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ABSTRACT

Who is Resilient in a Time of Crisis? The Importance of Financial and Non-Financial Resources*

We identify the individual resources that predicted psychological resilience during the COVID-19 lockdown. Using UK data, we compare psychological distress observed before COVID-19 with distress measured in April, May, and June 2020. After matching respondents on key characteristics, we find that the most important predictor of resilience is non-cognitive skills, as measured by self-efficacy. Self-efficacy also reduces the psychological effects of negative earnings shocks. Neither income, wealth, cognitive ability, nor social capital predicted resilience. Our findings hold when comparing differences between household members. These findings support investments in non-cognitive skill development in order to reduce the damage-function from adverse events.

JEL Classification: I10, C2, C5

Keywords: resilience, psychological health, resources, non-cognitive, COVID-19, panel

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1. Introduction

Building resilience is high on the economic, political, and public health agendas in many countries, and one of the strategic goals of national governments (see Asheim et al., 2020; Cutter et al., 2013; Longstaff et al., 2010). The COVID-19 pandemic has further raised the importance of enhancing resilience (Habersaat et al., 2020), with resilience being seen as an essential target for new interventions in a public health emergency (Holmes et al., 2020; Mukhtar, 2020; Ran et al., 2020). PeConga et al. (2020) suggest that the pandemic, "is a time to foster resiliency, not only protecting the most vulnerable but also facilitating the mental health equivalent of 'herd immunity' ".

In this paper we use the COVID-19 pandemic in the UK as an exogenous large-scale shock to identify the characteristics of psychologically resilient individuals. There are many definitions of resilience, but each relate to the ability of individuals to adequately cope with disruptive events and adversity (Bonanno, 2004), and even thrive in the face of adversity (Connor and Davidson, 2003). Learning who is resilient, and who is not, is important when thinking about the best interventions and targeted policies to promote resilience (Cunha and Heckman, 2009). Having a resilient population reduces the costs (i.e. reduces the 'damage function') of any future crisis, which is important in an increasingly uncertain global environment, including the greater threat of natural disasters (Intergovernmental Panel on Climate Change, 2014). Therefore, increased resilience provides a form of self-insurance against future risk. Even before COVID-19, the UK Government introduced its Community Resilience Development Framework (2019) including steps to develop community resilience, and Public Health England (2014) focused on building the resilience of school children. In tackling the COVID-19 crisis, UK Prime Minister Boris Johnson has paid tribute to the resilience of individuals and families who have been 'shielding' clinically vulnerable people, and measures to increase the resilience of the NHS have been recently proposed (Government Digital Service, 2020a; Malnick, 2020).

Leading researchers in different disciplines have explicitly asked for more "research on the dynamic processes of successful adaption to stressors in prospective longitudinal studies" (Kalisch et al., 2017). Specifically, with respect to the COVID-19 pandemic, Veer et al. (2020) note that, "There is urgent need for knowledge about factors that can protect mental health (resilience factors) in this world-wide crisis, which is different in nature from other crises that have so far been studied in resilience research." From an economics perspective, Clark (2016) states that, "The analysis of the distribution of resilience is of policy importance, as it would help to show us who needs more help, and in what circumstances". However, as recently noted

by Asheim et al. (2020), "There does not seem to be much of a literature within economics when it comes to the measurement of individual resilience. This is somewhat surprising because resilience might have important behavioral consequences and appears to be linked to individual and social well-being by reducing the high economic costs associated with adverse events".[1]

In this paper we respond to the call for more research by identifying the characteristics of resilient individuals. Data is sourced from the UK Household Longitudinal Study (Understanding Society), which conducted separate supplementary surveys in April, May, and June 2020. We focus on identifying the financial, cognitive, non-cognitive, and social resources (measured prior to the pandemic) that predict a resilient response on average, and that predict a resilient response to specific health and economic shocks (intense adversity) experienced by sub-samples of survey respondents in 2020. Importantly, we identify the role of these resources within a fixed-effects modelling approach in which individuals are matched on a wide range of pre-2020 demographic and socioeconomic characteristics. This means we identify the role of resources only as they differ between individuals with identical age, gender, ethnicity, health, number of children and adults in the household, education, employment status, rurality, and region of residence.[2]

Our measure of resilience, based on the difference in psychological distress before and during the COVID-19 lockdown period, is similar to studies in psychology that track individuals following a major life event to observe how their psychological health changes in order to classify them into resilience types.[3] The most researched event in this literature is death of a spouse. For example, Bonanno (2004) identified a number of distinct response profiles: 35% of individuals experience significant trauma (classified as 'chronic depression') before

[1] The two exceptions they highlight are Etilé et al. (2020) who measure resilience based on responses to ten major adverse events using Australian panel data, and Cissé and Barrett (2018) who estimate individual-specific conditional probabilities of being out of poverty using data from Kenya. Graham and Oswald (2010) is an additional noteworthy study. It proposes a theory of hedonic adaptation and resilience to explain how individuals recover psychologically from adverse events. In the model, individuals have a stock of hedonic capital that they can invest in themselves or have invested in by others (e.g. by parents, schools, government). This hedonic capital is drawn upon to cope with adverse events, potentially becoming depleted after a sequence of adverse events, which then triggers psychological distress.

[2] We are aware of two studies that use the supplementary UK Household Longitudinal Study surveys to explore changes in psychological health (Banks and Xu, 2020; Davillas and Jones, 2020). Both focus on inequalities in health rather than contributing to the literature on resilience, and use different econometric methodologies. Also, neither examines the role of cognitive or non-cognitive skills.

[3] An alternative approach to studying resilience is the use of resilience scales, such as the Connor-Davidson (2003) Resilience Scale (CD-RISC). Such scales measure resilience by asking individuals to self-rate their ability to cope in the face of adversity. Ran et al. (2020) found that psychological distress in China at the peak of COVID-19 was significantly lower for those with a high resilience score. Similarly, Killgore et al. (2020) found that Americans with lower resilience scores had worse mental health outcomes in the first weeks of the COVID-19 lockdown.

and after the loss, while 46% suffer no trauma (classified as 'resilient'). In the aftermath of the September 11th attack, Bonanno et al. (2006) found that 65% of exposed respondents were found to be resilient, defined as having either no or only one symptom of post-traumatic stress disorder (PTSD). Moreover, Bonanno et al. (2007) found that resilience in the face of the attack was predicted by demographic and socioeconomic characteristics including gender, age, ethnicity, education, income, and social support. Another example in this literature is Orcutt et al. (2014), who identified four response trajectories following a mass college campus shooting, with 90% of students classed as 'minimal impact-resilience' or 'high impact-recovery'.[4]

Our surprising result is that we find no evidence to suggest that financial resources, measured by household income, savings, and debt, predict resilience in the face of COVID-19. Neither do we find any protection from better cognitive ability, or that neighbourhood social capital is important. What we do find is robust evidence that non-cognitive skills, measured by self-efficacy, are strongly predictive of resilience. Self-efficacy is the belief that one can perform novel or difficult tasks to attain desired outcomes, and therefore represents a self-confident view of one's capability to deal with life's stressors (Bandura, 2006, 1997; Schwarzer and Warner, 2013). Importantly, developing self-efficacy is viewed as amenable, with the most effective method to install a strong sense of efficacy being through helping individuals master experiences and obstacles (Heckman and Kautz, 2013). This points to a clear target for investment that reduces psychological impact of future adverse events.

The paper is set out as follows. In Section 2 we provide the COVID-19 context when our main data was collected in the last week of April 2020. We describe the data we use from the UK's Understanding Society in detail in Section 3. Our empirical approach used to identify the characteristics of resilient individuals is detailed in Section 4. The results are discussed in Section 5, and conclusions are drawn in Section 6.

2. Context: COVID-19 Pandemic in the UK prior to data collection

In addition to information from earlier waves of Understanding Society, our main analyses use data from the COVID-19 follow-up survey collected in the week starting 24th April 2020 (described in more detail below). Here, we briefly provide details of the context of the COVID-19 pandemic experienced by the survey respondents prior to this date. We emphasise demographic, health, and economic aspects of the crisis that may have caused variation in the severity of the experience.

[4] A more detailed review and discussion of this literature can be found in Etilé et al. (2020).

The COVID-19 outbreak began as a 'viral pneumonia' in December 2019 in Wuhan, China, and the novel coronavirus was announced as its cause by the World Health Organization (WHO) on January 9, 2020. On January 30, WHO declared the outbreak to be a Public Health Emergency of International Concern, and evidence emerged regarding human-to-human and asymptomatic transmission of the coronavirus (WHO, 2020). On January 31, the UK confirmed its first two cases in Yorkshire. This was only several days after the UK government recommended against all but essential travel to mainland China, which by then had already confirmed nearly 10,000 cases and over 200 deaths (BBC, 2020). First cases in Wales, Scotland, and Northern Ireland were documented within the same week at the end of February (Government Digital Service, 2020b).

On March 12, 2020, the UK government announced COVID-19 to be 'high risk', and implemented new social distancing measures for individuals showing symptoms, where they were told to stay home and self-isolate for 7 days. By March 16, stricter guidelines were announced for all: those showing symptoms or living in households with symptoms were advised to self-isolate for 14 days, and the general public were advised to stop all non-essential contact with others and all unnecessary travel, and to work from home if they could. These guidelines were emphasised for pregnant women, individuals aged 70 and above, individuals with pre-existing health conditions, and London dwellers. All large gatherings and non-essential world-wide travel were also discouraged. From March 20, schools were closed (except for children of essential workers and vulnerable groups), along with all entertainment, hospitality, and indoor leisure premises. By March 23, people could only leave their home for a very limited number of reasons (e.g. shopping for essentials, exercise, and medical needs), and gatherings of two or more people in public were banned (Dunn et al., 2020).

These restrictions, enforceable by the police, were in place until the gradual easing of lockdown began on May 13 (Dunn et al., 2020); several weeks after respondents completed the survey.[5] By this date, the number of UK COVID-19 cases had reached 143,464, with 19,506 COVID-19-related deaths (Monthly Index of Medical Specialties, 2020). For around 90% of deaths, patients had at least one pre-existing condition (e.g. heart disease, dementia). The mortality rate increased consistently with age, and male patients showed a significantly higher rate than female patients (Office for National Statistics, 2020).

[5] The UK government was only responsible for the coronavirus response in England, while Scotland, Wales, and Northern Ireland governments could implement their own policies, such as those pertaining to public health, education, and public transport. However, lockdown restrictions were very similar across all countries (e.g. with regard to closure of schools, pubs and restaurants).

The pandemic had unprecedented effects on the UK economy. In the first quarter of 2020, the UK experienced a substantial economic contraction despite the full lockdown only commencing on March 23. Almost every sector experienced a Q1 reduction in GDP, with retail, hospitality, transport, and communications most heavily hit. The single-month fall in March equalled 5.8 per cent; at that time, the largest on record (Leslie and McCurdy, 2020). The shock to the UK labour market was similarly extraordinary. Between March and April, the number of PAYE employees fell by 450,000. The Office for National Statistics' claimant count, a measure of the number of jobseekers claiming benefits, rose by 850,000 between early March and early April (McCurdy, 2020).

We further highlight here aspects of the UK government's COVID-19 economic policy response that are relevant to our paper. On March 11, the UK Budget 2020 was released, which included several COVID-19 response measures to support the self-employed, businesses, and vulnerable people. Statutory sick pay would be extended to cover those advised to self-isolate, including asymptomatic individuals (full government cover for small and medium-sized businesses [SME]; otherwise covered by business); and funding for the welfare system and local authorities would increase, towards supporting economically vulnerable residents. Besides allowing businesses and the self-employed to defer tax payments, the government would also be a guarantor on "business interruption" loans of up to £1.2m for SMEs, and provide each eligible SME a cash grant of £3,000. There would also be an increase in business tax cuts, expanded to include a large range of leisure and hospitality businesses, saving each eligible business up to £25,000 (Government Digital Service, 2020c).

The following week, the Bank of England (2020) announced a reduction in interest rates. March 20 saw the introduction of the Coronavirus Job Retention Scheme, under which the government would pay up to 80% of wages for employees furloughed—that is, remaining on payroll but temporarily not working—due to COVID-19, up to a total of £2,500 per employee per month. Housing benefits were also increased to cover at least 30% of local residential market rents (Government Digital Service, 2020d). On March 25 it was announced that a new Coronavirus Act (2020) would increase the statutory notice period for residential evictions from two to three months; and protect commercial renters from forfeiture for non-payment of rent. The government also ensured the self-employed would be at par with furloughed employees under the Job Retention Scheme, announcing on March 26 plans for a direct cash grant of 80% of profits, up to £2,500 per month (Government Digital Service, 2020e).

3. Data

Understanding Society is an annual household panel survey encompassing England, Scotland, Wales, and Northern Ireland, that collects detailed information on health, socioeconomic circumstances, social life, attitudes, and behaviours. The survey began its Wave 1 interviews in 2009 with a representative probability sample of 26,089 households, which was further topped up with an Ethnic Minority Boost sample at Wave 1 (4,080 households), the former BHPS sample at Wave 2 (6,693), and an Immigrant and Ethnic Minority Boost sample at Wave 6 (2,468). Every sample member is interviewed approximately one year apart, even though fieldwork for each wave may run over two years (such that waves overlap). The most recently completed wave prior to the COVID-19 pandemic was Wave 9, for which data were collected between January 2017 and May 2019 from 36,055 respondents across 20,510 households. Data collection, which began with face-to-face computer-aided personal interviews and paper self-completion questionnaires in Wave 1, gradually moved towards online interviewing, such that 50.5% of Wave 9 respondents completed their survey online.

3.1. Special COVID-19 Survey

To enable research on the socio-economic and health consequences of the COVID-19 pandemic, a continuing monthly supplementary Understanding Society COVID-19 Study began in April 2020. In this paper we focus on the April 2020 survey, but also test the robustness of our main results using the May and June 2020 surveys.

On April 17, 2020, sample members were sent a pre-notification letter inviting them to participate in the new monthly online survey aimed at tracking how the COVID-19 virus is impacting lives in the UK. Fieldwork for the first monthly wave was scheduled for the week between April 24 (Friday) and April 30 (Thursday). They were then sent email and/or SMS invitations containing their personalised link to this April online survey, as well as subsequent reminders on days 2, 3, and 5 of the 7-day fieldwork period. Invitees for whom no email address or mobile number were known were sent postal invitations. Of the 42,330 invitees, 17,452 responded; of these, 15,928 also provided adult interviews at Wave 9.[6] Of these, we further drop 1,569 respondents with missingness on the mental health outcome variable in Wave 9 or in the April 2020 survey, 1,152 with very poor mental health in Wave 9 (explained below), and

[6] If we estimate a model of survey response to the COVID-19 April survey, we find that in respect to the financial and non-financial resources that we study, that household income, savings, debt, cognitive ability, and neighbourhood social capital are significant predictors of response. For example, a one-log point increase in income increases the probability of responding by 6.4 percentage points. However, self-efficacy is not predictive of response. These results are available on request.

a further 139 with missingness on key demographic characteristics. The characteristics of the remaining 13,068 respondents, who form our main estimation sample, are described in Appendix Table A1.

3.2. Measuring Psychological Distress

We measure psychological distress across time using the 12-item General Health Questionnaire (GHQ-12). The GHQ-12 is often used as a screening tool for the assessment of minor psychiatric morbidity, especially for depressive disorders (Romppel et al., 2013). Within economics it has also been used as a subjective wellbeing measure (Clark, 2003; Clark and Oswald, 1994; Powdthavee and van den Berg, 2011).

The 12 items of the GHQ-12 are: ability to concentrate, sleep loss, playing a useful part, capable of making decisions, constantly under strain, unable to overcome difficulties, enjoying normal daily activities, ability to face up to problems, feeling unhappy or depressed, losing confidence, feeling worthless, and feeling reasonably happy all things considered. The reference period is "over the last few weeks", and there are four response options, which vary slightly between items. An example set is: "more so than usual", "same as usual", "less so than usual", and "not at all". We use the Caseness scoring method, which involves summing 12 dichotomised responses, where 1 indicates the two highest distress options for each item. The final score ranges from 0 to 12 (least to most psychologically distressed) and can be interpreted as the number of symptoms of psychological distress a person is currently suffering. Scores above 3 are sometimes used as an indicator of a mental health condition (e.g. Davillas and Jones, 2020).

Figure 1 plots the average GHQ score from Wave 6 (beginning 2014) through Wave 9, as well as for the monthly COVID-19 surveys in April, May, and June 2020. Between 2014 and 2019, prior to the pandemic, approximate mean scores equal 1 (one symptom of psychological distress) for males and people aged ≥ 60, and 1.5 for females and people aged 25 to 59. In April 2020, with UK residents still in lockdown, it is clear that psychological distress drastically increased, with an approximate doubling of average scores. For women, the mean GHQ score equalled 3 (three symptoms of distress), which only 4.6% of women experienced pre-COVID. There was a slight decrease by the end of May, which is again seen in June, but scores remained far above pre-pandemic averages. This increase in psychological distress in the pandemic is consistent with that reported in Banks and Xu (2020) and Davillas and Jones (2020).

In Figure 2 we present a histogram of respondent's change in their GHQ score between the Wave 9 and April 2020 surveys. While 31% of the sample reported the same scores in both surveys, 54% reported a worsening by at least one symptom. In our main regression specifications, we model an increase in the GHQ score of 5 points or more; indicating a large increase in psychological distress due to COVID-19. This amounts to 14.4% of the sample; the shaded bars in Figure 2.

Table 1 compares individuals in our sample who experienced this large increase in psychological distress (n=1,887), with those who did not (n=11,181). Both groups show similar average pre-COVID-19 GHQ scores at Wave 9, but by April 2020, the former group reported an average 7.3-point increase, or a nine-fold rise in symptoms of psychological distress. In sharp contrast, the latter group reported an average increase in symptoms over the pandemic by only 0.5 points. Importantly, the groups experiencing increased distress tend to be younger, female, and living with more children. A smaller difference is seen between the groups with regard to employment, chronic health, and rurality status, as well as number of adults in the household.

We also show in Table 1 that the increase in psychological distress is associated with worse health and lifestyle-related behaviours, as measured in the April 2020 survey. The distressed are eating healthy and nutritious food less often, binge drinking more often, exercising less often, smoking more, and are more likely to have cancelled planned healthcare. These simple statistics clearly suggest that the significant increase in psychological distress has important real behavioural implications.

3.3. Measuring Key Resources

We consider seven different financial, human capital, and social resources that may be relevant for resilience during the pandemic and also during 'regular' hardships and adversities. These are all measured prior to 2020. These resources, along with sample means and year of measurement, are detailed in Table 2, and their distributions plotted in Appendix Figure A1.

The key financial resources we examine are: real total monthly household income, equivalised and averaged across Waves 6 to 9 (spanning 2014-2019); total household savings measured in Wave 8 (2016-2018); and total household (non-mortgage) debt measured in Wave 8 (2016-2018). We explore the effects of savings and debt separately, rather than using a net savings measure, because the assumption that they have equally sized but opposite signed effects is unlikely to be valid.

To measure cognitive ability, we use the predicted score from a principal-component factor analysis of five cognitive ability tests measured in Wave 3 (spanning 2011-13). The five tests are listed in Table 2 (McFall, 2013), and Appendix Figure A1 shows the measure has an approximate normal distribution.

For non-cognitive ability we use a self-efficacy (or self-mastery) index. Self-efficacy reflects a self-confident view of one's capability to deal with life's stressors (Bandura, 2006, 1997; Jerusalem and Schwarzer, 1992; Schwarzer and Warner, 2013).[7] In fact, Bandura (2010) described this belief as "the foundation of human motivation, performance accomplishments, and emotional well-being". We use the 10-item Generalised Self-Efficacy Scale (short-form) administered at Wave 5 (2013-2015), where items include: "I can always manage to solve difficult problems if I try hard enough", "I am confident that I could deal efficiently with unexpected events", "Thanks to my resourcefulness, I know how to handle unforeseen situations", "I can remain calm when facing difficulties because I can rely on my coping abilities", and "I can usually handle whatever comes my way". Respondents rate the extent to which each item describes them, from the options "not at all true", "hardly true", "moderately true", and "exactly true" (Schwarzer and Jerusalem, 1995).

We additionally explore two resources that have been hypothesised in the economics literature to help cushion or self-insure against the effects of negative shocks, namely religiosity and social capital (e.g. Dehejia et al., 2007; Munasinghe, 2007). We define religiosity as whether religious beliefs make at least some difference to the respondent's life, asked in Wave 8 (2016-18).[8] We measure neighbourhood social capital using eight items adapted from Buckner's (1988) Neighbourhood Cohesion Instrument, which captures the psychological sense of community and social interaction within a neighbourhood. Example items are "I feel like I belong to this neighbourhood", "The friendships and associations I have with other people in my neighbourhood mean a lot to me", "If I needed advice about something I could go to someone in my neighbourhood", "I borrow things and exchange favours with my neighbours", and "I regularly stop and talk with people in my neighbourhood". Our index is the standardised

[7] This is close to the concept of locus of control (Rotter, 1966), which is the focus of a growing literature on the role of non-cognitive skills in economic behaviour (see, for example, Caliendo et al., 2020, 2015; Cebi, 2007; Cobb-Clark et al., 2016; Lekfuangfu et al., 2018; McGee, 2015; Schurer, 2017). See Cobb-Clark (2015) for a discussion of the measurement of non-cognitive skills.

[8] We do not use "are you currently a member of …", or "whether you are a member or not, do you join in the activities of … on a regular basis" for "a religious group or church organisation" asked at the more recent Wave 9, as these may be less representative of prayer intensity. Moreover, religious gatherings and services in the UK were suspended during the pandemic, as part of the ban on mass events and gatherings, so individuals whose extent of religiosity is reliant on physical attendance would no longer have this as a resource during the pandemic, and may instead be negatively affected by this 'resource'.

sum of responses, which are a five-point Likert agreement scale (the distribution is shown in Appendix Figure A1).

4. Methodological Approaches

We aim to identify the type of resources that protect against the likelihood of a severe psychological response (being resilient) to the hardships and challenges caused by the COVID-19 pandemic. Our main approach uses multivariate linear regression to compare people with different levels of pre-COVID resources, but who are identical in terms of their key demographic characteristics. Specifically, we include a fixed-effect for every combination of the following ten multivalued variables: age (10-year bands), gender, ethnic background (White, South Asian, or Black and other), long-term illness or disability, number of children in the household, number of adults in the household, highest educational attainment (degree, A-level and diploma, or O-level and under), employment status (full-time employee, part-time employee, self-employed, or not employed), rurality[9], and area of the UK (Government Office Regions).[10] The combination of these variables generates 7,939 groups (fixed-effects), with 5,594 groups having only one person. The largest number of observations in any single group equals 18; consisting of healthy white females aged >70 years old, with low education levels, living in an urban neighbourhood of South East England, and who were not working prior to the pandemic. We opt for this tight identification strategy for our main estimates, but also provide results from models that do not include these demographic fixed effects.

This regression approach can be represented by the following equation:

$$y_{ijd} = \alpha_d + R'_{ijd}\delta + X'_{ijd}\beta + \varepsilon_{ijd} \quad (1)$$

where y_{ijd} is a binary variable representing whether individual i in household j with demographics d experienced a severe psychological response (increase of ≥ 5 symptoms of psychological distress).[11] α_d is the fixed-effect based on combinations of demographic

[9] Living in rural area indicates that the address of residence is not within urban settlements with a population of 10,000 and above.

[10] Banks and Xu (2020) stress the importance of controlling for pre-COVID trends in psychological distress, and in their trend prediction model they include a sub-set of the variables we use to define our fixed-effects (groupings). Since our identification then comes from within group changes in distress (i.e. same age, gender, education, employment, number of children, location, etc.), we believe that we account for this issue.

[11] Given this definition, we limit our main estimation sample to individuals for whom it is possible to have a 5-point worsening in mental health from Wave 9 to April 2020. This means that we need to exclude those with very high psychological distress before COVID-19, which accounted for 9% of respondents. We find that our main results are robust to this sample restriction.

variables defined above. R is the vector of individual resources that potentially reduced or exacerbated a person's negative psychological response. It includes the economic (income, savings, and debts), cognitive (cognitive ability measured using test scores) and non-cognitive resources (self-efficacy, religiosity), as well as neighbourhood social capital. X is a vector of covariates; importantly, this includes past mental health status.

While the COVID-19 pandemic was unexpected and universally felt, there was variation in the intensity of the shock across people. For example, those with chronic conditions or compromised immune systems, who had significantly higher fatality rates, may have had a more intense response than healthy people due to heightened anxiety. Similarly, parents who had to home school their children faced different challenges than non-parents. Importantly, for our interpretation of resources as being predictors of resilience, we need to control for heterogeneity in the severity of the pandemic shock. We believe that the covariates (fixed-effects) included in the regression, such as having a chronic illness and number of children, will control for a large proportion of this unobserved heterogeneity. Nevertheless, we estimate several additional regressions to establish the robustness of our main set of estimates.

First, we add household fixed-effects to Equation (1). That is, we compare differences in the psychological responses of family members (usually spouses or partners) with differences in their individual-level resources, controlling for differences in demographics and past mental health:

$$y_{ijd} = \tau_j + \alpha_d + R'_{ijd}\delta + X'_{ijd}\beta + \varepsilon_{ijd} \quad (2)$$

where τ_j represents the household fixed-effects. The number of households in our sample equals 9,351, the mean number of respondents per household equals 1.6, and there are 5,974 households with only one respondent. The additional household fixed-effects completely control for (observed and unobserved) household factors that may be correlated with our resources of interest (R), such as wealth, housing quality, neighbourhood amenities, area-level COVID-19 infection rates, and illness among family members and friends. We demonstrate that the estimates obtained from this specification are very similar to those from Equation (1).

Second, we use survey information on COVID-19-related shocks as measures of more intense adversity. From the survey we can identify people who experienced health, earnings, and loneliness shocks. The health shock is the experience of symptoms that could be caused by COVID-19 (11.9%); examples given in the survey include high temperature, a continuous

cough, and shortness of breath, amongst others.[12] The earnings shock is a reduction in total household earnings by 30% or more between January/February 2020 and April 2020 (17.8%). Finally, the loneliness shock is measured by an increase in reported loneliness from "hardly ever or never" feeling lonely in Wave 9 to "some of the time" or "often" feeling lonely in April 2020 (15.4%). We add to Equation (1) indicators of these shocks (s_{ijd}), and interactions between these indicators and variables representing resources and demographics (Z_{ijd}):

$$y_{ijd} = \theta s_{ijd} + \gamma s_{ijd} Z'_{ijd} + \alpha_d + R'_{ijd}\delta + X'_{ijd}\beta + \varepsilon_{ijd} \quad (3)$$

In these regressions, the parameters of primary interest are the γ coefficients on the interaction terms. They represent the extent to which individual resources are protective against health, economic, and loneliness shocks. Importantly, we show in Appendix Table A2 that the resources that improve resilience (i.e. reduce increased psychological distress) are not associated with the likelihood of experiencing the health, earnings, or loneliness shocks. In other words, during the COVID-19 pandemic, resources were not helpful in terms of avoiding the experience of negative events.

5. Regression Estimation Results

5.1. Effects of resources on the likelihood of a severe increase in psychological distress

We begin by estimating regression Equation (1), first without the extensive demographic covariates (what we refer to as 'demographic FEs'), and then with them included. These estimates are presented in Columns (1) and (2) of Table 3. The two sets of results highlight that the resource coefficient estimates are fairly insensitive to the set of included control variables. The point estimates in Columns (1) and (2) are quantitatively similar, while the standard errors are larger in Column (2), which is unsurprising given the reduction in the effective sample size used for identification (only those who have a similar person to compare with).[13] Overall, the comparison suggests that omitted variable bias is not a major concern in our context.

We find some evidence that pre-COVID-19 savings reduced the likelihood of experiencing severe psychological distress, and that having more debt increased such distress.

[12] We prefer using the "symptoms that could be coronavirus" variable, rather than variables indicating having been tested for coronavirus and/or tested positive for coronavirus (which were also recorded in the survey). These latter variables are more likely to suffer from selection bias, given the documented socioeconomic gradients in testing rates.

[13] The R-squared in Column (2) is a large 0.66. This is attributable to the inclusion of the demographic fixed-effects, which are based on all possible combinations of key demographic characteristics in our estimation sample.

The coefficient estimates are small and statistically significant in Column (1), but become statistically insignificant (p-values = 0.432 and 0.386) in Column (2) when the demographic fixed-effects are introduced. In neither model do we find any evidence that increased household income reduced psychological distress over this period (the point estimates are even positive). In other words, financial resources do not appear to be associated with a person's psychological resilience, once we have controlled for demographic factors such as age, gender, ethnic background, number of children and adults in the household, educational attainment, employment, health, and geography. *A priori* this finding was unexpected. For example, higher incomes in previous years may have allowed for more comfortable housing and amenities within which to isolate. In addition, more savings and less debt may provide a buffer during the economic recession, and therefore reduce financial-related stress and anxiety.

Neither do we find that an individual's cognitive ability plays a protective role: a one-standard deviation increase in cognition is estimated to increase the likelihood of a severe psychological response by 0.5 percentage points (p-value = 0.550). This is despite the well-established positive associations between cognition and labour market outcomes (Lindqvist and Vestman, 2011), strategic thinking (Carpenter et al., 2013), financial decision-making (Agarwal and Mazumder, 2013), and health (Bijwaard et al., 2015).

Perhaps unexpectedly, we find that religiosity seems to be negatively associated with resilience in the lockdown. Individuals for whom religious beliefs are an important part of their life are 2 percentage points more likely to experience a negative psychological response (statistically significant in Column 1, but not in Column 2). This effect may be due to closure of places of worship and banning of mass gatherings (including those of a religious nature) that occurred during the pandemic, rendering religious individuals potentially without an important 'external' resource. Only in Column (1) do we find some weak statistical evidence that increased neighbourhood social capital is associated with reduced psychological distress, although the point estimate is similar in Column (2).

Clearly, the strongest effect is for the non-cognitive skill 'self-efficacy'. A one-standard deviation increase in the self-efficacy index is estimated to reduce the likelihood of a large increase in psychological distress, by around 3 percentage points. Importantly, this significant negative effect is replicated across all three Columns of Table 3: self-efficacy appears to be an

important resilience resource in comparisons between-people (Column 1), in comparisons within demographic groups (Column 2), and in comparisons within households (Column 3).[14]

More generally, introducing household fixed-effects (Column 3) does not substantially alter any estimated effects. The point estimates for cognitive ability, religiosity, self-efficacy, and social capital are all similar across the columns. Unsurprisingly, the additional household fixed-effects have larger effects on standard errors, just as the demographic fixed-effects increase standard errors between Columns (1) and (2). Note that effects for income, savings, and debt levels are not identified in Column (3), because there is no within-household variation for these three household measures.

Finally, we explore whether there is heterogeneity in the protective (resilience enhancing) role of self-efficacy. Our approach is to re-estimate the regression in Column (2) of Table 3 for different population subgroups, and to plot the estimates in Figure 3. The sets of estimates reveal no significant differences in effect size between males and females; core working-age adults and older people; people with and without a university degree; and people above and below median household income. If we combine the subgroup characteristics with the highest point estimates and re-estimate the regression, we find that the effect of self-efficacy for women aged 25-59, with a degree and below median household income, equals 10.5 percentage points (p-value = 0.183; sample size = 735). This estimate implies that increasing self-efficacy from a low to a high value (a movement of four standard deviations) increases the probability of a resilient outcome in the pandemic by 41.9 percentage points (55% relative to the sample mean of 0.762).

5.2. Does self-efficacy moderate the negative effects of adverse events?

In this subsection we explore whether the relationship between self-efficacy and psychological resilience is stronger for people who experienced more intense adversity during the pandemic. Our approach is detailed in Equation (3) in Section 3. It involves including interaction terms between self-efficacy and health (measured by COVID-19-related symptoms), earnings, and loneliness shocks, as well as the main effects of these shocks, to Equation (1). The resulting coefficients are presented in Table 4**.**

[14] As shown in Figure 2, we do also observe individuals who experienced a reduction in psychological distress between Wave 9 and April 2020. When using an improvement in psychological health as the outcome (rather than a severe worsening), such as a reduction by 2 points or more in GHQ Caseness (experienced by 13.6%), our main finding is essentially reversed: that is, self-efficacy, which is protective against a deterioration in psychological health, also contributed to improved psychological health over the same period. The full results are available on request.

In Panel A, the only interaction term is the interaction between self-efficacy and the shock indicator. This interaction effect will be biased if other factors are also moderating the effect of the shocks, for instance if the effects of adversity are larger for men than for women, and self-efficacy is correlated with gender. To control for potential confounding, we additionally include interactions between the shock indicator and age, gender, employment, health, and education (measured prior to 2020). These estimates are presented in Panel B.

Large significant estimates for the 'main shock effects' imply that experiencing the health, earnings, and loneliness shocks are more likely to have had a severe deterioration in psychological health: by 4.4, 4.9, and 20.1 percentage points, respectively. For the health and loneliness shocks, having higher levels of self-efficacy does not reduce this likelihood. In contrast, self-efficacy lessens the negative effect of an earnings shock. Among individuals experiencing the earnings shock, a one-standard deviation increase in self-efficacy reduces the likelihood (or increases resilience) of a severe psychological response by 6.8 percentage points. Among those not experiencing the shock, the corresponding estimate equals 2.0 percentage points. This finding is robust to the inclusion of additional interaction terms. In Panel B of Table 4, the self-efficacy interaction effect remains large and statistically significant.

5.3. Is the self-efficacy effect sensitive to the definition of increased psychological distress?

Returning to using the 12-item GHQ caseness score, we examine in Figure 4 whether our results are robust to changing the cut-point that defines our outcome variable i.e. a significant increase in psychological distress during the pandemic. Using values higher than a 5-point increase in the score generates nearly identical estimates for self-efficacy (2.4-2.6 percentage points), whereas using smaller values (an increase of 2 or more, 3 or more, or 4 or more) leads to even larger self-efficacy effects (3.6-3.9 percentage points). However, in terms of percentage changes, relative to the respective sample means of each outcome variable, the largest estimated self-efficacy effect occurs when the outcome is defined as a 7-point worsening in psychological distress.

5.4. Is self-efficacy still important if we control for personality?

As highlighted in her discussion of the various measures of non-cognitive skills used by economists, Cobb-Clark (2015) cites the study by Judge et al. (2002) who conclude that self-efficacy, locus of control, and neuroticism are all markers of the same higher order concept. While locus of control has not been collected in Understanding Society, the Big-5 personality traits of agreeableness, conscientiousness, extraversion, neuroticism, and openness to

experience were collected in Wave 3. Table 5 presents the equivalent estimates to Table 3, but with the models additionally controlling for personality. In line with Judge et al.'s (2002) conclusion, we find for our main within-group comparison that neuroticism is associated with a significantly lower resilience (or higher increased psychological distress), while self-efficacy remains a significant predictor of resilience.

5.5. Using data from the May and June 2020 COVID-19 surveys

In Table 6 we check to see if our results change when using data from the May and June 2020 surveys. The May survey was conducted in the week between May 27 and June 2, and the June survey was collected in the week between June 25 and July 1. Using the same within group comparison (Column 2 in Table 3) we find that results in May and June are qualitatively similar to that in April. In particular, self-efficacy is again protective of increased psychological distress, and financial and cognitive resources are not. Relative to the self-efficacy coefficient in April (-0.026), the coefficient for self-efficacy is around 30% smaller in May (-0.018), but the same in June (-0.026).

In Columns (3) and (4) of Table 6 we explore the effects of resources on the likelihood of experiencing a sustained increase in psychological distress. In Column (3) self-efficacy is the only resource predicted to reduce the probability of reporting an increase of ≥ 5 symptoms of psychological distress (relative to Wave 9) in each of April, May, and June. The coefficient estimate suggests that a one-standard deviation increase in self-efficacy reduces the likelihood of persistent distress by 1.2 percentage points, or a 25% reduction relative to the sample mean of 4.7%. This compares to relative reductions of 14% in May (Column 1) and 20% in June (Column 2). Therefore, self-efficacy appears to be an important protective resource against severe and persistent psychological distress following a large unexpected event. Although the pandemic was still a major public health issue in the UK in June 2020, and the economic consequences of lockdown will be felt for many years, these results suggest that self-efficacy will continue to play an important role in reducing the overall psychological cost.

5.6. Other robustness and sensitivity checks

In this final subsection we further explore the sensitivity of our main results to differences in the measurement of our main variables, differences in our regression specification, and to sample selection bias. All results are presented in the Appendix.

First, not unexpectedly given the nature of the COVID-19 lockdown, we see large declines (worsening outcomes) in the responses to the questions (items), "Have you recently

felt that you were playing a useful part in things?", and "Have you recently been able to enjoy your normal day-to-day activities?" (see Section 3.2) Clearly, the ability to conduct normal day-to-day activities, so that they could be enjoyed, would be limited for most individuals in late April 2020. We test the robustness of our results excluding these two questions, and for the remaining 10-items we define severe psychological distress as an increase of three or more symptoms (19.6% of sample). The results, replicating Table 3, are shown in Table A3. We can see that the results are largely unchanged, with self-efficacy remaining protective of psychological distress for both the between-person and within-group comparisons. However, the point estimate using the within household comparison is smaller and no longer statistically significant. The same findings for self-efficacy hold if we increase the psychological distress cut-off to four or more symptoms (14.2%).

Second, in Tables A4 and A5 we present results for a restricted sample of people with reasonably good psychological health prior to the pandemic, which we define as a GHQ-12 Caseness score less than 3 in Wave 9 (sample size = 11,087). We find that even when using this smaller, psychologically healthier sample, the resulting estimates for self-efficacy and its interactions with COVID-19 shock indicators are robust and very similar to those presented in Tables 3 and 4. This suggests that self-efficacy is a protective resource for not only those with poor psychological health but also those with good health prior to a large unexpected shock. In addition, we demonstrate in Figure A2 that the significant role for self-efficacy is robust to using a range of different Wave 9 GHQ-12 scores to restrict the estimation sample.

6. Conclusion

There is considerable interest in identifying the characteristics of resilient people, which has only been intensified by the COVID-19 pandemic. In this paper we respond to calls for more research. Coming from an economics perspective, our focus has been on identifying whether financial and non-financial resources protect against increased psychological distress following a major adverse event.

Combining annual survey information and supplementary COVID-19 survey responses from participants in the United Kingdom Household Longitudinal Study (Understanding Society) collected in April, May, and June 2020, we find a substantial increase in the proportion of respondents reporting high levels of psychological distress in the COVID-19 lockdown. In fact, 50% reported a worsening by at least one symptom of distress, and staggeringly, around one in seven respondents reported an increase by five or more distress symptoms. This naturally leads to the question of who are the most and least resilient individuals.

Our main modelling approach is based on comparing the change in distress reported by individuals with different levels of resources, but who are identical in terms of their key characteristics. Specifically, we include fixed-effects based on matching individuals on key demographic and socioeconomic characteristics including age, gender, ethnicity, household composition, education, employment status, rurality, and region of residence. In addition to this within group comparison, we also use within-household variation to test the robustness of our key results.

Perhaps surprisingly we find no evidence that better financial resources, measured by household income, savings, and debts, predicted a more resilient response to the pandemic shock. That is, financial position did not predict increases in psychological distress. This finding is somewhat consistent with the conclusion of Davillas and Jones (2020) who found that the proportion of inequalities attributable to circumstances actually declined, with the pandemic being "a leveller as far as psychological distress is considered". Neither do we find a more resilient response associated with cognitive ability, religiosity, or neighbourhood social capital.

However, regardless of our model specification, we have found that non-cognitive skills, as measured by self-efficacy, are strongly associated with a more resilient response to the pandemic. This holds even when comparing individuals in the same household. Self-efficacy is a confident view of one's capability to deal with life's stressors (Bandura, 2006, 1997; Schwarzer and Warner, 2013), and is a similar non-cognitive skill to locus of control. This result is also robust when samples are restricted to different demographic groups and different levels of past psychological health, and when samples are observed at different time points in the pandemic. A one-standard deviation higher level of self-efficacy reduces the likelihood of a severe increase in psychological distress by around 3 percentage points, or around 20% relative to the sample mean.

The positive policy-relevant aspect of this finding is that developing self-efficacy is viewed as amenable to investment aimed at assisting individuals master experiences and obstacles. Watching individuals overcome obstacles can also have a social multiplier effect that can help others to develop their belief that they too can overcome challenges (Bandura, 2010). This points to a focus for building population resilience to limit the costs (damage-function) of future shocks. More generally, it supports the wider economics literature that have shown in recent decades the importance of investing in non-cognitive skills as they are strongly associated with better economic outcomes.

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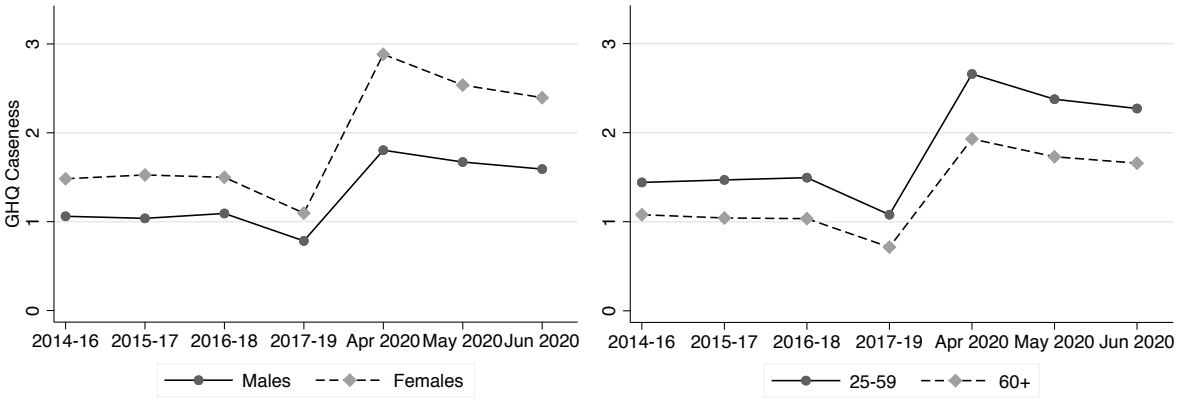

Figure 1: Average GHQ Caseness [0,12] score from Wave 6 (2014-2016) to the last measurement in June 2020, by gender and age group. Higher values indicate poorer mental health.

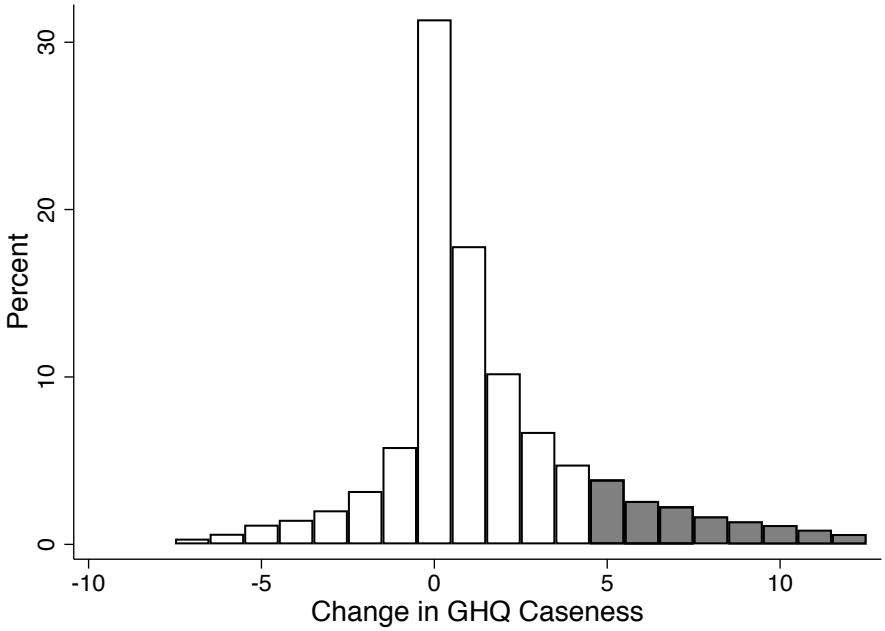

Figure 2: Histogram of change in GHQ Caseness score from Wave 9 (2017-2019) to April 2020. A positive value indicates an increase in GHQ Caseness Score and a deterioration in mental health. Shaded bars are used to indicate a substantive deterioration in mental health during the pandemic.

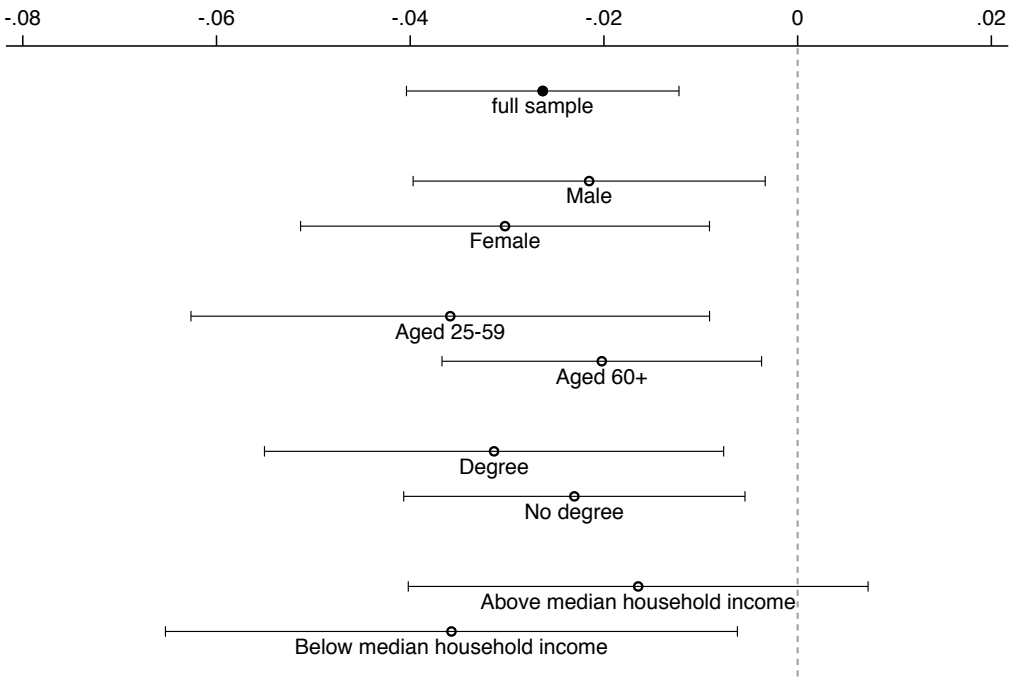

Figure 3: Plot of regression coefficient estimates for self-efficacy, for which higher scores reflect greater self-efficacy, for separate subgroup regressions. All regressions follow Column (2) in Table 3.

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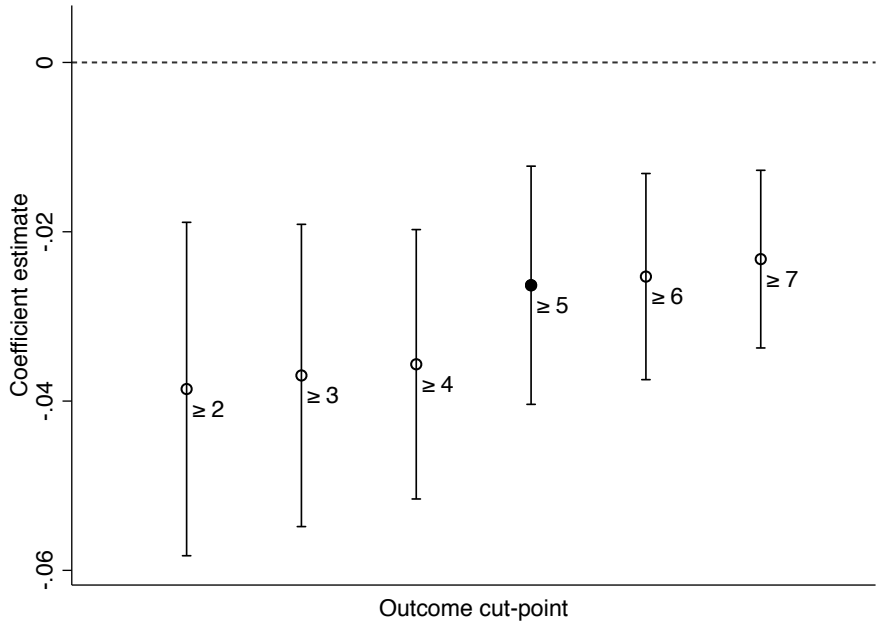


Figure 4: Plot of regression coefficient estimates for self-efficacy when the cut-point used to define the binary outcome (increase in GHQ Caseness between Wave 9 and April 2020) is altered. The darkened marker is the estimate displayed in Column (2) in Table 3.

Table 1:

Characteristics of Individuals Experiencing a Severe Increase in Psychological Distress

	Change in score < 5	Change in score ≥ 5
GHQ caseness score in Wave 9 [0,12]	0.982	0.807
GHQ caseness score in April 2020 [0,12]	1.463	8.095
Age in 2020	54.1	48.6
Male	0.452	0.285
Number of children in household	0.446	0.588
Number of adults in household	2.267	2.296
Employed	0.615	0.684
Have a long-term illness or disability	0.315	0.328
Live in rural area	0.270	0.237
Eating healthy and nutritious food	0.986	0.957
Drinking alcohol 4+ times per week	0.256	0.248
Drinking 5+ drinks when drinking	0.068	0.075
Exercising at least once per week	0.720	0.680
Cigarettes per day	0.938	1.166
Planned healthcare treatment cancelled	0.712	0.735
Sample size	11181	1887

Notes: Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 7 at Wave 9 (2017-19). Cigarettes include those self-rolled, but excludes e-cigarettes. Vigorous activities refer to physical activities that "take hard physical effort and make you breathe much harder than normal", done for "at least 10 minutes at a time". Moderate activities refer to physical activities that "take moderate physical effort and make you breathe somewhat harder than normal", done for "at least 10 minutes at a time".

Table 2:

Financial and Non-Financial Resources Measured Prior to COVID-19

Resource	Item description	Mean	Years
Household income	Monthly total household net income, equivalised using the modified OECD scale. Values averaged over four waves and adjusted using the UK Consumer Price Index	2107.2	2014-19
Savings	Sum in savings or deposit accounts, National Savings Accounts, and cash-only ISAs, solely or jointly held with other members of the household	20345.7	2016-18
Debts	Outstanding balance on all store and credit cards, and any other financial commitments apart from mortgages, including student loans, personal or private loans, and hire purchase agreements	3734.3	2016-18
Cognition	Score from a principal-component factor analysis of five tests: Serial 7 Subtraction (working memory), Immediate Word Recall Task (episodic memory), Number Series (fluid reasoning), Animal Naming Test (semantic verbal fluency), and Numeric Ability (practical numerical knowledge)	0.000	2011-13
Religiosity	Indicator that "religious beliefs" make "some difference" or "a great difference" to your life	0.338	2016-18
Social capital	Mean response across eight items adapted from Buckner's (1988) Neighbourhood Cohesion Instrument. Higher scores reflect greater neighbourhood social capital.	0.000	2017-19
Self-efficacy	Standardised sum of responses on the 10-item Generalised Self-Efficacy Scale. Higher scores reflect greater self-efficacy.	0.000	2013-15

Notes: Income, savings and debt are log-transformed before inclusion in regressions. Cognition, self-efficacy and social capital indices have been standardised to have a mean of 0 and a std deviation of 1 for the estimation sample.

Table 3:

Effects of Resources on Increased Psychological Distress in April 2020

	Between person comparison (1)	Within group comparison (2)	Within household comparison (3)
Log income	0.004	0.008	--
	(0.007)	(0.015)	
Log savings	-0.001***	-0.001	--
	(0.001)	(0.001)	
Log debts	0.002***	0.001	--
	(0.001)	(0.001)	
Cognition (standardised)	0.001	0.005	-0.008
	(0.003)	(0.008)	(0.009)
Religiosity (0/1)	0.021***	0.020	0.018
	(0.007)	(0.014)	(0.020)
Social capital (standardised)	-0.006*	-0.007	-0.011
	(0.003)	(0.007)	(0.011)
Self-efficacy (standardised)	-0.031***	-0.026***	-0.017**
	(0.004)	(0.007)	(0.009)
Wave 9 GHQ Score	-	-0.014***	-0.022***
		(0.004)	(0.005)
Demographic FEs	No	Yes	No
Household FEs	No	No	Yes
Mean outcomes	0.144	0.144	0.144
R-squared	0.013	0.660	0.782
Sample size	13068	13068	13068

Notes: $^{*}p<0.10,^{**}p<0.05,^{***}p<0.01$. Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 7 at Wave 9 (2017-19). Robust standard errors are in parentheses. Demographic controls used in household fixed-effects regressions (Column 3) are sex, educational attainment, ethnic background, and employment and health status. All regressions include dummies for year GHQ measured (in Wave 9), and dummies for date survey ended in April 2020. Columns (2) and (3) further include age and age squared.

Table 4:

Interaction effects between Intensity of COVID-19 Experience and Resources on Increased Psychological Distress in April 2020

	COVID-19 Symptoms (1)	Reduced earnings (2)	Increased loneliness (3)
(A) Self-Efficacy Interaction			
Main shock effect	0.044*	0.049**	0.201***
	(0.024)	(0.025)	(0.024)
Self-efficacy	-0.025***	-0.020**	-0.030***
	(0.008)	(0.010)	(0.007)
Self-efficacy x shock	-0.010	-0.048*	0.017
	(0.022)	(0.025)	(0.026)
(B) Additional Interactions			
Main shock effect	0.056	0.034	0.213***
	(0.047)	(0.049)	(0.043)
Self-efficacy	-0.026***	-0.019**	-0.030***
	(0.008)	(0.010)	(0.007)
Self-efficacy x shock	-0.006	-0.052**	0.016
	(0.023)	(0.025)	(0.027)
Age x shock	-0.002	0.000	0.002
	(0.002)	(0.002)	(0.002)
Male x shock	-0.028	-0.022	-0.025
	(0.043)	(0.047)	(0.047)
FT employed x shock	0.000	0.035	-0.022
	(0.052)	(0.056)	(0.052)
LT illness x shock	0.016	-0.024	-0.041
	(0.049)	(0.051)	(0.050)
No degree x shock	-0.010	0.044	0.035
	(0.044)	(0.049)	(0.046)
Sample size	13063	10562	13060

Notes: $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$. Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 7 at Wave 9 (2017-19). All regressions further include variables following Column (2) in Table 3. Robust standard errors are in parentheses.

Table 5:

Effects of Resources on Increased Psychological Distress in April 2020, Including Big-5

	Between person comparison (1)	Within group comparison (2)	Within household comparison (3)
Log income	0.005	0.009	--
	(0.007)	(0.015)	
Log savings	-0.001**	-0.001	--
	(0.001)	(0.001)	
Log debts	0.002***	0.001	--
	(0.001)	(0.001)	
Cognition (std)	0.000	0.004	-0.007
	(0.004)	(0.008)	(0.009)
Religiosity (0/1)	0.018***	0.016	0.013
	(0.007)	(0.014)	(0.020)
Social capital (std)	-0.007*	-0.008	-0.011
	(0.003)	(0.007)	(0.011)
Self-efficacy (std)	-0.024***	-0.019**	-0.008
	(0.004)	(0.008)	(0.009)
Agreeableness	0.005	0.009	0.008
	(0.004)	(0.008)	(0.009)
Conscientiousness	-0.001	-0.008	-0.002
	(0.004)	(0.007)	(0.009)
Extraversion	0.005*	0.004	-0.001
	(0.003)	(0.006)	(0.007)
Neuroticism	0.026***	0.022***	0.025***
	(0.003)	(0.006)	(0.006)
Openness to Experience	0.014***	0.012*	0.006
	(0.003)	(0.006)	(0.008)
Wave 9 GHQ Score	--	-0.016***	-0.024***
		(0.004)	(0.005)
Demographic FEs	No	Yes	No
Household FEs	No	No	Yes
Mean outcomes	0.144	0.144	0.144
R-squared	0.022	0.663	0.783
Sample size	13068	13068	13068

Notes: $^{*}p<0.10, ^{**}p<0.05, ^{***}p<0.01$. Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 7 at Wave 9 (2017-19). Robust standard errors are in parentheses. Demographic controls used in household fixed-effects regressions (Column 3) are sex, educational attainment, ethnic background, and employment and health status. All regressions include dummies for year GHQ measured (in Wave 9), and dummies for date survey ended in April 2020. Columns (2) and (3) further include age and age squared.

Table 6:

Effects of Resources on Increased Psychological Distress using the May and June 2020 COVID-19 Surveys

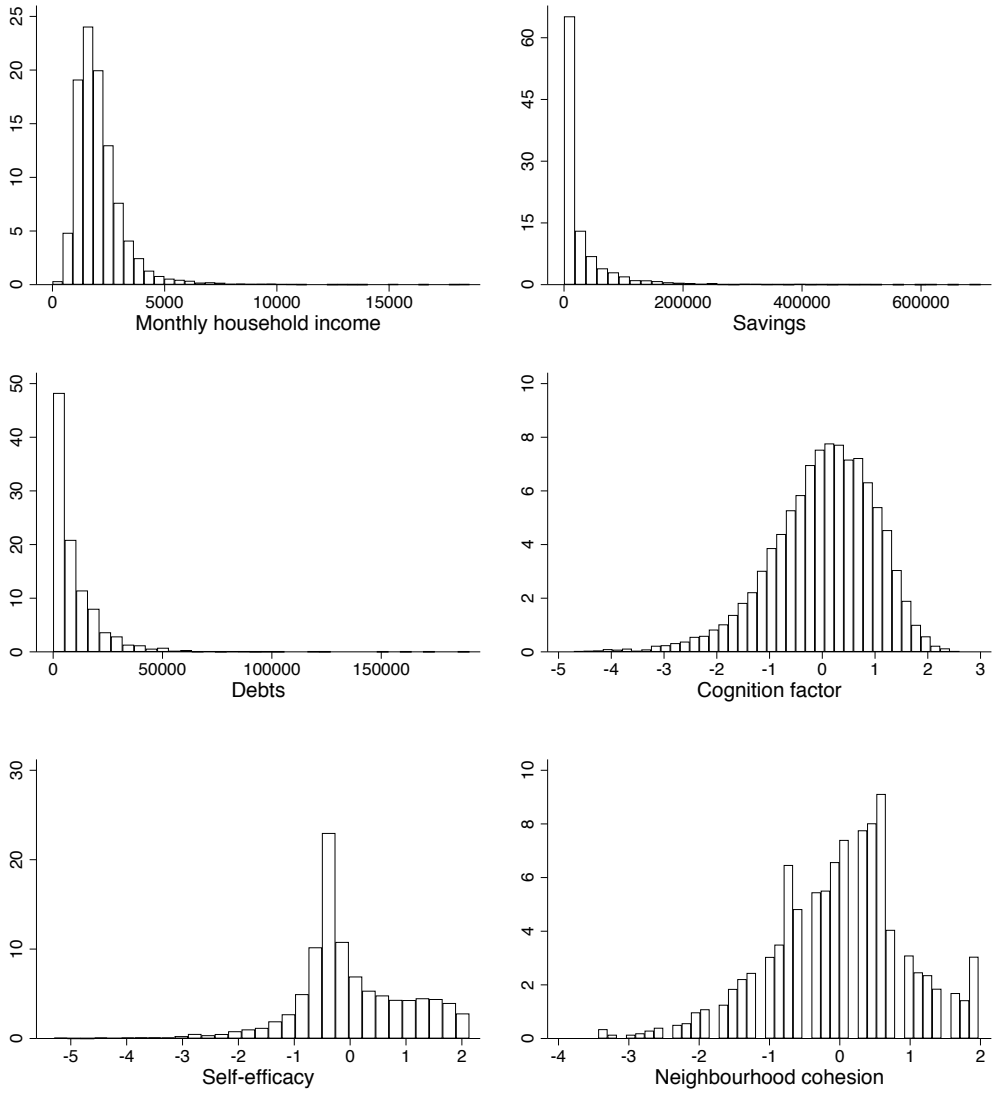
	Increased psychological distress in May (1)	Increased psychological distress in June (2)	Increased psychological distress in April, May, and June (3)
Log income	-0.015	-0.003	-0.001
	(0.015)	(0.015)	(0.010)
Log savings	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)
Log debts	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Cognition (standardised)	-0.003	0.008	0.002
	(0.008)	(0.008)	(0.005)
Religiosity (0/1)	0.013	0.013	0.006
	(0.014)	(0.014)	(0.010)
Social capital (standardised)	-0.013*	-0.012	-0.003
	(0.008)	(0.007)	(0.005)
Self-efficacy (standardised)	-0.018**	-0.026***	-0.012**
	(0.007)	(0.007)	(0.005)
Wave 9 GHQ Score	-0.008**	-0.003	-0.004
	(0.004)	(0.004)	(0.003)
Demographic FEs	Yes	Yes	Yes
Household FEs	No	No	No
Mean outcome	0.131	0.129	0.047
R-squared	0.667	0.671	0.704
Sample size	12151	11603	10195

Notes: $^{*}p<0.10,^{**}p<0.05,^{***}p<0.01$. Sample restricted to those having maximum Caseness score of 7 at Wave 9 (2017-19). All regressions further include variables following Column (2) in Table 3. Column (3) further restricts the sample to those with GHQ information in April, May, and June 2020. Robust standard errors are in parentheses.

Appendix

Figure A1:

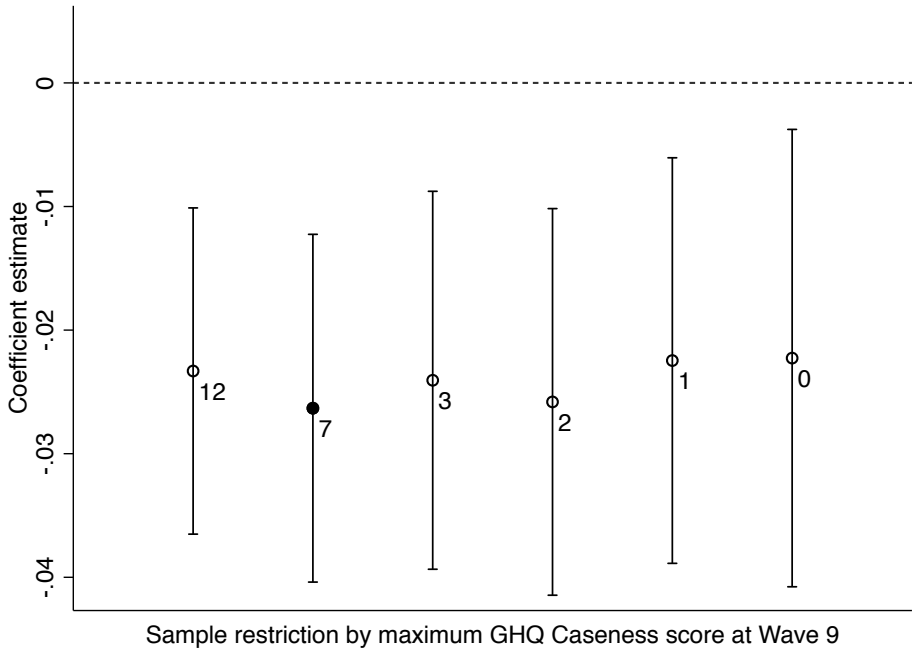
Distributions of Financial and Non-Financial Resource Measures



Notes: Y-axes are in percentages.

Figure A2:

Sensitivity of Self-Efficacy Estimates to Restrictions on Wave 9 Psychological Health



Notes: Plot of regression coefficient estimates for self-efficacy when the maximum Caseness score at Wave 9 (2017-2019) used for restricting the sample is altered. The darkened marker is the estimate displayed in Column (2) in Table 3.

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Table A1:

Descriptive statistics

	Mean (SD)	Wave measured
Age	53.3 (16.2)	April 2020
Male	0.428	9 (2017-19)
Number of children in household	0.467	9
Number of adults in household	2.271	9
Employment status:		9
Not employed	0.375	
Employed full time	0.416	
Employed part time	0.123	
Self-employed	0.086	
Have a long-term illness or disability	0.317	9
Live in rural area	0.265	9
Government Office Region:		9
North East	0.035	
North West	0.097	
Yorkshire and the Humber	0.084	
East Midlands	0.078	
West Midlands	0.083	
East of England	0.097	
London	0.094	
South East	0.145	
South West	0.096	
Wales	0.059	
Scotland	0.090	
Northern Ireland	0.042	
Health symptoms	0.119	April 2020
Reduced earnings	0.178	April 2020
Increased loneliness	0.154	April 2020
GHQ Caseness [0,12]		
Wave 9	0.957 (1.725)	9
April 2020	2.421 (3.005)	April 2020
Increase in GHQ Caseness by 5 points or more between Wave 9 and April 2020 [0,1]	0.144	
Sample size	13068	

Notes: Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 7 at Wave 9 (2017-19).

Table A2:

Effects of Resources on Experiencing a Health, Earnings and Loneliness Shock

	(1) Health symptoms (N=13063)	(2) Reduced earnings (N=10562)	(3) Increased loneliness (N=13060)
Log income	0.014	-0.012	0.009
	(0.014)	(0.022)	(0.016)
Log savings	-0.000	-0.003**	-0.001
	(0.001)	(0.002)	(0.001)
Log debts	-0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)
Cognition (std)	0.015**	-0.009	-0.004
	(0.007)	(0.011)	(0.009)
Religiosity (0/1)	-0.001	-0.005	0.013
	(0.012)	(0.019)	(0.015)
Social capital (std)	0.000	0.011	0.010
	(0.007)	(0.009)	(0.008)
Self-efficacy (std)	0.000	-0.001	0.009
	(0.006)	(0.009)	(0.007)

Notes: $^{*}p<0.10, ^{**}p<0.05, ^{***}p<0.01$. Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 7 at Wave 9 (2017-19). All regressions further include variables following Column (2) in Table 3. Robust standard errors are in parentheses.

Table A3:

Effects of Resources on Psychological Distress in April 2020 when using 10 GHQ items

	Between person comparison (1)	Within group comparison (2)	Within household comparison (3)
Log income	0.004	-0.010	--
	(0.007)	(0.018)	
Log savings	-0.002***	-0.002	--
	(0.001)	(0.001)	
Log debts	0.003***	0.001	--
	(0.001)	(0.001)	
Cognition (std)	0.003	0.006	-0.002
	(0.004)	(0.009)	(0.010)
Religiosity (0/1)	0.026***	0.024	0.034
	(0.008)	(0.016)	(0.022)
Social capital (std)	-0.009**	-0.006	-0.010
	(0.004)	(0.008)	(0.013)
Self-efficacy (std)	-0.038***	-0.029***	-0.012
	(0.004)	(0.008)	(0.010)
Wave 9 GHQ Score	--	-0.015***	-0.022***
		(0.004)	(0.005)
Demographic FEs	No	Yes	No
Household FEs	No	No	Yes
Mean outcome	0.196	0.196	0.196
R-squared	0.018	0.658	0.783
Sample size	13076	13076	13076

Notes: $^{*}p<0.10,^{**}p<0.05,^{***}p<0.01$. Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 7 at Wave 9 (2017-19). Robust standard errors are in parentheses. Demographic controls used in household fixed-effects regressions (Column 3) are sex, educational attainment, ethnic background, and employment and health status. All regressions include dummies for year GHQ measured (in Wave 9), and dummies for date survey ended in April 2020. Columns (2) and (3) further include age and age squared.

Table A4:

Effects of Resources on Increased Psychological Distress in April 2020, for Individuals in Good Psychological Health at Wave 9

	(1)	(2)	(3)
Log income	0.007	0.012	--
	(0.007)	(0.017)	
Log savings	-0.002***	-0.001	--
	(0.001)	(0.001)	
Log debts	0.002***	0.001	--
	(0.001)	(0.001)	
Cognition (standardised)	0.003	0.006	-0.008
	(0.004)	(0.009)	(0.011)
Religiosity (0/1)	0.016**	0.011	0.005
	(0.007)	(0.016)	(0.024)
Social capital (standardised)	-0.008**	-0.005	-0.007
	(0.004)	(0.008)	(0.014)
Self-efficacy (standardised)	-0.037***	-0.026***	-0.022**
	(0.004)	(0.008)	(0.010)
Wave 9 GHQ Score	-	-0.004	-0.015
		(0.013)	(0.017)
Demographic FEs	No	Yes	No
Household FEs	No	No	Yes
Mean outcomes	0.149	0.149	0.149
R-squared	0.017	0.687	0.816
Sample size	11087	11087	11087

Notes: $^{*}p<0.10,^{**}p<0.05,^{***}p<0.01$. Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 2 at Wave 9 (2017-19). Robust standard errors are in parentheses. Demographic controls used in household fixed-effects regressions (Column 3) are sex, educational attainment, ethnic background, and employment and health status. All regressions include dummies for year GHQ measured (in Wave 9), and dummies for date survey ended in April 2020. Columns (2) and (3) further include age and age squared.

Table A5:

Interaction effects between Intensity of COVID-19 Experience and Resources on Increased Psychological Distress in April 2020, for Individuals in Good Wave 9 Psychological Health

Shock indicator	COVID-19 Symptoms (1)	Reduced earnings (2)	Increased loneliness (3)
Shock	0.041	0.041	0.202***
	(0.027)	(0.029)	(0.027)
Self-efficacy	-0.025***	-0.021*	-0.027***
	(0.008)	(0.011)	(0.008)
Shock * self-efficacy	-0.013	-0.051*	-0.001
	(0.025)	(0.029)	(0.030)
Shock	0.014	0.054	0.214***
	(0.056)	(0.057)	(0.050)
Self-efficacy	-0.025***	-0.021**	-0.027***
	(0.008)	(0.011)	(0.008)
Shock * self-efficacy	-0.012	-0.054*	-0.001
	(0.026)	(0.029)	(0.031)
Shock * age	-0.001	-0.001	0.001
	(0.002)	(0.003)	(0.002)
Shock * male	-0.017	-0.039	-0.016
	(0.050)	(0.056)	(0.054)
Shock * employed FT or self-employed	0.037	0.022	-0.022
	(0.063)	(0.066)	(0.063)
Shock * LT illness	0.024	-0.024	-0.030
	(0.057)	(0.063)	(0.059)
Shock * no degree	0.017	0.024	0.015
	(0.050)	(0.057)	(0.054)
Sample size	11083	8942	11081

Notes: *p<0.10,**p<0.05,***p<0.01. Sample restricted to those having GHQ information in April 2020 and having a maximum Caseness score of 2 at Wave 9 (2017-19). All regressions further include variables following Column (2) in Table 3. Robust standard errors are in parentheses.