-0.081	0.003	0.003
	(0.058)	(0.011)	(0.049)	(0.004)	(0.012)
pre14	-0.122	-0.030*	-0.072	-0.001	0.008
	(0.067)	(0.013)	(0.049)	(0.004)	(0.012)
pre15	-0.123	-0.041*	-0.064	0.002	-0.004
	(0.075)	(0.017)	(0.053)	(0.005)	(0.014)
pre16	-0.150*	-0.046**	-0.087	0.001	-0.009
	(0.075)	(0.017)	(0.054)	(0.005)	(0.011)
pre17	-0.160*	-0.043*	-0.091	-0.001	-0.011
	(0.078)	(0.018)	(0.059)	(0.005)	(0.014)
pre18	-0.127	-0.048**	-0.046	0.006	-0.000
	(0.088)	(0.017)	(0.060)	(0.005)	(0.013)
pre19	-0.122	-0.054**	-0.065	0.005	-0.004
	(0.092)	(0.017)	(0.061)	(0.006)	(0.014)
pre20	-0.129	-0.048**	-0.066	0.003	-0.018
	(0.086)	(0.016)	(0.057)	(0.006)	(0.014)
pre21	-0.116	-0.050**	-0.059	0.003	-0.002
	(0.082)	(0.017)	(0.059)	(0.005)	(0.014)
pre22	-0.111	-0.055**	-0.071	0.001	-0.008
	(0.082)	(0.018)	(0.059)	(0.005)	(0.017)
pre23	-0.119	-0.051**	-0.083	-0.000	-0.015
	(0.076)	(0.016)	(0.055)	(0.004)	(0.015)
pre24	-0.126	-0.063***	-0.091	-0.001	-0.006
	(0.072)	(0.014)	(0.053)	(0.005)	(0.013)

Table S3. Sleep disorders

	Insomnia	Sleep deprivation	Sleep disorder	Hypersomnia	Excessive daytime sleepiness
pre25	-0.104	-0.056***	-0.087	-0.004	-0.017
	(0.063)	(0.015)	(0.051)	(0.005)	(0.013)
pre26	-0.086	-0.051***	-0.076	-0.003	-0.022
	(0.058)	(0.015)	(0.048)	(0.005)	(0.013)
pre27	-0.083	-0.049***	-0.063	-0.002	-0.021
	(0.056)	(0.015)	(0.045)	(0.005)	(0.011)
pre28	-0.072	-0.049**	-0.057	-0.003	-0.017
	(0.056)	(0.016)	(0.048)	(0.004)	(0.011)
pre29	-0.035	-0.034**	-0.038	0.004	-0.003
	(0.053)	(0.013)	(0.050)	(0.004)	(0.012)
pre30	-0.090	-0.027*	-0.060	0.005	-0.015
	(0.062)	(0.012)	(0.053)	(0.004)	(0.013)
pre31	-0.180**	-0.020	-0.096	-0.001	-0.013
	(0.062)	(0.014)	(0.057)	(0.004)	(0.012)
pre32	-0.218**	-0.013	-0.128*	0.002	-0.019
	(0.069)	(0.015)	(0.059)	(0.004)	(0.011)
pre33	-0.235**	-0.020	-0.136*	-0.004	-0.009
	(0.078)	(0.015)	(0.065)	(0.005)	(0.012)
pre34	-0.198*	-0.027	-0.125	-0.004	-0.007
	(0.080)	(0.016)	(0.065)	(0.004)	(0.012)
pre35	-0.187*	-0.018	-0.104	-0.004	-0.016
	(0.084)	(0.017)	(0.068)	(0.005)	(0.013)
pre36	-0.170*	-0.019	-0.100	-0.005	-0.014
	(0.082)	(0.016)	(0.068)	(0.005)	(0.014)
pre37	-0.166*	-0.016	-0.100	-0.004	-0.002
	(0.079)	(0.015)	(0.064)	(0.005)	(0.014)
pre38	-0.125	-0.013	-0.091	-0.009	-0.011
	(0.074)	(0.016)	(0.061)	(0.006)	(0.014)
pre39	-0.138*	-0.019	-0.101	-0.007	-0.021
	(0.069)	(0.015)	(0.059)	(0.004)	(0.014)
pre40	-0.116	-0.010	-0.080	-0.003	-0.009
	(0.059)	(0.012)	(0.050)	(0.004)	(0.012)
Observations	5199	5199	5199	5123	5198

Table S4. Personality and dissociative disorders

	Avoidant pers. disorder	Paranoia	Compulsive hoarding	Comp. behavior	Depersonalization
pre1	0.004	-0.014	0.004	-0.048	-0.003
	(0.009)	(0.010)	(0.019)	(0.040)	(0.006)
pre2	0.009	-0.015	0.006	-0.013	0.002
	(0.010)	(0.008)	(0.014)	(0.022)	(0.005)
pre3	-0.002	-0.013	-0.001	-0.011	0.001
	(0.009)	(0.009)	(0.010)	(0.017)	(0.006)
pre4	0.000	-0.020*	0.000	-0.014	0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.006)
pre5	-0.003	-0.017*	0.002	-0.016	-0.001
	(0.012)	(0.008)	(0.009)	(0.010)	(0.005)
pre6	-0.007	-0.010	0.005	-0.008	0.003
	(0.010)	(0.007)	(0.006)	(0.009)	(0.005)
pre7	0.005	-0.012	0.002	-0.004	0.005
	(0.010)	(0.006)	(0.005)	(0.007)	(0.005)
pre8	0.005	-0.010	0.005	-0.009	0.006
	(0.010)	(0.007)	(0.005)	(0.008)	(0.005)
pre9	0.010	-0.007	0.009	-0.008	0.004
	(0.009)	(0.009)	(0.005)	(0.009)	(0.004)
pre10	-0.001	-0.016	-0.001	-0.005	0.006
	(0.007)	(0.009)	(0.005)	(0.008)	(0.003)
pre11	0.001	-0.014	-0.003	-0.015	0.010**
	(0.008)	(0.011)	(0.007)	(0.011)	(0.004)
pre12	-0.010	-0.018	-0.009	-0.007	0.007
	(0.011)	(0.010)	(0.007)	(0.010)	(0.004)
pre13	-0.009	-0.018	-0.011	-0.021	0.003
	(0.011)	(0.010)	(0.008)	(0.012)	(0.005)
pre14	-0.013	-0.019	-0.009	-0.033*	0.003
	(0.010)	(0.010)	(0.008)	(0.014)	(0.005)
pre15	-0.012	-0.017	-0.004	-0.040*	-0.005
	(0.010)	(0.010)	(0.007)	(0.018)	(0.004)
pre16	-0.009	-0.025	-0.005	-0.051*	-0.004
	(0.007)	(0.013)	(0.009)	(0.020)	(0.005)
pre17	0.003	-0.023	-0.004	-0.038*	-0.001
	(0.011)	(0.014)	(0.010)	(0.018)	(0.005)
pre18	0.007	-0.029	-0.006	-0.045*	-0.001
	(0.009)	(0.018)	(0.012)	(0.021)	(0.006)
pre19	0.006	-0.017	0.002	-0.035	-0.001
	(0.010)	(0.018)	(0.012)	(0.023)	(0.007)
pre20	0.004	-0.016	-0.004	-0.020	-0.003
	(0.009)	(0.015)	(0.013)	(0.022)	(0.006)
pre21	-0.000	-0.010	-0.001	-0.026	0.001
	(0.011)	(0.014)	(0.012)	(0.020)	(0.005)
pre22	-0.003	-0.010	-0.001	-0.034*	-0.000
	(0.013)	(0.012)	(0.011)	(0.017)	(0.005)
pre23	-0.006	-0.018	-0.002	-0.036*	0.004
	(0.012)	(0.012)	(0.010)	(0.018)	(0.005)
pre24	-0.009	-0.016	-0.002	-0.037*	0.004
	(0.009)	(0.011)	(0.010)	(0.017)	(0.005)

Table S4. Personality and dissociative disorders

	Avoidant pers. disorder	Paranoia	Compulsive hoarding	Comp. behavior	Depersonalization
pre25	-0.005	-0.012	0.002	-0.033*	0.000
	(0.008)	(0.008)	(0.010)	(0.016)	(0.005)
pre26	-0.001	-0.014	-0.003	-0.036*	-0.003
	(0.008)	(0.008)	(0.009)	(0.017)	(0.005)
pre27	0.003	-0.012	-0.003	-0.030	-0.004
	(0.009)	(0.009)	(0.008)	(0.018)	(0.004)
pre28	-0.003	-0.014	0.007	-0.033	-0.004
	(0.008)	(0.008)	(0.008)	(0.022)	(0.005)
pre29	-0.005	-0.007	-0.002	-0.044*	-0.002
	(0.009)	(0.008)	(0.008)	(0.021)	(0.005)
pre30	-0.006	-0.006	0.001	-0.021	0.001
	(0.008)	(0.008)	(0.008)	(0.016)	(0.004)
pre31	-0.010	-0.007	-0.007	-0.022	-0.002
	(0.009)	(0.008)	(0.009)	(0.016)	(0.004)
pre32	0.000	-0.010	-0.017	-0.024	-0.006
	(0.006)	(0.007)	(0.015)	(0.023)	(0.004)
pre33	0.009	-0.012	0.015	-0.031	-0.003
	(0.008)	(0.009)	(0.025)	(0.020)	(0.004)
pre34	0.002	-0.011	-0.006	-0.005	0.001
	(0.008)	(0.010)	(0.009)	(0.022)	(0.004)
pre35	0.007	-0.005	-0.016	-0.011	-0.005
	(0.011)	(0.011)	(0.009)	(0.017)	(0.005)
pre36	0.002	-0.013	-0.019*	-0.006	-0.002
	(0.009)	(0.009)	(0.010)	(0.017)	(0.005)
pre37	-0.006	-0.005	-0.017	-0.014	-0.002
	(0.009)	(0.008)	(0.011)	(0.017)	(0.005)
pre38	-0.007	0.003	-0.016*	-0.017	-0.000
	(0.007)	(0.007)	(0.008)	(0.016)	(0.004)
pre39	-0.002	0.009	-0.008	-0.013	-0.001
	(0.006)	(0.007)	(0.006)	(0.016)	(0.004)
pre40	-0.002	0.009	-0.008	-0.016	-0.004
	(0.005)	(0.006)	(0.006)	(0.015)	(0.004)
Observations	5171	5189	5162	5199	5095

Table S5. Other disorders

	Sexual dysf.	Erectile dysf.	Binge eating	Attention deficit	Psychosis	Aud. Hall.	Epilepsy
pre1	-0.032	-0.085*	-0.005	-0.110	-0.023	-0.008	-0.038
	(0.017)	(0.036)	(0.011)	(0.065)	(0.031)	(0.005)	(0.033)
pre2	-0.031*	-0.085**	0.001	-0.129**	0.004	-0.003	-0.048
	(0.015)	(0.033)	(0.009)	(0.050)	(0.028)	(0.005)	(0.028)
pre3	-0.012	-0.041	-0.011	-0.141***	0.001	0.001	-0.049
	(0.012)	(0.037)	(0.009)	(0.042)	(0.027)	(0.005)	(0.027)
pre4	-0.004	-0.009	-0.014	-0.152***	-0.015	0.002	-0.054
	(0.012)	(0.034)	(0.012)	(0.046)	(0.025)	(0.005)	(0.030)
pre5	-0.004	-0.037	-0.012	-0.117**	0.002	0.000	-0.049
	(0.009)	(0.030)	(0.010)	(0.044)	(0.029)	(0.004)	(0.034)
pre6	-0.008	-0.035	0.003	-0.116*	-0.008	0.003	-0.049
	(0.011)	(0.030)	(0.009)	(0.052)	(0.027)	(0.003)	(0.035)
pre7	0.008	-0.006	0.002	-0.091	0.006	-0.001	0.002
	(0.009)	(0.032)	(0.007)	(0.061)	(0.032)	(0.004)	(0.036)
pre8	0.002	-0.011	0.010	-0.106*	-0.022	0.003	-0.014
	(0.008)	(0.033)	(0.011)	(0.053)	(0.026)	(0.004)	(0.030)
pre9	0.018	-0.010	0.007	-0.059	-0.021	0.003	0.003
	(0.010)	(0.036)	(0.010)	(0.046)	(0.024)	(0.004)	(0.025)
pre10	0.011	-0.016	0.015	-0.054	0.004	0.008*	-0.010
	(0.009)	(0.039)	(0.011)	(0.042)	(0.020)	(0.004)	(0.022)
pre11	0.009	-0.041	0.021	-0.041	0.009	0.007	0.001
	(0.011)	(0.043)	(0.015)	(0.045)	(0.023)	(0.004)	(0.025)
pre12	0.004	-0.080	0.012	-0.148**	-0.027	0.003	-0.010
	(0.010)	(0.044)	(0.014)	(0.048)	(0.024)	(0.004)	(0.025)
pre13	-0.002	-0.083*	0.001	-0.185***	-0.044	0.005	-0.050
	(0.011)	(0.042)	(0.014)	(0.053)	(0.024)	(0.004)	(0.033)
pre14	0.002	-0.042	-0.017	-0.211***	-0.053	0.003	-0.068
	(0.014)	(0.043)	(0.015)	(0.059)	(0.029)	(0.005)	(0.046)
pre15	0.003	-0.022	-0.027	-0.223***	-0.082*	0.002	-0.051
	(0.015)	(0.045)	(0.020)	(0.065)	(0.034)	(0.006)	(0.056)
pre16	0.013	-0.002	-0.029	-0.228***	-0.086*	0.001	-0.062
	(0.016)	(0.040)	(0.022)	(0.069)	(0.038)	(0.006)	(0.059)
pre17	0.004	-0.005	-0.024	-0.202**	-0.078*	-0.003	0.011
	(0.017)	(0.039)	(0.018)	(0.073)	(0.035)	(0.006)	(0.064)
pre18	-0.010	-0.007	-0.025	-0.193**	-0.069	-0.004	-0.028
	(0.021)	(0.044)	(0.016)	(0.073)	(0.037)	(0.007)	(0.062)
pre19	-0.007	0.001	-0.025	-0.209**	-0.067	-0.003	-0.035
	(0.018)	(0.047)	(0.014)	(0.075)	(0.036)	(0.007)	(0.065)
pre20	-0.009	0.004	-0.032*	-0.185*	-0.057	0.000	-0.028
	(0.021)	(0.047)	(0.015)	(0.076)	(0.032)	(0.006)	(0.075)
pre21	0.001	0.001	-0.032*	-0.157*	-0.045	-0.002	-0.045
	(0.018)	(0.047)	(0.015)	(0.073)	(0.033)	(0.006)	(0.068)
pre22	0.005	0.015	-0.045**	-0.183*	-0.044	-0.001	-0.105
	(0.015)	(0.051)	(0.015)	(0.076)	(0.031)	(0.007)	(0.060)
pre23	0.009	-0.002	-0.046**	-0.166*	-0.054	-0.007	-0.085
	(0.014)	(0.053)	(0.016)	(0.080)	(0.029)	(0.006)	(0.068)
pre24	0.001	0.008	-0.058***	-0.190*	-0.055	-0.003	-0.031
	(0.014)	(0.053)	(0.016)	(0.083)	(0.030)	(0.006)	(0.053)

Table S5. Other disorders

	Sexual dysf.	Erectile dysf.	Binge eating	Attention deficit	Psychosis	Aud. Hall.	Epilepsy
pre25	0.003	-0.003	-0.051*	-0.185*	-0.025	-0.003	-0.043
	(0.015)	(0.050)	(0.020)	(0.084)	(0.030)	(0.005)	(0.061)
pre26	-0.010	-0.008	-0.045*	-0.161	-0.035	-0.006	-0.013
	(0.016)	(0.048)	(0.021)	(0.090)	(0.030)	(0.004)	(0.048)
pre27	0.007	0.016	-0.023	-0.153	-0.033	-0.003	0.015
	(0.015)	(0.043)	(0.020)	(0.100)	(0.031)	(0.004)	(0.048)
pre28	0.010	0.006	-0.019	-0.146	-0.033	-0.003	0.021
	(0.014)	(0.044)	(0.015)	(0.106)	(0.031)	(0.005)	(0.044)
pre29	0.009	0.026	-0.013	-0.128	-0.021	-0.000	0.024
	(0.011)	(0.036)	(0.012)	(0.107)	(0.030)	(0.005)	(0.041)
pre30	0.018*	0.018	0.004	-0.150	-0.006	0.002	-0.016
	(0.009)	(0.036)	(0.012)	(0.104)	(0.032)	(0.006)	(0.041)
pre31	0.014	-0.038	0.006	-0.124	-0.017	-0.005	-0.036
	(0.012)	(0.037)	(0.012)	(0.107)	(0.034)	(0.006)	(0.048)
pre32	0.003	-0.061	0.006	-0.100	-0.016	-0.002	-0.059
	(0.011)	(0.033)	(0.009)	(0.101)	(0.035)	(0.006)	(0.057)
pre33	-0.008	-0.099**	-0.000	-0.081	-0.045	-0.002	-0.097
	(0.012)	(0.034)	(0.007)	(0.096)	(0.040)	(0.006)	(0.070)
pre34	-0.008	-0.104**	0.000	-0.073	-0.038	-0.006	-0.111
	(0.012)	(0.039)	(0.007)	(0.091)	(0.043)	(0.006)	(0.090)
pre35	-0.011	-0.097*	-0.004	-0.063	-0.049	-0.004	-0.090
	(0.012)	(0.041)	(0.008)	(0.086)	(0.043)	(0.005)	(0.095)
pre36	-0.009	-0.095*	-0.000	-0.082	-0.041	-0.002	-0.141
	(0.012)	(0.043)	(0.009)	(0.081)	(0.040)	(0.005)	(0.119)
pre37	-0.011	-0.094*	-0.000	-0.092	-0.009	0.003	-0.211
	(0.014)	(0.042)	(0.009)	(0.073)	(0.036)	(0.005)	(0.158)
pre38	-0.008	-0.063	0.009	-0.086	-0.022	0.002	-0.074
	(0.013)	(0.042)	(0.010)	(0.067)	(0.032)	(0.005)	(0.154)
pre39	-0.013	-0.062	0.012	-0.087	-0.025	-0.000	0.120
	(0.013)	(0.041)	(0.011)	(0.061)	(0.030)	(0.005)	(0.141)
pre40	0.002	-0.049	0.015	-0.033	-0.004	0.005	0.056
	(0.011)	(0.038)	(0.009)	(0.053)	(0.027)	(0.004)	(0.090)
Observations	5199	5199	5197	5199	5199	5105	5199

Event study results: treatment dynamics

Table S6. Anxiety disorders

	Anxiety	GAD	Panic attack	Hyperventilation	Palpitations	Tachycardia	Tachypnea
tau0	0.220*	0.065*	0.072*	0.013	0.002	0.054	-0.004
	(0.098)	(0.030)	(0.033)	(0.007)	(0.012)	(0.030)	(0.009)
tau1	0.381**	0.147**	0.107*	-0.014	0.058	0.106*	-0.029*
	(0.123)	(0.055)	(0.048)	(0.014)	(0.040)	(0.047)	(0.013)
tau2	0.443*	0.104*	0.097	-0.017	0.050	0.240***	-0.002
	(0.187)	(0.047)	(0.054)	(0.017)	(0.035)	(0.067)	(0.013)
tau3	0.575*	0.163**	0.085	-0.007	0.037	0.247**	0.007
	(0.238)	(0.057)	(0.057)	(0.026)	(0.038)	(0.079)	(0.016)
tau4	0.343	0.024	0.051	-0.003	0.036	0.209**	0.016
	(0.257)	(0.047)	(0.070)	(0.022)	(0.037)	(0.067)	(0.021)
tau5	0.669**	0.185*	0.146**	-0.010	0.020	0.178**	0.014
	(0.236)	(0.079)	(0.054)	(0.023)	(0.029)	(0.067)	(0.018)
tau6	0.263	0.055	0.034	-0.014	0.042	0.014	-0.013
	(0.250)	(0.057)	(0.055)	(0.027)	(0.053)	(0.068)	(0.022)
tau7	0.262	0.136*	0.086	-0.019	-0.034	0.074	-0.019
	(0.235)	(0.067)	(0.053)	(0.027)	(0.043)	(0.059)	(0.017)
tau8	-0.038	0.080	0.014	-0.021	-0.049	-0.029	-0.013
	(0.331)	(0.078)	(0.049)	(0.027)	(0.056)	(0.068)	(0.011)
tau9	-0.123	0.079	-0.014	-0.036	-0.094	0.036	-0.017
	(0.401)	(0.063)	(0.069)	(0.026)	(0.049)	(0.044)	(0.020)
tau10	-0.266	0.097	-0.027	-0.032	-0.059	0.001	-0.019
	(0.451)	(0.078)	(0.070)	(0.026)	(0.047)	(0.053)	(0.014)
tau11	-0.237	0.078	-0.019	-0.029	-0.057	-0.015	-0.023
	(0.462)	(0.058)	(0.086)	(0.024)	(0.045)	(0.055)	(0.023)
tau12	-0.566	0.048	-0.089	-0.038	-0.056	-0.017	-0.017
	(0.443)	(0.076)	(0.083)	(0.020)	(0.036)	(0.035)	(0.019)
tau13	-0.560	0.080	-0.057	-0.051*	-0.095	-0.144*	-0.028
	(0.443)	(0.060)	(0.088)	(0.022)	(0.058)	(0.067)	(0.029)
tau14	-0.603	0.017	-0.176	-0.057**	-0.063	-0.126	-0.038
	(0.450)	(0.075)	(0.096)	(0.020)	(0.048)	(0.065)	(0.026)
tau15	-0.725	0.026	-0.168	-0.049	-0.146*	-0.180*	-0.026
	(0.443)	(0.069)	(0.100)	(0.026)	(0.057)	(0.079)	(0.026)
tau16	-0.688	-0.066	-0.234**	-0.051*	-0.041	-0.149*	-0.019
	(0.442)	(0.065)	(0.084)	(0.024)	(0.049)	(0.072)	(0.024)
tau17	-0.828	-0.071	-0.088	-0.053	-0.086**	-0.083	-0.005
	(0.442)	(0.052)	(0.082)	(0.029)	(0.032)	(0.061)	(0.019)
tau18	-0.615	-0.061	-0.054	-0.061*	-0.002	-0.130*	-0.019
	(0.429)	(0.073)	(0.068)	(0.029)	(0.024)	(0.054)	(0.021)
tau19	-0.424	0.014	0.020	-0.060*	-0.087	-0.115**	-0.003
	(0.574)	(0.074)	(0.123)	(0.029)	(0.046)	(0.044)	(0.022)
tau20	-0.344	-0.018	-0.022	-0.030	-0.040	-0.111*	-0.011
	(0.549)	(0.068)	(0.105)	(0.025)	(0.039)	(0.054)	(0.024)
tau21	-0.260	-0.021	0.008	-0.075*	-0.111*	-0.092	-0.009
	(0.490)	(0.072)	(0.115)	(0.033)	(0.049)	(0.049)	(0.016)
tau22	-0.413	-0.032	-0.069	-0.026	-0.066	-0.014	0.001
	(0.353)	(0.047)	(0.080)	(0.020)	(0.048)	(0.052)	(0.019)

Table S6. Anxiety disorders

	Anxiety	GAD	Panic attack	Hyperventilation	Palpitations	Tachycardia	Tachypnea
tau23	-0.232	-0.053	-0.058	-0.039	-0.069	-0.011	0.024
	(0.295)	(0.055)	(0.075)	(0.025)	(0.054)	(0.045)	(0.032)
tau24	-0.336	0.010	-0.113	-0.030	-0.024	0.066	-0.012
	(0.282)	(0.050)	(0.068)	(0.017)	(0.037)	(0.048)	(0.017)
tau25	-0.122	-0.001	-0.108*	-0.018	-0.041	0.048	0.021
	(0.291)	(0.062)	(0.053)	(0.027)	(0.048)	(0.050)	(0.023)
tau26	-0.107	0.035	-0.100*	-0.021	0.060*	0.093	-0.000
	(0.298)	(0.092)	(0.043)	(0.018)	(0.024)	(0.078)	(0.027)
tau27	0.160	0.097	0.035	0.001	0.021	0.054	-0.002
	(0.327)	(0.070)	(0.036)	(0.017)	(0.032)	(0.078)	(0.029)
tau28	0.160	0.171***	0.033	0.042	0.080**	0.072	0.017
	(0.232)	(0.045)	(0.044)	(0.024)	(0.031)	(0.066)	(0.024)
tau29	0.222	0.216***	0.055	0.077**	0.025	0.022	0.028
	(0.179)	(0.051)	(0.056)	(0.025)	(0.026)	(0.071)	(0.020)
tau30	0.902**	0.295**	0.090	0.063*	0.079	0.060	0.052*
	(0.287)	(0.094)	(0.088)	(0.032)	(0.045)	(0.101)	(0.020)
tau31	0.510*	0.307***	0.049	0.043	0.058	0.037	0.040*
	(0.242)	(0.060)	(0.093)	(0.025)	(0.035)	(0.113)	(0.018)
tau32	0.851**	0.255**	0.026	0.021	0.026	0.090	0.055*
	(0.273)	(0.079)	(0.099)	(0.022)	(0.050)	(0.106)	(0.024)
tau33	0.562*	0.311***	0.103	0.017	0.049	0.048	0.057***
	(0.280)	(0.069)	(0.060)	(0.022)	(0.035)	(0.103)	(0.012)
tau34	0.539*	0.198**	0.121*	0.027	-0.021	0.096	0.050
	(0.218)	(0.070)	(0.051)	(0.023)	(0.053)	(0.118)	(0.029)
tau35	0.731**	0.334***	0.180***	0.010	-0.013	0.093	0.047*
	(0.282)	(0.072)	(0.048)	(0.023)	(0.053)	(0.111)	(0.020)
tau36	0.954**	0.332***	0.279***	0.010	0.081	0.082	0.037*
	(0.330)	(0.078)	(0.066)	(0.017)	(0.050)	(0.091)	(0.019)
tau37	1.005**	0.433***	0.238*	0.006	0.037	0.033	0.031
	(0.358)	(0.106)	(0.093)	(0.034)	(0.049)	(0.068)	(0.024)
tau38	0.716*	0.364***	0.181**	0.033	0.075	0.011	0.037*
	(0.318)	(0.105)	(0.067)	(0.024)	(0.087)	(0.067)	(0.018)
tau39	0.799*	0.414***	0.195*	0.052*	-0.019	-0.005	0.012
	(0.349)	(0.088)	(0.087)	(0.026)	(0.040)	(0.076)	(0.011)
Observations	5199	5199	5199	5154	5199	5151 5199	

Table S7. Mood disorders, self-harm, and sucidial ideation

	Mood swing	Mood disorder	Depression	Major dep. disorder	Self-harm	Suicidal ideation
tau0	-0.012	0.002	0.064	0.026	-0.028	-0.013
	(0.010)	(0.020)	(0.073)	(0.046)	(0.016)	(0.018)
tau1	0.008	-0.082	0.161	0.238*	0.003	-0.013
	(0.028)	(0.059)	(0.094)	(0.107)	(0.012)	(0.022)
tau2	-0.020	0.089	0.175	0.325*	-0.000	0.011
	(0.025)	(0.055)	(0.119)	(0.145)	(0.029)	(0.038)
tau3	-0.058	-0.008	0.162	0.392*	0.004	0.028
	(0.040)	(0.059)	(0.180)	(0.173)	(0.021)	(0.042)
tau4	-0.022	0.148*	0.078	0.516*	0.012	0.053
	(0.032)	(0.072)	(0.210)	(0.213)	(0.024)	(0.055)
tau5	-0.059	-0.012	0.085	0.556***	-0.023	0.077
	(0.031)	(0.058)	(0.184)	(0.160)	(0.028)	(0.046)
tau6	-0.000	0.060	0.119	0.593**	0.066	0.127*
	(0.029)	(0.077)	(0.224)	(0.210)	(0.035)	(0.056)
tau7	0.003	-0.050	-0.054	0.435*	-0.016	0.132*
	(0.029)	(0.089)	(0.250)	(0.212)	(0.031)	(0.062)
tau8	0.002	-0.025	-0.029	0.329	0.052*	0.070
	(0.044)	(0.107)	(0.333)	(0.272)	(0.022)	(0.059)
tau9	0.016	0.048	-0.213	0.216	0.033	0.073
	(0.045)	(0.111)	(0.376)	(0.272)	(0.037)	(0.055)
tau10	0.031	-0.066	-0.212	0.085	0.058	-0.000
	(0.040)	(0.104)	(0.376)	(0.232)	(0.042)	(0.065)
tau11	0.015	0.014	-0.258	0.084	0.037	0.006
	(0.053)	(0.092)	(0.367)	(0.185)	(0.028)	(0.072)
tau12	0.010	-0.115	-0.581	-0.083	0.007	-0.014
	(0.035)	(0.104)	(0.376)	(0.185)	(0.036)	(0.054)
tau13	-0.043	0.005	-0.458	0.002	-0.094	0.081
	(0.039)	(0.097)	(0.362)	(0.150)	(0.061)	(0.058)
tau14	-0.050	-0.090	-0.652	-0.100	-0.080	0.070
	(0.034)	(0.108)	(0.389)	(0.178)	(0.043)	(0.055)
tau15	-0.074*	-0.062	-0.425	0.035	-0.074	0.101
	(0.037)	(0.095)	(0.363)	(0.166)	(0.056)	(0.057)
tau16	-0.046	-0.065	-0.462	-0.040	-0.060**	-0.046
	(0.032)	(0.108)	(0.391)	(0.198)	(0.022)	(0.062)
tau17	-0.105	-0.045	-0.536	-0.015	0.010	-0.005
	(0.062)	(0.095)	(0.399)	(0.211)	(0.027)	(0.061)
tau18	-0.082*	-0.035	-0.488	-0.143	-0.051	-0.026
	(0.037)	(0.099)	(0.397)	(0.205)	(0.034)	(0.068)
tau19	-0.078	0.018	-0.387	-0.005	-0.009	0.035
	(0.048)	(0.108)	(0.503)	(0.262)	(0.045)	(0.062)
tau20	-0.069	-0.035	-0.501	-0.076	-0.035	0.057
	(0.038)	(0.113)	(0.485)	(0.239)	(0.022)	(0.058)
tau21	-0.028	0.057	-0.405	0.075	-0.081	0.053
	(0.042)	(0.116)	(0.467)	(0.258)	(0.047)	(0.051)
tau22	-0.038	-0.018	-0.747	0.019	-0.006	0.074
	(0.030)	(0.095)	(0.390)	(0.215)	(0.027)	(0.056)
tau23	-0.052*	0.038	-0.461	0.040	-0.044	-0.043
	(0.022)	(0.084)	(0.326)	(0.196)	(0.032)	(0.058)

Table S7. Mood disorders, self-harm, and sucidial ideation

	Mood swing	Mood disorder	Depression	Major dep. disorder	Self-harm	Suicidal ideation
tau24	-0.043	-0.032	-0.602*	0.166	0.050	-0.061
	(0.036)	(0.069)	(0.299)	(0.181)	(0.027)	(0.048)
tau25	-0.046	0.029	-0.358	0.015	0.056*	-0.088
	(0.030)	(0.053)	(0.251)	(0.144)	(0.022)	(0.054)
tau26	-0.032	0.022	-0.340	0.206	0.086*	-0.081
	(0.046)	(0.082)	(0.221)	(0.140)	(0.037)	(0.057)
tau27	-0.011	0.026	-0.128	0.157	0.040	0.012
	(0.036)	(0.086)	(0.299)	(0.201)	(0.036)	(0.064)
tau28	-0.026	0.049	-0.178	0.234	0.081*	-0.058
	(0.024)	(0.083)	(0.173)	(0.128)	(0.035)	(0.051)
tau29	0.029	0.001	-0.092	0.226	0.042	-0.007
	(0.023)	(0.062)	(0.181)	(0.131)	(0.041)	(0.055)
tau30	-0.030	0.106	0.303	0.549*	0.090***	-0.005
	(0.034)	(0.055)	(0.184)	(0.255)	(0.021)	(0.049)
tau31	-0.008	0.081	-0.033	0.446*	0.042	-0.011
	(0.021)	(0.063)	(0.176)	(0.174)	(0.024)	(0.042)
tau32	-0.032	0.097	0.323	0.535***	0.077***	0.005
	(0.037)	(0.062)	(0.245)	(0.151)	(0.022)	(0.056)
tau33	-0.020	0.122*	0.135	0.582***	0.075*	0.049
	(0.013)	(0.059)	(0.195)	(0.108)	(0.029)	(0.050)
tau34	-0.019	0.126*	0.075	0.421***	0.064*	0.024
	(0.028)	(0.057)	(0.162)	(0.094)	(0.031)	(0.050)
tau35	-0.007	0.143**	0.172	0.763***	0.085***	0.074
	(0.026)	(0.051)	(0.180)	(0.170)	(0.024)	(0.044)
tau36	-0.026	0.173**	0.223	0.604*	0.079**	0.083
	(0.034)	(0.065)	(0.171)	(0.235)	(0.026)	(0.046)
tau37	-0.036	0.141	0.182	0.761**	0.060	0.034
	(0.033)	(0.079)	(0.172)	(0.264)	(0.040)	(0.043)
tau38	-0.065	0.171*	0.329	0.670**	0.048	0.075
	(0.042)	(0.078)	(0.188)	(0.235)	(0.039)	(0.046)
tau39	-0.054*	0.293***	0.301	0.754***	-0.013	0.066
	(0.023)	(0.084)	(0.218)	(0.211)	(0.033)	(0.071)
Observations	5196	5199	5199	5199	5199	5199

Table S8. Sleep disorders

	Insomnia	Sleep deprivation	Sleep disorder	Hypersomnia	Excessive daytime sleepiness
tau0	-0.052	-0.013	-0.027	0.000	-0.003
	(0.051)	(0.019)	(0.034)	(0.004)	(0.011)
tau1	0.073	-0.095*	-0.055	0.002	0.037
	(0.051)	(0.042)	(0.054)	(0.005)	(0.021)
tau2	0.142	-0.074	-0.034	-0.001	-0.042
	(0.081)	(0.046)	(0.080)	(0.009)	(0.045)
tau3	0.070	-0.120*	-0.140	-0.010	0.009
	(0.079)	(0.054)	(0.109)	(0.009)	(0.041)
tau4	0.131	-0.024	-0.018	-0.036	-0.040
	(0.089)	(0.065)	(0.128)	(0.019)	(0.060)
tau5	0.085	0.042	-0.005	-0.019	0.005
	(0.073)	(0.053)	(0.132)	(0.015)	(0.032)
tau6	0.018	0.037	0.021	-0.031	0.046
	(0.089)	(0.074)	(0.130)	(0.020)	(0.047)
tau7	-0.049	0.005	-0.110	-0.005	0.057
	(0.106)	(0.045)	(0.134)	(0.013)	(0.039)
tau8	-0.094	-0.066	-0.168	0.008	0.118*
	(0.154)	(0.044)	(0.119)	(0.011)	(0.056)
tau9	-0.205	-0.037	-0.292	0.013	0.102*
	(0.120)	(0.054)	(0.188)	(0.019)	(0.051)
tau10	-0.051	-0.096	-0.257	0.004	0.052
	(0.191)	(0.062)	(0.170)	(0.021)	(0.062)
tau11	-0.103	-0.017	-0.273	-0.003	0.079
	(0.161)	(0.052)	(0.185)	(0.025)	(0.068)
tau12	-0.016	-0.007	-0.189	-0.058**	0.007
	(0.175)	(0.061)	(0.156)	(0.020)	(0.059)
tau13	-0.146	-0.025	-0.154	-0.065***	0.037
	(0.149)	(0.052)	(0.154)	(0.019)	(0.061)
tau14	-0.158	0.006	-0.125	-0.049**	0.026
	(0.160)	(0.073)	(0.156)	(0.018)	(0.057)
tau15	-0.285*	-0.078	-0.247	-0.024	0.046
	(0.132)	(0.057)	(0.139)	(0.021)	(0.054)
tau16	-0.392**	-0.055	-0.192	-0.027	-0.003
	(0.142)	(0.072)	(0.138)	(0.023)	(0.061)
tau17	-0.439***	-0.051	-0.319*	-0.021	0.038
	(0.118)	(0.066)	(0.154)	(0.022)	(0.048)
tau18	-0.311*	-0.094	-0.115	-0.011	-0.010
	(0.131)	(0.078)	(0.135)	(0.029)	(0.054)
tau19	-0.309	-0.024	-0.179	-0.029	-0.007
	(0.201)	(0.092)	(0.183)	(0.021)	(0.076)
tau20	-0.047	-0.070	-0.106	-0.020	0.063
	(0.179)	(0.091)	(0.175)	(0.032)	(0.071)
tau21	-0.127	0.008	-0.133	-0.037	0.055
	(0.176)	(0.083)	(0.162)	(0.019)	(0.076)
tau22	0.162	-0.046	-0.015	-0.033	0.104
	(0.147)	(0.071)	(0.180)	(0.024)	(0.071)
tau23	0.117	0.048	0.060	-0.018	0.113
	(0.141)	(0.076)	(0.133)	(0.013)	(0.068)

Table S8. Sleep disorders

	Insomnia	Sleep deprivation	Sleep disorder	Hypersomnia	Excessive daytime sleepiness
tau24	0.180	-0.066	0.031	-0.023	0.072
	(0.121)	(0.055)	(0.143)	(0.014)	(0.064)
tau25	0.069	0.011	0.149	-0.005	0.069
	(0.142)	(0.067)	(0.086)	(0.011)	(0.065)
tau26	0.313*	-0.065	0.109	-0.003	0.075
	(0.149)	(0.044)	(0.111)	(0.011)	(0.041)
tau27	0.324	-0.007	0.212	0.017	0.073
	(0.167)	(0.041)	(0.128)	(0.020)	(0.050)
tau28	0.401**	-0.003	0.180	-0.002	0.019
	(0.146)	(0.029)	(0.131)	(0.012)	(0.040)
tau29	0.394**	0.034	0.144	0.001	0.044
	(0.140)	(0.039)	(0.119)	(0.016)	(0.044)
tau30	0.566***	0.095	0.313*	-0.006	0.041
	(0.170)	(0.071)	(0.153)	(0.017)	(0.057)
tau31	0.441**	-0.024	0.206	0.009	0.084
	(0.169)	(0.061)	(0.111)	(0.015)	(0.059)
tau32	0.705***	0.048	0.381**	0.011	0.098*
	(0.182)	(0.066)	(0.120)	(0.017)	(0.043)
tau33	0.661***	-0.024	0.327**	0.008	0.144**
	(0.195)	(0.032)	(0.111)	(0.013)	(0.047)
tau34	0.773***	0.036	0.445***	-0.004	0.118**
	(0.205)	(0.051)	(0.131)	(0.017)	(0.045)
tau35	0.814**	0.049	0.425**	0.019	0.167***
	(0.255)	(0.031)	(0.160)	(0.016)	(0.048)
tau36	0.866***	0.112	0.541***	0.030	0.117*
	(0.246)	(0.074)	(0.145)	(0.022)	(0.055)
tau37	0.889***	0.023	0.537***	0.030*	0.146**
	(0.235)	(0.035)	(0.144)	(0.013)	(0.050)
tau38	0.827***	0.095	0.458**	0.029*	0.152*
	(0.197)	(0.051)	(0.140)	(0.014)	(0.065)
tau39	0.830***	0.037	0.489**	0.001	0.119*
	(0.184)	(0.075)	(0.157)	(0.015)	(0.059)
Observations	5199	5199	5199	5123	5198

Table S9. Personality and dissociative disorders

	Avoidant pers. disorder	Paranoia	Compulsive hoarding	Comp. behavior	Depersonalization
tau0	-0.005	-0.007	-0.004	-0.036	-0.005
	(0.005)	(0.012)	(0.012)	(0.023)	(0.003)
tau1	-0.035	-0.028	-0.001	0.036	0.002
	(0.031)	(0.019)	(0.018)	(0.032)	(0.006)
tau2	-0.052	-0.045	-0.006	0.092	-0.016
	(0.030)	(0.030)	(0.015)	(0.047)	(0.010)
tau3	0.000	-0.028	-0.002	0.050	0.002
	(0.039)	(0.039)	(0.014)	(0.043)	(0.022)
tau4	-0.009	0.001	0.002	0.102*	-0.027*
	(0.043)	(0.032)	(0.016)	(0.046)	(0.014)
tau5	0.076	0.040	0.023	0.094*	-0.014
	(0.041)	(0.034)	(0.033)	(0.045)	(0.016)
tau6	0.010	0.094*	-0.023	0.107	-0.001
	(0.032)	(0.038)	(0.028)	(0.058)	(0.028)
tau7	0.066*	0.056	0.026	0.115	-0.006
	(0.030)	(0.033)	(0.034)	(0.066)	(0.024)
tau8	0.048	0.077*	0.009	0.046	0.006
	(0.030)	(0.035)	(0.020)	(0.060)	(0.030)
tau9	0.029	-0.009	0.026	0.007	-0.003
	(0.024)	(0.037)	(0.028)	(0.063)	(0.012)
tau10	0.062***	0.018	0.048	-0.040	-0.001
	(0.019)	(0.023)	(0.025)	(0.065)	(0.012)
tau11	-0.001	0.066	0.032	-0.016	-0.008
	(0.032)	(0.042)	(0.023)	(0.060)	(0.016)
tau12	0.047	-0.019	-0.048*	-0.067	-0.038*
	(0.029)	(0.037)	(0.022)	(0.068)	(0.017)
tau13	0.017	0.063	-0.003	0.021	-0.022
	(0.036)	(0.041)	(0.018)	(0.074)	(0.019)
tau14	0.035	-0.063	-0.059	0.024	-0.045*
	(0.034)	(0.046)	(0.044)	(0.074)	(0.018)
tau15	0.045	0.031	-0.034*	0.044	-0.023
	(0.037)	(0.022)	(0.015)	(0.079)	(0.014)
tau16	0.010	-0.017	0.004	-0.070	-0.036*
	(0.037)	(0.039)	(0.032)	(0.082)	(0.015)
tau17	0.058	0.025	-0.015	-0.039	0.002
	(0.055)	(0.019)	(0.030)	(0.078)	(0.012)
tau18	0.011	-0.025	0.027	-0.071	0.002
	(0.049)	(0.019)	(0.024)	(0.086)	(0.016)
tau19	0.110*	0.020	0.135	0.095	0.000
	(0.047)	(0.038)	(0.122)	(0.088)	(0.021)
tau20	0.035	0.002	0.040	0.036	-0.006
	(0.050)	(0.019)	(0.044)	(0.073)	(0.021)
tau21	0.085*	0.025	0.120	0.065	-0.022
	(0.043)	(0.028)	(0.112)	(0.078)	(0.018)
tau22	0.035	0.035	-0.011	-0.025	-0.038
	(0.060)	(0.027)	(0.017)	(0.069)	(0.020)
tau23	0.011	0.015	-0.000	-0.057	-0.039*
	(0.073)	(0.013)	(0.024)	(0.067)	(0.019)

Table S9. Personality and dissociative disorders

	Avoidant pers. disorder	Paranoia	Compulsive hoarding	Comp. behavior	Depersonalization
tau24	-0.010	0.023	-0.084**	-0.083	-0.053***
	(0.070)	(0.023)	(0.026)	(0.084)	(0.014)
tau25	-0.028	0.024	-0.044*	-0.109	-0.043*
	(0.038)	(0.026)	(0.022)	(0.107)	(0.019)
tau26	-0.004	0.058	-0.040	-0.055	-0.032*
	(0.034)	(0.039)	(0.028)	(0.049)	(0.013)
tau27	0.005	0.032	-0.023	-0.089	-0.017
	(0.032)	(0.039)	(0.017)	(0.055)	(0.023)
tau28	-0.017	0.067**	-0.026	0.048	-0.040
	(0.036)	(0.023)	(0.022)	(0.036)	(0.023)
tau29	-0.027	0.027	-0.024	-0.022	-0.054**
	(0.035)	(0.033)	(0.013)	(0.039)	(0.021)
tau30	-0.006	0.023	-0.056***	0.062	-0.050**
	(0.032)	(0.023)	(0.015)	(0.050)	(0.018)
tau31	-0.035	0.031	-0.002	-0.029	-0.062**
	(0.026)	(0.025)	(0.013)	(0.043)	(0.019)
tau32	-0.033	0.038	-0.054**	0.087	-0.015
	(0.031)	(0.034)	(0.018)	(0.045)	(0.014)
tau33	-0.032	-0.006	-0.015	0.043	-0.025
	(0.034)	(0.031)	(0.011)	(0.048)	(0.015)
tau34	-0.050	0.013	-0.018	0.113	-0.015
	(0.028)	(0.025)	(0.024)	(0.062)	(0.015)
tau35	0.026	-0.008	-0.014	0.012	-0.021
	(0.036)	(0.024)	(0.015)	(0.054)	(0.011)
tau36	-0.032	0.013	0.033**	0.103	-0.025**
	(0.050)	(0.025)	(0.010)	(0.057)	(0.009)
tau37	0.059	0.036	-0.033	0.031	-0.032***
	(0.036)	(0.026)	(0.018)	(0.047)	(0.009)
tau38	-0.010	0.080*	-0.004	0.092	-0.041**
	(0.029)	(0.041)	(0.030)	(0.057)	(0.013)
tau39	0.037	0.062	-0.068**	0.065	-0.057***
	(0.030)	(0.036)	(0.021)	(0.050)	(0.017)
Observations	5171	5189	5162	5199	5095

Table S10. Other disorders

	Sexual dysf.	Erectile dysf.	Binge eating	Attention deficit	Psychosis	Aud. Hall.	Epilepsy
tau0	-0.031	0.016	-0.016	0.088	-0.010	-0.002	0.067
	(0.021)	(0.042)	(0.019)	(0.066)	(0.036)	(0.005)	(0.050)
tau1	-0.027	0.082	-0.007	0.232	0.064	0.010	0.208
	(0.021)	(0.065)	(0.023)	(0.147)	(0.055)	(0.010)	(0.115)
tau2	-0.041	0.005	-0.011	0.264	0.093	-0.015	0.250
	(0.028)	(0.079)	(0.022)	(0.162)	(0.068)	(0.014)	(0.135)
tau3	-0.050	-0.080	-0.031	0.349	0.146	0.019	0.238
	(0.051)	(0.103)	(0.026)	(0.201)	(0.084)	(0.015)	(0.156)
tau4	-0.026	-0.070	-0.003	0.447*	0.146*	-0.022	0.258*
	(0.058)	(0.127)	(0.026)	(0.179)	(0.074)	(0.018)	(0.127)
tau5	0.023	-0.121	0.048	0.632***	0.245***	0.007	0.220*
	(0.058)	(0.104)	(0.032)	(0.185)	(0.069)	(0.011)	(0.111)
tau6	-0.006	-0.175	0.022	0.618***	0.293**	0.003	0.192*
	(0.027)	(0.121)	(0.035)	(0.176)	(0.110)	(0.019)	(0.085)
tau7	0.034	-0.236**	0.085	0.545**	0.266*	-0.001	0.146
	(0.027)	(0.089)	(0.049)	(0.186)	(0.105)	(0.012)	(0.091)
tau8	-0.001	-0.308*	-0.033	0.405	0.261	0.014	-0.044
	(0.029)	(0.128)	(0.049)	(0.208)	(0.153)	(0.009)	(0.086)
tau9	-0.007	-0.220	0.024	0.160	0.156	-0.016	-0.094
	(0.018)	(0.128)	(0.056)	(0.203)	(0.108)	(0.009)	(0.182)
tau10	0.011	-0.246	0.007	0.152	0.005	0.003	-0.155
	(0.020)	(0.147)	(0.060)	(0.224)	(0.082)	(0.009)	(0.147)
tau11	0.028	-0.054	0.042	-0.132	0.024	-0.002	-0.039
	(0.029)	(0.133)	(0.058)	(0.198)	(0.063)	(0.013)	(0.139)
tau12	-0.029	-0.111	0.083	0.007	-0.062	0.000	0.011
	(0.047)	(0.112)	(0.050)	(0.148)	(0.058)	(0.008)	(0.145)
tau13	0.025	-0.107	-0.009	-0.046	-0.029	0.000	0.070
	(0.044)	(0.114)	(0.078)	(0.171)	(0.042)	(0.016)	(0.082)
tau14	-0.083	-0.180	-0.018	0.042	0.096	-0.011	0.172
	(0.054)	(0.153)	(0.057)	(0.142)	(0.059)	(0.013)	(0.103)
tau15	-0.025	-0.272	-0.055	0.100	0.054	-0.021	0.084
	(0.023)	(0.163)	(0.051)	(0.171)	(0.082)	(0.015)	(0.104)
tau16	-0.075	-0.224	-0.018	-0.001	0.083	-0.026	0.142
	(0.041)	(0.160)	(0.057)	(0.156)	(0.079)	(0.022)	(0.092)
tau17	-0.091	-0.358	0.005	-0.029	0.041	-0.021	0.069
	(0.061)	(0.188)	(0.063)	(0.179)	(0.100)	(0.021)	(0.130)
tau18	-0.086*	-0.355*	-0.042	-0.002	-0.059	-0.015	0.029
	(0.037)	(0.165)	(0.066)	(0.207)	(0.071)	(0.025)	(0.103)
tau19	-0.061	-0.296	0.042	0.041	-0.037	-0.017	0.093
	(0.059)	(0.266)	(0.070)	(0.285)	(0.098)	(0.023)	(0.083)
tau20	0.031	-0.165	-0.026	-0.009	-0.042	-0.010	0.196
	(0.059)	(0.222)	(0.060)	(0.289)	(0.099)	(0.021)	(0.125)
tau21	0.080	0.049	0.025	-0.098	-0.030	-0.011	0.316*
	(0.043)	(0.152)	(0.062)	(0.244)	(0.104)	(0.023)	(0.148)
tau22	0.047	0.054	-0.006	-0.121	-0.017	-0.029	0.485*
	(0.031)	(0.116)	(0.050)	(0.138)	(0.050)	(0.022)	(0.230)
tau23	0.037	0.154*	-0.032	-0.114	-0.035	-0.029	0.522**
	(0.047)	(0.066)	(0.051)	(0.108)	(0.083)	(0.018)	(0.186)

Table S10. Other disorders

	Sexual dysf.	Erectile dysf.	Binge eating	Attention deficit	Psychosis	Aud. Hall.	Epilepsy
tau24	0.024	0.015	-0.100	-0.066	-0.058	-0.041***	0.660**
	(0.039)	(0.086)	(0.067)	(0.094)	(0.042)	(0.012)	(0.214)
tau25	-0.003	0.132*	-0.059	-0.007	-0.002	-0.041*	0.629**
	(0.071)	(0.061)	(0.072)	(0.136)	(0.043)	(0.019)	(0.222)
tau26	0.023	0.186	-0.061	0.007	0.078	-0.034*	0.500*
	(0.054)	(0.119)	(0.060)	(0.170)	(0.071)	(0.015)	(0.217)
tau27	0.050	0.143	-0.017	0.167	0.031	-0.025	0.375
	(0.052)	(0.109)	(0.071)	(0.111)	(0.060)	(0.013)	(0.220)
tau28	0.071	0.261	0.048	0.042	0.029	-0.025	0.345
	(0.052)	(0.135)	(0.059)	(0.112)	(0.047)	(0.020)	(0.195)
tau29	0.113	0.039	0.051	0.072	-0.013	-0.023	0.262
	(0.066)	(0.134)	(0.059)	(0.113)	(0.049)	(0.020)	(0.174)
tau30	0.114*	0.266	0.030	0.296	0.125	-0.004	0.528**
	(0.045)	(0.164)	(0.054)	(0.230)	(0.087)	(0.024)	(0.199)
tau31	0.088	0.049	0.037	0.292	0.094	0.020	0.503*
	(0.054)	(0.150)	(0.045)	(0.176)	(0.050)	(0.015)	(0.207)
tau32	0.084	0.208	0.008	0.463**	0.243**	0.003	0.601**
	(0.049)	(0.155)	(0.049)	(0.170)	(0.086)	(0.019)	(0.197)
tau33	0.064	0.114	0.048	0.427**	0.262***	0.053*	0.577***
	(0.044)	(0.140)	(0.047)	(0.151)	(0.071)	(0.022)	(0.161)
tau34	0.113**	0.132	0.063	0.578***	0.278***	0.024	0.501***
	(0.036)	(0.114)	(0.057)	(0.120)	(0.078)	(0.022)	(0.129)
tau35	0.090	0.196	0.077	0.558***	0.267***	0.042*	0.635***
	(0.051)	(0.155)	(0.046)	(0.143)	(0.072)	(0.018)	(0.152)
tau36	0.086	0.147	0.010	0.551**	0.234**	0.026	0.639**
	(0.054)	(0.122)	(0.052)	(0.171)	(0.081)	(0.016)	(0.197)
tau37	0.089	0.141	0.073	0.557**	0.144	0.015	0.745***
	(0.066)	(0.145)	(0.066)	(0.185)	(0.098)	(0.017)	(0.216)
tau38	0.127**	0.016	0.023	0.675***	0.169*	0.006	0.714**
	(0.048)	(0.128)	(0.059)	(0.189)	(0.084)	(0.013)	(0.241)
tau39	0.076	-0.101	0.075	0.734***	0.179*	-0.003	0.822***
	(0.051)	(0.102)	(0.090)	(0.150)	(0.082)	(0.015)	(0.244)
Observations	5199	5199	5197	5199	5199	5105	5199