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Lina Anaya; Peter Howley; Muhammad Waqas and Gaston Yalonetzky

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# Locked down in distress: a causal estimation of the mental-health fallout from the COVID-19 pandemic in the UK

**Lina Anaya**[1]
University of Bradford

**Peter Howley**[2]
University of Leeds

**Muhammad Waqas**[3]
University of Bradford

**Gaston Yalonetzky**[4]
University of Leeds

**Abstract**

There is an extensive literature documenting the economic impacts of the Covid-19 pandemic. A nascent literature is also beginning to detail the mental health impact. This research has, for instance, told us much regarding the initial impacts of lockdowns and stay-at-home orders for mental well-being, but a limitation with much of this work is that any reported findings generally cannot be taken as causal estimates. In this study, we use a large-scale longitudinal survey coupled with differences-in-differences and a regression-discontinuity design to estimate the impact of the Covid-19 pandemic on mental health. We find substantive estimated increases in psychological distress for the population overall but these impacts are not uniformly distributed. Specifically, the costs in terms of mental health appear to be much more pronounced for females, those with children, members of the BAME community and migrants. A further particularly important moderating variable appears to be people's own subjective assessment as to the adequacy of their income.

Keywords: well-being; Covid-19; lockdown; UK

JEL: I12, I31, J22

[1] Postdoctoral Research Associate, University of Bradford. Email: l.anaya@bradford.ac.uk

[2] Professor of Economics and Behavioural Science, Leeds University Business School. Email: p.howley@leeds.ac.uk

[3] Lecturer in Economics, University of Bradford. Email: M.Waqas9@bradford.ac.uk

[4] Lecturer in Economics, Leeds University Business School. Email: G.Yalonetzky@leeds.ac.uk

## 1. Introduction

The Covid-19 pandemic has become one of the most significant public health crises of our time. In response, governments in the UK and elsewhere have taken unprecedented and perhaps previously unimaginable steps to protect public health. One of the major weapons used by governments to save as many lives as possible in the short and medium term has been to impose lockdowns or other less restrictive measures such as social distancing guidelines in order to minimise the spread of Covid-19. There has been much research quantifying the economic cost associated with such initiatives coupled with the economic benefit of lives saved (Benzeval et al., 2020; Goolsbee & Syverson, 2021; Gupta et al., 2020; Miles et al., 2021; Rojas et al., 2020). In addition to these economic impacts, there are a number of other likely impacts in terms of mental health and well-being.

The implementation of physical distancing measures has, for instance, profoundly impacted the way people live their lives and such changes will inevitably have consequences for people's mental well-being. Recognising this issue, there is a nascent literature concerned with quantifying the mental health burden associated with the pandemic. Such efforts are an important endeavour, as it is only by ascertaining the full welfare consequences of the pandemic and associated mitigation strategies such as lockdowns, that we can begin to make more informed decisions regarding the scope and nature for government intervention when it comes to responding to this or indeed future pandemics. Additionally, having a better understanding of the extent to which restrictions placed on people may affect mental health, and perhaps most importantly for whom, will be essential in informing policies that could help mitigate these detrimental impacts. In this paper, we employ longitudinal data from the UK Household Longitudinal Study (UKHLS or Understanding Society) and the UKHLS COVID-19 panel coupled with a Difference in Difference and Regression Discontinuity research design to evaluate the impact of the pandemic on mental health.

A consistent finding in the emerging literature on this topic is that the Covid-19 pandemic is associated with a substantive rise in psychological distress (see Banks et al., 2021 for a recent review). This information pertaining to the mental health impacts has come from a wide array of sources. A number of bespoke surveys have, for instance, been set up to track people's mental well-being during the pandemic. This includes the UCL Covid-19 Social Study which has been collecting mental health and loneliness data from a large sample of UK adults since the start of the first lockdown (Fancourt et al., 2020) and the USC Understanding America Study (Kapteyn et al., 2020). The key advantage of these surveys is that they provide high frequency data and are able to rapidly tailor their design to capture a variety of issues of direct relevance to the pandemic. The disadvantage is that they do not contain estimates relating to how people felt before the pandemic which makes it challenging to capture the causal impact of the pandemic.

A further source of data comes from a number of pre-existing cross sectional or longitudinal surveys, many of which have adapted their design (and/or data collection strategies) in order to specifically collect data of relevance to the Covid-19 pandemic. The main advantage of this approach relative to the bespoke surveys described earlier is that such pre-existing surveys contain information from people before the pandemic. This means that one can develop a before-and-after comparison when it comes to the mental health response to the pandemic. As an example of this approach, in the UK the ONS reported a 29% point rise in those reporting elevated anxiety between the last quarter of 2019 and March 2020 which gives an indication of the initial mental health burden of the pandemic (ONS 2020a; 2020b). Similarly, several studies in the US showed on average significantly higher levels of psychological distress and loneliness in surveys carried out in 2020 than similar surveys in 2018 (McGinty et al., 2020; Swaziek & Wozniak, 2020).

An important feature of this existing research is that it suggests that there may be significant inequalities in the degree to which different groups will experience poor mental health in response to the pandemic. In particular, studies have reported that women, ethnic minorities, young adults, working parents, and people who face financial insecurity have been disproportionately impacted in their mental well-being (Banks & Xu, 2020; Cheng et al., 2021; Daly et al., 2020; Etheridge & Spantig, 2020; Giovanis & Ozdamar, 2020; Niedzwiedz et al., 2021; Swaziek & Wozniak, 2020; Zamarro & Prados, 2021). As an illustration, using data from the UKHLS, Etheridge & Spantig (2020) showed that women's average mental wellbeing declined by 0.25 standard deviations from 2018 to April 2020, which is twice as large as the well-being loss observed by men during the same period. This result is also consistent with further studies from the UK (Cheng et al., 2021; Daly et al., 2020; Giovanis & Ozdamar, 2020; Zamarro & Prados, 2021), as well as evidence from the Worldwide COVID-19 Attitudes and Beliefs survey data (Buyukkececi, 2021; Cheng et al., 2021).

Another demographic group that seems to face a disproportionately high burden on their mental health is young adults. Using data from Understanding Society, Daly et al. (2020) reported that 18–34-year-olds showed the largest increase in mental health issues during the pandemic, relative to other socio-demographic groups. There is also some evidence to suggest that the immigrant population and Black, Asian, and Minority Ethnic (henceforth BAME) communities, experienced larger declines in mental health in comparison to host country residents and people from a White ethnic background respectively (Proto & Quintana-Domeque, 2021; Shen & Bartram, 2021).

In summary, the existing evidence suggests that the initial mental health burden from the pandemic can be substantive, but these estimated impacts are far from uniformly distributed. While this research has been important, a limitation is that even when data is available before the pandemic, any estimated effects cannot be taken as causal. The main reason is because these studies are not able to precisely identify an appropriate counterfactual, namely what would have happened in the absence of the pandemic. This identification is important as some mental health measures have been trending downwards in the UK prior to the pandemic and therefore before-and-after comparisons may overstate the mental health burden (Banks et al., 2021). Additionally, there are seasonal patterns to reported mental health measures meaning that any reported difference in mental health pre-and post-pandemic may be partly confounded with seasonal trends.

Some recent studies have tackled these causality issues with innovative research designs. Banks & Xu, 2020, for example, developed estimates related to counterfactual levels of mental health that would be observable in the absence of the pandemic using UKHLS data spanning many years pre-pandemic. Using the General Health Questionnaire, as their measure of mental health, they estimate that average GHQ scores rose by 0.9 points indicating a worsening of mental health of approximately 0.17 of a standard deviation of the pre-pandemic distribution. The advantage of this approach is that by modelling counterfactuals it can directly take into account seasonal, age and gender specific trends. The disadvantage is that results are sensitive to different model specifications designed to estimate the counterfactual as well as the time period used to fit the model (Banks & Xu, 2020).

In an innovative approach, Brodeur et al. (2021) used google trends data to test whether Covid-19 and the associated lockdowns led to changes in well-being-related search terms. Their main results came from a Difference-in-Difference (henceforth DiD) estimation that compared search terms pre-and post-lockdown to the same dates in 2019. They also supplemented this approach by simultaneously combining a regression discontinuity design (henceforth RDD) and a DiD model to estimate the immediate impact of lockdowns. They report a significant increase in search intensity for boredom in Europe and the US during lockdown periods and also significant increases in searches for loneliness, worry and sadness, while searches for stress, suicide and divorce fell.

Our approach is close in spirit to the approach by Brodeur et al. (2021). We also implement a DiD model and RDD in order to estimate the impact of lockdowns (in this case the one implemented in the UK on March 23rd 2020) for mental health but with some important additions. First, by using the UKHLS (as opposed to search terms from google trends) we are able to take advantage of a more direct measure of mental health, namely the General Health Questionnaire (commonly referred to as the GHQ-12). Second, we are able to explore heterogeneity in impact across the population. Finally, we are also able to estimate the immediate impact of lockdowns on mental health by employing different bandwidths around the lockdown announcement date. The idea behind this approach is that, by focusing on measurements of people's mental health close to the lockdown announcement date, we can compare a more homogenous sample of individuals who are exposed to relatively similar circumstances right before and after the lockdown announcement to obtain a cleaner measure of the immediate effect on mental health.

Our main findings suggest that people's mental health may have been severely impacted by the pandemic. As an illustration, the average estimated well-being loss observed between March 23rd and May 31st 2020 in the UK (the dates of the first nationwide lockdown) as compared to the same period in 2019 equates to approximately half the estimated impact of unemployment for mental health and exceeds that of other commonly observed negative correlates with well-being such as divorce and widowhood. Given that these are net population estimates (as opposed to a specific sub-group such as the unemployed) it suggests the initial utility loss (as proxied by the GHQ-12) associated with the pandemic was substantive. Our findings are also indicative of significant inequalities in impact with females, those with children, members of the BAME community, migrants and in particular those who feel under stress financially much more negatively impacted in terms of their mental health than other cohorts.

The rest of the paper proceeds as follows. Section 2 describes our dataset based on the UK Household Longitudinal Study and its special covid-19 pandemic supplement. Section 3 presents our two estimation strategies: a set of DID models, followed by an augmented set of models combining RDD with DID features. Section 4 presents our results and discusses its implications. The paper concludes with some remarks in section 5.

## 2. Data

We employ data from the UK Household Longitudinal Study (UKHLS) also known as Understanding Society. The UKHLS is a household panel that captures, among other things, information from adults about their economic and social circumstances, lifestyle, employment, family relationships, and mental health. Our key outcome variable of mental health contained in this survey dataset is the 12-item version of the General Health Questionnaire (GHQ-12). This 12-item scale is designed to assess somatic symptoms, anxiety and insomnia, social dysfunction, and general happiness (Goldberg & Hillier, 1979). It is possibly the most commonly used measure of subjective (self-reported) well-being (Jackson, 2007). The GHQ offers an advantage over single question measures of subjective well-being, such as happiness and life satisfaction as it is based on responses to 12 separate questions.[1] Each of the 12 items is scored on a four-point scale. The overall GHQ score can take values from 0 to 36, with 36 representing the lowest level of psychological well-being. The higher the score, the more likely it is that respondents are suffering from some form of psychological distress.

The UKHLS contains information from approximately 50,000 individuals for the ‘mainstage waves’ 1-8 which were collected from 2009 to 2018. Each wave spans three overlapping years, albeit the vast majority of interviews take place in the first two years, so that wave 1 runs from 2009 to 2011, wave 2 from 2010 to 2012 and so on. All adults aged 16 or older in each household are re-interviewed approximately one year apart, which means we can track changes in mental health as well as other characteristics of the same people over time. The sample is weighted to be nationally representative. Beginning in April 2020 (and thereafter continued monthly), participants of the UKHLS were asked to complete a short online survey on the impact of the COVID-19 pandemic. This included the General Health Questionnaire (GHQ-12) as well as socio-demographic characteristics. By including the GHQ-12 in this special Covid-19 survey[2], we are able to track to what extent the mental health of people changed over the course of the pandemic.

[1] Factor analysis shows that most of the variance within these 12 item measures can be explained by one overall general factor. In essence the GHQ-12 is unidimensional (Gnambs & Staufenbiel, 2018).
[2] Full details of sample design, response rates and response patterns are given in Institute for Social and Economic Research (2020).

## 3. Methodology

### *a.* Difference-in-difference (DiD) model

Quantifying the impact of the COVID-19 pandemic on mental health requires an estimate of the counterfactual, namely how mental health would have changed in the absence of the pandemic. While one could conduct a simple before-and-after comparison to ascertain how much people's mental health changed after the pandemic, such an approach may confound the impact of the pandemic with seasonal patterns or other trends in mental health measures over time. To overcome this potential issue, we adopt a differences-in-differences research design. In implementing this approach, we compare the mental health changes observed for people interviewed pre and post March 23rd 2020, which is the start date for the first UK lockdown, with that of those interviewed pre and post the same date in 2019. We select May 31st 2020 as our end point as that is when the first statewide lockdown in force in the UK ended.

Our main assumption with this approach is that the pandemic was an unanticipated shock and that, in the absence of the pandemic, the mental health during the lockdown period between March 23^rd^ and May 31st of 2020 would have changed identically to that of the period of March 23^rd^ and May 31st of 2019 simply because the interview dates are randomised across individuals in each survey year. By adopting this approach, any trends such as seasonal patterns should not impact our results. Upon adopting these time periods we are left with a baseline of 50,812 observations (which shrinks in some alternative specifications depending on the choice of covariates).

Table 1 presents the summary statistics for the DiD analytical sample for the periods between January 1^st^ 2019 and May 31^st^ of 2020. The subjective wellbeing in 2019 is on average about 25 out of 36 points, while in 2020 it is about 24 points. More than half of the individuals in our sample are female, between 8 and 10 percent are BAME, and roughly between 7 and 10 percent were not born in the UK. On average, on each period, more than 70 percent of the participants on each period report their financial situation as living comfortably or doing alright.

Formally we can write our DiD models as follows:

$$MH_{it} = \beta_0 + \beta_1 L_{it} * Year \quad + \beta_2 L_{it} + \beta_3 Year \quad + \alpha' X_{it} + \varepsilon_{it} \tag{1}$$

Where our dependent variable $MH_{it}$ corresponds to the mental health (GHQ-12) of individual $i$ reported at the beginning of the data collection interview on date $t$. The variable $L_{it}$ is a dummy that takes the value of one after the lockdown date was announced. The variable $Year$ represents a dummy for the 2020 year.

The vector $X_{it}$ includes demographic characteristics such as a dummy of female, BAME (i.e., Black, Asian, and Minority Ethnic), whether the respondent was not born in the UK, and an indicator of subjective financial situation. Finally, $\varepsilon_{it}$ corresponds to the error term,

Our estimate of interest is $\beta_1$, representing the change in mental health levels as a result of the implementation of the lockdown policy in 2020. The key assumption in our estimation is that the mental health levels we observe in 2019 would have been those of 2020 in the absence of lockdown and that other determinants of the outcome do not behave discontinuously at the cut-off.

### ***b. RDD-DID* models**

To test for the immediate impact caused by the lockdown we also adopt a regression discontinuity design (RDD) which identifies the initial structural break in two parametric series estimated pre-and post-lockdown. Similarly to our DiD estimates we compare these structural breaks to those that occur over the same period in 2019. Thus, we end up with an RDD-DiD model that can be written as follows:

$$MH_{it} = \beta_0 + \beta_1 L_{it} * Year_i + \beta_2 L_{it} + \beta_3 Year_i + \beta_4 D_{it} + \beta_5 D_{it} * L_{it} + \beta_6 D_{it} * Year_i + \beta_7 L_{it} * Year_i * D_{it} + \varepsilon_{it} \quad (2)$$

$D_{it}$ is a running variable that captures the beginning date of the data collection interview $t$ for individual $i$. This variable is measured in days elapsed since the lockdown announcement. It takes negative values if the interview began days before the lockdown and positive values if the interview began days after. The variable equals zero if the interview began on the date of the lockdown announcement. Therefore, here our estimate of interest is $\beta_1 + \beta_7 * D_{it}$, representing the change in mental health levels as a result of the implementation of the lockdown policy in 2020. That is, now we are allowing for heterogeneity in the causal estimate of the lockdown effect due to timing differences between the respective lockdown and initial interview dates.

One of the key methodological choices in RDD is the bandwidth magnitude (Lee & Lemieux, 2010) determining the sample sizes of the treated and untreated groups (lockdown and pre-lockdown experiences in our setting, respectively). The proposed optimal rules for bandwidths strike a balance between the need for sufficiently large sample sizes (calling for wider bandwidths) and the need to minimise heterogeneity between the two compared groups (calling for narrower bandwidths), which in our setting requires prioritising the closest days before and after the lockdown announcement date. To select the appropriate bandwidth, we follow optimal bandwidth algorithms developed by Calonico et al. (2017) and Cattaneo & Vazquez-Bare (2016). These methods feature, inter alia, data-driven bandwidth optimal selection as well as different bandwidths on either side of the cut-off point. Our preferred model specification employs the bandwidth of 17.5 days around the threshold since it produces more conservative estimates and a more balanced sample in observable characteristics (see Table 3 and appendix A1).

## 4. Results

### *a. DID estimates*

Table 2 presents our initial DiD estimates of the impact of the pandemic during the lockdown period of March 23rd and May 31st of 2020 on mental health. The first column presents the net mental health impact of the pandemic for the population as a whole. The DiD estimate, namely our interaction term *Interviewed Post Lockdown*Year 2020,* attracts a statistically significant coefficient and suggests that the lockdown or more precisely the mental health impact of the pandemic during the March 23rd to May 31st of 2020 period is associated with an increase of 0.76 units in psychological distress as measured by the GHQ.

How large/small is this effect? We can compare it to the impacts of other major life events on this measure of psychological distress found in the wider literature. It would, for example, be approximately 40-60% of the estimated disutility associated with unemployment and at least as large as the typical estimated effects of divorce and widowhood for mental health.[3] Clearly then, the consequences of the pandemic for mental health are substantive, all the more so considering that these initial estimates relate to the overall population impact, as opposed to specific sub-groups such as the unemployed.

After calculating the initial population impact, we tested whether these estimated impacts were moderated by gender, ethnicity, and migrant status. Additionally, we supplemented our DiD design with a subjective measure relating to people's own perception as to the adequacy of

[3] For example, Howley and Knight (2021), Clark and Oswald (1994) and Flint et al. (2013) estimate an impact of 1.58, 1.55 and 2.2 units respectively when it comes to unemployment.

their income. In this subjective measure, respondents are simply asked how well they are managing their finances these days, where 1 is “Living comfortably”, 2 is “Doing alright”, 3 is “Just about getting by”, 4 is “Finding it quite difficult”, and 5 is “Finding it very difficult”. In the analysis that follows, Living comfortably is the reference category. For simplicity, this variable appears as *subjective financial health (SFH).*[4]

In column 2 to 7 we present the results of three-way interaction models combining each of our potential moderating variables with our *Interview post lockdown*Year 2020* interaction term. Column 2 shows that *Female*Interview post Covid*Year 2020* attracts a statistically significant coefficient. There is of course uncertainty around these estimates, but they do suggest that Females endured a higher mental health toll from the pandemic vis-a-vis Males. Likewise, we find that both migrants (as opposed to natives, see column 4), and members of the BAME community (as opposed to White, see column 3), were more negatively affected. In column 5 we can see that people with children experienced worse mental health relative to people without children.

Finally we find that people’s own subjective evaluation of how well they are managing their finances ‘these days’ plays an important moderating role in shaping the psychological distress associated with the pandemic. Looking at columns 6 and 7 we can see, for example, that individuals who perceive themselves as doing less well financially are much more negatively impacted by the pandemic in terms of their mental health. The relationship also appears broadly monotonic, albeit there looks to be a more considerable jump in psychological distress when we get to people who report finding it very difficult to manage their finances these days.

[4] We considered also including an objective measure of income. However, there are understandably many missing observations in the special covid-19 monthly surveys which makes direct comparisons between our pre and treatment period challenging.

### *b. RDD-DID estimates*

To test for the immediate mental health impact associated with the lockdown enforced on March 23rd we adopted a regression discontinuity design (RDD). To further improve precision we compare our estimated structural break on March 23rd to that estimated over the same period in 2019 (RDD-DiD estimation). These estimated breaks are visually illustrated in Figures 1 and 2**.** We present the associated RDD-DiD estimates in Table 3. Looking first at Figure 1 which illustrates the predicted mental health for the periods between January and May of 2020 and 2019 we can see that a discontinuity in mental health occurs, which is indicative of higher mental distress after the lockdown announcement. We observe here, however, that the upward trend in mental distress started 30 days before the lockdown date. This result is not surprising given that many of the policies aimed at containing the spread of the virus occurred before the official lockdown date (i.e., social distancing policies, school closures, cancelation of public events, etc).

In Table 3, we present the RDD-DiD estimates. Column 1 shows the estimates associated with the preferred bandwidth of 17.5 days. The initial lockdown was associated with an increase in psychological distress of 2.33 units. By focusing on the immediate impact we are relying on roughly 2,000 observations either side of the lockdown announcement, of which 130 observations correspond to the year of 2020 for the period after the lockdown, and so we note the wide 95-percent confidence interval surrounding this estimate ($\beta$ =0.19 to 4.4).

Both the RDD-DiD and DiD measure different types of effect and so, unsurprisingly, the estimated effects using RDD-DiD are much larger than the DiD estimates in Table 2. The latter pick up the average mental health impact of the pandemic between March 23rd and May 31st of 2020, whereas the former pick up the immediate effect of the lockdown in the few days surrounding the lockdown announcement. Because the immediate impact is much larger than the full impact observed during March and May 2020, this result is indicative perhaps of some adaptation towards social distancing measures over time. In Table 3 we present our RDD estimates using different bandwidths and we note the same general picture: a substantive initial impact of lockdown on people's mental health.

## 5. Conclusions

In this paper, we use data from the UKHLS waves 9 and 10 and the COVID-19 survey waves of April and May of 2020 to study the impact of the pandemic on people's mental health. We simultaneously employ two quasi-experimental approaches namely a differences-in-differences and regression discontinuity design. Such an approach allowed us to present a snapshot of the initial impact of the first lockdown in the UK for people's mental health as well as broader impacts of the pandemic over a longer time period. Considering first the period March 23rd to May 31s of 2020 which corresponds to the period of the first national lockdown in the UK, we find that the pandemic led to an average increase in GHQ scores of 0.76 units. To put this into context, this would be approximately half the estimated disutility associated with unemployment and at least as large as the typical estimated impacts associated with other negative life events such as divorce and widowhood.

While the net population impact is substantive we find that it masks significant heterogeneity across groups. We find, for example, that the mental health burden associated with the pandemic is much more keenly felt by women than men. The presence of children appears to be another important moderating factor. Additionally, we find that BAME groups and migrants, as opposed to whites and natives, are much more likely to suffer mental health consequences, thus reinforcing many pre-existing inequalities. A particularly important factor appears to be people's own subjective feelings about their income as we find that the mental health burden associated with the pandemic for those who feel under financial stress was particularly pronounced.

We observe that the initial impact of the first UK lockdown on mental health was substantive. Specifically, we observed that the initial lockdown led to a 2.33 increase in our GHQ measure. The differences between our DiD estimates relating to the period March 23rd and May 31st of 2020 and these estimates relating to the initial impact of lockdown would indicate that a substantive part of this initial impact may have dissipated over time.

In summary, our estimates suggest that the initial impact of the pandemic for mental health was substantive. These impacts were however not uniformly felt with many groups experiencing much more substantive increases in psychological distress than others. These estimates, alongside previous research, provide us with rich insights into the initial consequences of the pandemic for mental health. Going forward, a useful avenue for future work would be to supplement this study with more information relating to the likely long-term consequences. This approach might include an examination of the long-term mental health consequences associated with the economic and social disruption caused by the pandemic. The possibility of long-term changes to our behaviour associated with living with this disease indefinitely, though in less lethal forms, may also be a factor that warrants some consideration. Finally, there may be long-term scarring effects associated with living under these restrictions and/or general anxiety related to the possibility of future pandemics.

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**Figures and Tables**

**Figure 1:** Mental distress before and after the lockdown announcement between January and May of 2020 and 2019

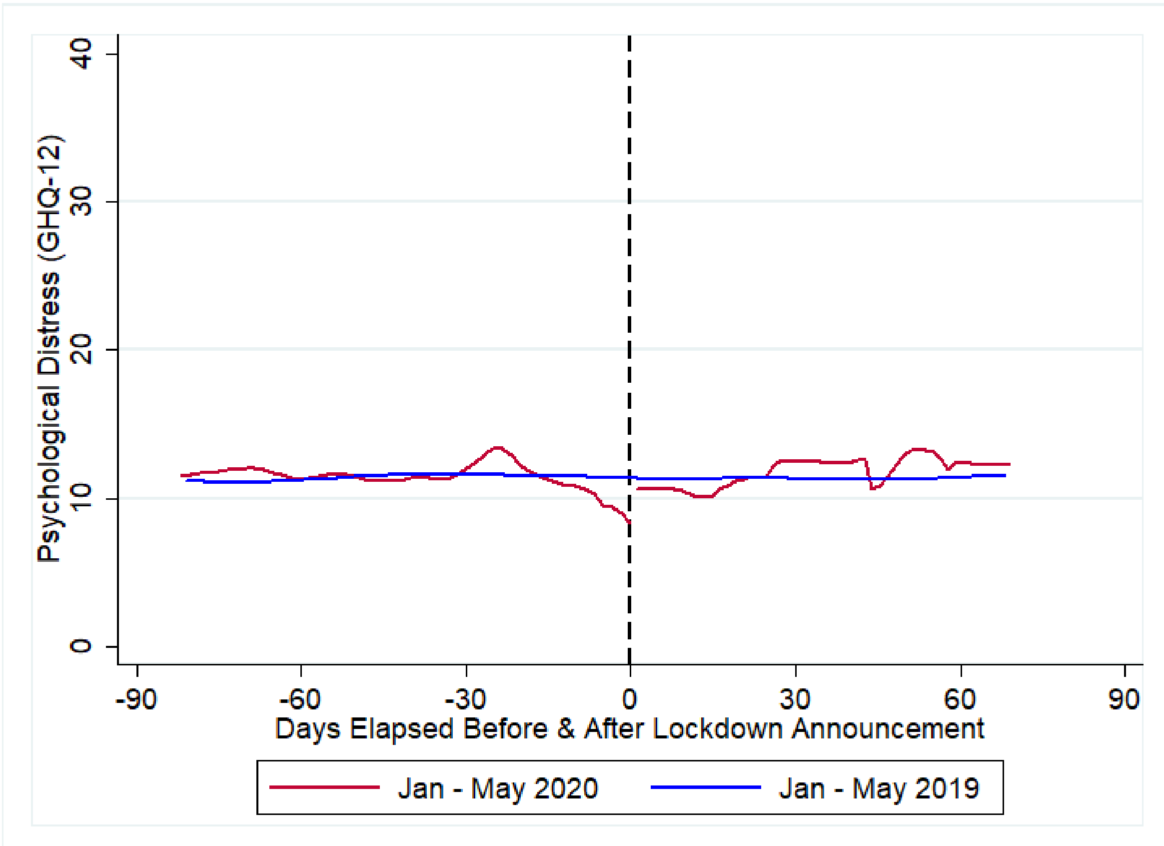

**Figure 2:** Mental distress before and after the lockdown announcement around the selected bandwidth (17.5 days)

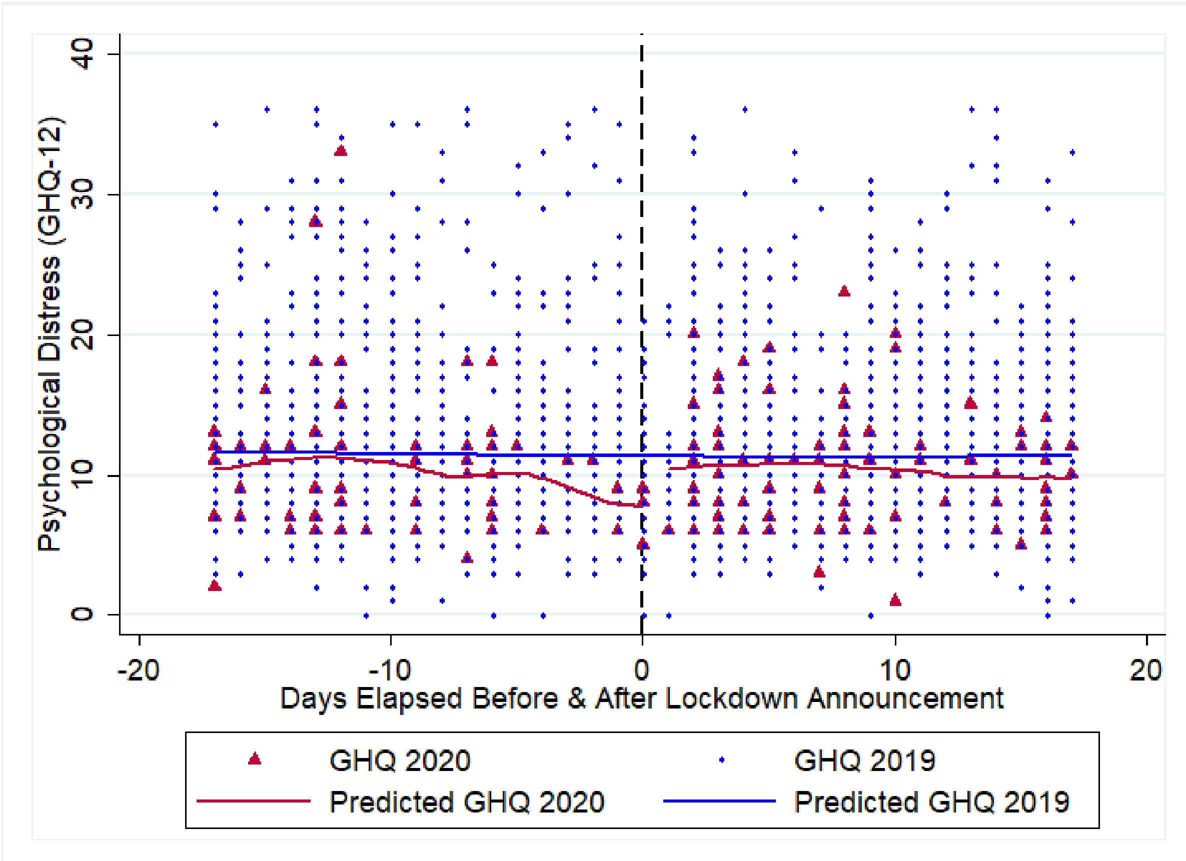

**Table 1:** Summary statistics of the analytical sample

| | DiD Sample From January to May | |
|---|---|---|
| Year | 2019 | 2020 |
| Psychological Distress (GHQ-12) | 11.39 | 12.23 |
| | (5.60) | (5.92) |
| Female (%) | 0.55 | 0.58 |
| | (0.50) | (0.49) |
| BAME (%) | 0.07 | 0.08 |
| | (0.26) | (0.28) |
| Not Born in UK (%) | 0.08 | 0.10 |
| | (0.27) | (0.30) |
| Children in household | 0.51 | 0.48 |
| | (0.92) | (0.87) |
| Subjective Financial Health (SFH): Living comfortably (%) | 0.31 | 0.35 |
| | (0.46) | (0.48) |
| Subjective Financial Health (SFH): Alright (%) | 0.40 | 0.43 |
| | (0.49) | (0.50) |
| Subjective Financial Health (SFH): Getting By (%) | 0.20 | 0.17 |
| | (0.40) | (0.37) |
| Subjective Financial Health (SFH): Difficult (%) | 0.06 | 0.04 |
| | (0.24) | (0.19) |
| Subjective Financial Health (SFH): Very Difficult (%) | 0.02 | 0.01 |
| | (0.15) | (0.12) |
| Observations | 17,918 | 23,205 |

Note: statistics represent the mean unless otherwise specified. Standard deviations in parenthereses.

**Table 2:** DiD estimation results of the pandemic effect on mental health

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Psychological Distress (GHQ-12) | | | | | | |
| Interview Post Lockdown (IPL)*Year=2020 | 0.76*** | 0.24 | 0.65*** | 0.72*** | 0.63*** | 0.57*** | -0.01 |
| | (0.14) | (0.15) | (0.14) | (0.14) | (0.14) | (0.14) | (0.15) |
| Interview Post Lockdown (IPL) | -0.06 | -0.05 | -0.05 | -0.07 | -0.06 | -0.00 | -0.02 |
| | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) |
| Year=2020 | 0.25** | 0.25** | 0.25** | 0.24** | 0.23* | 0.29*** | 0.29*** |
| | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.11) | (0.11) |
| Female | | 1.11*** | | | | | 1.03*** |
| | | (0.08) | | | | | (0.07) |
| IPL*Year=2020*Female | | 0.83*** | | | | | 0.87*** |
| | | (0.10) | | | | | (0.11) |
| BAME | | | 0.23 | | | | 0.23 |
| | | | (0.16) | | | | (0.18) |
| IPL*Year=2020*BAME | | | 1.12*** | | | | 0.61** |
| | | | (0.22) | | | | (0.25) |
| Not Born in UK | | | | -0.41*** | | | -1.04*** |
| | | | | (0.14) | | | (0.16) |
| IPL*Year=2020*Not UK born | | | | 0.60*** | | | 0.34 |
| | | | | (0.19) | | | (0.22) |
| Children in household (#) | | | | | 0.17*** | | -0.10** |
| | | | | | (0.04) | | (0.04) |
| IPL*Year=2020*Children | | | | | 0.23*** | | 0.12* |
| | | | | | (0.07) | | (0.07) |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 2 (Cont.):** DiD estimation results of the pandemic effect on mental health

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Psychological Distress (GHQ-12) | | | | | | |
| Subjective Financ Health (SFH): Alright | | | | | | 1.12*** | 1.14*** |
| | | | | | | (0.08) | (0.08) |
| SFH: Getting By | | | | | | 3.28*** | 3.30*** |
| | | | | | | (0.11) | (0.11) |
| SFH: Difficult | | | | | | 6.29*** | 6.34*** |
| | | | | | | (0.21) | (0.21) |
| SFH: Very Difficult | | | | | | 9.20*** | 9.28*** |
| | | | | | | (0.40) | (0.40) |
| IPL*Year=2020*SFH: Alright | | | | | | 0.59*** | 0.47*** |
| | | | | | | (0.10) | (0.11) |
| IPL*Year=2020*SFH: Getting by | | | | | | 0.81*** | 0.72*** |
| | | | | | | (0.15) | (0.17) |
| IPL*Year=2020*SFH: Difficult | | | | | | 0.94*** | 0.50 |
| | | | | | | (0.31) | (0.35) |
| IPL*Year=2020*SFH: Very Difficult | | | | | | 2.43*** | 1.30** |
| | | | | | | (0.59) | (0.64) |
| Constant | 11.42*** | 10.80*** | 11.40*** | 11.45*** | 11.33*** | 9.69*** | 9.23*** |
| | (0.06) | (0.07) | (0.06) | (0.06) | (0.06) | (0.07) | (0.08) |
| Observations | 50,812 | 50,812 | 50,812 | 50,812 | 41,180 | 50,748 | 41,123 |
| R-squared | 0.01 | 0.03 | 0.01 | 0.01 | 0.01 | 0.13 | 0.14 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 3:** RDD-DiD estimation results of the immediate effect of the lockdown on mental health

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Psychological Distress (GHQ-12) | | | | | |
| Bandwidth in elapsed days: | +/-17.53 | +/-10.2 | +/-12.29 | +/-21.13 | [-11.77, 12.29] | [-11.77, 12.39] |
| Interview Post Lockdown (IPL)*Year=2020 | 2.33** | 2.68** | 3.31** | 1.50 | 2.64** | 2.64** |
| | (1.09) | (1.35) | (1.40) | (1.16) | (1.26) | (1.26) |
| Interview Post Lockdown (IPL) | 0.09 | -0.09 | -0.06 | -0.01 | 0.02 | 0.02 |
| | (0.37) | (0.49) | (0.44) | (0.33) | (0.45) | (0.45) |
| Year=2020 | 2.73*** | 3.46*** | 3.86*** | 2.78*** | 3.20*** | 3.20*** |
| | (0.84) | (0.85) | (1.07) | (0.90) | (0.88) | (0.88) |
| Running Variable Intervew date | 0.01 | 0.01 | 0.02 | 0.02 | 0.00 | 0.00 |
| | (0.02) | (0.06) | (0.04) | (0.02) | (0.05) | (0.05) |
| Running_Var*Lockdown | -0.02 | 0.03 | -0.01 | -0.02 | 0.01 | 0.01 |
| | (0.03) | (0.08) | (0.06) | (0.03) | (0.06) | (0.06) |
| Running_Var*Year=2020 | 0.15* | 0.26* | 0.36* | 0.15** | 0.19 | 0.19 |
| | (0.08) | (0.15) | (0.20) | (0.06) | (0.15) | (0.15) |
| IPL*Year=2020*Running_Var | -0.08 | -0.28 | -0.33 | -0.22** | -0.16 | -0.16 |
| | (0.10) | (0.25) | (0.24) | (0.10) | (0.20) | (0.20) |
| Constant | 24.66*** | 24.66*** | 24.72*** | 24.72*** | 24.64*** | 24.64*** |
| | (0.27) | (0.36) | (0.33) | (0.25) | (0.34) | (0.34) |
| Observations | 4,535 | 2,522 | 3,231 | 5,590 | 3,056 | 3,056 |
| R-squared | 0.0025 | 0.003 | 0.0028 | 0.0026 | 0.0026 | 0.0026 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

## Appendix

**Table A1:** Probit point estimates balance-check of the demographic characteristics between the 2019 and 2020 sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Variable: Year=2020 | | | |
| | Same Bandwidth Above & Below the Cutoff | | | |
| Bandwidth in elapsed days: | **+/-10.2** | **+/-12.292** | **+/-17.526** | +/-21.131 |
| Female | -0.11 | -0.08 | -0.08 | -0.09* |
| | (0.08) | (0.08) | (0.06) | (0.05) |
| BAME | -0.09 | -0.13 | 0.01 | 0.07 |
| | (0.18) | (0.17) | (0.14) | (0.12) |
| Not Born in UK | -0.09 | -0.09 | -0.07 | -0.07 |
| | (0.16) | (0.15) | (0.13) | (0.11) |
| Children in household (#) | 0.03 | 0.04 | 0.05 | 0.00 |
| | (0.04) | (0.04) | (0.03) | (0.03) |
| Subjective Financ Health (SFH): Alright | 0.25** | 0.21** | 0.14* | 0.11* |
| | (0.10) | (0.09) | (0.08) | (0.06) |
| SFH: Getting By | -0.22 | -0.07 | 0.05 | 0.01 |
| | (0.14) | (0.12) | (0.09) | (0.08) |
| SFH: Difficult | -0.17 | -0.26 | -0.01 | -0.05 |
| | (0.24) | (0.22) | (0.15) | (0.13) |
| SFH: Very Difficult | -0.49 | -0.54 | -0.40 | -0.43* |
| | (0.40) | (0.38) | (0.29) | (0.24) |
| Constant | -1.67*** | -1.72*** | -1.70*** | -1.58*** |
| | (0.08) | (0.08) | (0.07) | (0.06) |
| Observations | 2,656 | 3,420 | 4,793 | 5,881 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Bandwidths in bold represent bandwidths that have a more balanced sample in observable characteristics

**Table A1 (Cont.):** Probit point estimates balance-check of the demographic characteristics between the 2019 and 2020 sample

| | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| | Dependent Variable: Year=2020 | | | |
| | Different Bandwidth Above & Below the Cutoff | | | |
| Bandwidth in elapsed days: | **[-11.77, 12.29]** | **[-11.77, 12.39]** | [-20.23, 21.13] | [-20.23, 21.3] |
| Female | -0.09 | -0.09 | -0.08 | -0.08 |
| | (0.08) | (0.08) | (0.05) | (0.05) |
| BAME | -0.13 | -0.13 | 0.08 | 0.08 |
| | (0.18) | (0.18) | (0.12) | (0.12) |
| Not Born in UK | -0.05 | -0.05 | -0.06 | -0.06 |
| | (0.16) | (0.16) | (0.12) | (0.12) |
| Children in household (#) | 0.05 | 0.05 | 0.00 | 0.00 |
| | (0.04) | (0.04) | (0.03) | (0.03) |
| Subjective Financ Health (SFH): Alright | 0.19** | 0.19** | 0.11* | 0.11* |
| | (0.09) | (0.09) | (0.06) | (0.06) |
| SFH: Getting By | -0.15 | -0.15 | 0.02 | 0.02 |
| | (0.13) | (0.13) | (0.08) | (0.08) |
| SFH: Difficult | -0.25 | -0.25 | -0.03 | -0.03 |
| | (0.23) | (0.23) | (0.13) | (0.13) |
| SFH: Very Difficult | -0.52 | -0.52 | -0.42* | -0.42* |
| | (0.39) | (0.39) | (0.24) | (0.24) |
| Constant | -1.72*** | -1.72*** | -1.59*** | -1.59*** |
| | (0.08) | (0.08) | (0.06) | (0.06) |
| Observations | 3,229 | 3,229 | 5,744 | 5,744 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Bandwidths in bold represent bandwidths that have a more balanced sample in observable characteristics