

The coronavirus outbreak has caused significant disruptions to people's lives. We exploit variation in lockdown measures across states to document the impact of stay-at-home orders on mental health using real-time survey data in the United States. We find that the lockdown measures lowered mental health by 0.083 standard deviations. This large negative effect is entirely driven by women. As a result of the lockdown measures, the existing gender gap in mental health has increased by 61%. The negative effect on women's mental health cannot be explained by an increase in financial worries or caring responsibilities.

JEL codes: I10, I14, I18, I30

—Abi Adams-Prassl, Teodora Boneva, Marta Golin and Christopher Rauh

The impact of the coronavirus lockdown on mental health: evidence from the United States

Abi Adams-Prassl, Teodora Boneva, Marta Golin and Christopher Rauh* 

University of Oxford, UK; University of Bonn, Germany; University of Zurich, Switzerland; Trinity College, University of Cambridge, UK

1. INTRODUCTION

The outbreak of the Covid-19 pandemic has caused significant disruptions to people's lives. To slow the spread of the disease, lockdown measures have been put in place that limit people's ability to leave their homes and interact with others. How these measures impact people's mental health is a major public health concern.

* Ethics approval was obtained from the Central University Research Ethics Committee (CUREC) of the University of Oxford: ECONCIA20-21-09. We are grateful to seminar participants at the University of Warwick, the two discussants and participants at the 73rd Economic Policy Panel Meeting and two anonymous referees for their valuable comments, the Economic and Social Research Council, the Social Sciences and Humanities Research Council of Canada, the University of Oxford, the University of Zurich, the Keynes Fund and the Cambridge INET for generous financial support and Marlis Schneider for excellent research assistance.

The Managing Editor in charge of this paper was Jerome Adda, guest editor of the special issues on the Economics of Covid-19.

We study the impact of state-wide stay-at-home orders on mental health in a large sample of the economically active population in the United States. We use three waves of geographically representative survey data collected in the United States in March, April and May 2020, with a total of 12,010 respondents. While at the time of our first survey wave, only 13 states had stay-at-home orders in place, this number rose to 40 by the time we ran our April survey. By end of May 2020, 24 states had eased the stay-at-home orders. We exploit this cross-sectional variation in the implementation of stay-at-home orders to study the effect of these measures on mental health. To measure mental health, we administer the WHO five-question module, which is a validated mental health measure that has been used in a variety of different contexts (see, e.g., [Bech et al., 2003](#); [Krieger et al., 2014](#); [Downs et al., 2017](#)).

Several findings emerge from our study. First, state-wide stay-at-home orders led to a significant reduction in self-reported mental health. By mid-April, the mental health scores of individuals living in states with stay-at-home orders in place were 0.083 standard deviations lower than the mental health scores of individuals in states that had not issued such orders (p -value = 0.012). We perform placebo tests to rule out that individuals in states that issued such orders had systematically different mental health scores at baseline. Focusing on the subset of states which had not introduced lockdown measures in late March, we find no significant differences in mental health scores between states that were to introduce such measures by mid-April and those that did not introduce them. By mid-April, however, we clearly see the gap in mental health scores emerging. When we pool all three survey waves and exploit changes in lockdown status over time, we similarly find a significant negative impact of being in lockdown on self-reported mental health.

Second, the impact of state-wide stay-at-home orders on mental health varies significantly by gender. By mid-April, as a result of the stay-at-home orders, the gender gap in mental health increased from 0.21 to 0.34 standard deviations, constituting a 61% increase in the mental health gender gap. Surprisingly, we find that the significant negative impact of state-wide stay-at-home orders on mental health scores is *entirely* driven by women. The estimated impact of stay-at-home orders on women's self-reported mental health is -0.123 standard deviations (p -value = 0.011), while the estimated impact on men's mental health is close to zero and insignificant. We rule out a number of potential mechanisms that could explain the negative impact of stay-at-home orders on women's mental health. The negative health impacts can neither be explained by an increase in financial worries nor by an increase in childcare responsibilities nor by the local number of Covid-19 cases or deaths (per capita).

This paper relates to several strands of the literature. First, it contributes to the literature studying the effect of economic downturns on mental disorders (see, e.g., [Chang et al., 2013](#); [Dagher et al., 2015](#); [Frasquilho et al., 2015](#); [Reibling et al., 2017](#)). Second, it contributes to the large literature documenting gender gaps in mental health (e.g., [Astbury, 2001](#); [Seedat et al., 2009](#); [Stevenson and Wolfers, 2009](#)). Finally, it contributes to the emerging literature studying the impact of the pandemic on well-being and

mental health (Armbruster and Klotzbücher, 2020; Béland *et al.*, 2020; Brooks *et al.*, 2020; Fancourt *et al.*, 2020; Pierce *et al.*, 2020; Huebener *et al.*, 2021; Giuntella *et al.*, forthcoming).¹ We contribute to this literature by documenting how state-wide stay-at-home orders implemented to slow the spread of the Covid-19 pandemic impact of men's and women's self-reported mental health. Closest to our study is recent work by Banks and Xu (2020), Etheridge and Spantig (2020) and Proto and Quintana-Domeque (2021) on the effect of the Covid-19 outbreak on mental well-being in the United Kingdom. Consistent with our findings, Banks and Xu (2020) and Etheridge and Spantig (2020) document that the pandemic has brought about a severe decline in well-being, with the negative effects being disproportionately borne by women. Proto and Quintana-Domeque (2021) also document a widening gender gap among white British individuals. While in the United Kingdom, the lockdown measures were introduced in all regions at the same time, this was not the case in the United States, allowing us to exploit the variation across states.

2. DATA

To study the impact of state-wide stay-at-home orders on mental health, we collect real-time survey data on large geographically representative samples of individuals in the United States. The data were collected by a professional survey company in March, April and May 2020.² We merge our survey data with information on measures that state governments imposed in response to the coronavirus outbreak as well as local data on the number of confirmed cases and deaths attributable to Covid-19.

2.1. Survey data

We collected three waves of survey data. The first wave of data ($N=4,003$) was collected on 24 and 25 March 2020, the second wave of data ($N=4,000$) was collected on 9–11 April 2020 and the third wave ($N=4,007$) was collected on 20 and 21 May 2020.³ To be eligible to participate in the study, participants had to be resident in the United

- 1 Evidence from Google searches in different countries also points to an increase in searches on topics related to well-being (e.g., boredom, loneliness and sadness) and concerns over the economic consequences of the crisis, following the implementation of lockdowns (Brodeur *et al.*, 2020; Fetzer *et al.*, 2020; Knipe *et al.*, 2020; Tubadji *et al.*, 2020).
- 2 All participants were part of the company's online panel and participated in the survey online. The survey was completely anonymous, that is, no information was collected that would allow researchers to identify survey participants. The survey was scripted in the online survey software Qualtrics. Participants received modest incentives for completing the survey.
- 3 The data were collected as part of a broader study that aimed at documenting the impact of the Covid-19 pandemic on workers. To ensure that the results are comparable across waves, we chose to draw independent study samples for each wave of data collection, that is, there are no participants who participated in the survey more than once. We used the same sampling methodology each time, which allows us to make comparisons across waves.

States, be at least 18 years old and report having engaged in any paid work during the previous 12 months. The samples were selected to be representative in terms of region (i.e., area codes).⁴ [Online Appendix Table A.1](#) shows the sample distribution of respondents for each survey wave in comparison to the national distribution across the different regions. As can be seen from this table, the distributions are very similar.

We compare the characteristics of the respondents in our sample to a nationally representative sample of the working population in the United States. [Online Appendix Table A.2](#) shows the demographic characteristics of our samples and the February 2020 monthly current population survey (CPS) data. While our samples are characterized by a higher proportion of women and a somewhat higher proportion of respondents with a university degree, we note that our results are robust to re-weighting our sample using survey weights.⁵ We present unweighted results throughout the text and weighted results in the [Online Appendix](#). We further control for a range of different background characteristics in all of our analyses.

We focus our analysis on the second wave of data collected in mid-April. By that time, 40 states had already put lockdown measures in place, providing us with variation we can exploit to identify the effect of interest. In late March, only 13 states had lockdowns in place and the states that had implemented lockdowns only had them in place for a few days. By the end of May, on the other hand, 24 states had already lifted restrictions. We therefore primarily focus on the April wave and use the March and May survey data to perform robustness checks and provide some additional insights.

2.1.1. Mental health. To measure mental health, we administer the WHO five-question module. The module consists of five statements about positive feelings. Respondents have to report the frequency with which they have experienced each different feeling in the two weeks prior to the interview. Answers are expressed on a Likert scale ranging from 0 ('At no time') to 5 ('All of the time').⁶ This module has been validated and used in a variety of different contexts (see, e.g., [Bech et al., 2003](#); [Krieger et al., 2014](#); [Downs et al., 2017](#)).⁷ An overall mental health score is obtained by summing answers to the five

4 'Area codes' refer to groups of states identified by the first digit of their postcode. We use the terms 'area code' and 'region' interchangeably. There are 10 area codes in total in the United States, numbered 0–9.

5 We re-weight our samples to ensure that the joint density of gender, education and age in our samples matches that of the economically active population in the February 2020 monthly CPS data.

6 See [Online Appendix C](#) for the exact wording of the questions.

7 The WHO-5 index has been shown to perform well as a tool to screen individuals who experience symptoms, or are at risk, of depression and anxiety ([Krieger et al., 2014](#); [Topp et al., 2015](#)) and successfully identify individuals whose mental health has deteriorated over the recent past ([Bech et al., 2003](#)). Furthermore, individuals who attempt suicides on average report significantly lower scores on the WHO-5 index compared with subjects with no suicidal intentions, and the WHO-5 index negatively correlates with the severity of suicidal attempts ([Awata et al., 2007](#); [Sisask et al., 2008](#)).

questions, with a higher score indicating better mental health. Within each survey wave, we standardize the mental health score to have mean 0 and standard deviation of 1.

2.1.2. Economic impacts. We obtain information on the immediate economic impact of the coronavirus crisis. More specifically, we ask respondents to report whether they had trouble paying their usual bills and expenses, worked fewer hours, earned less than usual or had to change their work patterns to care for others in the week before completing the survey. We further obtain information on the employment status of the respondents in February 2020 and at the time of data collection.

2.2. Other data sources

In our surveys, we collect information on the state and county of residence of the respondents, which we use to merge the survey data with information on state-level policies adopted in response to the pandemic and county-level measures of the health impact of Covid-19.

2.2.1. State-wide stay-at-home orders. We use publicly available information on state measures that were adopted in response to the coronavirus pandemic (Raifman *et al.*, 2020).⁸ For each survey wave, we construct a binary variable indicating whether or not the state had stay-at-home orders (also referred to as ‘lockdowns’) in place at the time the data collection was launched. Stay-at-home orders refer to directives or orders that apply to the entire state and that restrict movements of people by ordering residents to stay home except for essential reasons.⁹ We further calculate how many days the stay-at-home orders had already been in place. From the same dataset, we also collect information on the population density, share of unemployed residents and share of residents at risk of serious illness due to Covid-19, for each state.

2.2.2. Coronavirus cases and deaths. We use information on the county of residence of survey participants to merge the data from each survey wave with county-level information on the cumulative number of reported Covid-19 cases and deaths (per capita) at the time the data collection was launched. We obtain this information from the ongoing repository made available by The New York Times.¹⁰ Detailed geographic information on the location of our survey respondents allows us to merge this data with our survey data at the county level.

8 The data were first downloaded on 27 April 2020 and updated on 5 June 2020.

9 While not uniform across states, studying heterogeneity in how exactly the measures adopted in response to the pandemic were implemented lies outside the scope of this paper and may provide an interesting avenue for future research.

10 The data are freely available at the following URL: <https://github.com/nytimes/Covid-19-data>.

3. INSTITUTIONAL CONTEXT

In the United States, the first COVID-19 case was confirmed on 21 January 2020, marking the beginning of the coronavirus outbreak. Since then, events unfolded at rapid speed. The first confirmed COVID-19-related death was recorded on 1 March 2020, with President Trump declaring a state of emergency on 13 March 2020, and the country totalling 100 COVID-19-related deaths on 18 March 2020. During the month of March 2020, state governments started to impose restrictions to combat the spread of the virus. California was the first state to issue a state-wide stay-at-home order, which took effect on 19 March 2020. Many other US states adopted similar measures in the weeks following California's imposition of a state-wide lockdown, although there was a substantial degree of heterogeneity in the imposition of restrictions across US states. At the time of our first survey wave, 13 states had issued state-wide stay-at-home orders. Between the end of March and our second survey wave, this number rose to 40. With lockdowns being effective in bringing down the number of new COVID-19 cases and deaths, many states started easing or lifting their restrictions from the end of April. Alaska was the first state to relax its lockdown orders on 24 April 2020. By the end of May, when we ran our third survey, only 24 states still had state-wide stay-at-home orders in place. [Online Appendix Figure B.1](#) shows the timeline of the coronavirus outbreak and main policy responses in the United States.

4. RESULTS

4.1. The impact of lockdowns on mental health

We first estimate the impact of state-wide stay-at-home orders on mental health using the mid-April survey wave. We regress self-reported mental health on a dummy variable indicating whether a lockdown was in place in mid-April as well as a range of individual background characteristics.¹¹ The results are presented in Column 1 of [Table 1](#). Standard errors are clustered at the state level. The lockdown coefficient is estimated to be negative and significant. Living in a state which has stay-at-home orders in place at the time of the survey is associated with a decrease in mental health by 0.083 standard deviations (p -value = 0.012), suggesting that stay-at-home orders have led to a significant reduction in mental health.¹² To put this number into context, the literature on the drivers of mental health has documented that other major life events such as bereavement

11 All regressions control for a dummy variable indicating whether the respondent is female, household income, whether or not the respondent has a university degree, age (in bins) and whether or not the respondent is single. Household income refers to annual household income (in 1,000s of USD) in the year 2019.

12 We note that this is likely to be a lower bound to the negative mental health consequences of the different state and local lockdown measures as states which did not have state-wide stay-at-home orders in place also had some local restrictions.

Table 1. Mental health score

	April		March
	Full sample	Restricted sample	Placebo
Lockdown (April)	-0.0834** (0.0322)	-0.0667* (0.0359)	0.0066 (0.0345)
Female	-0.3289*** (0.0375)	-0.2973*** (0.0484)	-0.2517*** (0.0555)
Household income (in 1,000 USD)	0.0019*** (0.0004)	0.0016** (0.0006)	0.0025*** (0.0004)
University degree	0.1168*** (0.0386)	0.1693*** (0.0501)	0.1500*** (0.0394)
30–39	0.0565 (0.0390)	0.0431 (0.0562)	0.0723 (0.0602)
40–49	0.0018 (0.0424)	-0.0629 (0.0411)	0.0263 (0.0746)
50–59	-0.0809 (0.0568)	-0.1405* (0.0747)	-0.0126 (0.0592)
60+	0.0657 (0.0529)	0.0477 (0.0663)	0.1202* (0.0619)
Single	-0.1131** (0.0437)	-0.0983** (0.0364)	-0.0668 (0.0439)
Constant	0.0947* (0.0551)	0.0952 (0.0635)	-0.0579 (0.0794)
Observations	3,990	2,396	2,372
R ²	0.0648	0.0606	0.0575

Notes: OLS regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level in parentheses. The dependent variable is the standardized mental health score. Lockdown is a dummy variable indicating whether the state of residence of the respondent had stay-at-home measures in place at the time of the second data collection. Column 1 reports results for the full sample of wave 2. Column 2 restricts the sample to respondents of the second wave who lived in states that did not have lockdown measures in place at the time of the first data collection. Column 3 shows results from a placebo test where the sample is restricted to respondents of the first wave who lived in states that did not have lockdown measures in place at the time of the first data collection.

or unemployment can lead to changes in mental health or depression scores of a quarter of a standard deviation or more (Burton *et al.*, 2006; Marcus, 2013).

Several other patterns are worth noting. Consistent with the results from previous studies, we find that being female is associated with significantly lower self-reported mental health (e.g., Astbury, 2001; Seedat *et al.*, 2009; Stevenson and Wolfers, 2009). Household income and having a university degree are positively associated with mental health. Individuals who report being single have significantly lower mental health scores.

A potential concern with the analysis is that the states that introduced lockdown measures by April may have systematically differed from the other states in terms of baseline mental health. For example, it is possible that individuals living in states that introduced lockdown measures by April had systematically lower mental health scores at baseline, that is, before the lockdown measures were introduced. If this was the case, then the negative ‘lockdown’ coefficient may not capture the negative consequences of the state-wide stay-at-home orders but it may be picking up differences in mental health across states that existed even before the pandemic. We perform a number of placebo exercises to show that this is not the case. In particular, we first restrict the

April sample to only those individuals living in states that had not introduced lockdown measures by late March. As can be seen in Column 2 of [Table 1](#), the results are very similar when we impose this sample restriction. We then apply the same sample restriction to the data collected in late March and we examine whether *future* lockdown predicts mental health scores in late March. If the results were driven by differences in baseline mental health levels, we would expect the coefficient on future lockdown to be negative and significant. The results of this placebo test are presented in Column 3 of [Table 1](#). The estimated coefficient is positive and not statistically different from zero, indicating that the mental health scores at baseline were not systematically different between states which introduced lockdowns by mid-April and those that did not.

The data allow us to perform two additional placebo exercises. In [Online Appendix Table B.1](#), we perform the same analysis but using the number of days since the lockdown was introduced rather than a binary lockdown measure.¹³ Similarly, the coefficient on the number of days the state had been in lockdown for by mid-April is statistically significant when we use the April survey wave, but not in the placebo test in which we use the March survey wave.¹⁴ We also test whether the number of days *until* a future lockdown predicts mental health in March. Reassuringly, we find that whether the future lockdown is closer or further away in time does not significantly affect the mental health of respondents in the first survey wave. Overall, we conclude that neither the levels nor the trends in self-reported mental health are likely to differ between states that were in lockdown by mid-April and those that were not: if baseline levels or trends had been different, we would expect to see a systematic relationship between the future implementation of the lockdown measures and mental health in March.

We further investigate whether controlling for additional state-level characteristics affects any of the results. In [Online Appendix Table B.3](#), we run the same specification as in Column 1 of [Table 1](#) and additionally control for population density, the share of unemployed residents in the state and the share of residents at risk of serious illness due to Covid-19. Controlling for these additional characteristics does not affect the estimated impact of the lockdown on mental health.

Before we explore the results for the mid-April survey wave in more detail, we turn to the analysis that pools all three survey waves. Exploiting the variation in lockdown status over time, we still find a significant negative effect of state-wide lockdown measures on mental health (see [Online Appendix Table B.4](#)).¹⁵ As suggested by the results in Column 1, the estimated lockdown coefficient is -0.058 (p -value = 0.015). Overall, we

13 [Online Appendix Figure B.2](#) shows the distribution of the number of days since the lockdown was introduced by the time of our April data collection.

14 [Online Appendix Table B.2](#) shows results from regressions where we include the number of days since the lockdown restrictions were imposed in 5-day bins. While some of the coefficients are not statistically significant, we interpret their sign and magnitude as evidence of potential convexities in the relationship between lockdown duration and self-reported mental health.

15 All regressions include state-fixed effects and the standard errors are clustered at the state-wave level. The regressions presented in [Online Appendix Table B.4](#) control for annual individual income in the year 2019 (in 1,000s of USD) as we did not measure household income in the third survey wave.

conclude that there is a significant negative effect of lockdown measures on mental health.

4.2. Heterogeneity by gender

Evidence from previous studies suggests that economic downturns can affect the mental health of men and women differently (Chang *et al.*, 2013; Dagher *et al.*, 2015). We investigate whether the mental health impact of the state-wide stay-at-home orders varies by gender. For this purpose, we estimate the same specification as in Column 1 of Table 1, additionally including an interaction term between the dummy variable indicating whether the state was in lockdown in mid-April and gender. The results from this analysis are presented in Column 1 of Table 2.¹⁶ The estimated gender gap in mental health scores is 0.217 standard deviations in states that did not have lockdown measures in place (p -value = 0.000). As indicated by the negative and significant interaction coefficient, this gender gap is significantly higher in states that introduced lockdown measures by mid-April. The estimated gender gap is 0.133 standard deviations larger in states that had a lockdown in place (p -value = 0.055), which constitutes a 61% increase in the estimated gender gap in mental health. The estimated coefficient on the lockdown dummy is insignificant and close to zero, suggesting that the negative impact of stay-at-home orders on mental health is driven by women.¹⁷ Our results from the United States are consistent with findings from Etheridge and Spantig (2020), who find that in the United Kingdom the Covid-19 pandemic has had larger effects on the mental well-being of women.¹⁸

Columns 2 and 3 show the results for the same specification estimated separately on the subsample of women and men, respectively. The coefficient associated with the lockdown dummy is significant and negative for women and close to zero and insignificant for men. For women, living in a state which introduced stay-at-home orders is associated with a reduction in mental health by 0.123 standard deviations (p -value = 0.011). Taken together, these results point to a substantial widening of the gender gap in mental health as a result of the implementation of stay-at-home orders.¹⁹

16 Weighted results are presented in Online Appendix Table B.5.

17 Online Appendix Figure B.3 presents the average unconditional standardized mental health scores for men (left) and women (right) in mid-April, separately by whether the state the respondent lived in had issued a stay-at-home order (blue) or not (white). The graph illustrates the gender gaps in mental health scores as well as the larger gender gap in mental health in states that were in lockdown.

18 While it is possible that there may be gender differences in the social stigma attached to mental health issues, which may result in women being more likely to report changes in mental health, we believe that gender differences in social stigma are unlikely to be driving our results. All surveys were conducted online and were completely anonymous, minimizing social desirability bias. Nonetheless, we note that actual mental health may differ from self-reported mental health, which is what our study focuses on.

19 As can be seen in Online Appendix Tables B.3 and B.4 we also find that the results are entirely driven by women when we control for additional state characteristics or when we pool the different waves.

Table 2. Gender gaps in mental health score

	All	Women	Men
Female	-0.2168 ^{***} (0.0504)		
Female × Lockdown (April)	-0.1330 [*] (0.0676)		
Lockdown (April)	-0.0012 (0.0420)	-0.1234 ^{**} (0.0468)	-0.0127 (0.0399)
Household income (in 1,000 USD)	0.0019 ^{***} (0.0004)	0.0013 ^{**} (0.0005)	0.0025 ^{***} (0.0006)
University degree	0.1178 ^{***} (0.0390)	0.0870 ^{**} (0.0372)	0.1411 ^{**} (0.0634)
30–39	0.0565 (0.0396)	0.0445 (0.0369)	0.0706 (0.0922)
40–49	0.0011 (0.0425)	0.0003 (0.0441)	-0.0303 (0.0851)
50–59	-0.0814 (0.0574)	-0.0158 (0.0635)	-0.1944 [*] (0.1071)
60+	0.0655 (0.0528)	0.0720 (0.0631)	0.0412 (0.0838)
Single	-0.1147 ^{**} (0.0435)	-0.0626 (0.0419)	-0.1917 ^{**} (0.0797)
Constant	0.0267 (0.0579)	-0.1756 ^{***} (0.0641)	0.0186 (0.0965)
Observations	3,990	2,323	1,667
R ²	0.0654	0.0145	0.0524

Notes: OLS regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level in parentheses. The dependent variable is the standardized mental health score. Lockdown is a dummy variable indicating whether the state of residence of the respondent had stay-at-home measures in place at the time of the second data collection. Column 1 reports results for the full sample of wave 2. Columns 2 and 3 restrict the sample to female and male respondents, respectively.

As documented in Adams-Prassl *et al.* (2020), the Covid-19 pandemic has had large and unequal impacts on the labour market outcomes of people living in the United States. Women were more likely to lose their jobs due to the pandemic compared with men. Social-distancing measures also led to an increase in care responsibilities towards children and other vulnerable groups. Stress arising from financial difficulties or additional care responsibilities is likely to negatively affect mental health during the crisis and may mediate some of the impact of the lockdown on mental health. The health impacts of the coronavirus outbreak have also been highly unequal, with large regional differences in the number of cases and deaths attributable to Covid-19.

In Tables 3 and 4, we investigate whether controlling for realized impacts of the coronavirus outbreak changes the estimated effect of the state-wide lockdown measures on the mental health of women and men, respectively. In Column 1, we additionally control for whether the respondent reports having had trouble paying their usual bills/expenses, earned less money, worked fewer hours in the week before the data collection or lost their job between February and the time of data collection. In Column 2, we control for whether the respondent has children below the age of 18 years living with them

Table 3. Controlling for realized impacts – women

	(1)	(2)	(3)	(4)	(5)
Lockdown (April)	-0.1231*** (0.0455)	-0.1229** (0.0531)	-0.0974** (0.0467)	-0.0968** (0.0463)	-0.0868* (0.0505)
Lost job since February	-0.0486 (0.0436)				-0.0579 (0.0494)
Had troubles paying bills	-0.2443*** (0.0469)				-0.2763*** (0.0503)
Worked fewer hours	-0.0090 (0.0468)				-0.0176 (0.0532)
Earned less money	0.0065 (0.0515)				0.0006 (0.0528)
Children (below 18)		0.0716 (0.0828)			0.0866 (0.0774)
Time spent on childcare		-0.0104 (0.0067)			-0.0118* (0.0066)
Change work patterns		-0.0386 (0.0502)			0.0258 (0.0580)
Cases per 1,000 inhabitants			-0.0254*** (0.0076)		-0.0064 (0.0158)
Deaths per 1,000 inhabitants				-0.7740*** (0.2204)	-0.6208 (0.4931)
Constant	0.0170 (0.0754)	-0.1607** (0.0748)	-0.1557** (0.0642)	-0.1566** (0.0636)	0.0400 (0.0808)
Observations	2,321	1,830	2,214	2,214	1,747
R ²	0.0313	0.0196	0.0162	0.0165	0.0426
Controls	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level in parentheses. The dependent variable is the standardized mental health score. Lockdown is a dummy variable indicating whether the state of residence of the respondent had stay-at-home measures in place at the time of the second data collection. Had troubles paying bills, worked fewer hours, earned less money and changed work patterns are dummy variables that take the value of 1 if the respondent reported experiencing the given outcome in the week before data collection. Children is a binary variable that takes the value of 1 if the respondent has children under the age of 18 living at home with him/her. Cases and deaths per 1,000 inhabitants refer to confirmed coronavirus cases and deaths at the county level. Controls include household income, binary variables for different age groups and dummy variables for whether the respondent has a university degree and is single. All columns report results for the sample of female respondents to the second survey wave.

in their home, total time spent on childcare and whether the respondent reports having had to change their work patterns to care for others.²⁰ In Columns 3 and 4, we control for the cases and deaths attributable to Covid-19 (per 1,000 inhabitants) in the respondent’s county, while in Column 5, we include all additional regressors in the same specification. The results in Table 3 show that neither controlling for realized economic

20 We note that additional caring responsibilities that arose as a result of the pandemic could also involve caring for other vulnerable or elderly members of the household. The question was worded without specific reference to children, and therefore answers could also capture additional responsibilities related to elderly care or care of vulnerable individuals. Overall, 41% of respondents to the April survey wave reported having changed their work patterns to care for others. Among respondents with children under 18, the share is 56%, while it is 29% for respondents without children (p -value < 0.01).

Table 4. Controlling for realized impacts – men

	(1)	(2)	(3)	(4)	(5)
Lockdown (April)	-0.0242 (0.0419)	-0.0075 (0.0629)	0.0015 (0.0394)	-0.0034 (0.0400)	-0.0182 (0.0623)
Lost job since February	-0.1899*** (0.0440)				-0.2259*** (0.0609)
Had troubles paying bills	-0.0452 (0.0630)				-0.0318 (0.0562)
Worked fewer hours	0.0965 (0.0635)				0.0805 (0.0745)
Earned less money	-0.1057* (0.0609)				-0.1199* (0.0602)
Children (below 18)		0.2129*** (0.0778)			0.2103*** (0.0751)
Time spent on childcare		0.0076 (0.0100)			0.0044 (0.0104)
Change work patterns		0.0171 (0.0523)			0.0040 (0.0535)
Cases per 1,000 inhabitants			-0.0242*** (0.0071)		-0.0123 (0.0160)
Deaths per 1,000 inhabitants				-0.5095 (0.4317)	-0.1287 (0.6413)
Constant	0.1210 (0.0911)	-0.0879 (0.0895)	0.0251 (0.1006)	0.0210 (0.1010)	0.0507 (0.1024)
Observations	1,661	1,397	1,528	1,528	1,280
R ²	0.0579	0.0589	0.0510	0.0502	0.0645
Controls	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors clustered at the state level in parentheses. The dependent variable is the standardized mental health score. Lockdown is a dummy variable indicating whether the state of residence of the respondent had stay-at-home measures in place at the time of the second data collection. Had troubles paying bills, worked fewer hours, earned less money and changed work patterns are dummy variables that take the value of 1 if the respondent reported experiencing the given outcome in the week before data collection. Children is a binary variable that takes the value of 1 if the respondent has children under the age of 18 living at home with him/her. Cases and deaths per 1,000 inhabitants refer to confirmed coronavirus cases and deaths at the county level. Controls include household income, binary variables for different age groups and dummy variables for whether the respondent has a university degree and is single. All columns report results for the sample of male respondents to the second survey wave.

impacts nor controlling for care responsibilities or cases/deaths related to Covid-19 in the respondent's county significantly alters the estimated coefficient on the lockdown dummy. For women, the estimated coefficient on the lockdown dummy is -0.087 in Column 5 (p -value = 0.092) and it is not significantly different from the lockdown coefficient estimated in Column 2 of Table 2, indicating that these mechanisms are unlikely to explain the negative impact of the state-wide stay-at-home measures on the mental health of women.²¹ For men, in all specifications, the lockdown dummy is estimated to

21 Galasso *et al.* (2020) present evidence of significant gender differences in perceptions of the severity of the pandemic and compliance with restraining measures. We note that these mechanisms could partially explain why the impact of lockdowns was more severe for women, but the data at hand do not allow us to shed light on this issue.

be close to zero and it is insignificant (see Columns 1–5 in [Table 4](#)). [Online Appendix Tables B.6](#) and [B.7](#) show that our results are robust to re-weighting the sample to match the distribution of observable characteristics of the economically active population in the February 2020 monthly CPS data.²²

5. CONCLUSION

Following the outbreak of the Covid-19 pandemic, several states in the United States have introduced stay-at-home measures to slow the spread of the disease. By mid-April, these state-wide measures had severely affected people's mental health. Individuals living in states that implemented lockdown measures scored 0.083 standard deviations lower on the standardized WHO-5 mental health index compared with those living in states that did not implement such measures. The negative impact of the lockdown orders is entirely driven by a negative effect on women, thus contributing to widening the existing gender gap in mental health by 61%. The results further show that stay-at-home measures affect the mental health of women in the United States over and beyond their impact through increased financial worries and childcare responsibilities. The health impact of the crisis, measured by the number of confirmed Covid-19 cases and deaths per capita, also cannot explain the negative impact of state-wide lockdown orders on women's mental health.

Taken together, the evidence presented in this paper shows that the health costs of the coronavirus pandemic are likely to go well beyond the rising death toll and the number of cases. Given the already high costs of mental health to the global economy ([WHO, 2019](#)), the importance for policymakers to take the mental health impact of lockdown measures into consideration when designing policies to slow the spread of the pandemic and guide countries through the recovery phase cannot be understated. Going forward, more funding should be directed towards mental health services and prevention programmes aimed at at-risk individuals. Finally, as countries experience more waves of coronavirus, with new restrictions being imposed to tackle the pandemic, it will be crucial to increase online social connectedness to combat isolation and lack of social support. Further research into understanding which measures could help reduce the widening gender gap in mental health is of high policy importance.

FUNDING

We are grateful to the Economic and Social Research Council (UKRI grant number ES/V004042/1), the University of Oxford, the University of Zurich, the Cambridge INET, and the Cambridge Keynes Fund for generous financial support.

²² We note that the results may be different for a population that is not economically active. Given that our study focuses on the economically active population, our data do not allow us to speak to that.

SUPPLEMENTARY DATA

Supplementary data are available at *Economic Policy* online.

REFERENCES

- Adams-Prassl, A., T. Boneva, M. Golin and C. Rauh (2020). 'Inequality in the impact of the coronavirus shock: Evidence from real time surveys', *Journal of Public Economics*, 189, 104245.
- Armbruster, S. and V. Klotzbücher (2020). *Lost in Lockdown? COVID-19, Social Distancing, and Mental Health in Germany*. Diskussionsbeiträge.
- Astbury, J. (2001). *Gender Disparities in Mental Health*. Mental Health – Ministerial Round Tables 54th World Health Assembly, WHO, Geneva, Switzerland.
- Awata, S., P. Bech, Y. Koizumi, T. Seki, S. Kuriyama, A. Hozawa, K. Ohmori, N. Nakaya, H. Matsuoka and I. Tsuji (2007). 'Validity and utility of the Japanese version of the WHO-five well-being index in the context of detecting suicidal ideation in elderly community residents', *International Psychogeriatrics*, 19, 77–88.
- Banks, J. and X. Xu (2020). 'The mental health effects of the first two months of lockdown during the COVID-19 pandemic in the UK', *Fiscal Studies*, 41, 685–708.
- Bech, P., L.R. Olsen, M. Kjoller and N.K. Rasmussen (2003). 'Measuring well-being rather than the absence of distress symptoms: A comparison of the SF-36 mental health subscale and the WHO-five well-being scale', *International Journal of Methods in Psychiatric Research*, 12, 85–91.
- Béland, L.-P., A. Brodeur, D. Mikola and T. Wright (2020). 'The short-term economic consequences of Covid-19: Occupation tasks and mental health in Canada'. IZA DP No. 13254.
- Brodeur, A., A.E. Clark, S. Fleche and N. Powdthavee (2020). 'COVID-19, lockdowns and well-being: evidence from Google Trends', *Journal of Public Economics*, 193, 104346.
- Brooks, S.K., R.K. Webster, L.E. Smith, L. Woodland, S. Wessely, N. Greenberg and G.J. Rubin (2020). 'The psychological impact of quarantine and how to reduce it: Rapid review of the evidence', *The Lancet*, 395, 912–20.
- Burton, A.M., W.E. Haley and B.J. Small (2006). 'Bereavement after caregiving or unexpected death: Effects on elderly spouses', *Aging and Mental Health*, 10, 319–26.
- Chang, S.-S., D. Stuckler, P. Yip and D. Gunnell (2013). 'Impact of 2008 global economic crisis on suicide: Time trend study in 54 countries', *BMJ*, 347, f5239–f5239.
- Dagher, R.K., J. Chen and S.B. Thomas (2015). 'Gender differences in mental health outcomes before, during, and after the great recession', *PLoS ONE*, 10, e0124103.
- Downs, A., L.A. Boucher, D.G. Campbell and A. Polyakov (2017). 'Using the WHO-5 well-being index to identify college students at risk for mental health problems', *Journal of College Student Development*, 58, 113–7.
- Etheridge, B. and L. Spantig (2020). 'The gender gap in mental well-being during the Covid-19 outbreak: Evidence from the UK', *Covid Economics*, 33, 46–72.
- Fancourt, D., F. Bu, H. Wan Mak and A. Steptoe (2020). 'COVID-19 social study', *Results Release*, 3.
- Fetzer, T., L. Hensel, J. Hermle and C. Roth (2020). 'Coronavirus perceptions and economic anxiety', *Review of Economics and Statistics*, 1–36.
- Frasquilho, D., M. Gaspar Matos, F. Salonna, D. Guerreiro, C.C. Storti, T. Gaspar and J.M. Caldes-de-Almeida (2015). 'Mental health outcomes in times of economic recession: A systematic literature review', *BMC Public Health*, 16, 115.
- Galasso, V., V. Pons, P. Profeta, M. Becher, S. Brouard and M. Foucault (2020). 'Gender differences in COVID-19 attitudes and behavior: Panel evidence from eight countries', *Proceedings of the National Academy of Sciences of the United States of America*, 117, 27285–91.
- Giuntella, O., K. Hyde, S. Saccardo and S. Sadoff (2021). 'Lifestyle and mental health disruptions during Covid-19.' *Proceedings of the National Academy of Sciences of the United States of America*, 118, e2016632118.
- Huebener, M., S. Waights, C.K. Spiess, N.A. Siegel and G.G. Wagner (2021). 'Parental well-being in times of COVID-19 in Germany', *Review of Economics of the Household*, 19, 91–122.

- Knipe, D., H. Evans, A. Marchant, D. Gunnell and A. John (2020). 'Mapping population mental health concerns related to COVID-19 and the consequences of physical distancing: A Google trends analysis', *Wellcome Open Research*, 5, 82.
- Krieger, T., J. Zimmermann, S. Huffziger, B. Ubl, C. Diener, C. Kuehner and M. Grosse Holtforth (2014). 'Measuring depression with a well-being index: Further evidence for the validity of the WHO well-being index (WHO-5) as a measure of the severity of depression', *Journal of Affective Disorders*, 156, 240–4.
- Marcus, J. (2013). 'The effect of unemployment on the mental health of spouses – evidence from plant closures in Germany', *Journal of Health Economics*, 32, 546–58.
- Pierce, M., H. Hope, T. Ford, S. Hatch, M. Hotopf, A. John, E. Kontopantelis, R. Webb, S. Wessely, S. McManus and K.M. Abel (2020). 'Mental health before and during the COVID-19 pandemic: A longitudinal probability sample survey of the UK population', *The Lancet Psychiatry*, 7, 883–92.
- Proto, E. and C. Quintana-Domeque (2021). 'COVID-19 and mental health deterioration by ethnicity and gender in the UK', *PLoS ONE*, 16, e0244419.
- Raifman, J., K. Nocka, D. Jones, J. Bor, S. Lipson, J. Jay and P. Chan (2020). *COVID-19 US State Policy Database*. Available at: <https://www.tinyurl.com/statepolicies>.
- Reibling, N., J. Beckfield, T. Huijts, A. Schmidt-Catran, K.H. Thomson and C. Wendt (2017). 'Depressed during the depression: Has the economic crisis affected mental health inequalities in Europe? Findings from the European Social Survey (2014) special module on the determinants of health', *European Journal of Public Health*, 27, 47–54.
- Seedat, S., K.M. Scott, M.C. Angermeyer, P. Berglund, E.J. Bromet, T.S. Brugha, K. Demyttenaere, G. de Girolamo, J.M. Haro, R. Jin, E.G. Karam, V. Kovess-Masfety, D. Levinson, M.E. Medina Mora, Y. Ono, J. Ormel, B.-E. Pennell, J. Posada-Villa, N.A. Sampson, D. Williams and R.C. Kessler (2009). 'Cross-national associations between gender and mental disorders in the World Health Organization World Mental Health Surveys', *Archives of General Psychiatry*, 66, 785.
- Sisask, M., A., Värnik, K. Kolves, K. Konstabel and D. Wasserman (2008). 'Subjective psychological well-being (WHO-5) in assessment of the severity of suicide attempt', *Nordic Journal of Psychiatry*, 62, 431–5.
- Stevenson, B. and J. Wolfers (2009). 'The paradox of declining female happiness', *American Economic Journal: Economic Policy*, 1, 190–225.
- Topp, C.W., S.D. Øtergaard, S. Søndergaard and P. Bech (2015). 'The WHO-5 well-being index: A systematic review of the literature', *Psychotherapy and Psychosomatics*, 84, 167–76.
- Tubadji, A., F. Boy and D. Webber (2020). 'Narrative economics, public policy and mental health', *Center for Economic Policy Research*, 20, 109–31.
- U.S. Census Bureau, Population Division. (2019). *Estimates of the Total Resident Population and Resident Population Age 18 Years and Older for the United States, States, and Puerto Rico: 1 July 2019 (SCPRC-EST2019-18+POP-RES)*. Data retrieved from <https://www.census.gov/newsroom/press-kits/2019/national-state-estimates.html>.
- WHO (2019). *WHO Mental Health Information Sheet*. Available at: https://www.who.int/mental_health/in_the_workplace/en/.