Received: 15 July 2022 | Accepted: 11 September 2023

DOI: 10.1111/ecin.13181

ORIGINAL ARTICLE

Economic Inquiry

Locked down in distress: A quasi-experimental estimation of the mental-health fallout from the COVID-19 pandemic

Lina Anaya[1] | **Peter Howley**[2] | **Muhammad Waqas**[1] | **Gaston Yalonetzky**[2]

[1]University of Bradford, Bradford, UK

[2]University of Leeds, Leeds, UK

Correspondence
Gaston Yalonetzky, Leeds University Business School, Maurice Keyworth Building, Leeds LS6 1AN, UK.
Email: G.Yalonetzky@leeds.ac.uk

Funding information
Economic and Social Research Council

Abstract

We use a large-scale longitudinal survey with a differences-in-differences research design to estimate the impact of the COVID-19 pandemic on mental health in the United Kingdom. We report substantial increases in psychological distress for the population overall during the first wave. These impacts were not uniformly distributed, with the mental health costs being more pronounced for females, younger cohorts, the black, Asian and minority ethnic community, and migrants. We also identified characteristics capable of predicting resilience to the mental health effects. We find that people with financial worries, loneliness or living in overcrowded dwellings experienced significantly worse mental health deterioration during the first wave.

KEYWORDS

Covid-19, lockdown, mental health, well-being

JEL CLASSIFICATION

I12, I31, J22

1 | INTRODUCTION

The Covid-19 pandemic has become the most significant public health crisis of our time. In response, governments in the UK and elsewhere have taken unprecedented steps to protect public health such as the imposition of lockdowns and other social distancing requirements. The implementation of physical distancing measures has profoundly impacted the way people live their lives and such changes will inevitably have mental health consequences. Looking beyond the impact of changes in behavior, general health anxiety (such as the fear of infection or, as the case for many, actual infection), is also likely to have negative repercussions on mental health.

A nascent literature seeks to quantify the mental health burden associated with the pandemic, in particular lockdowns and related restrictions (see Banks et al., 2021 for a review of this literature). Such efforts are an important endeavor, as it is only by ascertaining the full welfare consequences of such decisions, that we can begin to make more

Abbreviations: ATT, average treatment on the treated; BAME, black, Asian and minority ethnic; DiD, difference-in-difference; GHQ, General health questionnaire; SFH, subjective financial health; UK, United Kingdom; UKHLS, UK Household Longitudinal Survey.

Managing Editor: D. Mark Anderson

informed choices regarding the scope and nature of government intervention in response to this or indeed future pandemics. Additionally, having a better understanding of the extent to which the pandemic impacts different socio-demographic groups will be essential in informing targeted policies that could help mitigate these detrimental impacts.

We contribute to this literature by employing longitudinal data from the UK Household Longitudinal Study (UKHLS or Understanding Society) coupled with Difference-in-Difference (DiD) techniques to evaluate the causal impact of the initial wave of the pandemic on mental health. This framework allows us to calculate the impact of the pandemic and the resulting social restrictions on mental health more reliably than in previous work. An additional novel contribution of this work is that we explore factors/moderators capable of predicting the relative magnitude of these detrimental mental health impacts. A limitation of existing research is that there has been little, if any, attempt to understand the potential moderators behind the detrimental effects of the pandemic on mental health. The principal focus has been on documenting the main population impact as well as various inequalities of impact.

Our main findings suggest that the mental health burden of the pandemic at the population level is substantive. As an illustration, the average estimated well-being loss observed between March 23 and May 31, 2020 in the UK (which coincide with the dates of the first nationwide lockdown), as compared to the same period in 2019 equates to approximately one half to two-thirds of the estimated impact of unemployment for mental health and significantly exceeds that of other commonly observed negative correlates with well-being such as divorce and widowhood. While we find the population-level impact of the pandemic on mental health to be substantive, the overall impact is heavily dependent on who you are. Our findings indicate, for instance, that females, younger age groups, those born overseas, and members of the black, Asian and minority ethnic (BAME) community, were much more negatively impacted than other groups. Hence, they resonate with similar findings in the literature pertaining to differential impacts by gender (e.g., Banks & Xu, 2020; Daly et al., 2020; Etheridge & Spantig, 2020; Staneva et al., 2022; Zamarro & Prados, 2021), age (e.g., Banks & Xu, 2020; Daly et al., 2020; Staneva et al., 2022) and ethnicity (Swaziek & Wozniak, 2020).

Looking beyond demographics we also identify an array of factors which predict who was least resilient to the adverse mental health effects associated with the first wave of the pandemic. These include the presence of financial worries, loneliness and household density. People reporting more financial concern, loneliness or living in denser dwellings all experienced worse mental health deterioration. For instance, in the case of loneliness, each categorical increase in more acute loneliness reporting led to marginal mental health impacts greater than the population-level average effect.

The rest of the paper proceeds as follows. Section 2 discusses previous literature in this rapidly evolving field. Section 3 describes our dataset based on the UK Household Longitudinal Study and its special covid-19 pandemic supplement. Section 4 presents our estimation strategy, namely a set of DID models. Section 5 presents our results and discusses their implications. The paper concludes with some remarks in Section 6.

2 | PREVIOUS RESEARCH

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). The results regarding the mental health impacts have come from a wide array of surveys; some of them, for instance, track people's mental well-being during the pandemic. These surveys include 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 can 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 data source comes from some 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 pre-existing surveys contain information from people before the pandemic, which means that one can develop a before-and-after comparison of the mental health response to the pandemic. As an example of this approach, Davillas and Jones (2021), using the UKHLS, report a substantive worsening of mental health during the peak of the pandemic as captured by the General Health Questionnaire (GHQ). Additionally, Staneva et al. (2022) also using the UKHLS, document that the first months of the pandemic were associated with an increase in psychological distress and that this impact was larger for younger adults.

Similarly, to these UK-based studies, several studies in the US showed, on average, significantly higher levels of psychological distress and loneliness in surveys carried out in 2020 than in similar surveys in 2018 (McGinty et al., 2020; Swaziek & Wozniak, 2020). In Germany, Schmidtke et al. (2021) use monthly panel data from December 2018 to December 2020, coupled with individual fixed-effects, and document that workers in Germany underwent a significant decline in mental health during the first and second wave of the pandemic.

Remarkably, this existing research suggests 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 and working parents have been disproportionately impacted when it comes to their mental well-being (Banks & Xu, 2020; Daly et al., 2020; Etheridge & Spantig, 2020; Paudel, 2021; Staneva et al., 2022; Swaziek & Wozniak, 2020; Zamarro & Prados, 2021).

Notwithstanding these socio-demographic differences, Davillas and Jones (2021) find no increase in relative socioeconomic inequality at the onset of the pandemic, suggesting that the greater total inequality that is evident in terms of psychological distress remains broadly diffused across the population. In addition to socio-demographic differences, there also appears to be some initial evidence that personality traits may play a significant role in predicting psychological distress. Johnston et al. (2021) report, for example, that self-efficacy defined as confidence in one's capability to deal with life stresses has a protective effect. On the other hand, both openness and extraversion seem to be positive predictors of psychological distress (Proto & Zhang, 2021). Additionally, Staneva et al. (2022) outline that neuroticism may also predict psychological distress at least for certain socio-demographic groups.

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 that 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 key as some mental health measures were trending downwards in the UK before 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.

A small number of recent studies have tackled these causality issues with innovative research designs. Banks and 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 GHQ, as their measure of mental health, they estimated 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 modeling 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 period used to fit the model (Banks & Xu, 2020).

By exploiting different timings in the implementation of lockdowns between England and Scotland, Serrano-Alarcon et al. (2021) were able to take advantage of a quasi-natural experiment in order to assess the impact of lockdowns on mental health. They found that the easing of lockdown restrictions was associated with a significant improvement in mental health and their observed improvement was principally driven by people with lower socio-economic status.

In a further innovative approach, Brodeur et al. (2021) used Google trends data to test whether Covid-19 and associated lockdowns led to changes in well-being-related search terms. Their main results came from a DiD estimation that compared search terms pre-and post-lockdown to the same dates in 2019. They report a significant increase in search intensity for boredom in both Europe and the US during lockdown periods and significant increases in searches for loneliness, worry and sadness, while searches for stress, suicide and divorce fell. Silverio-Murillo et al. (2021) conducted a similar study to evaluate the association between the COVID-19 lockdowns and mental health-related Google searches in Latin America. Similar to Brodeur et al. (2021), they find that Google searches for words associated with mild mental health disorders increased during the COVID-19 stay-at-home orders and also note that searches related to suicide and insomnia fell following the passage of each country's income support policies.

Regarding previous studies that tried to quantify the impact of lockdowns for mental health, Hensel et al. (2022) made an important point about how challenging it is to identify an appropriate counterfactual. If the aim is quantifying the impact of lockdowns as opposed to the pandemic, comparing the mental well-being of people before and during lockdown is not enough. Before the implementation of lockdowns, people may have been more concerned about covid, at least in the early stages, as it would signal government inaction. Hensel et al. (2022) in a cross-country analysis find that lockdowns, during their early stage, were associated with greater optimism about the governments' responses and improvements in mental well-being. In this context, it becomes important to state that in our study we are capturing the levels of psychological distress experienced during the first wave of the pandemic, which we define as the whole first lockdown period, as opposed to the impact of the lockdown itself.

2.1 | Current aims

Our approach is close in spirit to that of Brodeur et al. (2021) and Silverio-Murillo et al. (2021). We also implement a DiD model in order to estimate the causal impact of the first wave of the pandemic on mental health (corresponding to the dates of the first lockdown period), but with some important additions. First, by using the UKHLS (as opposed to search terms from Google trends) we take advantage of a more direct measure of mental health, namely the GHQ (commonly referred to as the GHQ-12).

An additional advantage of our work is that we explore socio-demographic differences in impact across the population given the relatively large survey dataset at our disposal. This, we suggest, may help better characterize those whose mental health is most at risk. Our definition of socio-demographic groups is informed by the ethics of responsible egalitarianism (e.g., see Roemer & Trannoy, 2016) and its emphasis on characteristics largely beyond people's control, that is, those for which they cannot be held responsible. Thus, we look into differential mental health impacts by sex at birth, location at birth (British-born vs. foreign-born), age, and ethnicity (BAME vs. non-BAME). A further novel feature of our work is that we go beyond demographics and look at characteristics which help us identify who was least resilient to the adverse mental health impacts from the first wave of the pandemic. Our analysis points first to the importance of financial worries and loneliness. Our proposed explanation is that those with comparatively fewer financial worries and least likely to feel lonely are more likely to have the financial resources as well as social support in place to deal with many of the challenges brought on by the pandemic. Additionally, we find that household density is an important factor in predicting who was most likely to be negatively impacted. Our proposed explanation is that higher density households are more likely to experience crowding stress brought on by the lockdown restrictions.

3 | DATA

We employ data from the UKHLS also known as Understanding Society. The UKHLS is a household panel dataset 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). It is possibly the most commonly used measure of subjective (self-reported) well-being (Jackson, 2007).[1] 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.[2] 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" 1–11 which were collected from 2009 to 2020. Each wave spans three overlapping years, albeit most 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. Notably, the survey fieldwork is not constrained to certain time periods, and sample members from the main-stage waves are interviewed every year as long as they continue to live in the UK and can be located. Every individual's interview is ensured to be at approximately 12-month interval by an overlapping fieldwork; that is, in any given year, interviews for two consecutive waves are conducted. Thus, even though an individual interviewed in March one year is more likely to be interviewed around March the next year (as opposed to any random date), we do not expect any systematic bias related to timing of interviews, in the sense that individuals as a whole are no more likely to be interviewed in March as opposed to, say, June.

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,[3] we can track to what extent the mental health of people changed throughout the pandemic and examine if there were any differences across population sub-groups.

3.1 | Resilience

We take advantage of variables contained in the UKHLS dataset in order to test whether financial stress, loneliness and household density were all important factors in helping to explain the mental distress experienced during the first wave of the pandemic in the UK. We describe each of these variables as well as our rationale for including them below (see Table 1 for summary details).

3.1.1 | Subjective financial health

We hypothesize that the initial wave of the pandemic, in particular the lockdown restrictions, would have led to considerable financial distress for many people and this, in turn, would have had adverse consequences for mental health. As an illustration, nearly 9 million jobs were furloughed during the initial wave of the pandemic (Francis-Devine et al., 2021, chart 1). We posit that people with existing financial worries would have been less resilient to the impact of this external shock when it comes to their own mental health.

In order to examine the importance of financial worries, we take advantage of a unique survey measure in the UKHLS dataset. This variable asks individuals to evaluate how well they are managing their finances on a five-point scale, where 1 is "Living comfortably," 2 is "Doing all right," 3 is "Just about getting by," 4 is "Finding it quite difficult," and 5 is "Finding it very difficult." For simplicity, we label this variable as subjective financial health (SFH).[4] On average, just over 70% of the participants report their financial situation as living comfortably or doing all right in each period. To assess the importance of this variable, we evaluate whether there are significant differences in the mental health impacts associated with the first wave of the pandemic based on how individuals respond to this survey question. One thing we need to bear in mind is that the pandemic itself likely led to financial distress for many and so, in addition to contemporaneous values, we use lagged values of SFH in a separate model specification. In this latter case, we are looking at whether financial worries in the year prior to the pandemic predicted the mental health impacts associated with the first wave of the pandemic.

3.1.2 | Loneliness

A wealth of literature in the economics of happiness field has documented the importance of social support or, more broadly, social capital for psychological well-being (e.g., see Helliwell & Putnam, 2004). Looking outside economics, the harmful consequences of poor social support for mental health have also been well documented. Sippel et al. (2015) explain how health, both physical and mental, is inextricably tied to people's human connections. Indeed, social support has been shown to positively impact mental health through a variety of mechanisms (see Smith & Christakis, 2008; Thoits, 2011 for a review of this literature). One of the most common reasons put forward is that social support helps individuals cope with current difficulties. This can be due to emotional support, information exchange as well exchange of goods or services, and also advice on how best to deal with challenging circumstances (Ozbay et al., 2007; Sippel et al., 2015).

Following on from this line of literature, we posit that social support will help to predict who was least resilient to the first wave of the pandemic when it comes to mental health. In order to examine the importance of social support, we take advantage of a survey item in the UKHLS which records the degree to which people report feeling lonely. Specifically, individuals are asked to indicate how often they feel lonely with three options, namely "often feel lonely," "some of the time feel lonely" and finally our baseline category "hardly ever or never feel lonely." Our idea behind using this variable as a proxy for social support is simply that one of the main reasons why people self-report being lonely is a lack of social support (Zhang & Dong, 2022). Given that loneliness may be caused in part by restrictions imposed in relation to the pandemic, we test whether mental health impacts vary across different loneliness categories using both contemporaneous and lagged values (in separate, respective statistical models).

TABLE 1 Summary statistics.

	DiD sample	
	01/Jun/2018 to 31/May/2019	**01/Jun/2019 to 31/May/2020**
Outcome & demographic variables		
Psychological distress (GHQ-12)	11.33	11.94
	(5.60)	(5.83)
Female (%)	0.56	0.57
	(0.50)	(0.49)
BAME (%)	0.11	0.08
	(0.31)	(0.27)
Not born in UK (%)	0.12	0.09
	(0.33)	(0.29)
Age: 18 to 34 (%)	0.21	0.17
	(0.41)	(0.38)
Age: 35 to 49 (%)	0.25	0.25
	(0.43)	(0.43)
Age: 50 to 64 (%)	0.28	0.30
	(0.45)	(0.46)
Age: 65 and above (%)	0.26	0.28
	(0.44)	(0.45)
Observations	30,313	48,683
Predictors		
Subjective financial health (SFH): Living comfortably (%)	0.31	0.34
	(0.46)	(0.47)
Subjective financial health (SFH): All right (%)	0.40	0.43
	(0.49)	(0.49)
Subjective financial health (SFH): Getting by (%)	0.21	0.18
	(0.41)	(0.38)
Subjective financial health (SFH): Difficult & very difficult (%)	0.08	0.06
	(0.27)	(0.24)
Crowding	0.97	0.93
	(0.51)	(0.48)
Hardly ever or never feels lonely (%)	0.62	0.64
	(0.48)	(0.48)
Feels lonely some of the time (%)	0.30	0.29
	(0.46)	(0.45)
Often feels lonely (%)	0.08	0.07
	(0.27)	(0.25)
Observations	23,925	33,211

Note: Statistics represent the mean unless otherwise specified. Standard deviations in parentheses.

Abbreviation: BAME, black, Asian and minority ethnic.

3.1.3 | Household density

Finally, we posit that household density will be a significant marker of psychological distress. Our rationale here is that being constrained to one's home for long periods, as was required during the first wave of the pandemic, will result in what psychologists refer to as crowding stress (Regoeczi, 2008). Crowding stress is closely related to density in that when density is perceived as being too high it can lead to crowding stress (Churchman, 1999; Evans & Cohen, 2004). Our intuition here is that while crowding stress is unobservable, it will be closely related to density within the household. Single people, for example, living in large dwelling units are on the whole likely to be much less impacted by crowding stress than families living in multiple occupancy dwelling units.

To construct our household density variable, we divide the total number of people living in the household by the number of bedrooms in their dwelling unit, information that is collected in the UKHLS. We then simply examine to what degree the mental health impact of the first wave of the pandemic varies according to household density.

4 | METHODOLOGY

4.1 | 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 23, 2020, which is the start date for the first UK lockdown, with that of those interviewed before and after the same date on the year before (i.e., March 23, 2019). We select May 31, 2020 as our endpoint as the first nationwide lockdown measures reduced significantly thereafter (e.g., see Institute for Government, 2021).

In summary, with our DiD approach, we are first simply estimating and subtracting the average GHQ score observed for individuals surveyed between June 1, 2019 and March 23, 2020, from the average GHQ score observed for individuals interviewed between March 23 and May 31, 2020 (i.e., during the first wave of the pandemic). This difference can be deemed as a simple pre-and-post lockdown comparison.

Next, we again calculate changes in the GHQ score, using the same month-and-day dates as reference points, but this time using 2018 (replacing 2019) and 2019 (replacing 2020). Thus, these two sets of observations form our counterfactual group, namely observations from those interviewed between June 1, 2018 and March 23, 2019 which we compare to people surveyed between March 23, 2019 and May 31, 2020. Subtracting the before-and-after difference in GHQ within the “control” group from the respective difference in the “treatment” group allows us to control for any trends and/or seasonal patterns that could bias any estimation of the pandemic's impact on mental health if relying on a simple before and after comparison (e.g., mental health scores pre vs. post lockdown). Effectively, we end up with an estimate of the “average treatment on the treated effect (ATT).” Our main assumption with this approach is that the pandemic was an unanticipated shock and that, in the absence of the pandemic, the change in mental health before and after March 23, 2020, would have been very similar to that observed pre-and-post March 23, 2019 simply because the interview dates are randomized across individuals in each survey year.

Upon adopting these periods, we are left with a baseline of 78,996 observations (which shrinks in some alternative specifications depending on the choice of covariates). Table 1 presents the summary statistics for the DiD analytical samples for the periods between June 1, 2018 and May 31, 2020. The average subjective well-being reported between June 2018 and May 2019 is about 11.3 out of 36 points, while from June 2019 to May 2020 it is about 12 points.

Formally we can write our baseline DiD model as follows:

$$M_{it} = \beta_0 + \beta_1 L_i * T_i + \beta_2 L_i + \beta_3 T_i + \varepsilon_{it} \qquad (1)$$

where our dependent variable M_{it} corresponds to the mental health (GHQ-12) of individual i reported on month-and-day date t (running from June 1, 2018 to May 31, 2020). L_i (“Interview Post Lockdown” in the results' tables), is a dummy variable that takes the value of one if the individual was interviewed after March the 23d, 2020 (which coincides with the date after the lockdown announcement). T_i ("Jun2019–May2020" in the results' tables) is another dummy taking the value of one if the interview occurs between June 1, 2019 and May 31, 2020 (treatment group observations), or zero if it takes place between June 1, 2018 and May 31, 2019 (control group observations). Finally, ε_{it} is an error term.

Our Dif-in-Dif coefficient of interest, β_1, corresponds to an "average treatment on the treated effect" estimate and represents the change in mental health levels as a result of the first wave of the pandemic which in our case corresponds to the dates of the first UK nationwide lockdown (March 23 to May 31, 2020). In order to properly estimate the ATT, the key assumption in our estimation is that the changes in mental health observed between 2018 and 2019 would have been roughly the same as those observed between 2019 and 2020 in the absence of the pandemic (i.e., common trends). Given that the interview dates are randomized across individuals in each survey year we have no a priori reason to believe that this assumption would not hold. In Section 5.4.1, however, we formally test for this assumption.

In order to test for heterogeneity in impacts, we expand the baseline model specified in Equation (1) as follows:

$$M_{it} = \beta_0 + \beta_1 L_i * T_i + \beta_2 L_i + \beta_3 T_i + \sum_{k=1}^{n} \alpha_k X_{kit} + \sum_{k=1}^{n} \gamma_k X_{kit} L_i * T_i + \varepsilon_{it} \tag{2}$$

The vector of n X_{kit} elements includes demographic characteristics such as binary indicators for sex at birth (equal to one if female), BAME identity (i.e., Black, Asian, and Minority Ethnic), born outside the UK (labeled as not UK-Born), and four binary indicators capturing different age cohorts. In most models, we look into one characteristic at a time (i.e., $n = 1$), namely female (column 2 of Table 2), BAME identity (column 2, Table 2), born outside the UK (column 3, Table 2), and age cohorts (column 4, Table 2) We also estimate one Dif-in-Dif model including all the aforementioned demographic covariates (column 6, Table 2). We follow a similar approach with the three sets of resilience-related variables (financial concerns, loneliness and crowding); namely, we estimate one-set-at-a-time models and a model including all resilience variables. For all models we estimate versions with and without demographic covariates (Tables 4 and 5, respectively).

5 | RESULTS

5.1 | DiD estimates—Main effects

Table 2 presents our initial DiD estimates of the pandemic's first wave impact during the lockdown period of March 23 to May 31 of 2020 on mental health. The first column presents the net population-level mental health impact. The DiD estimate, namely the coefficient of our interaction term *Interview Post Lockdown*JunMay19/20,* is statistically significant and suggests that the initial wave of the pandemic led to an average increase of 0.91 units in psychological distress as measured by the GHQ.

An important question is how large/small this 0.91 unit increase in the GHQ is. Fortunately, this measure of psychological distress is widely used in the literature which means we can compare this effect to the estimated impacts of other major life events. It would, for example, be approximately one half to two-thirds of the estimated disutility associated with unemployment and significantly larger than the typical estimated effects associated with divorce and widowhood for mental health.[5] It is worth noting that these are "average" effects, and that unemployment alongside disability would be the factors most strongly associated with the largest increases in psychological distress in the wider "economics of happiness" literature. Thus, the consequences of the initial wave of the pandemic for mental health were 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.

5.2 | DiD estimates—Inequality

After calculating the initial population impact, we tested whether these estimated impacts differed according to demographic variables. In columns 2 to 6 of Table 2, we present the results of three-way interaction models combining each of these potential moderating variables with our *Interview Post Lockdown (IPL)*JunMay19/20* interaction term.

TABLE 2 Difference-in-differences estimates (01-Jun-2018/31-May-2019 to 01-Jun-2019/31-May-2020).

	(1)	(2)	(3)	(4)	(5)	(6)
	Psychological distress (GHQ-12)					
Interview post lockdown (IPL)*Jun2019–May2020 = 1	0.91***	0.43***	0.80***	0.87***	0.51***	0.19*
	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.12)
Interview post lockdown (IPL)	0.01	0.02	0.02	−0.01	0.04	0.03
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Jun2019–May2020 = 1 (2019–2020)	0.12**	0.11**	0.13**	0.10*	0.14***	0.13**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Female		1.19***				1.17***
		(0.05)				(0.05)
IPL*2019–2020*female		0.75***				0.61***
		(0.08)				(0.08)
BAME			0.29***			0.31***
			(0.09)			(0.11)
IPL*2019–2020*BAME			1.06***			0.62***
			(0.17)			(0.19)
Not born in UK				−0.36***		−0.68***
				(0.08)		(0.09)
IPL*2019–2020*not UK born				0.54***		0.40**
				(0.14)		(0.16)
Age 18–34					1.69***	1.64***
					(0.07)	(0.07)
IPL*2019–2020*age 18–34					1.31***	1.01***
					(0.13)	(0.13)
Age 35–49					1.44***	1.45***
					(0.07)	(0.07)
IPL*2019–2020*age 35–49					0.58***	0.34***
					(0.11)	(0.11)
Age: 50–64					1.28***	1.28***
					(0.06)	(0.06)
IPL*2019–2020*age 50–64					0.06	−0.06
					(0.11)	(0.10)
Constant	11.33***	10.67***	11.30***	11.38***	10.26***	9.67***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Observations	78,996	78,996	78,996	78,996	78,996	78,996
R-squared	0.01	0.02	0.01	0.01	0.03	0.04

Note: Robust standard errors in parentheses.

Abbreviation: BAME, black, Asian and minority ethnic.

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$.

Column 2 shows that *Female*IPL*JunMay19/20* attracts a statistically significant coefficient suggesting that Females experienced a significantly higher deterioration in mental health than Males during the initial wave of the pandemic.

We also find that both Migrants (as opposed to Natives, see column 4), and members of the BAME community (as opposed to non-BAME, see column 3), were more negatively impacted. In column 5, we examine any possible differences across age groups. Our reference category is those aged over 64. We find that the age dummies are statistically significant when interacted with *Interview post lockdown*JunMay19/20*, except for the 50–64 years bracket. This would indicate that relatively older groups were less impacted when it comes to their mental health.

To provide a further illustrative picture of differences across groups, Table 3 summarizes the predicted mental health impacts for different population groups based on the model results presented in Table 2. The column titled "Difference-in-difference" computes, for each population group mentioned in the first column, the difference in the average prediction of mental health before and after March 23, 2020 (i.e., between the periods 1/06/19–23/03/20 and 24/03/20–31/05/20) minus the same difference for 2019. That is, it provides the average treatment effect on the treated (ATT):

$$ATT = (E[M_{it}|L_i = T_i = 1, X_{it}] - E[M_{it}|L_i = 0, T_i = 1, X_{it}]) - (E[M_{it}|L_i = 1, T_i = 0, X_{it}] - E[M_{it}|L_i = T_i = 0, X_{it}]) \tag{3}$$

For each group partition (e.g., by sex at birth, BAME ethnicity, born in the UK, etc.) the average predictions feeding into the impact estimations stem from the models where each group appears alone. For example, for the female and male groups, we predicted mental health using the model in column (2) of Table 2 (and so forth).

Noting that predicted mental health deterioration is pervasive across all groups, several interesting comparisons emerge from Table 3. For instance, the predicted mental health impact among women is more than double that of men. A similar situation holds for people of BAME background relative to non-BAME ethnicity. We also observe significant differences when we compare people born in the UK versus those born outside the UK, albeit the difference in impact between both groups is less pronounced (vis-a-vis the previous comparisons). Finally, we observe a health gradient in the mental health impact whereby its severity decreases among older age groups. In other words, younger age groups appear to experience a larger reduction in mental health than older cohorts.

5.3 | Who was least resilient to the pandemic?

Having established that the pandemic is associated with a statistically significant and substantial decline in mental health, and that these impacts were not uniformly distributed according to socio-demographic characteristics, we now look to better understand who was least resilient to the mental health impacts associated with the pandemic. We predicted that SFH, loneliness and household density all play an important moderating role. To examine the importance of these variables, we present the results of three-way interaction models again, but this time combining our variables capturing the presence of subjective perceptions relating to financial health, reported loneliness and household density with our *Interview Post Lockdown (IPL)*JunMay19/20* interaction term (Table 4). In separate specifications (Table 5), we also include the socio-demographic variables we found to be important moderators in the previous section, namely gender, age, birth location and ethnicity.

TABLE 3 Predicted difference-in-difference impacts (based on Table 2 results).

Sex at Birth	**Female**		**Male**	
Change in mental health	1.18		0.43	
Ethnicity	**BAME**		**Non-BAME**	
Change in mental health	1.86		0.80	
Birth location	**Not born in UK**		**Born in UK**	
Change in mental health	1.41		0.87	
Age groups	**18 to 34**	**34 to 49**	**50 to 64**	**65 and above**
Change in mental health	1.82	1.09	0.57	0.51

Abbreviation: BAME, black, Asian and minority ethnic.

TABLE 4 Difference-in-differences estimates (01-Jun-2018/31-May-2019 to 01-Jun-2019/31-May-2020).

	(1)	(2)	(3)	(4)	(5)
	Psychological distress (GHQ-12)				
Interview post lockdown (IPL)*Jun2019–May2020 = 1	0.91***	0.76***	0.65***	0.46***	0.39***
	(0.10)	(0.10)	(0.12)	(0.13)	(0.15)
Interview post lockdown (IPL)	0.01	0.06	−0.02	0.01	0.00
	(0.08)	(0.08)	(0.10)	(0.08)	(0.10)
Jun2019–May2020 = 1 (2019–2020)	0.12**	0.14***	0.10	0.11**	0.05
	(0.05)	(0.05)	(0.07)	(0.05)	(0.06)
SFH: All right		1.21***			0.69***
		(0.05)			(0.06)
SFH: Getting by		3.25***			1.98***
		(0.07)			(0.08)
SFH: Difficult & very difficult		7.14***			4.70***
		(0.13)			(0.14)
IPL*2019–2020*SFH: All right		0.51***			0.20**
		(0.08)			(0.09)
IPL*2019–2020*SFH: Getting by		0.85***			0.38***
		(0.13)			(0.13)
IPL*2019–2020*difficult & very difficult		1.34***			0.63**
		(0.25)			(0.25)
Sometimes lonely			3.98***		3.49***
			(0.06)		(0.06)
Often lonely			9.35***		8.31
			(0.15)		(0.15)
IPL*2019–2020*sometimes lonely			1.12***		1.16***
			(0.09)		(0.10)
IPL*2019–2020*often lonely			2.04***		2.00***
			(0.23)		(0.23)
Crowding				0.73***	0.04
				(0.05)	(0.06)
IPL*2019–2020*crowding				0.49***	0.35***
				(0.10)	(0.09)
Constant	11.33***	9.60***	9.39***	10.62***	8.51***
	(0.04)	(0.04)	(0.03)	(0.06)	(0.06)
Observations	78,996	78,883	61,510	74,345	57,136
R-squared	0.01	0.12	0.29	0.01	0.33

Note: Robust standard errors in parentheses.

Abbreviation: SFH, subjective financial health.

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$.

TABLE 5 Difference-in-differences estimates (01-Jun-2018/31-May-2019 to 01-Jun-2019/31-May-2020) including socio-demographic variables.

	(1)	(2)	(3)	(4)	(5)
	Psychological distress (GHQ-12)				
Interview post lockdown (IPL)*Jun2019–May2020 = 1	0.85***	0.74***	0.63***	0.55***	0.39***
	(0.10)	(0.10)	(0.12)	(0.13)	(0.14)
Interview post lockdown (IPL)	0.05	0.05	−0.02	0.03	0.03
	(0.08)	(0.08)	(0.10)	(0.08)	(0.10)
Jun2019–May2020 = 1 (2019–2020)	0.14***	0.12**	0.10	0.13**	0.09
	(0.05)	(0.05)	(0.07)	(0.05)	(0.06)
Female	1.41***	1.34***	0.78***	1.38***	0.80***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
BAME	0.52***	0.11	0.23***	0.47***	0.03
	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)
Not born in the UK	−0.55***	−0.91***	−0.41***	−0.61***	−0.70***
	(0.08)	(0.07)	(0.07)	(0.08)	(0.70)
Age 18–34	1.99***	1.28***	0.65***	1.78***	0.20***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
Age 35–49	1.59***	0.72***	1.09***	1.39***	0.44***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Age 50–64	1.25***	0.58***	0.94***	1.22***	0.48***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
SFH: All right		1.05***			0.66***
		(0.05)			(0.06)
SFH: Getting by		3.06***			1.94***
		(0.07)			(0.08)
SFH: Difficult & very difficult		6.91***			4.69***
		(0.13)			(0.14)
IPL*2019–2020*SFH: All right		0.52***			0.18**
		(0.08)			(0.09)
IPL*2019–2020*SFH: Getting by		0.89***			0.39***
		(0.12)			(0.13)
IPL*2019–2020*difficult & very difficult		1.35***			0.62**
		(0.25)			(0.25)
Sometimes lonely			3.84***		3.40***
			(0.06)		(0.06)
Often lonely			9.15***		8.18***
			(0.15)		(0.15)
IPL*2019–2020*sometimes lonely			1.06***		1.13***
			(0.09)		(0.10)
IPL*2019–2020*often lonely			2.00***		1.97***
			(0.22)		(0.23)

TABLE 5 (Continued)

	(1)	(2)	(3)	(4)	(5)
	Psychological distress (GHQ-12)				
Crowding				0.26***	0.09
				(0.06)	(0.06)
IPL*2019–2020*crowding				0.34***	0.24***
				(0.10)	(0.09)
Constant	9.39***	8.46***	8.37***	9.26***	7.89***
	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)
Observations	78,996	78,883	61,510	74,345	57,136
R-squared	0.04	0.15	0.30	0.04	0.34

Note: Robust standard errors in parentheses.

Abbreviations: BAME, black, Asian and minority ethnic; SFH, subjective financial health.

***$p < .01$; **$p < .05$; *$p < .1$.

Table 4 presents our estimates of the impact of the pandemic during the lockdown period of March 23 to May 31 of 2020 on mental health with the three sets of proxy variables described in Section 3.1 added as moderators using triple interactions. For ease of reference, column 1 presents our estimate of the net population impact again, as described in Table 2. In columns 2 to 4, we control for each of our proxies for SFH, loneliness and crowding stress. Column 5 shows the overall estimates when all three sets of proxy variables are included.

Notwithstanding a degree of uncertainty around each of these individual point estimates, Table 4 provides evidence of these factors' individual importance in predicting the mental distress experienced during the pandemic. Indeed, adding Subjective Financial Health (SFH; column 2) produces a gradient of mental health impacts whereby the latter worsens together with grimmer self-appraisals. All the associated triple-interaction coefficients are statistically significant at the standard 1% level and the effect sizes are non-trivial in comparison to the reference average population effect (column 1, top row). Likewise, including the loneliness dummies (column 3) also generates a gradient based on statistically significant triple-interaction coefficients. Ceteris paribus, the movement from absent or rare loneliness (baseline category) to occasional nearly triples the mental health impact (from 0.65 to 1.77). Meanwhile, the movement from occasional loneliness to frequent represents a marginal increase greater than average population effect (1.77 to 2.69 vis-à-vis 0.91).

The triple-interaction coefficient of crowding is also statistically significant (column 4). Ceteris paribus, every additional person per bedroom worsens the pandemic's mental health by nearly 50% of the average population effect (0.49 vs. 0.91). Finally, column 5 presents the specification with these variables added together. Notably, all triple-interaction coefficients remain statistically significant, and the gradients associated with SFH and loneliness do not disappear, even though most effect sizes expectedly decrease. While there are undoubtedly other important factors, our variables taken together significantly predict differences in mental health resilience in the wake of the pandemic. For instance, ceteris paribus, according to our model, a person reporting rare or absent loneliness and no financial concerns and living in the average crowded dwelling (0.93 people per bedroom post-pandemic; see Table 1) would have experienced a mental health deterioration less severe than the average population impact (0.72 vs. 0.91). By contrast, someone reporting difficult financial circumstances and frequent loneliness and living in a dwelling with one person per bedroom would have suffered from a remarkably worse mental health deterioration (3.37 vs. the 0.91 average in the population).

We note that we have some reduction in our sample size when examining the three moderators, mainly due to the addition of our loneliness variable. The roughly 17,000 missing observations stem from a UKHLS wave in which this variable was not collected (as opposed to people hypothetically declining to answer the question non-randomly). As a way to gauge whether this sample size reduction is likely to substantially bias the results reported when examining the impact of our measure of loneliness, we re-estimated Equation (1), namely our main DiD coefficient estimate, but this time restricting it to the sample size observed when we estimate our DiD regression adding only loneliness (i.e., column 3 of Table 4). Our estimate of the overall mental health impact just using this sample, 0.86, is qualitatively similar to the full sample's (0.91; full results available upon request).

Table 5 estimates the models in Table 4 but adding the demographic variables from Section 5.2. The results do not change qualitatively, and all moderators' (triple-interaction) coefficients remain statistically significant at the same level. Meanwhile, only the effect sizes of the crowding moderator notably decrease when controlling for demographic traits (although the difference is not statistically significant).[6]

We note in both tables the substantial contribution of the loneliness indicators to the models' goodness-of-fit, especially vis-à-vis other posited predictors and demographic controls (Table 5). Indeed, the loneliness dummies just by themselves can explain 29% of the variance in the mental health dependent variable (Table 4, column 3, bottom row). In comparison, the model including all considered explanatory variables features an *R*-squared of 34%. Thus, our results echo an extensive literature identifying loneliness as a predictor of general mental health (see e.g., Jaspal & Breakwell, 2022; Mann et al., 2022; Wang et al., 2020). Together with a presumption of bi-directional prediction, this may help explain why loneliness engenders such a larger increase in goodness-of-fit.

Table 6 summarizes the results with an overview of average marginal effects for the three moderators (based on columns 2 to 4 of Tables 4 and 5). Besides the inconspicuous differences between the models with and without demographic controls, we note the gradients of average mental health impacts for every set of moderators. Finally, Table 7 provides the average marginal effects from models in which the SFH and the loneliness dummies have been lagged. Remarkably, the results do not change qualitatively (further details are available upon request).

5.4 | Supporting analysis

5.4.1 | Common trends test

As explained in the methodology section, a key assumption to ensure the internal validity of a DiDs estimation is that of common trends (also known as parallel trends). This assumption states that in the absence of treatment, the difference

TABLE 6 Predicted difference-in-difference impacts (based on Tables 4 and 5 results).

Subjective financial situation	**1 (Best)**	**2**	**3**	**4 (Worst)**
Change in mental health	0.76	1.27	1.61	2.10
(With controls)	0.74	1.26	1.63	2.09
Lonely	**Hardly ever or never**		**Some of the time**	**Often**
Change in mental health	0.65		1.77	2.69
(With controls)	0.63		1.69	2.63

Crowding	**1st quintile**	**2nd**	**3rd**	**4th**	**5th**
Change in mental health	0.67	0.78	0.93	1.10	1.38
(With controls)	0.68	0.77	0.88	1.00	1.20

TABLE 7 Predicted difference-in-difference impacts from models with lagged variables.[a]

Subjective financial situation	**1 (Best)**	**2**	**3**	**4 (Worst)**
Change in mental health	0.75	1.12	1.42	2.34
(with controls)	0.73	1.09	1.37	2.32
Lonely	**Hardly ever or never**		**Some of the time**	**Often**
Change in mental health	0.49		1.96	3.02
(with controls)	0.46		1.87	2.95

Crowding	**1st quintile**	**2nd**	**3rd**	**4th**	**5th**
Change in mental health	0.85	0.92	1.01	1.12	1.30
(with controls)	0.80	0.85	0.92	1.00	1.14

[a]Underlying model estimations available upon request.

between treatment and comparison groups is constant over time. In other words, in the absence of the pandemic, the observed difference in mental health between June 2018 to May 2019 ("control" period) should be comparable to that observed between June 2019 to May 2020 ("treatment" period). If it is not, our estimated mental health impact of the initial wave of the pandemic may be biased.

Although it is not possible to know how mental health would have behaved in the absence of the pandemic, one way to provide evidence in support of this assumption is to study the difference between treatment and comparison groups, before treatment. If this difference is constant over time (i.e., common trends), it is likely it would also have remained constant in the absence of treatment. In the Supporting Information S2: Section 1, we discuss the results of a common trends test, which provides supporting evidence that our DiD design satisfies the common trends assumption.

5.4.2 | Robustness and sensitivity checks

In Table 2 we presented baseline estimates of the pandemic's impact on mental health during the first UK nationwide lockdown. In a series of sensitivity checks, we examined what impact, if any, would using different cut-off points (dates) have on our main results. We also examined a more conservative approach in which we conducted an individual fixed-effect-DiD estimation. Finally, we implemented a placebo test. With this placebo test we again estimated a differences-in-differences regression but instead of using March 23, 2020 as our cutoff date, we used March 23, 2019. We present these results, as well as a detailed discussion of these sensitivity checks, in the Supporting Information S2: Section 2.

6 | CONCLUSION

We use data from the UKHLS, to study the impact of the initial wave of the pandemic on people's mental health in the UK. In order to quantify the initial mental health burden of the pandemic, we employed a DiDs research design where we compare reported mental health pre-and-post the first UK nationwide lockdown in 2020 to the reported mental health pre-and-post the same date in 2019, thus ensuring that seasonal patterns or long-term trends in mental health are not impacting our results. A further valuable feature of our analysis is that, due to the large sample size at our disposal, we can probe for differences in the mental health burden across socio-demographic groups.

Considering first the period March 23 to May 31, 2020 which corresponds to the period of the first national lockdown in the UK, our DiD estimates suggest that the initial wave of the pandemic led to an average increase in GHQ scores of 0.91 units. To put this into context, this would be approximately one half to two-thirds of the estimated disutility associated with unemployment and significantly larger than the typically estimated impacts associated with other negative life events such as divorce and widowhood.

While the net population impact is substantive, it is important to recognize that it masks significant heterogeneity across groups. In keeping with existing cross-sectional work, we find, for example, that the mental health burden associated with the pandemic is more keenly felt by women than men and also appears to be more pronounced for relatively younger age groups. 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 further novel feature of our analysis is that we looked beyond socio-demographics and sought to identify who was least resilient to the adverse effects of the pandemic. Put differently, what were the characteristics of people most likely to witness substantive increases in psychological distress during the first wave of the pandemic. Our analysis points to the importance of subjective perceptions regarding how well individuals feel they are able to manage their finances and loneliness. Arguably, people who feel best in control of their finances and least likely to be lonely are more likely to have the financial wherewithal and social support in place to help deal with the challenges brought on by the pandemic. Finally, we find that household density played an important moderating role. Our proposed explanation is that crowding stress is likely to be more of a factor in larger households when under lockdown restrictions.

Given the size of the estimated mental health impacts, an important area for future research will be to ascertain to what extent people will recover to baseline levels of well-being. We know that for some adverse life events there can be long-term psychological scarring meaning that recovery is not always complete (e.g., unemployment see Hetschko et al., 2019; Mousteri et al., 2018). Similarly to other life events, it will be important, therefore, to establish if there are any long term consequences for mental health due to the economic and social disruption caused by the pandemic, much like there will inevitably be long term consequences for some people's physical health. The possibility of long-term changes to our behavior as a result of having to live with this disease indefinitely, though in less lethal forms, may also be a factor that warrants some consideration.

ACKNOWLEDGMENTS

We would like to thank participants at the UKRI Workshop on Mental Health and the COVID-19 Pandemic (Leeds, April the 4th, 2022) for valuable comments. This work was funded by the Economic and Social Research Council (ESRC), as part of UK Research and Innovation's rapid response to COVID-19.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Anaya et al. (2023) ECIN Replication Package for Locked down in distress: a quasi-experimental estimation of the mental-health fallout from the COVID-19 pandemic at https://doi.org/10.3886/E193081V2. Special license data can be acquired from the UK Data Service.

ORCID

Peter Howley https://orcid.org/0000-0002-3385-629X

ENDNOTES

[1] We include a full list of the questions included in the GHQ-12 in the Supporting Information S2.

[2] 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).

[3] Full details of sample design, response rates and response patterns are provided by the Institute for Social and Economic Research (2021).

[4] We considered also including an objective measure of income. However, there are many missing observations in the special COVID-19 monthly surveys which significantly hinder direct comparisons before and after the pandemic.

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

[6] Testing with the standard z statistics (Clogg et al., 1995).

REFERENCES

Anaya, L., Howley, P., Waqas, M. & Yalonetzky, G. (2023) *ECIN replication package for "Locked down in distress: a quasi-experimental estimation of the mental-health fallout from the COVID-19 pandemic"*. Ann Arbor: Inter-University Consortium for Political and Social Research [distributor]. Available from: https://doi.org/10.3886/E193081V2

Banks, J., Fancourt, D. & Xu, X. (2021) Mental health and the COVID-19 pandemic. Available from: https://ifs.org.uk/publications/15368

Banks, J. & Xu, X. (2020) The mental health effects of the first two months of lockdown during the COVID-19 pandemic in the UK. *Fiscal Studies*, 41(3), 685–708. Available from: https://doi.org/10.1111/1475-5890.12239

Brodeur, A., Clark, A.E., Fleche, S. & Powdthavee, N. (2021) COVID-19, lockdowns and well-being: evidence from Google trends. *Journal of Public Economics*, 193, 104346. Available from: https://doi.org/10.1016/j.jpubeco.2020.104346

Churchman, A. (1999) Disentangling the concept of density. *Journal of Planning Literature*, 13(4), 389–411. Available from: https://doi.org/10.1177/08854129922092478

Clogg, C.C., Petkova, E. & Haritou, A. (1995) Statistical methods for comparing regression coefficients between models. *American Journal of Sociology*, 100(5), 1261–1293. Available from: https://doi.org/10.1086/230638

Daly, M., Sutin, A. & Robinson, E. (2020) Longitudinal changes in mental health and the COVID-19 pandemic: evidence from the UK Household Longitudinal Study. *Psychological Medicine*, 52(13), 2549–2558. Available from: https://doi.org/10.1017/S0033291720004432

Davillas, A. & Jones, A. (2021) The first wave of the covid-19 pandemic and its impact on socioeconomic inequality in psychological distress in the UK. *Health Economics*, 30(7), 1668–1683. Available from: https://doi.org/10.1002/hec.4275

Etheridge, B. & Spantig, L. (2020) The gender gap in mental well-being during the Covid-19 outbreak: evidence from the UK. ISER Working Paper Series. Available from: https://www.iser.essex.ac.uk/research/publications/working-papers/iser/2020-08

Evans, G. & Cohen, S. (2004) Environmental stress. *Encyclopedia of Applied Psychology*, 1, 815–824.

Fancourt, D., Bu, F., Mak, H.W. & Steptoe, A. (2020) COVID-19 social study. 15. Available from: http://allcatsrgrey.org.uk/wp/download/public_health/3d9db5_c99f0f8bb89545a6a10040f27949f7f9.pdf

Flint, E., Shelton, N., Bartley, M. & Sacker, A. (2013) Do local unemployment rates modify the effect of individual labour market status on psychological distress? *Health and Place*, 23, 1–8. Available from: https://doi.org/10.1016/j.healthplace.2013.04.004

Francis-Devine, B., Powell, A. & Clark, H. (2021) Coronavirus Job Retention Scheme: statistics, House of Commons Library, 9152.

Gnambs, T. & Staufenbiel, T. (2018) The structure of the General Health Questionnaire (GHQ-12): two meta-analytic factor analyses. *Health Psychology Review*, 12(2), 179–194. Available from: https://doi.org/10.1080/17437199.2018.1426484

Helliwell, J. & Putnam, R. (2004) The social context of well–being. *Philosophical Transactions B*, 359(1449), 1435–1446. Available from: https://doi.org/10.1098/rstb.2004.1522

Hensel, L., Witte, M., Caria, A.S., Fetzer, T., Fiorin, S., Götz, F.M., et al (2022) Global behaviors, perceptions, and the emergence of social norms at the onset of the COVID-19 pandemic. *Journal of Economic Behavior and Organization*, 193, 473–496. Available from: https://doi.org/10.1016/j.jebo.2021.11.015

Hetschko, C., Knabe, A. & Schöb, R. (2019) Looking back in anger? Retirement and unemployment scarring. *Demography*, 56(3), 1105–1129. Available from: https://doi.org/10.1007/S13524-019-00778-2

Howley, P. & Knight, S. (2021) Staying down with the Joneses: neighbourhood differences in the well-being effects of unemployment. *Work, Employment and Society*, 36(6), 1097–1117. Available from: https://doi.org/10.1177/09500170211003483

Institute for Government. (2021) *Timeline of UK government coronavirus lockdowns and measures, March 2020 to December 2021*. Available from: https://www.instituteforgovernment.org.uk/sites/default/files/2022-12/timeline-coronavirus-lockdown-december-2021.pdf

Institute for Social and Economic Research. (2021) *Understanding society COVID-19 user guide, Version 10.0, October 2021*. Colchester: University of Essex.

Jackson, C. (2007) The General Health Questionnaire. *Occupational Medicine*, 57(1), 79. Available from: https://doi.org/10.1093/occmed/kql169

Jaspal, R. & Breakwell, G. (2022) Socio-economic inequalities in social network, loneliness and mental health during the COVID-19 pandemic. *International Journal of Social Psychiatry*, 68(1), 155–165. Available from: https://doi.org/10.1177/0020764020976694

Johnston, D., Kung, C. & Shields, M. (2021) Who is resilient in a time of crisis? The importance of financial and non-financial resources. *Health Economics*, 30(12), 3051–3073. Available from: https://doi.org/10.1002/hec.4428

Kapteyn, A., Angrisani, M., Bennett, D., de Bruin, W.B., Darling, J., Gutsche, T., et al (2020) Tracking the effect of the COVID-19 pandemic on American households. *Survey Research Methods*, 14(2), 179–186. Available from: https://doi.org/10.18148/srm/2020.v14i2.7737

Mann, F., Wang, J., Pearce, E., Ma, R., Schlief, M., Lloyd-Evans, B., et al (2022) Loneliness and the onset of new mental health problems in the general population. *Social Psychiatry and Psychiatric Epidemiology*, 57(11), 2161–2178. Available from: https://doi.org/10.1007/s00127-022-02261-7

McGinty, E.E., Presskreischer, R., Han, H. & Barry, C.L. (2020) Psychological distress and loneliness reported by US adults in 2018 and April 2020. *JAMA - Journal of the American Medical Association*, 324(Issue 1), 93–94. Available from: https://doi.org/10.1001/jama.2020.9740

Mousteri, V., Daly, M. & Delaney, L. (2018) The scarring effect of unemployment on psychological well-being across Europe. *Social Science Research*, 72, 146–169. Available from: https://doi.org/10.1016/J.SSRESEARCH.2018.01.007

Ozbay, F., Johnson, D., Dimoulas, E., Morgan, C., Charney, D. & Southwick, S. (2007) Social support and resilience to stress. *Psychiatry*, 4(5), 35–40.

Paudel, J. (2021) Home alone: implications of COVID-19 for mental health. *Social Science and Medicine*, 285, 114259. Available from: https://doi.org/10.1016/j.socscimed.2021.114259

Proto, E. & Zhang, A. (2021) Covid-19 and mental health of individuals with Different personalities. IZA DP No. 14388. Available from: https://ssrn.com/abstract=3862240

Regoeczi, W.C. (2008) Crowding in context: an examination of the differential responses of men and women to high-density living environments. *Journal of Health and Social Behavior*, 49(3), 254–268. Available from: https://doi.org/10.1177/002214650804900302

Roemer, J. & Trannoy, A. (2016) Equality of opportunity: theory and measurement. *Journal of Economic Literature*, 54(4), 1288–1332. Available from: https://doi.org/10.1257/jel.20151206

Schmidtke, J., Hetschko, C., Schob, R., Steoan, G., Eid, M. & Lawes, M. (2021) The effects of the COVID-19 pandemic on the mental health and subjective well-being of workers: an event study based on high-frequency panel data. IZA DP No. 14638.

Serrano-Alarcón, M., Kentikelenis, A., Mckee, M. & Stuckler, D. (2021) Impact of COVID-19 lockdowns on mental health: evidence from a quasi-natural experiment in England and Scotland. *Health Economics*, 31(2), 284–296. Available from: https://doi.org/10.1002/HEC.4453

Silverio-Murillo, A., Hoehn-Velasco, L., Tirado, A.R. & de la Miyar, J.R.B. (2021) COVID-19 blues: lockdowns and mental health-related Google searches in Latin America. *Social Science and Medicine*, 281, 114040. Available from: https://doi.org/10.1016/j.socscimed.2021.114040

Sippel, L.M., Pietrzak, R.H., Charney, D.S., Mayes, L.C. & Southwick, S.M. (2015) How does social support enhance resilience in the trauma-exposed individual? *Ecology and Society*, 20(4), art10. Available from: https://doi.org/10.5751/es-07832-200410

Smith, K. & Christakis, N. (2008) Social networks and health. *Annual Review of Sociology*, 34(1), 405–429. Available from: https://doi.org/10.1146/annurev.soc.34.040507.134601

Staneva, A., Carmignani, F. & Rohde, N. (2022) Personality, gender, and age resilience to the mental health effects of COVID-19. *Social Science and Medicine*, 301, 114884. Available from: https://doi.org/10.1016/j.socscimed.2022.114884

Swaziek, Z. & Wozniak, A. (2020) Disparities old and new in US mental health during the COVID-19 pandemic. *Fiscal Studies*, 41(3), 709–732. Available from: https://doi.org/10.1111/1475-5890.12244

Thoits, P.A. (2011) Mechanisms linking social ties and support to physical and mental health. *Journal of Health and Social Behavior*, 52(2), 145–161. Available from: https://doi.org/10.1177/0022146510395592

Wang, J., Lloyd-Evans, B., Marston, L., Mann, F. & Johnson, S. (2020) Loneliness as a predictor of outcomes in mental disorders among people who have experienced a mental health crisis: a 4-month prospective study. *BMC Psychiatry*, 20(1), 249. Available from: https://doi.org/10.1186/s12888-020-02665-2

Zamarro, G. & Prados, M.J. (2021) Gender differences in couples' division of childcare, work and mental health during COVID-19. *Review of Economics of the Household*, 19(1), 11–40. Available from: https://doi.org/10.1007/s11150-020-09534-7

Zhang, X. & Dong, S. (2022) The relationship between social support and loneliness: a meta-analysis and review. *Acta Psychologica*, 227, 103616. Available from: https://doi.org/10.1016/j.actpsy.2022.103616

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Anaya, L., Howley, P., Waqas, M. & Yalonetzky, G. (2023) Locked down in distress: a quasi-experimental estimation of the mental-health fallout from the COVID-19 pandemic. *Economic Inquiry*, 1–18. Available from: https://doi.org/10.1111/ecin.13181