



HCEO WORKING PAPER SERIES

Working Paper



HUMAN CAPITAL AND
ECONOMIC OPPORTUNITY
GLOBAL WORKING GROUP

The University of Chicago
1126 E. 59th Street Box 107
Chicago IL 60637

www.hceconomics.org

The Impact of the Coronavirus Lockdown on Mental Health: Evidence from the US

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

May 6, 2020

Abstract

The coronavirus outbreak has caused significant disruptions to people's lives. We document the impact of state-wide stay-at-home orders on mental health using real time survey data in the US. The lockdown measures lowered mental health by 0.085 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 66%. The negative effect on women's mental health cannot be explained by an increase in financial worries or childcare responsibilities.

JEL: I10, I14, I18, I30

Keywords: Mental health, Gender, Recessions, Coronavirus

*Adams-Prassl: University of Oxford (email: abi.adams@economics.ox.ac.uk). Boneva: University of Zurich (email: teodora.boneva@econ.uzh.ch). Golin: University of Oxford (email: marta.golin@nuffield.ox.ac.uk). Rauh: University of Cambridge, Trinity College Cambridge (email: cr542@cam.ac.uk). Ethics approval was obtained from the Central University Research Ethics Committee (CUREC) of the University of Oxford: ECONCIA20-21-09. We are grateful to the Economic and Social Research Council, the Social Sciences and Humanities Research Council of Canada, the University of Oxford, the University of Zurich, and the Cambridge INET for generous financial support, and Marlis Schneider for excellent research assistance.

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, limiting people's ability to leave their homes and interact with other people. A major public health concern relates to how these measures impact people's mental health.

We study the impact of state-wide stay-at-home orders on mental health using two waves of geographically representative survey data collected in the United States in March and April 2020, with a total of 8,003 respondents. While in late March only 14 states had put stay-at-home orders in place, this number rose to 40 by mid-April. To measure mental health, we administer the WHO 5-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 mental health. By mid-April, the mental health scores of individuals living in states with stay-at-home orders in place were 0.085 standard deviations lower than the mental health scores of individuals in states that had not issued such orders (p-value=0.038). We perform a placebo test 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. Second, the impact of state-wide stay-at-home orders on mental health significantly varies by gender. As a result of the stay-at-home orders, the gender gap in mental health increased from 0.21 standard deviations to 0.35 standard deviations, which constitutes a 66% 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 is *entirely* driven by women. The estimated impact of stay-at-home orders on women's mental health is -0.126 standard deviations (p-value=0.014), while the estimated impact on men's mental health is close to zero and insignificant. Third, 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 or 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, Chen and Thomas 2015; Frاسquilho 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. For instance, Fetzer et al. (2020) document an increase in google searches related to economic anxieties upon arrival of the virus in the US. 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 men’s and women’s mental health. The negative mental health consequences of stay-at-home orders for women highlight the importance for policymakers to take these impacts into consideration when designing policies to slow the spread of the pandemic.

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 and April 2020.¹ 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 two waves of survey data. The first wave of data ($N = 4,003$) was collected on March 24-25, 2020, while the second wave of data ($N = 4,000$) was collected on April 9-11, 2020.² To be eligible to participate in the study, participants had to be resident in the US, 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. Appendix Table A.1 shows the distribution of respondents across

¹All participants were part of the company’s online panel and participated in the survey online. The survey was scripted in the online survey software Qualtrics. Participants received modest incentives for completing the survey.

²We deliberately chose to survey new participants in the second survey wave, i.e. there are no participants who participated in the survey twice.

regions (i.e. area codes) and the comparison to the national distribution of individuals across the different regions, separately for each survey wave. 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 US. Appendix Table A.2 shows the demographic characteristics of our sample and the February 2020 monthly Current Population Survey (CPS) data. While there are some differences between our samples and the nationally representative sample, we note that our results are robust to re-weighting our sample using survey weights.³ We present unweighted results throughout the text and weighted results in the Appendix. We further control for a range of different background characteristics in all of our analyses.

Mental health To measure mental health, we administer the WHO 5-question module.⁴ 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).⁵ An overall mental health score is obtained by summing answers to the 5 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.

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.

2.2 Other Data Sources

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.

³We 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.

⁴See Appendix C for the exact wording of the questions.

⁵The 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 to 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).

2020).⁶ 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. We further calculate how many days the stay-at-home orders had already been in place.

Coronavirus cases and deaths We 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.⁷ Detailed geographic information on the location of our survey respondents allows us to merge this data with our survey data at the county level.

3 Results

We estimate the impact of state-wide stay-at-home orders on mental health using the mid-April survey wave. More specifically, we regress 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.⁸ The results are presented in Column 1 of Table 1. 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 0.085 standard deviations (p-value=0.038), suggesting that stay-at-home orders have led to a significant reduction in mental health.

A valid concern that arises is whether individuals living in states that introduced lockdown measures had systematically lower mental health scores at baseline, i.e. before the lockdown measures were introduced. We perform a placebo exercise to rule out this explanation. 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. The results of this placebo test are presented in Column 3 of Table 1. The

⁶The data were downloaded on 27 April 2020.

⁷The data is freely available at the following URL: <https://github.com/nytimes/Covid-19-data>

⁸All 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.

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.⁹

Table 1: Mental health score

	Early April		Late March
	Full sample	Restricted sample	Placebo
Lockdown (April)	-0.0850 (0.0409)	-0.0759 (0.0442)	0.0148 (0.0455)
Female	-0.3316 (0.0319)	-0.2972 (0.0420)	-0.2379 (0.0437)
Household income	0.0258 (0.0052)	0.0219 (0.0067)	0.0361 (0.0070)
University degree	0.1196 (0.0327)	0.1765 (0.0423)	0.1422 (0.0446)
30-39	0.0554 (0.0425)	0.0356 (0.0555)	0.0796 (0.0546)
40-49	0.0058 (0.0463)	-0.0615 (0.0589)	0.0270 (0.0645)
50-59	-0.0799 (0.0504)	-0.1361 (0.0646)	-0.0035 (0.0652)
60+	0.0636 (0.0515)	0.0574 (0.0684)	0.1396 (0.0703)
Single	-0.1116 (0.0333)	-0.1048 (0.0429)	-0.0627 (0.0442)
Observations	3990	2313	2294
R^2	0.0639	0.0616	0.0583

Notes: OLS regressions. Robust standard errors 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 to 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 to the *first* wave who lived in states that did not have lockdown measures in place at the time of the first data collection.

⁹In 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. Similarly, the coefficient on the number of days the state has been in lockdown in 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.

Several other patterns are worth noting. Consistent with the results from previous studies, we find that being female is associated with significantly lower 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.

Evidence from previous studies suggests that economic downturns can affect the mental health of men and women differently (Chang et al., 2013; Dagher, Chen and Thomas, 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. The estimated gender gap in mental health scores is 0.213 standard deviations in states that did not have lockdown measures in place (p-value=0.006). 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 0.140 standard deviations larger in states that had a lockdown in place (p-value=0.098), which constitutes a 66% 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.¹⁰

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 0.126 standard deviations (p-value=0.014). 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.

¹⁰Appendix Figure B.1 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 as well as the larger gender gap in mental health in states that were in lockdown.

Table 2: Gender gaps in mental health score

	All	Women	Men
Female	-0.2133 (0.0774)		
Female \times Lockdown (April)	-0.1403 (0.0846)		
Lockdown (April)	0.0017 (0.0674)	-0.1261 (0.0514)	-0.0095 (0.0676)
Household income	0.0256 (0.0052)	0.0188 (0.0064)	0.0342 (0.0088)
University degree	0.1204 (0.0327)	0.0839 (0.0405)	0.1468 (0.0559)
30-39	0.0555 (0.0425)	0.0441 (0.0518)	0.0676 (0.0731)
40-49	0.0048 (0.0462)	-0.0011 (0.0556)	-0.0206 (0.0804)
50-59	-0.0805 (0.0505)	-0.0167 (0.0616)	-0.1919 (0.0878)
60+	0.0633 (0.0515)	0.0700 (0.0673)	0.0384 (0.0826)
Single	-0.1131 (0.0333)	-0.0566 (0.0409)	-0.1930 (0.0582)
Observations	3990	2323	1667
R^2	0.0646	0.0149	0.0502

Notes: OLS regressions. Robust standard errors 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 labor market outcomes of people living in the United States. The study documents that women were more likely to lose their jobs due to the pandemic compared to men and that working mothers spent more time caring for their children than working fathers. 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, or worked fewer hours in the week before the data collection. In Column 2, we control for whether the respondent has children below the age of 18 living with them in their home and whether the respondent reports having had to change their work patterns to care for others. In Columns 3 and 4, we control for the cases and deaths attributable to Covid-19 (per 1000 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 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 -0.098 in Column 5 (p-value=0.065), 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. For men, in all specifications, the lockdown dummy is estimated to be close to zero and it is insignificant (see Columns 1-5 in Table 4). Tables B.2 and B.3 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.

Table 3: Controlling for realised impacts - Women

	(1)	(2)	(3)	(4)	(5)
Lockdown (April)	-0.1254 (0.0512)	-0.1262 (0.0515)	-0.1000 (0.0529)	-0.0997 (0.0529)	-0.0988 (0.0529)
Had troubles paying bills	-0.2431 (0.0449)				-0.2597 (0.0464)
Worked fewer hours	-0.0136 (0.0473)				-0.0217 (0.0485)
Earned less money	0.0005 (0.0507)				-0.0049 (0.0520)
Children (below 18)		-0.0067 (0.0430)			0.0039 (0.0436)
Change work patterns		-0.0451 (0.0415)			0.0073 (0.0431)
Cases per 1000 inhabitants			-0.0260 (0.0117)		-0.0029 (0.0244)
Deaths per 1000 inhabitants				-0.7706 (0.3291)	-0.6806 (0.6852)
Constant	-0.0139 (0.0795)	-0.1882 (0.0760)	-0.1931 (0.0733)	-0.1950 (0.0733)	0.0194 (0.0840)
Observations	2321	2322	2214	2214	2211
R^2	0.0310	0.0154	0.0168	0.0170	0.0360
Controls	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Robust standard errors 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 value of one if the respondent reported experiencing the given outcome in the week before data collection. Children is a binary value that takes value one if the respondent has children under the age of 18 living at home with him / her. Cases and deaths per 1000 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.

Table 4: Controlling for realised impacts - Men

	(1)	(2)	(3)	(4)	(5)
Lockdown (April)	-0.0206 (0.0677)	-0.0101 (0.0672)	0.0031 (0.0688)	-0.0019 (0.0686)	-0.0122 (0.0682)
Had troubles paying bills	-0.0420 (0.0600)				-0.0717 (0.0626)
Worked fewer hours	0.0845 (0.0601)				0.0436 (0.0621)
Earned less money	-0.1194 (0.0609)				-0.1171 (0.0629)
Children (below 18)		0.1841 (0.0609)			0.2061 (0.0615)
Change work patterns		0.0243 (0.0536)			0.0352 (0.0567)
Cases per 1000 inhabitants			-0.0231 (0.0132)		-0.0151 (0.0236)
Deaths per 1000 inhabitants				-0.4706 (0.3765)	-0.2101 (0.6397)
Constant	0.0458 (0.1189)	-0.1453 (0.1130)	-0.0273 (0.1101)	-0.0311 (0.1101)	-0.0144 (0.1234)
Observations	1661	1665	1528	1528	1524
R^2	0.0517	0.0545	0.0492	0.0484	0.0590
Controls	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Robust standard errors 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 value of one if the respondent reported experiencing the given outcome in the week before data collection. Children is a binary value that takes value one if the respondent has children under the age of 18 living at home with him / her. Cases and deaths per 1000 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 as a university degree and is single.

4 Conclusion

Following the outbreak of the Covid-19 pandemic, several states in the US have introduced stay-at-home measures to slow the spread of the disease. These state-wide measures have severely affected people’s mental health. Individuals living in states that implemented lockdown measures scored 0.085 standard deviations lower on the standardized WHO-5 mental health index compared to 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 66%. The results further show that stay-at-home measures affect the mental health of women in the US 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. Further research into understanding which measures could help reduce the widening gender gap in mental health is of high policy importance.

References

- Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh.** 2020. “Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys.” CEPR Discussion Paper 14665.
- Astbury, Jill.** 2001. “Gender disparities in mental health.” Mental Health–Ministerial Round Tables 54th World Health Assemble, WHO, Geneva, Switzerland.
- Awata, S, P Bech, Y Koizumi, Tadahiko Seki, Shinhou 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(1): 77–88.
- Bech, Per, Lis Raabaek Olsen, Mette Kjoller, and Niels Kristian 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(2): 85–91.
- 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(sep17 1): f5239–f5239.
- Dagher, Rada K., Jie Chen, and Stephen B. Thomas.** 2015. “Gender differences in mental health outcomes before, during, and after the Great Recession.” *PLOS ONE*, 10(5): e0124103.
- Downs, Andrew, Laura A. Boucher, Duncan G. Campbell, and Anita Polyakov.** 2017. “Using the WHO5 Well-Being Index to identify college students at risk for mental health problems.” *Journal of College Student Development*, 58(1): 113–117.
- Fetzer, Thimeo, Lukas Hensel, Johannes Hermle, and Chris Roth.** 2020. “Coronavirus Perceptions and Economic Anxiety.” *arXiv:2003.03848*.
- Frasquilho, Diana, Margarida Gaspar Matos, Ferdinand Salonna, Diogo Guerreiro, Cláudia C. Storti, Tânia Gaspar, and José M. Caldas-de Almeida.** 2015. “Mental health outcomes in times of economic recession: A systematic literature review.” *BMC Public Health*, 16(1): 115.
- Krieger, Tobias, Johannes Zimmermann, Silke Huffziger, Bettina Ubl, Carsten Diener, Christine Kuehner, and Martin 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: 240–244.
- Raifman, J, K Nocka, D Jones, J Bor, S Lipson, J Jay, and P Chan.** 2020. “COVID-19 US state policy database.” Available at: www.tinyurl.com/statepolicies.
- Reibling, Nadine, Jason Beckfield, Tim Huijts, Alexander Schmidt-Catran, Katie H. Thomson, and Claus 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(suppl_1): 47–54.
- Seedat, Soraya, Kate Margaret Scott, Matthias C. Angermeyer, Patricia Berglund, Evelyn J. Bromet, Traolach S. Brugha, Koen Demyttenaere, Giovanni de Girolamo, Josep Maria Haro, Robert Jin, Elie G. Karam, Viviane Kovess-Masfety, Daphna Levinson, Maria Elena Medina Mora, Yutaka Ono, Johan Ormel, Beth-Ellen Pennell, Jose Posada-Villa, Nancy A. Sampson, David Williams, and Ronald 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(7): 785.
- Sisask, Merike, Airi Värnik, Kairi Kolves, Kenn Konstabel, and Danuta Wasserman.** 2008. “Subjective psychological well-being (WHO-5) in assessment of the severity of suicide attempt.” *Nordic Journal of Psychiatry*, 62(6): 431–435.
- Stevenson, Betsey, and Justin Wolfers.** 2009. “The paradox of declining female happiness.” *American Economic Journal: Economic Policy*, 1(2): 190–225.
- Topp, Christian Winther, Søren Dinesen Østergaard, Susan Søndergaard, and Per Bech.** 2015. “The WHO-5 Well-Being Index: A systematic review of the literature.” *Psychotherapy and Psychosomatics*, 84(3): 167–176.
- 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: July 1, 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/.

Online Appendix A: Data Description

Table A.1: Distribution of respondents across area codes

Region	National	Late March	Early April
Area code 0	7.40	7.39	7.40
Area code 1	10.33	10.32	10.32
Area code 2	10.04	10.04	10.05
Area code 3	14.41	14.41	14.40
Area code 4	10.02	10.02	10.03
Area code 5	5.25	5.25	5.25
Area code 6	7.17	7.17	7.18
Area code 7	11.94	11.94	11.95
Area code 8	7.13	7.12	7.13
Area code 9	16.30	16.34	16.30
Observations		4003	4000

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above and come from the United States Census Bureau. Data source: U.S. Census Bureau, Population Division (2019).

Table A.2: Demographic Variables in the Population & Surveys

	CPS	March	April
Female	0.472	0.621	0.581
University	0.395	0.440	0.494
<30	0.231	0.322	0.255
30-39	0.224	0.262	0.264
40-49	0.203	0.179	0.215
50-59	0.198	0.130	0.136
60+	0.144	0.107	0.130

Notes: The table shows the mean demographic characteristics of economically active individuals in the US. These were calculated using the frequency weights provided in the February 2020 monthly CPS. The unweighted averages of these demographic variables in our survey waves are also reported.

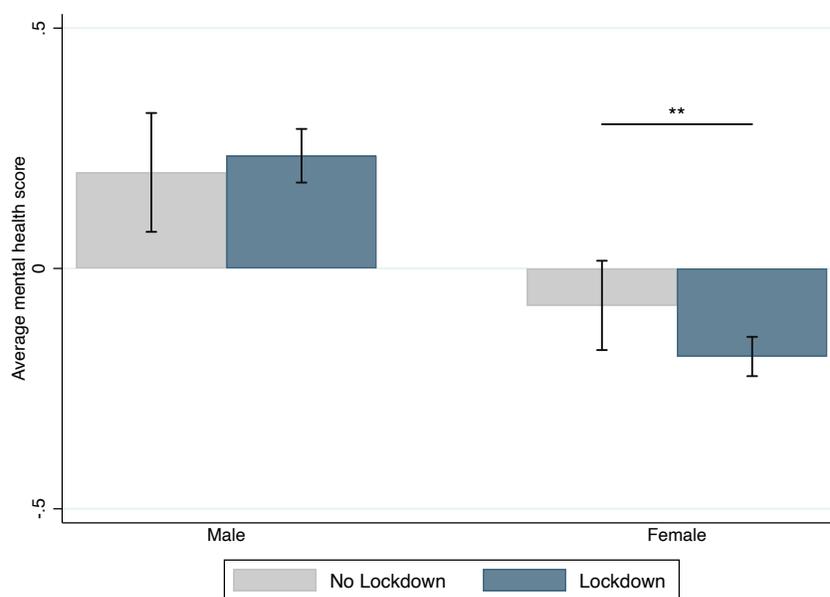
Online Appendix B: Additional Tables and Figures

Table B.1: Mental health score - Days since lockdown

	Early April		Late March
	Full sample	Restricted sample	Placebo
Days of Lockdown (April)	-0.0048 (0.0021)	-0.0092 (0.0037)	-0.0015 (0.0040)
Female	-0.3340 (0.0319)	-0.2959 (0.0420)	-0.2385 (0.0437)
Household income	0.0263 (0.0052)	0.0222 (0.0067)	0.0364 (0.0070)
University degree	0.1208 (0.0327)	0.1788 (0.0423)	0.1423 (0.0445)
30-39	0.0555 (0.0424)	0.0323 (0.0554)	0.0795 (0.0546)
40-49	0.0030 (0.0463)	-0.0657 (0.0589)	0.0261 (0.0645)
50-59	-0.0806 (0.0504)	-0.1414 (0.0647)	-0.0036 (0.0653)
60+	0.0639 (0.0515)	0.0581 (0.0684)	0.1411 (0.0703)
Single	-0.1111 (0.0333)	-0.1052 (0.0429)	-0.0617 (0.0442)
Constant	0.0407 (0.0612)	0.0692 (0.0780)	-0.1167 (0.0764)
Observations	3990	2313	2294
R^2	0.0642	0.0627	0.0583

Notes: OLS regressions. Robust standard errors in parentheses. The dependent variable is the standardized mental health score. Days of Lockdown indicates the number of days between the time when the state of residence of the respondent imposed stay-at-home measures and the second data collection. Column 1 reports results for the full sample of wave 2. Column 2 restricts the sample to respondents to 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 to the *first* wave who lived in states that did not have lockdown measures in place at the time of the first data collection.

Figure B.1: Mental health score by gender and whether state is in lockdown



Notes: The graph shows the average mental health score separately by gender and by whether the state the respondent was living in had stay-at-home orders in place in mid-April. The thin black bars represent the 95% confidence intervals.

Table B.2: Controlling for realized impacts - Women (Weighted)

	(1)	(2)	(3)	(4)	(5)
Lockdown (April)	-0.1291 (0.0527)	-0.1334 (0.0532)	-0.1043 (0.0547)	-0.1042 (0.0547)	-0.1012 (0.0543)
Had troubles paying bills	-0.2739 (0.0470)				-0.2935 (0.0484)
Worked fewer hours	-0.0280 (0.0493)				-0.0346 (0.0505)
Earned less money	0.0037 (0.0529)				-0.0033 (0.0540)
Children (below 18)		-0.0164 (0.0447)			-0.0024 (0.0451)
Change work patterns		-0.0484 (0.0433)			0.0119 (0.0448)
Cases per 1000 inhabitants			-0.0278 (0.0114)		-0.0028 (0.0245)
Deaths per 1000 inhabitants				-0.8443 (0.3233)	-0.7625 (0.6860)
Constant	0.0009 (0.0828)	-0.1944 (0.0794)	-0.2034 (0.0762)	-0.2044 (0.0762)	0.0414 (0.0876)
Observations	2321	2322	2214	2214	2211
R^2	0.0358	0.0162	0.0176	0.0179	0.0418
Controls	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Robust standard errors 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 value of one if the respondent reported experiencing the given outcome in the week before data collection. Children is a binary value that takes value one if the respondent has children under the age of 18 living at home with him / her. Cases and deaths per 1000 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 as a university degree and is single.

Table B.3: Controlling for realized impacts - Men (Weighted)

	(1)	(2)	(3)	(4)	(5)
Lockdown (April)	-0.0309 (0.0729)	-0.0126 (0.0730)	0.0022 (0.0752)	0.0022 (0.0751)	-0.0159 (0.0748)
Had troubles paying bills	-0.1034 (0.0647)				-0.1309 (0.0675)
Worked fewer hours	0.0619 (0.0641)				0.0363 (0.0666)
Earned less money	-0.1291 (0.0644)				-0.1315 (0.0672)
Children (below 18)		0.1431 (0.0666)			0.1662 (0.0675)
Change work patterns		0.0158 (0.0573)			0.0388 (0.0599)
Cases per 1000 inhabitants			-0.0117 (0.0137)		0.0066 (0.0262)
Deaths per 1000 inhabitants				-0.3656 (0.3979)	-0.5479 (0.7800)
Constant	0.1246 (0.1254)	-0.1220 (0.1228)	-0.0435 (0.1180)	-0.0447 (0.1180)	0.0728 (0.1326)
Observations	1661	1665	1528	1528	1524
R^2	0.0450	0.0430	0.0393	0.0394	0.0522
Controls	Yes	Yes	Yes	Yes	Yes

Notes: OLS regressions. Robust standard errors 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 value of one if the respondent reported experiencing the given outcome in the week before data collection. Children is a binary value that takes value one if the respondent has children under the age of 18 living at home with him / her. Cases and deaths per 1000 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 as a university degree and is single.

Online Appendix C: Questionnaire

WHO 5-Question Module *Over the last two weeks, ...* [Answers on a scale from 0 - “At no time” to 5 - “All of the time”.]

- *I have felt cheerful and in good spirits*
- *I have felt calm and relaxed*
- *I have felt active and vigorous*
- *I woke up feeling fresh and rested*
- *My daily life has been filled with things that interest me*

Realized impacts *Think about the last week compared to your life in February. Due to the coronavirus outbreak, did you...* [Yes / No answers]

- *Work fewer hours than usual*
- *Earn less money than usual*
- *Have troubles paying your usual bills and expenses*
- *Have to change your work patterns to care for others*