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COVID-19, lockdowns and well-being: Evidence from Google Trends

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ABSTRACT

The COVID-19 pandemic and government intervention such as lockdowns may severely affect people's mental health. While lockdowns can help to contain the spread of the virus, they may result in substantial damage to population well-being. We use Google Trends data to test whether COVID-19 and the associated lockdowns implemented in Europe and America led to changes in well-being related topic search-terms. Using difference-in-differences and a regression discontinuity design, we find a substantial increase in the search intensity for boredom in Europe and the US. We also found a significant increase in searches for loneliness, worry and sadness, while searches for stress, suicide and divorce on the contrary fell. Our results suggest that people's mental health may have been severely affected by the pandemic and lockdown.

1. Introduction

The COVID-19 pandemic that was declared by the World Health Organization in March 2020 has led governments around the world to take unprecedented responses in an attempt to contain the spread of the virus. At the time of writing, some form of State-imposed lockdown has been applied to the residents of most European countries, including France, Italy, Spain and the United Kingdom. Guided by epidemiological models (Ferguson et al., 2020; Lourenço et al., 2020), the rationale for restricting movement is to save as many lives as possible in the short and medium run. In much of the discourse, the main cost of this confinement has been in terms of the economy. However, while the cost of the pandemic and lockdown on GDP is considerable, there are a number of other potential costs in terms of trust in government, disruption to schooling and population well-being (see the calculations in Layard et al., 2020). We here focus on well-being: joblessness, social isolation and the lack of freedom, which are some of the by-products of lockdown, are all well-known risk factors for mental health and unhappiness (Clark and Oswald, 1994; Leigh-Hunt et al., 2017; Verme, 2009).

There is on-going research tracking the evolution of well-being during the pandemic and lockdown. For example, a team of researchers at University College London has been collecting mental health and loneliness data of a large sample of adults living in the UK since the day of the lockdown. However, to fully assess how the pandemic and lockdown affect population well-being we also require data from before the pandemic and lockdown began. This is not available in much of the existing research, as most of the lockdown dates were unanticipated. Equally, many standard household surveys that would have been in the field around the lockdown date are likely to have been halted.

In this paper, we circumvent this problem by analysing data from Google Trends between January 1st 2019 and April 10th 2020 in countries that had introduced a full lockdown by the end of this period. This produces data on nine Western European countries. We also run a comparable analysis at the State level in the US.

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This is to our knowledge the first study to estimate the impact of lockdown on well-being related searches using Google trends data. As in previous work using Google Trends to successfully predict disease outbreaks (Carneiro and Mylonakis, 2009), tourism flows (Siliverstovs and Wochner, 2018) and trading behaviour in financial markets (Preis et al., 2013), we assume that search indicators provide accurate and representative information about Google Search users' current behaviours and feelings.[3] Furthermore, Google search data shows aggregate measures of search activity in a location (e.g. a State or Country), and is thus less vulnerable to small-sample bias (Baker and Fradkin, 2017).

Our main results come from a Difference-in-Difference (DiD) estimation that compares well-being related searches pre- and post-lockdown in 2020 to well-being related searches pre- and post- the same date in 2019, thus ensuring that seasonal changes within countries or State do not drive our findings. As set out in our pre-analysis plan (OSF; https://osf.io/4ywjc/), we submitted the following well-being related topic search-terms to Google Trends: Boredom, Contentment, Divorce, Impairment, Irritability, Loneliness, Panic, Sadness, Sleep, Stress, Suicide, Well-being and Worry. We have daily data on searches for all of these. This allows us to estimate not only the effect of lockdown on well-being, but also to see whether the intensity of searches changes with the duration of lockdown.

Our findings indicate that people's mental health may have been severely affected by the pandemic and lockdown. There is a substantial increase in the search intensity for boredom, at two times the standard deviation in Europe and over one standard deviation in the US. We also find a significant increase in searches for loneliness, worry and sadness: these estimated coefficients are over one half of a standard deviation in Europe, but lower in the US. Applying an event study approach, we see evidence of mean-reversion in some of these measures, perhaps reflecting individuals' hopes that the lockdown will only be relatively short. Nevertheless, the pandemic and lockdown effects on boredom and worry have not dissipated over time, and have shown a gradual increase throughout the period.

Our study contributes to a growing literature documenting the impacts of COVID-19 lockdowns (e.g., Briscese et al., 2020; Brodeur et al., 2020a; Brooks et al., 2020; Fang et al., 2020),[4] and more generally the economic consequences of COVID-19 (e.g., Alon et al., 2020; Béland et al., 2020; Berger et al., 2020; Fetzer et al., 2020; Jones et al., 2020; Jordá et al., 2020; Ramelli et al., 2020; Stephany et al., 2020; Stock, 2020).[5] We contribute to this literature by focusing on the mental health consequences of restriction, using search data from both pre- and post-lockdown announcement for our analysis.

The remainder of the paper is structured as follows. Section 2 describes the data for the analysis and Section 3 presents the empirical approach. The estimation results then appear in Section 4. Last, Section 5 concludes.

2. Data

2.1. Google Trends data

Google Trends data provides an unfiltered sample of search requests made to Google. It supplies an index for search intensity by topic over the time period requested in a geographical area. This is the number of daily searches for the specified topic divided by the maximum number of daily searches for this topic over the time period in question in that geographical area. This is scaled from zero to 100, where 100 is the day with the most searches for that topic and zero indicates that a given day did not have sufficient search volume for the specific term.

A search-term query on Google Trends returns searches for an exact search-term, while a topic query includes related search-terms (in any language). For our project, we submitted the thirteen following well-being related topic search-terms to Google Trends between January 1st 2019 and April 10th 2020: Boredom, Contentment, Divorce, Impairment, Irritability, Loneliness, Panic, Sadness, Sleep, Stress, Suicide, Well-being, and Worry.

We tried to choose topics that are as close as possible to the different items in the General Health Questionnaire. We unfortunately could not choose searches that matched all of the questions in the GHQ.[6]

Daily data on searches is only provided for a query period shorter than 9 months and up to 36 h before the moment that the search request is made. Weekly data is provided for query periods between 9 months and 5 years. To obtain daily search trends between January 1st 2019 and April 10th 2020, we first downloaded daily data between January 1st and April 10th in both 2019 and 2020. As the daily data in 2019 comes from a separate request to the daily data in 2020, the scaling factors used to calculate the 0–100 score are not the same in the two periods. We therefore need to re-scale the two series so that they are comparable.[7]

2.2. Scaling procedure

Let us denote by $D_{i,c,2019}$ the number of Google daily searches for a topic on day i in country c, over the period January 1st 2019 to April 10th 2019, with an analogous number $D_{i,c,2020}$ for the period January 1st 2020 to April 10th 2020. This data is obtained for each individual day i and takes on values between 0 and 100 for each day during the period considered (either January 1st 2019 to April 10th 2019, or January 1st 2020 to April 10th 2020). We cannot however directly compare the numbers from 2019 and 2020 as their denominator (the maximum number of searches during one day in the period) is not the same. A figure of 40, say, during the 2019 period may well reflect fewer searches than a figure of 35 in the 2020 period. To be able to compare these figures, we rescale the daily data for each period by the respective week search interest weights that we calculate using weekly data that is available continuously over the entire period between January 1st 2019 and April 10th 2020.

We denote by $D_{i,c,2019-2020}$ the rescaled number of Google daily searches for this topic on day i in country c over the period January 1st 2019 to April 10th 2020. This is the number we wish to calculate. The following describes the calculation that allows us to obtain this figure and so make inter-day comparisons over the entire period.

We first calculate the respective weekly search interest weights for all weeks between January 1st 2019 and April 10th 2020. We take the daily data from January 1st 2019 to April 10th 2019 and aggregate them to calculate the weekly average searches for the topic in country c over this period: $\overline{D_{i,c,2019}}$. We then carry out the

[3] Askitas and Zimmermann (2009) provide evidence of a strong correlation between Online searches and unemployment rates using monthly German data.

[4] See Brodeur et al. (2020b) for a literature review.

[5] A related contribution is Hamermesh (2020), which uses data from the 2012–13 American Time Use Survey to show that happiness is correlated with both the people with whom the respondent spends time and how this time is spent.

[6] A growing number of studies rely on sentiment analysis to build indicators of well-being (e.g., Hills et al., 2019). Settanni and Marengo (2015) provide evidence that individuals with higher levels of depression, anxiety expressed negative emotions on Facebook more frequently. Their list of words on Facebook resembles our list of topics. See Durahim and Coşkun (2015) for an example of a study looking at well-being using Twitter.

[7] Note that our figures are normalised within each country and then weighted to Western Europe (or the US).

same exercise for the period January 1st 2020 to April 10th 2020: $\overline{D_{i,c,2020}}$.

From the weekly data downloaded over the entire period (i.e., from January 1st 2019 to April 10th, 2020), we also observe: $\overline{D_{i,c,2019-2020}}$. From the above, we obtain the respective weekly search interest weights, $w_{c,2019}$ and $w_{c,2020}$:

$$w_{c,2019} = \frac{\overline{D_{i,c,2019-2020}}}{\overline{D_{i,c,2019}}} \quad \text{and} \quad w_{c,2020} = \frac{\overline{D_{i,c,2019-2020}}}{\overline{D_{i,c,2020}}}$$

Using these weekly search interest weights, we can now rescale the daily data for each separate period by multiplying $D_{i,c,2019}$ by $w_{c,2019}$ in 2019, and $Di, c, 2020$ by $w_{c,2020}$ in 2020. We obtain:

$$D_{i,c,2019-2020} = D_{i,c,2019} * \frac{\overline{D_{i,c,2019-2020}}}{\overline{D_{i,c,2019}}} \qquad \text{in 2019}$$

$$\text{and } D_{i,c,2019-2020} = D_{i,c,2020} * \frac{\overline{D_{i,c,2019-2020}}}{\overline{D_{i,c,2020}}} \qquad \text{in 2020}$$

Last, we normalize these figures to obtain figures between 0 and 100, replacing $D_{i,c,2019-2020}$ by:

$$D*_{i,c,2019-2020} = \frac{D_{i,c,2019-2020}}{max(D_{i,c,2019-2020})} * 100$$

2.3. Sample selection

We collected these search data for countries that had introduced a full lockdown by the end of the period considered. This produces data on nine Western European countries: Austria, Belgium, France, Ireland, Italy, Luxembourg, Portugal, Spain and the United Kingdom. We also run a comparable analysis at the State level in the US. Appendix Figure A1 and Appendix Table A1 provide the date of lockdown for each of the countries and US States in our analysis.

The use of Google Trends data presents a number of key advantages over survey data. First, the data are not self-reported by a sub-sample of respondents, but rather capture the impact of lockdown on the behaviours of all Google Search users. Furthermore, Google Trends data do not suffer from biases such as the observer-expectation effect or interviewer bias. Third, Google Trends data are less vulnerable to small-sample bias. However, Google Trends data obviously have limitations. One of these is that younger individuals are relatively more likely than older individuals to use Google Search (although internet use is widespread in Europe, with 89% of EU-28 households having home internet access in 2018, from Eurostat Digital economy and society statistics). Another limitation is that we cannot look at heterogenous effects of lockdown by demographic groups, and especially on the most vulnerable populations. Our results should thus be read as the average impact of the stay-at-home orders on the health and well-being of Google Search users, rather than the effect on people with, say, pre-COVID-19 mental-health disorders. Last, lockdown policies could in theory change what people Google without changing their well-being or mental health. For instance, individuals under lockdown may now have more free time spent at the computer.

3. Identification strategy

3.1. Difference-in-differences estimators of lockdown effects

To estimate the joint effect of the COVID-19 pandemic and associated lockdown on well-being related searches, we rely on a Difference-in-Differences (DiD) estimation that compares searches pre- and post-lockdown in 2020 to searches pre- and post- the same date in 2019, thus ensuring that seasonal changes within countries or States are not behind our findings.

The lockdown date in our analysis is the date at which the lockdown was announced, not the implementation date, as we imagine that the psychological effects of the lockdown may have started to become apparent as soon as the policy was announced to the public.[8]

We write the difference-in-differences regression model for a topic W as:

$$W_{i,c} = \alpha T_{i,c} * Year_i + \beta T_{i,c} + \gamma X_{i-1,c} + \mu_i + \rho_c + \epsilon_{i,c} \tag{1}$$

where α reflects the effect of the lockdown on Google searches for topic $W_{i,c}$ on day i in country or State c. $T_{i,c}$ is a dummy that takes value one in the days after the stay-at-home order was announced and is zero beforehand. The year of the lockdown is $Year_i$ and corresponds to 2020. The model includes country or State fixed effects, ρ_c, as well as year, week and day (Monday to Sunday) fixed effects that appear in the vector μ. The identification strategy in Eq. (1) thus relies on first the fact that the dates at which lockdown was announced differed between countries or States, and second the comparison within-country or State of the Google search intensity for topic W before and after the lockdown announcement in 2020 to the difference in search intensity for the same topic pre- and post- the same lockdown announcement date in 2019. The standard errors are robust and are clustered at the day level.

The variable $X_{i-1,c}$ controls for the lagged number of new deaths of COVID-19 per day per million in country or State c. One limitation of our study is that the lockdown is possibly closely associated with an individual's awareness of the COVID-19 pandemic. For instance, individuals may engage in social distancing for other reasons than the lockdown policy which could lead to loneliness and decreased well-being.

Our key assumption is that, in the absence of lockdown, Google users' behaviors would have evolved in the same way as in the year prior to the lockdown, i.e. a common-trend assumption. This assumption will be violated if the countries or States that have implemented a full lockdown have experienced specific shocks that are different to those in the previous year.

3.2. RDD-DID estimators of lockdown effects

To test for the immediate structural break caused by the lockdown, we also adopt a regression discontinuity design (RDD), which identifies potential breaks in two parametric series estimated pre- and post-lockdown. As with the DiD estimates, we compare these breaks to those estimated over the same period in 2019 (an RDD-DiD estimation). These estimated breaks are depicted in Appendix Figures A2 and A3 for 2020 and 2019.

Let the running variable be D, which is defined as the absolute distance in days from the stay-at-home order announcement; it is negative for the days before and positive for the days after, while the date of the actual or counterfactual announcement is set as day zero (and dropped from the empirical model, as is standard). The lockdown announcement $T_{i,c}$ is defined as above. The RDD-DiD model can be written as follows:

$$\begin{aligned} W_{i,c} = {} & \alpha' T_{i,c} * Year_i + \psi f(D_{i,c}) * T_{i,c} * Year_i + \theta f(D_{i,c})(1 - T_{i,c}) \\ & * Year_i + \phi f(D_{i,c}) * T_{i,c} + \lambda f(D_{i,c})(1 - T_{i,c}) + \beta' T_{i,c} \\ & + \gamma' X_{i-1,c} + \mu'_i + \rho'_c + \epsilon'_{i,c} \end{aligned} \tag{2}$$

where α' reflects the effect of the lockdown on Google searches for topic $W_{i,c}$ on day i in country or State c. $f(D_{i,c})$ is a polynomial

[8] Appendix Table A2 shows that we obtain qualitatively-similar results when we instead use the implementation date as the cut-off.

function of the distance in days from the lockdown announcement interacted with the lockdown variable $T_{i,c}$, to allow for different effects on either side of the cutoff. Our regression analyses use polynomials of order one. We include the same controls as in the DID models.

3.3. Additional robustness checks

Finally, we conduct a number of additional robustness checks for the main DiD estimates, including using the date of implementation instead of the date of announcement, estimating the results splitting our samples into early and late lockdowns, and including countries with partial lockdowns in the analysis. We also estimate an event study model to test for any adaptation effects to the lockdown.

The event study model can be written as follows:

$$W_{i,c} = \sum_{k=-3}^{k=4} \alpha''_k E_{k,c} * Year_i + \sum_{k=-3}^{k=4} \beta''_k E_{k,c} + \gamma'' X_{i-1,c} + \mu''_i + \rho''_c + \epsilon''_{i,c} \qquad (3)$$

where $E_{k,c}$ are dummy variables for the three weeks before the lockdown announcement and the four weeks after the lockdown announcement (interacted with the dummy variable $Year_i$ for year 2020). The fourth week before the lockdown announcement (in 2019 and 2020) is the reference period. The estimated coefficients on the $E_{k,c}$ dummies should therefore be interpreted as the effect of being in (for example) the third week after the lockdown announcement ($E_{3,c}$) as compared to four weeks before it.

4. Results

4.1. Graphical analysis

We begin our analysis by comparing the raw data searches pre- and post-lockdown in 2020 to those pre- and post- the same date in 2019. Fig. 1 plots daily search activity for three of our search topics: boredom, loneliness and sadness. The results for all topics appear in Appendix Figure A4. Searches for boredom in Europe experienced a sharp increase around the announcement date in

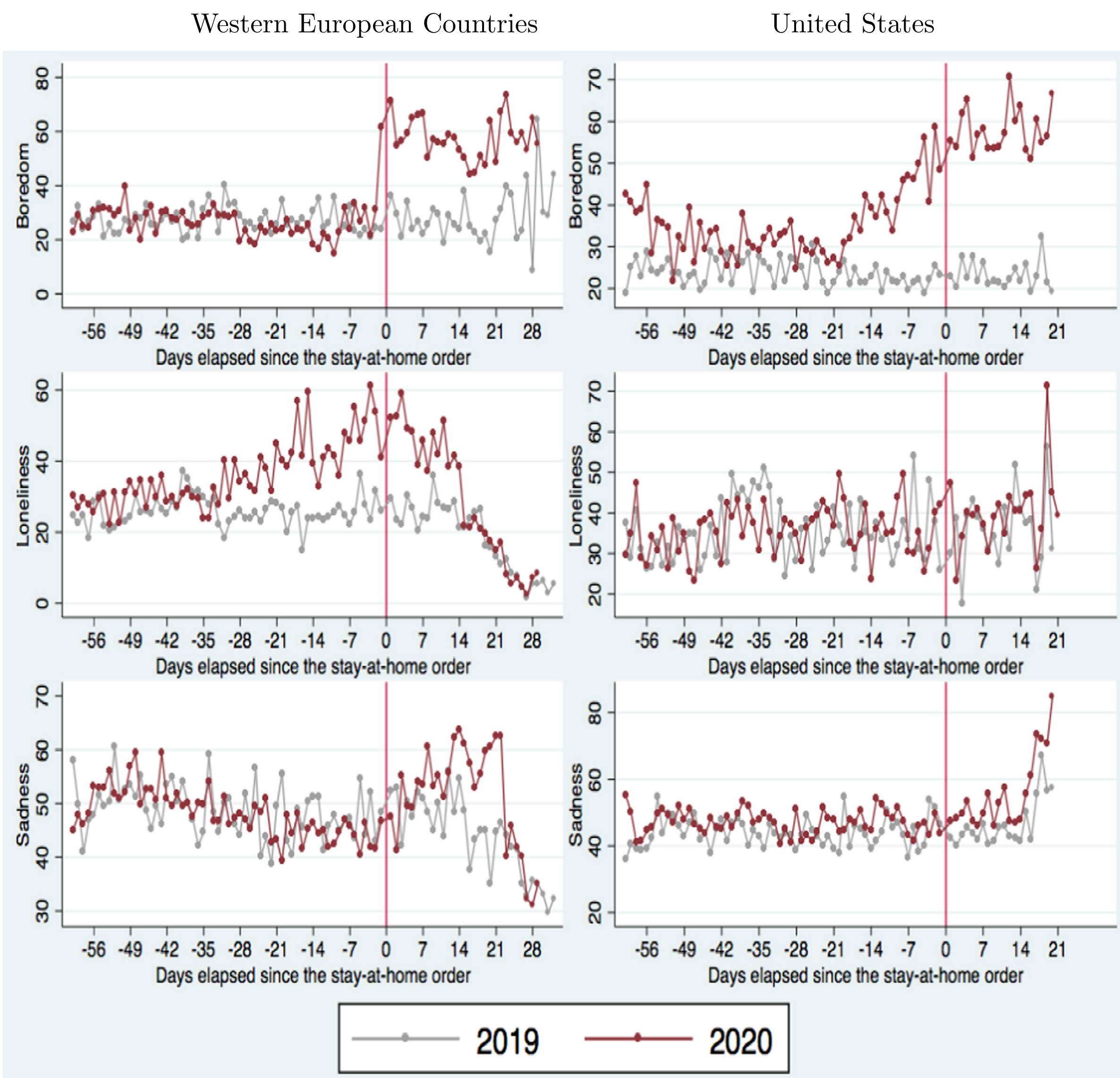

Fig. 1. Google Trends in boredom, loneliness and sadness before and after the stay-at-home orders. The vertical axis shows the average searches (on a scale from 0 to 100) in the days before (negative values) and after (positive values) the stay-at-home order was announced (set equal to day zero) in 2020 (red dots) and the same date in 2019 (grey dots) for nine European countries (left) and 42 US States (right). The eight US States without a lockdown are excluded from the analysis. The dots correspond to the raw averages by bins of one day, weighted by the number of inhabitants per country/State. The European countries included are: Austria, Belgium, France, Ireland, Italy, Luxembourg, Portugal, Spain and the UK.

2020, while in the US, where the lockdown started later, they began to rise about ten days before the announcement date. This pattern is only seen in 2020, with no sharp changes on the same date in 2019 in either sample. There was a noticeable increase in searches for loneliness in Europe following the lockdown announcement, but not in the US. On the other hand, searches regarding sadness increased in both samples around one to two weeks after the lockdown.

Why do certain search topics - such as boredom in the US - register an uptick in the days before the lockdown announcement? One explanation is that a partial lockdown, which includes school and venue closures, may have already been implemented in these countries (or in some sub-regions within the US State) days before the full lockdown date was announced. It may also reflect people's anticipation of the impending lockdown date based on their observation of areas that had entered lockdown earlier, or the effect of the developing pandemic itself. Last, it may be due to the severity of the pandemic.

4.2. Difference-in-differences estimation results

To gauge the size of the estimated effects, Fig. 2 depicts the Difference-in-Difference (DiD) estimates (the actual numbers appear in Tables 1 and 2). The top and bottom panels refer respectively to Europe and the US. Our lockdown variable is associated with a significant rise in search intensity for boredom in both Europe and the US. The estimates are statistically significant at the 1% level. We also found a significant increase in searches for loneliness, worry and sadness. The effect size for boredom is large, at two times the standard deviation in Europe and over one standard deviation in the US. The loneliness and worry coefficients are over one half of a standard deviation in Europe, but lower in the US. These can be compared to the estimated standard-deviation effect of 9/11 on mental health of 0.1 to 0.3 (Tsai and Venkataramani, 2015) and depression of 0.5 (Knudsen et al., 2005) in the US, and an effect on psychological well-being in the UK of 0.07 (Metcalfe et al., 2011). The Boston Bombing had an estimated effect on happiness and net affect of one-third of a standard deviation (Clark et al., 2020).

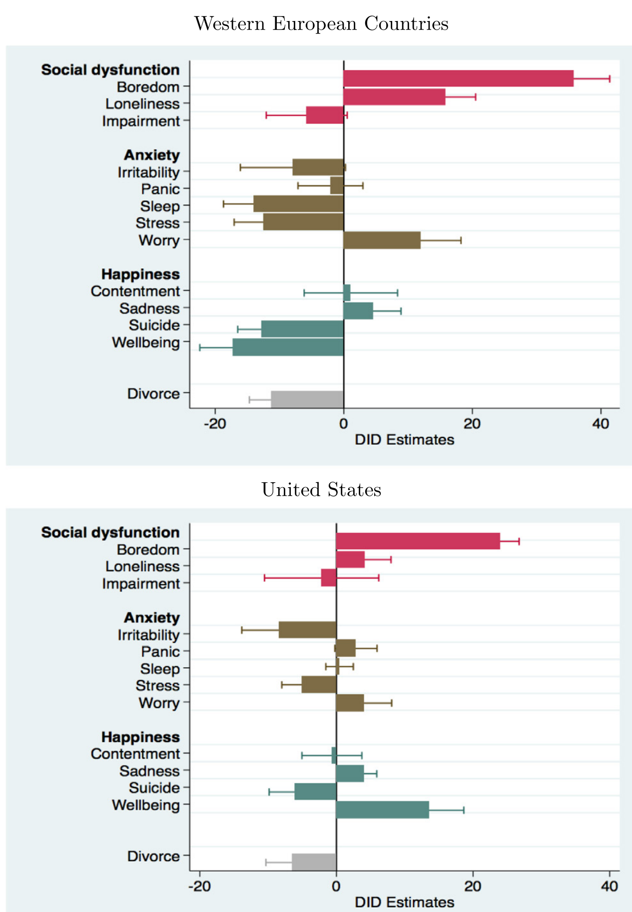

Fig. 2. The effects of the stay-at-home orders on well-being. Each bar represents Differences-in-Differences estimates using the 2019 period as a counterfactual. All models control for a dummy that takes the value of 1 in the days after the stay-at-home order was announced, as well as country/State, year, week, day of the week fixed effects and the one-day lagged number of new deaths from Covid-19 per million. Weights are applied. Robust standard errors are plotted. Standard errors are clustered at the day level.

We also see noticeable, and statistically significant, drops in stress, suicide and divorce in both samples.[9] We found no discernible effect on impairment, and an effect on sleep only in Europe.

Strikingly, we document a positive effect on the search intensity for the topic of well-being in the US but a negative effect in Europe. This could reflect the date at which lockdown was implemented. When we split Europe into early and late lockdowns (this latter group is composed of Ireland, Portugal and the UK), we do indeed find a positive well-being effect of lockdown in this latter group. In general, the effect of lockdown on our measures of well-being is often more positive in countries with a later lockdown (Appendix Figure A5). Similar conclusions are reached when we use the implementation date as the cut-off (see Appendix Table A4). Those entering later lockdowns may be less stressed as they have seen the public-health benefits in the countries that entered lockdown earlier.

4.3. Event study results

Is there evidence of adaptation to the pandemic and lockdown? The event study depicted in Fig. 3 shows that searches for boredom continued to be higher throughout the lockdown period. Loneliness increased briefly at lockdown announcement before dropping back towards zero in both samples. There was also a gradual increase in sadness after the lockdown. The event-study results for all of our variables are depicted in Appendix Figure A4, with the estimated coefficients appearing in Appendix Table A3.

4.4. Results from combined RDD and difference-in-differences

To test for the immediate structural break caused by the lockdown, we also adopted a regression discontinuity design (RDD), which identifies potential breaks in two parametric series estimated pre- and post-lockdown. As with the DiD estimates, we compare these breaks to those estimated over the same period in 2019 (an RDD-DiD estimation). These estimated breaks are depicted in Appendix Figures A2 and A3 for 2020 and 2019, and the estimated coefficients are listed in Appendix Table A4. These immediate effects are consistent with those in the event studies: the immediate effect of lockdown was to increase boredom and impairment, reduce panic, but to have little short-run impact on stress, sadness, suicide or worry. DiD and RDD-DiD measure different lockdown effects. The former compares all pre-lockdown observations to all post-lockdown observations, whereas RDD-DiD picks up the immediate effect in the few days around lockdown announcement. This difference is evident in the event-study results in Fig. 3.

[9] See the following Guardian article for a brief discussion about suicide falling in Japan in April, under lockdown: https://www.theguardian.com/world/2020/may/14/japan-suicides-fall-sharply-as-covid-19-lockdown-causes-shift-in-stress-factors.

Table 1
The Effects of Stay-at-Home-Orders - DiD Estimates (Fig. 2.) Western European Countries.

Panel A	Boredom	Contentment	Divorce	Impairment	
T_i,c*Year_i	35.80***	1.10	−11.26***	−5.77	
	(3.35)	(4.37)	(2.06)	(3.79)	
Country FE	Yes	Yes	Yes	Yes	
Year, Week and Day FE	Yes	Yes	Yes	Yes	
Death	Yes	Yes	Yes	Yes	
Observations	1441	1078	1624	643	
Panel B	Irritability	Loneliness	Panic	Sadness	
T_i,c*Year_i	−7.91	15.87***	−2.07	4.61*	
	(4.92)	(2.79)	(3.04)	(2.58)	
Country FE	Yes	Yes	Yes	Yes	
Year, Week and Day FE	Yes	Yes	Yes	Yes	
Death	Yes	Yes	Yes	Yes	
Observations	679	1422	1445	1615	
Panel C	Sleep	Stress	Suicide	Wellbeing	Worry
T_i,c*Year_i	−14.01***	−12.49***	−12.80***	−17.28***	12.04***
	(2.83)	(2.75)	(2.23)	(3.09)	(3.72)
Country FE	Yes	Yes	Yes	Yes	Yes
Year, Week and Day FE	Yes	Yes	Yes	Yes	Yes
Death	Yes	Yes	Yes	Yes	Yes
Observations	1745	1638	1653	1418	1193

Notes: This table shows differences-in-differences estimates. The models include controls for a dummy that takes value 1 in the days after the stay-at-home order was announced, as well as country, year, week, day fixed effects and the one-day lagged number of new deaths from Covid-19 per million. Weights are applied. Robust standard errors are in parentheses. Standard errors are clustered at the day level.

Table 2
The Effects of Stay-at-Home-Orders - DiD Estimates (Fig. 2.) United States.

Panel A	Boredom	Contentment	Divorce	Impairment	
T_i,c*Year_i	24.04***	−0.66	−6.53***	−2.17	
	(1.63)	(2.64)	(2.29)	(5.03)	
State FE	Yes	Yes	Yes	Yes	
Year, Week and Day FE	Yes	Yes	Yes	Yes	
Death	Yes	Yes	Yes	Yes	
Observations	6871	2473	9049	741	
Panel B	Irritability	Loneliness	Panic	Sadness	
T_i,c*Year_i	−8.37**	4.15*	2.86	4.09***	
	(3.29)	(2.31)	(1.85)	(1.09)	
State FE	Yes	Yes	Yes	Yes	
Year, Week and Day FE	Yes	Yes	Yes	Yes	
Death	Yes	Yes	Yes	Yes	
Observations	1846	4311	6727	8387	
Panel C	Sleep	Stress	Suicide	Wellbeing	Worry
T_i,c*Year_i	0.47	−5.04***	−6.09***	13.65***	4.12*
	(1.21)	(1.78)	(2.26)	(3.00)	(2.39)
State FE	Yes	Yes	Yes	Yes	Yes
Year, Week and Day FE	Yes	Yes	Yes	Yes	Yes
Death	Yes	Yes	Yes	Yes	Yes
Observations	9445	6027	9029	3159	5938

Notes: This table shows shows differences-in-differences estimates. The models include controls for a dummy that takes value 1 in the days after the stay-at-home order was announced, as well as State, year, week, day fixed effects and the one-day lagged number of new deaths from Covid-19 per million. Weights are applied. Robust standard errors are in parentheses. Standard errors are clustered at the day level.

4.5. Robustness checks

Our results represent the estimated effects for countries with a full lockdown. But what about countries such as Germany, the Netherlands and Switzerland where there have only been partial lockdowns (Appendix Table A1)? We can include these countries in the analysis to see if any lockdown is equivalent to full lockdown. Appendix Figure A7 compares our main results (in blue) to those for any lockdown (in red). The two figures are similar. We also repeat the same exercise for the US, where there was a partial

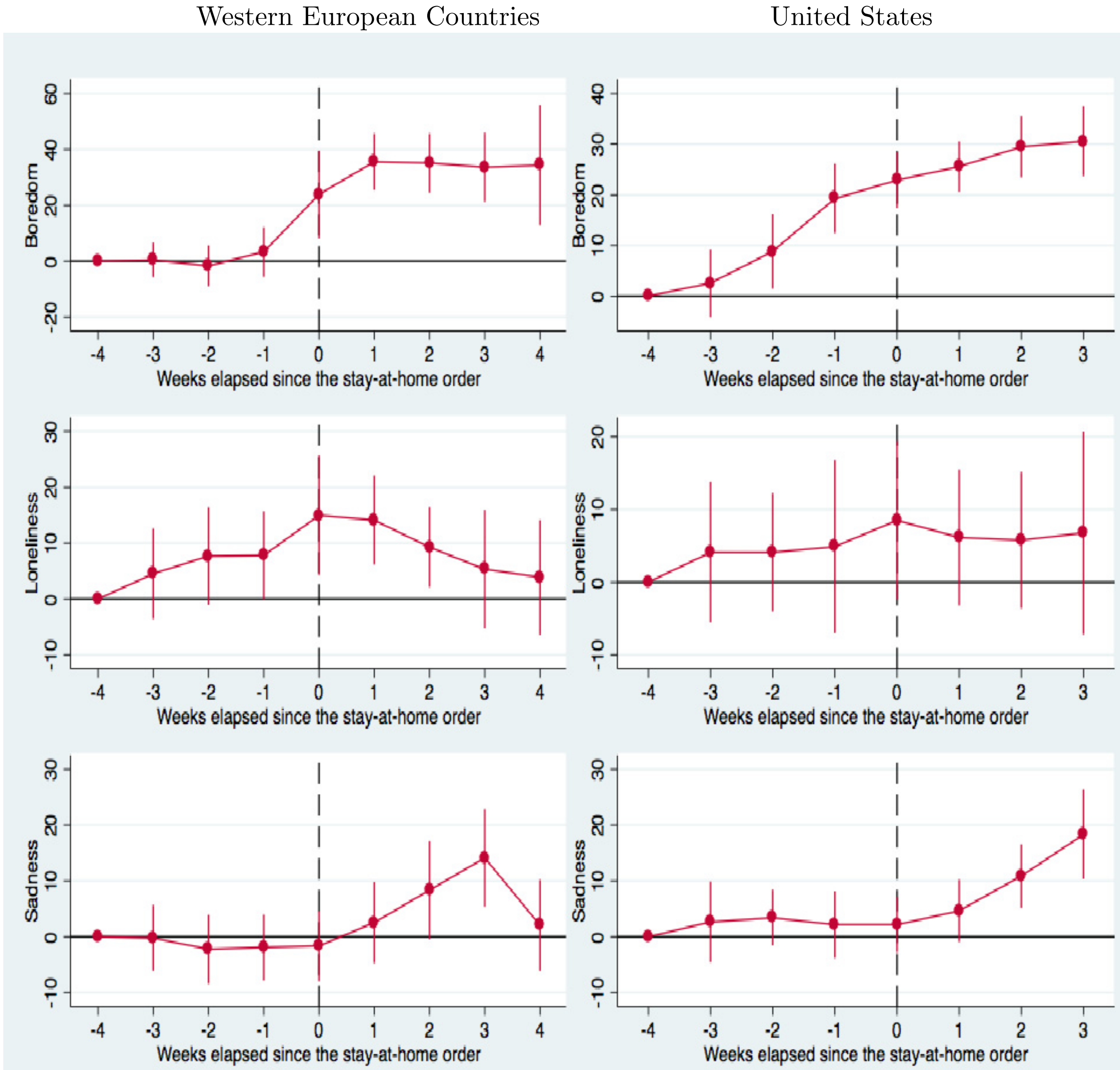

Fig. 3. Duration of the effects of the stay-at-home orders on boredom, loneliness and sadness. The vertical axis shows event-study estimates using the 2019 period as the counterfactual. The 4th week before the stay-at-home-order (in 2019 or 2020) is the reference period. The models include dummies for each week from three weeks before to four weeks after the stay-at-home order. Controls: country/State, year, week, day of the week fixed effects as well as the one-day lagged number of new deaths from Covid-19 per million. Weights are applied. Robust standard errors are plotted. Standard errors are clustered at the day level.

lockdown in some cities and counties before the implementation of a full lockdown at the State level. Appendix Figure A8 shows the results when we use the date of the first partial lockdown rather than the date of the full State lockdown. As was the case in Europe, there are only small differences in the estimated DiD coefficients. Any announcement of lockdown has substantial effects on a number of measures of well-being.

5. Conclusion

Our use of Google Trends to assess the well-being impacts of the pandemic and lockdown has important policy implications. Despite the clear message from the government that we should all stay at home to save lives, the evidence of a substantial increase in the search intensity on boredom, sadness, loneliness and worry post-lockdown suggests that people's mental health has been adversely affected during the first few weeks of lockdown.

We see evidence of mean-reversion in some of these measures, perhaps reflecting individuals' hopes that the lockdown will only be relatively short. Nevertheless, the lockdown effects on boredom and worry have not dissipated over time, and more generally well-being in the first few weeks of lockdown may be only a poor guide to its level after one or two months: we may see accumulated "behavioural fatigue" (Sibony, 2020) as individuals grow increasingly tired of self-regulating as time passes, which is an issue that is becoming more relevant again now that many countries are currently going through a second wave of the pandemic. To avoid social unrest, it may be necessary to emphasize the health benefits of lockdown (including preparation for testing and tracing after release to avoid a second wave), and make sure that appropriate support is provided to help those struggling the most with lockdown, starting with the younger generations (Oswald and Powdthavee, 2020).

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jpubeco.2020.104346.

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