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Abstract

Using new data from the Understanding Society: COVID 19 survey collected in April 2020, we show how the aggregate shock caused by the pandemic affects individuals across the distribution. The survey collects data from existing members of the Understanding Society panel survey who have been followed for up to 10 years. Understanding society is based on probability samples and the Understanding Society Covid19 Survey is carefully constructed to support valid population inferences. Further the panel allows comparisons with a pre-pandemic baseline. We document how the shock of the pandemic translates into different economic shocks for different types of worker: those with less education and precarious employment face the biggest economic shocks. Some of those affected are able to mitigate the impact of the economic shocks: universal credit protects those in the bottom quintile, for example. We estimate the prevalence of the different measures individuals and households take to mitigate the shocks. We show that the opportunities for mitigation are most limited for those most in need.

Keywords: COVID-19, job loss, inequality, mitigation, financial distress

JEL codes: C83, D31, G51, I31, J31, J63,

1 Introduction

The onset of COVID-19 has caused a substantial contraction in economic activity, partly through individuals changing their behaviour in the face of the health risks and partly because of restrictions introduced by governments. In this paper we show that the scale of the economic impact of the COVID shock is very different for different people. These differences arise partly because the direct shock differs depending on what sort of work people do, and partly because individuals have differing abilities to mitigate the shock. The aim of the paper is to highlight the reasons for the idiosyncratic nature of the economic shocks and to show how heterogeneity in circumstances mean the same economic shock has very different implications.

There is already a sizable literature documenting how individuals and households have fared through the pandemic.[1] Our work makes three contributions to this literature: first, our results are based on a large, high quality survey derived from probability samples. In the UK, "Understanding Society" has interviewed individuals annually pre-COVID, creating a panel since 2009 (Institute for Social and Economic Research, NatCen Social Research and Kantar Public, 2019), and additionally since the onset of COVID, individuals are being interviewed monthly (Institute for Social and Economic Research, 2020*a*). The use of carefully modelled inverse probability weights and proper probability samples is necessary to understand the effects of an aggregate shock and avoids the ad-hoc use of calibration weights (Benzeval et al., 2020). Second, the long panel data pre-COVID provides a clear picture of the situation different households were in when COVID struck. In particular, we know details of their long-run income, job security, financial fragility and economic situation, and this provides crucial context of households situations pre-COVID. Third, to get at the question of who is best able to mitigate the crisis, the questions post-COVID provide information on what steps individuals are taking to mitigate losses, combined with information pre-COVID. These three contributions enable us to provide a unique perspective on how differently COVID has changed the economic reality faced by different households in the UK.

We split our analysis into showing differences in the economic shock; into showing differences in the ability to mitigate the economic shock; and into showing differences in outcomes and financial security.

We find substantial heterogeneity in economic outcomes. Those who have been least

[1] Among many others, on the labour market outcomes, see Adams-Prassl et al. (2020), Bell and Blanchflower (2020); on consumption outcomes, see Baker et al. (2020*b*), Baker et al. (2020*a*).

affected are a combination of those who have not experienced much of a shock and those who despite receiving a negative shock, are able to mitigate. The first group includes those in professional jobs able to work from home and those in industries with less-human facing contact. The second group includes those with precarious employment at the bottom of the income distribution but who are potentially well insured by the universal credit system. The worst outcomes are for those experiencing severe shocks but without mechanisms to mitigate, such as single parents, those in the lowest education groups and ethnic minorities. Further, at this point in the crisis, the most widely used mechanisms of mitigation of earnings losses are through self-insurance via saving and borrowing, rather than through external help.

Related Literature The immediate research on the labour market impacts of COVID provided predictions of the likely impacts (Alon et al., 2020; Dingel and Neiman, 2020; Yasenov, 2020). In contrast to other economic downturns, a stronger impact on women was predicted because of the large initial negative shock to service occupations that have high female employment shares (Alon et al., 2020); and also on industries with a concentration of workers unable to work at home (Dingel and Neiman, 2020; Yasenov, 2020). Several studies provide estimates of the most immediate labour market impacts of COVID (Coibion, Gorodnichenko and Weber, 2020; Adams-Prassl et al., 2020; Brynjolfsson et al., 2020), although these estimates are derived from non-probability samples making population level inference challenging. Differently, a small but growing body of evidence has exploited individual level survey data from probability samples to estimate the labour market shocks of the early weeks of the crisis (Béland, Brodeur and Wright, 2020; Cortes, 2020; Montenovo et al., 2020; Mongey, Pilossoph and Weinberg, 2020). Evidence derived from the March 2020 US Current Population Survey shows increased unemployment, decreased working hours, but little fall in wages (Béland, Brodeur and Wright, 2020). The labour market impacts have been shown to be bigger for men, younger workers, Hispanics, and the less educated (Cortes, 2020); although (Montenovo et al., 2020) finds larger effects for women and those with larger families. Those who cannot work remotely have also been shown to be amongst the most adversely effected (Béland, Brodeur and Wright, 2020; Montenovo et al., 2020; Mongey, Pilossoph and Weinberg, 2020). Larger shocks for vulnerable populations have also been documented for the Netherlands (von Gaudecker et al., 2020) and for Norway (Alstadsæter et al., 2020); the latter being derived from the population benefit register. A separate stream of research has used high frequency data to study the labour market impacts of COVID: Kahn, Lange and Wiczer (2020) (job frequency data); Bell and Blanchflower (2020) (Labour market indicators); Watanabe and Omori (2020) (credit card transactions). Differently, the present paper is able to track individuals over multiple pre-crisis years and so provides a fuller contextual setting than does the early literature. It moves beyond the narrow measures of labour market shocks studied above to give a more complete picture of labour market outcomes by documenting mitigation strategies of individuals and the combined effect of shocks and mitigation on individual's economic outcomes.

Roadmap: The paper proceeds as follows: in section 2, we outline the data, the method of weighting the data and the basis of population inferences. Section 3 reports the size of the economic shocks facing different individuals. Section 4 reports the extent that individuals are able to mitigate the impact of the shocks. Section 5 reports the overall impact on measures of welfare.

2 Data and Methods

This paper is based on the *Understanding Society COVID-19* study (Institute for Social and Economic Research, 2020*a*). *The Understanding Society COVID-19* study is built upon *Understanding Society*: the UK Household Longitudinal Study, and uses frequent web surveys to capture the experiences and behaviours of the *Understanding Society* participants during the COVID-19 pandemic. This means, first, that the *Understanding Society COVID-19* study inherits the properties of *Understanding Society* that ensure reliable population inferences. Second, data collected by the *The Understanding Society COVID-19* study can be linked to data collected on the same participants, and their households, in past waves of the Main study (and it will, in the future, be possible to link them to future waves as well, opening up the possibility of tracking longer term changes.) The current paper employs data from the first wave of the *Understanding Society COVID-19* study, which was fielded in late April 2020, alongside contextual information from past waves of *Understanding Society.*

2.1 Understanding Society

Understanding Society (University of Essex Institute for Social and Economic Research, NatCen Social Research and Kantar Public, n.d.) is the UK's main longitudinal Household Survey, and one of the largest household panel studies in the world. It began in 2009 but carries on from (and incorporates the sample of) the earlier *British Household Panel* survey which ran from 1991 to 2008. *Understanding Society* attempts to interview all adults in sample households annually. *Understanding Society* began with entirely face-to-face interviews but has transitioned so that it is a mixed mode design, with some panel members responding via a face-to-face interview and some completing a web interview.

Understanding Society comprises four distinct samples.[2] Each began as a probability sample. All samples other than the Northern Ireland sample had a clustered and stratified design.

A key feature of probability samples is every unit in the target population has a knowable, nonzero probability of selection (Valliant and Dever, 2018). This offers two advantages over other types of samples (such as convenience or quota samples). First, the fact that all units in the target population have a nonzero probability of selections ensures that, with sufficiently large sample sizes, the full range of heterogeneity in the target population will be captured. Second, known selection probabilities mean that consistent estimates of population parameters and associated inferences can be obtained with well established statistical methods involving inverse-probability weighting.

Of course, real samples deviate form the theoretical ideal of a probability sample because of non-response, including, in the case of longitudinal studies, attrition. It is, nevertheless, of great advantage to begin from probability samples. Other types of samples may have a zero probability that certain parts of the target population will enter the sample. Second, while statistical adjustments may be needed to account for nonrandom non-response and attrition, such adjustments have less work to do if the initial selection probabilities are known. A further point is that when a study begins with a probability sample, information is typically available on non-respondents. This is particularly true in longitudinal studies where rich information on individuals who attrit is available from past waves of the survey. Such information is obviously of great value in modeling response and attrition. This contrasts with convenience or quota samples where information is only available for respondents, and differences between respondents and non-respondents can only be inferred indirectly.

Understanding Society makes considerable efforts, and employs state of the art methods, to minimize non-response and attrition. At the same time, it provides weights to account for the nonrandom nature of the residual unavoidable attrition. These inverse-probability weights are based on very carefully modeling of response and attrition. Although the probability that a given individual is included in the sample at a given wave is not known ex ante, it can be very credibly estimated, combining the best available statistical methods in conjunc-

[2]These are: the General Population Sample, The Ethnic Minority Boost Sample, The Immigrant and Ethnic Minority Boost sample, and the former British Household Panel Survey sample.

tion the rich information available from past waves. The development of the *Understanding Society* weights is described in (Lynn and Kaminska, 2010).

The extent to which *Understanding Society* is "representative", in the sense of supporting high quality inferences about population quantities, is continually evaluated: see Benzeval et al. (2020) and the references therein. The study has been repeatedly judged to be of high quality. As just one example, *Understanding Society* income data aligns well with national statistics on the income distribution in the UK (Fisher et al., 2019).

2.2 The Understanding Society COVID-19 Web Survey

The first wave of the *Understanding Society* COVID-19 Study was fielded between April 24 and 29 2020. The study was issued to all members of the four *Understanding Society* samples who were aged sixteen or over in April 2020 and who belonged to active households (one that had participated in at least one of the last two waves of the main *Understanding Society* study).[3]

Pre-notification letters introducing the study were sent to sample members on 17 April. Respondents were offered a small financial incentive for each wave of the *Understanding Society* COVID-19 Study [4]. Invitations to the survey were then sent by email and/or SMS text message, or by post. Reminders were sent on days 2, 3, and 6 of the seven day fieldwork period.

The first wave web questionnaire took approximate 20 minute to complete. In addition to economics and household finances content analyzed in this paper, the questionnaire asked questions about health, health behaviours and home schooling. Further information can be found in Institute for Social and Economic Research (2020*b*).

2.3 Population Inferences

Economists often eschew the use of survey weights (both design weights and non-response adjustments). The justification that is that where the object is to estimate a correctly specified model, weights may have no benefits, and come at cost of lost efficiency (Moffitt, Fitzgerald and Gottschalk, 1999). However, in a distributional analysis such as the one un-

[3]There were some minor exceptions, including individuals who were adamant refusals to the main study, who had a foreign address.

[4]Respondents were offered a 2 pound incentive for each monthly survey, which they could accumulate and exchange for a range of gift cards and vouchers.

dertaken in this paper, this argument does not apply. The objective is to estimate population statistics, rather than an economic model. As a consequence, it is of utmost important to use survey weights to ensure consistent estimates of those statistics.

Given the robust evidence that (suitably weighted) waves of the *Understanding Society* main survey provide reliable population evidence, the key consideration is non-response to *Understanding Society* COVID-19 Study among respondents to the last complete wave of the main survey (Wave 9). Among those who had given a full adult interview in the Wave 9 annual interview, the response rate to to the COVID-19 Wave 1 Survey was 48.6%.[5]. This is a very good response rate for a voluntary web survey when such surveys attempt to reach a target list (convenience and quota samples do not have a knowable response rate). It is also close to the response rate of large government surveys in the UK.[6] Nevertheless, this is significantly below the 85-90 % overall wave-on-wave retention rate that the *Understanding Society* main survey achieves by following up web non-respondents by direct interviewer contact. [7]

Cross-sectional individual weights are provided with the *Understanding Society* COVID-19 Wave 1 data.[8] These inverse-probability weights were created via an adjustment to the cross-sectional weights available for Wave 9 of the main survey. This means that probability of response to the COVID-19 Wave 1 Survey is modeled as the product of the probability of COVID-19 Wave 1 response conditional on main survey Wave 9 response and the probability of Wave 9 response. The conditional probability of COVID-19 Wave 1 response is modeled by logistic regression, with a step-wise variable selection. The choice set of predictors include basic demographics, household composition, economic variables and health variables. In addition, both econometrics and survey statistics literature emphasize the importance of including in weighting models variables that predict response and potentially correlated with outcomes being studied, but unlikely to be including in standard economic or social science models. Key variables sources of such variables are previous survey outcomes, survey design variables and survey para data. Several such variables turn out to be good predictors of the probability of COVID-19 Wave 1 response conditional on main survey Wave 9 response, and are included in the weighting models. These include indicator variables for the types

[5] or 46.0% if partial interviews are excluded

[6] For example, the Labour Force Survey - to which many web surveys with quota or convenience samples calibrate - has response rate of about 55% at the first wave, falling with subsequent and about 40 % overall. The Family Resources Survey which is the basis for official income statistics had a response rate of 52% in 2017/18.

[7] In the main survey, the individual-level online response rate is 50%-55% (of those invited).

[8] The weights were created by the authors of this paper

of contact information the survey team held about the respondent prior to the COVID-19 Wave 1 survey (email address, mobile phone number, both, neither) and the realized mode of previous waves of the main survey (recall that the *Understanding Society* main survey is multi-mode). The former may affect the salience of the survey request while the latter may be related to how easy the respondent would find it to complete a web survey. Either could quite plausibly be related to whether the respondent is employed or the kind work they do.

The final *Understanding Society* COVID-19 Wave 1 cross-sectional weights are calculated as the inverse of the estimated response propensity, and bounded at 3.5 times the median to control variability.

It is worth contrasting these weights with the ex post calibration weights that are often produced for other web surveys with convenience or quota samples. *Understanding Society* COVID-19 Wave 1 survey weights are based on a rich set of covariates, and on information both respondents and non-respondents (or non-attritors). Ex post calibration weights are typically based on a small set of covariates (age, education and gender is common) and typically no information is available on non-respondents, so that response or retention probabilities cannot be estimated directly. Instead, necessary adjustments are inferred indirectly by comparison to external sources; those sources are often surveys, such as the Labour Force Survey, which have quality markers (such as response rates) comparable to *Understanding Society*.

2.4 Two Tests for Attrition Bias

Given the consistent estimates of population statistics in a distributional analysis such as the one we present before, it is important to assess the extent to which the *Understanding Society* COVID-19 weights deal with nonrandom attrition from Wave 9 of the main study. We implemented two types of test.

As noted above, non-response to the COVID-19 Wave 1 Survey, conditional on response to Wave 9 of the main survey, can be viewed as attrition between the two. The econometrics literature contains several suggestions for tests of nonrandom attrition in panel data (Becketti et al., 1988; Fitzgerald, Gottschalk and Moffitt, 1998), where typically the test is for whether attrition is nonrandom with respect to a lagged outcome, conditional on some set of (regression) model covariates, and without using weights. These are not suitable for our purposes, where the focus is on distributional population statistics, and where weights will be employed. We therefore propose a straight-forward test of weights in panel data which we have not been able to find in the previous literature.

Consider two waves, t and $t+k$ of a panel survey. In our application these will be Wave 9 of the main *Understanding Society* survey and Wave 1 of the COVID-19 survey. Let i index wave t respondents and N_t the total number of such respondents (the wave t sample size). Let Y be some variable of interest and $\mu_Y t^r$ be the r^{th} uncentered population moment of Y at the time of wave t which we assume exists and is finite (when $r = 1$, this is the population mean). Then let $Y_{t,i}$ be the observation of Y for individual i in wave t. Let $R_{t+k,i}$ indicate wave $t+k$ response. Among wave t respondents, $R_{t+k,i} = 1$ if the individual responds to wave $t+k$ (that is, does not attrit) and 0 otherwise. Finally, let w_{ti} and $w_{t+k,i}$ be the wave t and $t+k$ cross-sectional survey weights.

Under the null hypothesis that w_{ti} and $w_{t+k,i}$ are, respectively, the inverse response probabilities for waves t and $t+k$, the following are both consistent estimators of μ^r:

$$\frac{\sum_{i=1}^{N_t} w_{t,i} Y_{t,i}^r}{\sum_{i=1}^{N_t} w_{t,i}} \tag{1}$$

$$\frac{\sum_{i=1}^{N_t} R_{t+k,i} w_{t+k,i} Y_{t,i}^r}{\sum_{i=1}^{N_t} R_{t+k,i} w_{t+k,i}} \tag{2}$$

Note however, that estimator (1) is more efficient. This gives us a natural "Hausman-type" test of the null hypothesis based on the difference between (1) and (2) (divided by the appropriate variance of the difference.) This test can be implemented for any Y (and for different values of r, though of course if Y is a binary variable, only $r = 1$ is of interest.)

Table 6 reports the results of this test for a selection of *Understanding Society* Main Survey Wave 9 variables, using Wave 9 respondents and associated weights for (1) and COVID-19 web survey respondents and associated weights for (2). The differences between (1) and (2) and the associated p-values are reported in the final column of Table 6.

For comparison purposes, we also constructed a "basic" set of weights in which the probability of COVID-19 Wave 1 response conditional on main survey Wave 9 response is modeled as a function of just age, gender and education. These illustrate the advantage of the rich background and survey information that is used to model that probability in the actual ("refined") COVID-19 Wave 1 weights (though note that even the basic weights we create here benefit from the fact that we have direct information on non-respondents). The parallel test based on (1) and (2) using these basic weights is reported in the penultimate column of Table 6.

Unsurprisingly, both the refined and basic COVID-19 Wave 1 weights lead to values of estimate (2) which are close to estimate (1) (based on Wave 9 Main Survey respondents and weights) if Y is chosen from the variables included in the basic weight model (age, gender and education). For brevity, these tests are omitted from the Table. The variables Y reported in Table 6 are divided into two groups. Those that are included in the refined weight model (but not the basic weight) and those that are not in either of the probability models that underpin the basic and refined weights. Table 6 shows, first, that with the actual (refined) COVID-19 Wave 1 weights, for most variables we are unable to reject the null hypothesis (that these weights and the Wave 9 main stage weights both capture the probability of response for their respective samples). The COVID-19 Wave 1 sample and associated weights does seem to lead to an mean income estimate at Wave 9 that is a bit too high, and, conversely, a probability of core benefit receipt which is a bit too low. The second thing that Table 6 demonstrates is that that refined weights improve on the basic weights, and not just for variables included in the weighting model.

Because the COVID-19 Wave 1 weights are based on prior wave observables, they cannot correct for selection into response based on contemporaneous shocks (this is of course also true of weights based on permanent characteristics such as age, education and gender). Similarly, the tests presented in Table 6, which are based on prior observables, cannot test for selection on contemporaneous shocks. This may be of particular concern during the COVID-19 pandemic. Response is plausibly related to time demands, and could be related to very recent shocks to employment, hours, or caring or home-schooling responsibility. The ability and willingness to complete a survey may also be related to health shocks. This would mean that survey non-response was not missing at random (NMAR) with respect to past observables. It is possible to test for this if an instrument for response is available. That is, one requires a variable Z, that predicts response but is uncorrelated with outcomes of interest. Unusually, in the COVID-19 Wave 1 survey we tried to generate such a variable. In particular, we randomly assigned potential respondents to "batches" and varied the time when batches were invited to take the survey across the first day of the seven-day field work period. This means that early batches had almost an additional day to complete the survey relative to the latest batches, and also that the invitation (for example email or SMS message) was first received at a different time of day. This turns out to have good predictive power for response. Note that despite the batch number being a useful predictor of response, it is not a variable to include in weighting models. This is because the randomization of assignment to batch implies that it is uncorrelated with any outcomes of interest Y, including at time $t + k$. If the outcome Y is not uncorrelated with Z, in the sample of respondents, this is evidence of selection.

We have implemented this test in all the regressions we run the selection instrument is never significant at conventional levels in those regressions. Thus this instrument does not lead us to reject the null hypothesis of no selection on contemporaneous shocks.

2.5 Analysis Sample and Additional Methods

The analysis that follows is based on the subset of respondents aged 20 to 65, and so capture the UK population of this age range.

The underlying *Understanding Society* samples are clustered unit (PSU) and stratified random samples, and so the COVID-19 sample inherits this structure. We use the SVYSET suite of commands in STATA to appropriately adjust standard errors for the resulting design effects.

3 Labour Market Shocks

In this section, we show results on the extent of the labour market shocks that individuals face and the reasons for these shocks.

We describe labour market status using four measures: whether an individual is employed and whether they are working a positive number of hours; and for those who are employed, average hours worked and average earnings. In Table 1, Table 2 and Figure 1, we show mean values for these four measures using reports from February 2020 and April 2020. Tables 1 and 2 and Figure 1 show variation in mean values by individual characteristics. Table 3 shows the changes in the measures using regression to identify the marginal effects of individual characteristics. We allocate individuals to quintiles of "long run income" where the 3 waves prior to the start of COVID-19 are averaged to define long run income. Income includes earned and unearned income, net of tax and inclusive of any benefits received, equivalised by household composition.

Table 1 and Figure 1 show that across all individuals, employment has held up well. On the other hand, there was a significant fall in the fraction working positive hours: by the end of April only 56% of working age individuals were working positive hours, down from almost 80% in February. This is not surprising given the Job Protection and Retention (furlough) scheme introduced in March 2020.[9] However, this difference between employment and working-positive-hours does highlight starkly the potential unemployment problem in the coming months. The fall in the fraction working positive hours and in average hours worked was particularly acute for those educated to less than degree level and for single parents, and for those in lower long-run income quintiles. We verify these unconditional mean effects through multivariate regressions of the changes reported in Table 3.

Table 2 shows the variation in mean values of labour market outcomes by the characteristics of the job, including contract type and occupation. This table uses occupation reports from the wave 9 survey in 2017/18 and conditions on being employed in February 2020. In the Appendix, in Table 14, we show the variation by industry. We split job characteristics according to how hours of work are set, [10] by whether the individual worked from home at all prior to February, and by the occupation. Here the heterogeneity in the extent of labour market shocks is striking: hardest hit are those individuals where the employer does not guarantee any minimum number of hours, with the fraction of those employed in February that work positive hours has fallen from 97% to 41%. Similarly badly hit are those who never worked at home prior to the crisis; and those in industries which involve contact with people. In "elementary" occupations[11], the fall in those working positive hours is from 98% to 51%, whereas in "professional" occupations, the fall is only from 99% to 85%. The split by industry shown in Table 14 in the Appendix reinforces this picture: substantial falls in hours worked are in food service and construction, with minimal falls in finance.

Table 4 shows reported reasons for the fall in hours worked for those who have experienced a decline. It may be caused directly by the health shock, or indirectly by restrictions in the economy in the face of the health shock, or for non-health related reasons. The key point to take from Table 4 is that the decline in hours is driven by the economic restrictions. Over 43% of those reporting a decline in hours were furloughed, and this is even more prevalent among those who have never worked at home. A further 14% of all those experiencing a decline cite the loss of self-employment business either due directly to restrictions or due to reductions in demand. Among the self-employed, this rises to 61%. By contrast, only 7% report health as a reason for the decline in hours, and 7% report caring for others. For some

[9]This scheme allowed workers to be "furloughed" by their firms, which meant 80% of workers pay would be covered by a government subsidy, conditional on the worker not actually providing any hours of work.

[10]We additionally have information on how payment is determined, but this is closely correlated with how hours are set.

[11]Occupation codes are those used by the ONS and described at https://onsdigital.github.io/dp-classification-tools/standard-occupational-classification/ONS_SOC_hierarchy_view.html

households, however, these health and caring reasons are much more important: caring for others is capturing those with children needing caring; and health restricting work has a steep age gradient.

A further point to draw from Table 4 is the differential prevalence of furlough and of unemployment by ethnicity. BAME individuals are 14 percentage points less likely to be furloughed and 13 percentage points more likely to be unemployed than non-BAME individuals.

4 Mechanisms of Mitigation

Section 3 showed that the effect of the COVID-19 crisis on labour market outcomes varies substantially across individuals. These individuals differ also in their ability to mitigate these shocks. In this section, we start by considering how the labour market shocks translate into a change in net household earnings. We then show how individuals have been able to mitigate these losses, distinguishing between using self-insurance, such as running down saving or borrowing, and using external sources, such as universal credit and transfers from friends and family.

The measure of earnings we use is net, equivalised weekly household earnings of the individual respondents, including earnings from employment and self-employment. We use an inverse-hyperbolic sine transformation, as in Burbidge, Magee and Robb (1988), to transform earnings changes into growth rates.

Figure 2 shows the level of household earnings in February and April by long-run income quintile. We further break the earnings change down by characteristics of the individual in Table 5. The figure highlights that the decline in household earnings is seen across the distribution, although the proportional decline is greatest for the bottom quintile. The fall in average household earnings is 8%, and 23% of individuals reported a loss of more than 20% of household earnings. The loss of household earnings was particularly severe for single parents, with almost a third facing a decline of over 20%.

In Table 6 we further explore the distribution of household earnings losses within quintile. For each quintile of long-run income, we report the proportional chance in household income at the 10th, 20th, 25th, 50th, 75th and 90th percentiles. Within each quintile, the median individual experiences no change in household earnings. However, within each of the quintiles, there is a substantial decline at the 10th percentile: even in the top quintile, the proportional change is a decline of 43%. However, as shown earlier, the bottom quintiles have the largest declines and the highest fraction of people experiencing declines.

These decline in household earnings do not necessarily translate into declines in household income or living standards, partly because households have other sources of income, such as universal credit, but also because different households have different possibilities of mitigation.

Figure 3 summarizes actions taken to mitigate earnings losses by individuals who have reported a decline in household earnings. We split methods of mitigation into self-insurance, which are changes within the household through saving, borrowing or additional work, and into external sources, which includes transfers from other family of friends as well as state benefits. At this stage in the crisis, individuals are relying more on self-insurance, and in particular on their own savings, than external help to mitigate losses: more than a quarter have drawn down their savings. Significant numbers have also increased borrowing or asked for a mortgage holiday. However, different individuals have used different mechanisms: multiple adult households have relied more on savings compared to single parents, whereas single parents have relied more on borrowing compared to multiple adult families. Further, in terms of differences by ethnicity, BAME individuals are more than twice as likely to have resorted to borrowing than non-BAME individuals.

External support is more widespread among the bottom quintiles, with transfers from friends or family somewhat larger than increased applications for Universal Credit. This financial assistance from friends and family is much more common for individuals within the lowest quintile of household income, for the young, and for single parents.

5 Economic Outcomes

The variation in labour market shocks and their implications for household earnings, and the variation in mechanisms of mitigation leave households in very different financial situations. We would typically use changes in consumption for the different households to capture the loss in standard of living associated with the shocks. In this crisis, however, the change in consumption may be misleading as a measure of welfare loss because of changes in supply: many usual spending categories, such as spending on food out of the home, have been substantially reduced by government restrictions. On the other hand, some of the consumption falls will reflect reduced demand in the face of earnings losses. We start this section on the economic outcomes for households by showing the heterogeneity in consumption changes. We then turn to more direct measures of welfare loss, looking first at the extent that individuals report having fallen into arrears, and then at subjective assessments of their financial situation. We end the section by showing expectations of their future situation.

Figure 4 shows the fraction of individuals who report cutting their spending since February 2020, by income quintile. For those whose household earnings have fallen by at least 5%, more than two-thirds report cutting their spending. This fall in spending reflects the insufficiency of mechanisms of mitigation to prevent a loss in living standards. However, almost 20% of those with no loss in household earnings (or even an increase) also report a cut in their spending, and this must reflect either anticipating hard times to follow or a reduction in opportunities to spend. To the extent that falls in consumption are simply reductions in opportunities to spend, this suggests a build up of demand that would generate a rebound. To the extent that falls reflect necessary cut backs, there is likely to be more persistent demand shortages.

To further identify the extent that the different sources of mitigation have not protected living standards, we report in Table 8 and Figure 5 the incidence of financial arrears. We show financial arrears by showing the fraction of respondents reporting that their household was behind with housing payments (mortgage or rent), and the fraction behind with other bills. We compare here to wave 9 of the main survey, which occurred in 2017-18. Table 8 also reports the fraction of respondents reporting that their household was hungry but did not eat at some time in the last week.

Overall, there is an increase in the fraction behind with bills from 5.2% to 7.4%. But this overall average masks the heterogeneity: the fraction who are behind with bills has risen by 5 percentage points (and from a high base) for single parents, and similarly for those in the bottom quintile, those with the lowest education and for BAME individuals. However, in a multivariate regression shown in Table 10, the conditional effects are insignificant.

In terms of arrears in housing, there is no significant difference in the fraction who report now being behind with housing. Where the increase in housing arrears shows up is in the highest two quintiles, but this is from a very low level. For the bottom quintiles, housing arrears are high but there is no evidence of the situation worsening. By contrast, BAME individuals are now 4.3 percentage points more likely to report being behind with housing. The size of this unconditional difference remains when we calculate conditional effects using regression, but the conditional effect is not statistically significant.

The final column of Table 8 shows the fraction reporting a decline in spending by individual characteristics. The fraction is particularly high for BAME individuals, households with children, and those at the bottom of the income distribution.

An alternative measure of the consequences of the crisis is to use subjective measures of individual's financial situations. Table 9 reports the subjective financial situation of individuals as they assess it now and compared to 2017-2018. Table 11 reports how individuals expect their financial situation to change in the next month.

When we compare how each individual perceives their financial situation now with how they perceived it in 2017-2018, households are not reporting a worsening situation, and if anything the situation has improved. These comparisons are for the same set of individuals in each period. However, the anchoring of this question into the aggregate situation may make comparisons difficult as the financial situation may lose salience compared to concerns about health.

Further, while we show evidence that the current situation is not perceived to be worse than the past, Table 11 shows how individuals expect this to change by the end of May. Overall, more than twice as many people expect their financial situation to get worse as those who expect it to get better over this month. Further, those who we have shown to be in the worst situation currently are also those with the most concerns going forward: the fraction expecting their situation to get worse rises to two and a half times those expecting an improvement for BAME individuals, to three times for those in the bottom income quintile, and to more than three times for single parents.

6 Conclusions

The COVID-19 pandemic has clearly resulted in a substantial aggregate economic shock: countries all around the world are affected and within country, all individuals are affected. This paper shows that the aggregate effects mask considerable differences in which individuals are affected and considerable differences in how individuals are able to mitigate the effects.

We use new high-quality UK data derived from probability samples: the *Understanding Society COVID-19 Survey.* These data confirm that impacts are hugely heterogeneous. One month after the "stay at home" policy was introduced, 60% of individuals in the UK had had essentially no loss of household earnings (either no loss or a loss of less than 5%). At the same time, 23% reported household income had fallen by more than 20%. Part of this limited impact on household earnings is due to government furlough scheme that protected employment alongside requiring furloughed individuals to work zero hours. We see this in the data: the fall in employment is only two percentage points, whereas the fraction working positive hours has fallen by 24 percentage points.

We show how these economic losses differ across individual characteristics and the characteristics of jobs that people do. The economic losses have been highly regressive. The welfare cost of the economic shocks depend both on the size of these direct shocks and also on the resources and mechanisms households have to mitigate the shocks. We show that, to date, self-insurance through using savings and additional borrowing is more prevalent than external support from universal credit and transfers from friends and family. Further, the largest economic shocks have fallen on those least able to mitigate. Those most affected are BAME individuals, single parents and those in the lowest quintile of long-run income.

Future waves of the *Understanding Society COVID-19* survey will enable an assessment of how this striking heterogeneity across individuals evolves as the crisis proceeds.

References

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2020. "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys." Institute of Labor Economics (IZA) IZA Discussion Papers 13183.

Alon, Titan M, Matthias Doepke, Jane Olmstead-Rumsey, and Michèle Tertilt. 2020. "The Impact of COVID-19 on Gender Equality." National Bureau of Economic Research Working Paper 26947.

Alstadsæter, Annette, Bernt Bratsberg, Gaute Eielsen, Wojciech Kopczuk, Simen Markussen, Oddbjorn Raaum, and Knut Røed. 2020. "The First Weeks of the Coronavirus Crisis: Who Got Hit, When and Why? Evidence from Norway." National Bureau of Economic Research Working Paper 27131.

Baker, Scott R, R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis. 2020*a*. "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic." National Bureau of Economic Research Working Paper 26949.

Baker, Scott R, R. A Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis. 2020*b*. "Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments." National Bureau of Economic Research Working Paper 27097.

Becketti, Sean, William Gould, Lee Lillard, and Finis Welch. 1988. "The Panel Study of Income Dynamics after Fourteen Years: An Evaluation." *Journal of Labor Economics*, 6(4): 472–492.

Béland, Louis-Philippe, Abel Brodeur, and Taylor Wright. 2020. "The short-term economic consequences of Covid-19: exposure to disease, remote work and government response."

Bell, David, and David Blanchflower. 2020. "US and UK Labour Markets Before and During the COVID-19 Crash." *National Institute Economic Review*, 252: 52 – 69.

Benzeval, Michaela, Christopher R. Bollinger, Jonathan Burton, Thomas F. Crossley, and Peter Lynn. 2020. "The representativeness of Understanding Society." , (2020-08).

Brynjolfsson, Erik, John Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong Yi Tu Ye. 2020. "COVID-19 and Remote Work: An Early Look at US Data." Mimeo, available at http://ide.mit.edu/publications/covid-19-and-remote-work-early-look-us-data.

Burbidge, John B., Lonnie Magee, and A. Leslie Robb. 1988. "Alternative Transformations to Handle Extreme Values of the Dependent Variable." *Journal of the American Statistical Association*, 83(401): 123–127.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2020. “Labor Markets during the COVID-19 Crisis:A Preliminary View.” IZA Institute of Labor Economics Working Paper 13139.

Cortes, Guido Matias. 2020. “Heterogeneous Labor Market Impacts During the Early Stages of the Covid-19 Pandemic.” Rimini Centre for Economic Analysis Working Paper series 20-13.

Dingel, Jonathan I, and Brent Neiman. 2020. “How Many Jobs Can be Done at Home?” National Bureau of Economic Research Working Paper 26948.

Fisher, Paul, Laura Fumagalli, Nick Buck, and Silvia Avram. 2019. “Understanding Society and its income data.” , (2019-08).

Fitzgerald, John, Peter Gottschalk, and Robert Moffitt. 1998. “An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics.” *Journal of Human Resources*, 33(2): 251–299.

Institute for Social and Economic Research. 2020*a*. *Understanding Society COVID-19 Study, 2020. [data collection]. 1st Edition.* UK Data Service. SN: 8644, 10.5255/UKDA-SN-8644-1.

Institute for Social and Economic Research. 2020*b*. *Understanding Society COVID-19 User Guide. Version 1.0.* University of Essex, Colchester.

Institute for Social and Economic Research, NatCen Social Research, and Kantar Public. 2019. “Understanding Society: Waves 1-9, 2009-2018 and Harmonised BHPS: Waves 1-18, 1991-2009.” [data collection]. 12th Edition. UK Data Service. SN: 6614.

Kahn, Lisa B, Fabian Lange, and David G Wiczer. 2020. “Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims.” National Bureau of Economic Research Working Paper 27061.

Lynn, Peter, and Olena Kaminska. 2010. “Weighting strategy for Understanding Society.” , (2010-05).

Moffitt, Robert, John Fitzgerald, and Peter Gottschalk. 1999. “Sample Attrition in Panel Data: The Role of Selection on Observables.” *Annals of Economics and Statistics*, , (55-56): 129–152.

Mongey, Simon, Laura Pilossoph, and Alex Weinberg. 2020. “Which Workers Bear the Burden of Social Distancing Policies?” National Bureau of Economic Research Working Paper 27085.

Montenovo, Laura, Xuan Jiang, Felipe Lozano Rojas, Ian M Schmutte, Kosali I Simon, Bruce A Weinberg, and Coady Wing. 2020. “Determinants of Disparities in Covid-19 Job Losses.” National Bureau of Economic Research Working Paper 27132.

University of Essex Institute for Social and Economic Research, NatCen Social Research, and Kantar Public. n.d.. “Understanding Society: Waves 1-9, 2009-2018 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection]. 12th Edition.”

Valliant, Richard, and Jill Dever. 2018. *Survey weights: a step-by-step guide to calculation.* Stata Press College Station, TX.

von Gaudecker, Hans-Martin, Radost Holler, Lena Janys, Bettina Siflinger, and Christian Zimpelmann. 2020. "Labour Supply in the Early Stages of the COVID-19 Pandemic: Empirical Evidence on Hours, Home Office, and Expectations." IZA Institute of Labor Economics Working Paper 13158.

Watanabe, Tsutomu, and Yuki Omori. 2020. "How Much Did People Refrain from Service Consumption due to the Outbreak of COVID-19?" Center for Advanced Research in Finance, Faculty of Economics, The University of Tokyo CARF F-Series 477.

Yasenov, Vasil. 2020. "Who Can Work from Home?" IZA Institute of Labor Economics Working Paper 13197.

Figures and Tables

Table 1: Labour Market Shocks by Individual Characteristics

	Employed (Feb)	Employed (April)	Positive hours (Feb)	Positive hours (April)	Hours (Feb)	Hours (April)	Earnings (Feb)	Earnings (April)
All	80.4	78.4	79.5	55.8	34.7	23.0	429.0	380.6
Gender:								
Men	84.5	82.3	83.8	59.5	38.6	25.5	506.1	439.1
Women	76.9	75.1	75.9	52.7	31.0	20.6	357.4	326.2
Ethnicity:								
Not BAME	81.1	79.4	80.4	56.2	34.8	22.9	429.7	382.5
BAME	72.0	67.4	70.6	50.9	33.7	23.5	421.4	358.5
Age:								
Age 20-29	79.8	75.1	78.4	48.2	33.5	20.3	326.0	290.2
Age 30-39	86.8	85.1	85.7	60.9	35.4	23.6	448.2	394.1
Age 40-49	86.2	85.8	85.7	65.2	35.9	25.7	484.2	439.2
Age 50-59	81.8	80.4	81.3	58.7	35.0	23.5	451.8	401.6
Age 60-65	58.8	56.4	57.9	36.8	31.4	18.4	376.2	313.0
Education:								
GCSE or lower	72.6	70.0	71.7	43.6	34.1	19.6	332.1	284.5
A-level	79.5	76.9	78.8	49.7	34.1	20.3	363.9	316.0
Degree	85.8	84.4	84.9	66.7	35.3	26.0	509.6	461.4
Household type:								
Single adult, no children	71.5	70.4	70.9	51.5	35.8	24.4	427.3	385.7
Single adult, children	74.6	74.2	74.3	48.8	32.1	18.8	399.6	319.3
Multiple adult, no children	78.6	75.8	77.8	54.2	34.9	23.2	414.7	368.2
Multiple adult, children	85.2	83.9	84.2	59.4	34.4	22.7	448.6	399.0
Long-run income quintile:								
1	64.8	62.0	64.0	39.1	31.6	17.8	291.4	240.1
2	78.9	76.2	78.2	49.2	33.9	20.2	335.9	293.6
3	85.2	84.0	84.7	57.8	35.3	22.5	381.1	355.7
4	86.8	85.1	86.3	64.5	35.8	25.6	464.5	412.1
5	85.4	83.8	83.8	67.4	35.9	27.1	620.2	549.6

Notes: Employment, hours and earnings include both employees and self-employees. Columns 1-4 are population percentages and refer to all individuals; columns 5-8 are weekly means and refer to those employed in February. Sample sizes are: 10,803 (col 1-4), 8745 (col 5-6), and 8015 (col 7-8).

Table 2: Labour Market Shocks by Job Characteristics

	Employed (April)	Positive hours (Feb)	Positive hours (April)	Hours (Feb)	Hours (April)	Earnings (Feb)	Earnings (April)
Worker type:							
Fixed hours	97.1	99.4	72.4	35.0	24.7	433.7	407.0
Flexible hours	96.2	97.1	74.2	35.9	27.6	522.1	490.2
Employer sets (sure min.)	94.7	98.4	58.9	34.2	20.3	346.4	308.1
Employer sets (no sure min.)	85.7	96.5	41.2	32.5	14.9	350.0	277.5
Self-employed	94.9	98.8	59.2	33.3	15.8	417.7	256.1
Works at home (Feb):							
Sometimes or always	97.6	99.1	78.6	35.5	26.6	548.4	485.1
Never	95.6	98.9	64.2	34.3	21.4	376.6	334.7
Elementary	90.7	98.0	50.9	31.4	15.6	264.7	212.9
Skilled trades	96.8	99.7	55.0	40.0	18.6	416.1	318.7
Sales, customer service	94.4	99.0	55.2	30.4	17.1	269.1	246.0
Process, plant, machine operatives	96.4	99.3	61.1	40.0	24.4	389.6	328.0
Caring, leisure, other service	97.2	98.8	63.8	31.1	19.2	284.0	266.8
Administrative, secretarial	96.5	99.4	71.5	32.7	23.1	346.1	307.5
Managers, directors	97.0	99.4	72.9	39.3	27.3	608.5	548.4
Associate professional, technical	98.1	99.2	77.4	35.4	26.3	484.3	445.4
Professional	97.3	98.5	84.7	36.0	29.3	554.1	512.4

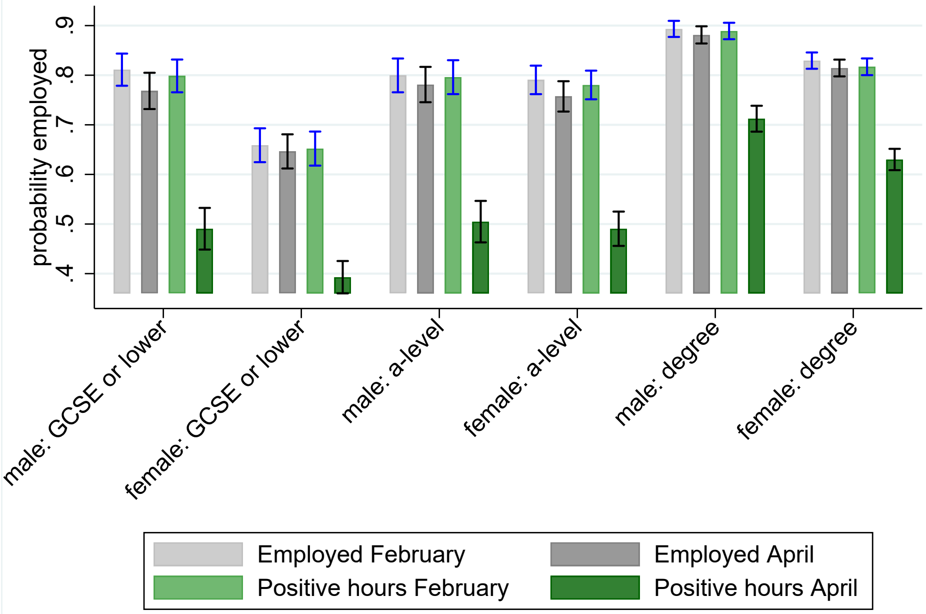
Notes: See table 1 notes. The sample is individuals in employment in February 2020 who reported a wave 9 occupation. This is 5613 individuals. The fraction employed in February is therefore 100%. Occupation is ordered by column 4 (fraction working positive hours in April) and is collected at the wave 9 (2017-18) interviews.

Table 3: Changes in Labour Market Status

	Employed	Positive hours	Hours	Earnings
Constant	-0.03	-0.23***	-12.08***	-0.02
	(0.02)	(0.04)	(1.63)	(0.01)
Gender:				
Male	ref	ref	ref	ref
Women	0.00	0.01	2.78***	0.00
	(0.01)	(0.01)	(0.53)	(0.00)
Ethnicity:				
Not BAME	ref	ref	ref	ref
BAME	-0.03*	0.05*	1.43	-0.03*
	(0.01)	(0.02)	(0.96)	(0.01)
Age:				
40-49	ref	ref	ref	ref
20-29	-0.04**	-0.09***	-3.19**	-0.03**
	(0.01)	(0.02)	(0.98)	(0.01)
30-39	-0.01	-0.05*	-1.90*	-0.01
	(0.01)	(0.02)	(0.83)	(0.01)
50-59	-0.01	-0.02	-1.30	-0.01
	(0.01)	(0.02)	(0.72)	(0.01)
60-65	-0.01	-0.01	-2.57*	-0.01
	(0.01)	(0.02)	(1.00)	(0.01)
Education:				
A-level	ref	ref	ref	ref
GCSE or lower	-0.01	-0.01	-1.02	-0.01
	(0.01)	(0.02)	(0.86)	(0.01)
Degree	0.01	0.09***	3.99***	0.00
	(0.01)	(0.02)	(0.70)	(0.01)
Household type:				
Multiple adult, no children	ref	ref	ref	ref
Single adult, no children	0.01	0.03	-0.16	0.01
	(0.01)	(0.02)	(1.00)	(0.01)
Single adult, children	0.02	-0.03	-3.40*	0.02
	(0.02)	(0.04)	(1.59)	(0.02)
Multiple adult, children	0.01	-0.03	-0.80	0.01
	(0.01)	(0.01)	(0.62)	(0.01)

Notes: Standard errors in parentheses. Dependent variables are the change from February to April. Earnings are transformed by the hyperbolic sine function. Employment, hours and earnings include both employees and self-employees. Columns 1-2 are for all individuals; columns 3-4 refer to those employed in February. Sample sizes (All) are: 10,803 (col 1-2), 8747 (col 3), and 8015 (col 4).* $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Figure 1: Employment Changes for Men and Women



Notes: N=10708.

Table 4: Reasons for Decline in Hours

	Employer cuts	Furloughed	Loss of self-employment business	Unemployed	Health	Caring
All reporting a decline in hours	9.8	43.3	13.8	8.0	7.4	7.2
Gender:						
Men	9.6	43.9	17.4	8.0	7.5	5.3
Women	9.9	42.7	10.7	8.1	7.4	8.8
Ethnicity:						
Not BAME	9.7	44.2	13.7	7.1	7.2	6.9
BAME	10.7	30.9	15.5	20.9	10.6	11.1
Age:						
Age 20-29	9.1	54.0	5.7	14.2	4.2	2.5
Age 30-39	9.7	44.9	13.4	7.1	5.0	15.8
Age 40-49	8.8	40.3	15.7	4.5	8.3	12.1
Age 50-59	11.9	39.9	16.5	6.0	8.9	3.0
Age 60-65	7.3	35.0	19.3	10.7	12.5	1.5
Education:						
GCSE or lower	11.6	47.8	14.1	8.3	7.6	4.7
A-level	7.8	50.8	10.9	8.6	9.2	4.5
Degree	9.8	35.3	15.6	7.6	6.2	10.4
Household type:						
Single adult, no children	10.6	43.5	15.8	7.9	9.8	1.4
Single adult, children	11.1	46.4	11.0	5.7	3.7	13.2
Multiple adult, no children	9.3	44.7	12.8	9.9	8.3	1.5
Multiple adult, children	10.1	41.3	14.9	6.2	6.3	14.2
Long-run income quintile:						
1	10.6	43.1	15.5	11.3	9.4	6.7
2	10.0	49.9	12.9	8.0	7.7	7.2
3	10.9	50.7	11.2	4.6	7.4	6.0
4	8.0	40.1	11.8	8.3	7.0	6.8
5	9.1	30.2	18.5	8.8	5.7	9.5
Worker type:						
Fixed hours	11.4	53.8	0.0	7.3	6.2	5.9
Flexible hours	9.5	43.4	0.0	8.7	3.3	13.6
Employer sets (sure min.)	16.0	59.2	0.0	9.0	6.9	3.2
Employer sets (no sure min.)	14.8	58.8	0.0	19.7	6.1	3.8
Self-employed	2.1	7.4	61.0	7.1	12.2	10.8
Works at home (Feb):						
Sometimes or always	8.1	25.6	25.7	5.5	5.8	13.8
Never	10.4	50.1	9.3	9.0	8.1	4.7

Notes: Each cell refers to a percentage of those reporting a decline in weekly work hours. Respondents are allowed to report multiple reasons for an hours decline and so the rows do not sum to one. Sample size (All): 3993.

Figure 2: Household Earnings across the Distribution

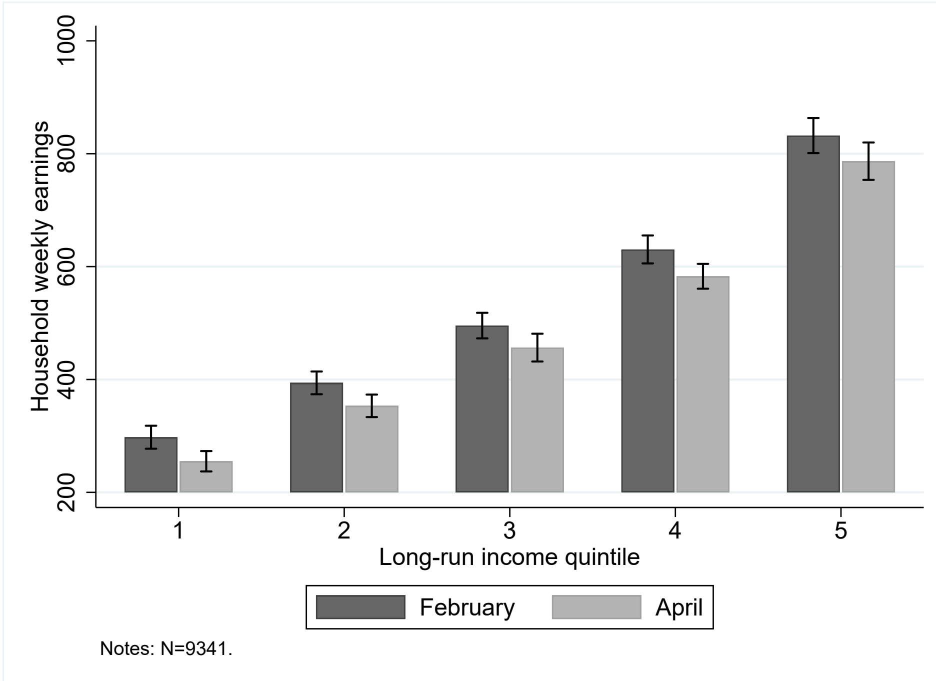


Table 5: Household Earnings Pre and Post Covid

	Full sample		Positive February Earnings			
	February	April	February	April	Lost 5% or more (%)	Lost 20% or more (%)
All	538	495	586	530	38	23
Gender:						
Men	560	515	607	548	37	23
Women	519	478	567	513	38	24
Age:						
Age 20-29	518	482	566	522	40	23
Age 30-39	556	521	585	542	37	21
Age 40-49	568	528	607	551	37	23
Age 50-59	561	512	605	544	36	23
Age 60-65	436	379	525	440	39	31
Ethnicity:						
Not BAME	547	503	594	537	38	23
BAME	441	404	495	445	36	27
Education:						
GCSE or lower	418	365	469	403	42	27
A-level	487	449	531	484	40	25
Degree	632	591	675	619	34	21
Household type:						
Single adult, no children	491	446	616	513	39	32
Single adult, children	327	254	427	308	47	35
Multiple adult, no children	582	536	630	574	37	23
Multiple adult, children	512	476	538	495	37	21
Long-run income quintile:						
1	298	255	351	292	44	31
2	394	353	437	380	42	25
3	496	456	530	482	35	21
4	630	583	670	607	36	20
5	832	787	868	813	33	21

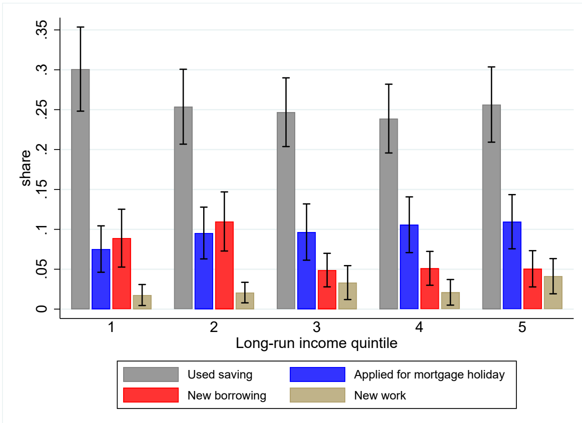
Notes: Household earnings are means, weekly, net and equivalised. Columns 1-2 refer to all individuals and columns 3-6 to individuals in households with positive earnings in February. Sample sizes (All): 9208 (col 1-2), 8511 (col 3-6).

Table 6: Distribution of Changes in Household Earnings

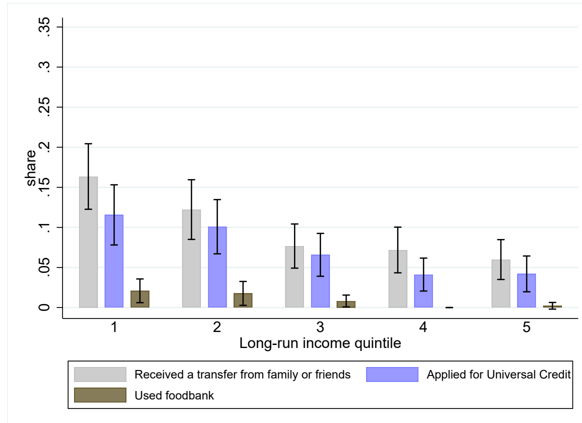
	p10	p20	p25	p50	p75	p90
Long-run income quintile:						
q1	-1.00	-.43	-.32	.00	.00	.00
q2	-.60	-.29	-.20	.00	.00	.00
q3	-.52	-.22	-.16	.00	.00	.02
q4	-.50	-.20	-.14	.00	.00	.02
q5	-.43	-.20	-.12	.00	.00	.02

Notes: The change in household earnings is the proportional change calculated using the Inverse-Hyperbolic Sine transformation. Earnings are weekly, net and equivalised.

Figure 3: Sources of Mitigation



(a) Self-Insurance



(b) External

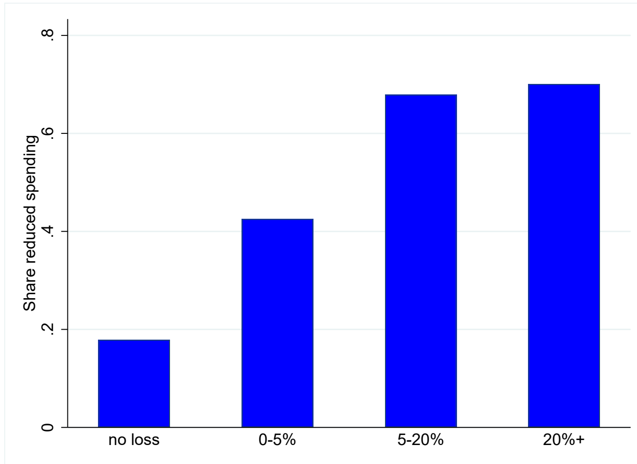
Notes: The sample is individuals who experienced a household earnings loss between February and April 2020. Respondents can report multiple methods of mitigation. Sample size: 3345

Table 7: Mitigating Earnings Losses

	Used savings	Borrowed	New work	Mortgage hol.	Universal credit	Family transfer etc.	Used foodbank
All	25.9	7.0	2.7	9.7	7.3	9.9	1.0
Gender:							
Men	24.7	5.6	3.0	9.0	7.6	7.6	1.0
Women	26.9	8.4	2.3	10.3	7.1	11.9	1.0
Ethnicity:							
Not BAME	25.3	6.4	2.7	9.4	6.9	9.7	1.0
BAME	33.0	15.7	2.7	13.3	12.8	12.0	1.1
Age:							
Age 20-29	26.1	7.0	3.1	4.5	9.5	15.8	0.3
Age 30-39	21.6	9.4	3.0	14.7	9.8	11.7	2.0
Age 40-49	24.5	7.6	2.3	15.1	5.8	9.6	0.2
Age 50-59	30.1	7.1	3.1	7.7	6.9	7.8	1.3
Age 60-65	25.8	1.9	1.2	2.9	3.8	3.2	0.9
Education:							
GCSE or lower	24.6	6.1	2.4	9.8	8.7	11.8	1.9
A-level	24.5	7.2	3.2	7.9	7.0	11.3	0.7
Degree	27.5	7.4	2.6	10.5	6.7	7.9	0.5
Household type:							
Single adult, no children	20.3	5.5	0.7	3.6	10.0	12.1	4.1
Single adult, children	18.4	12.7	2.0	3.3	5.3	25.6	0.0
Multiple adult, no children	28.5	5.4	3.0	5.4	7.1	6.9	0.5
Multiple adult, children	24.5	8.8	2.7	16.2	7.2	11.7	1.1
Long-run income quintile:							
1	30.1	8.9	1.8	7.5	11.6	16.4	2.1
2	25.4	11.0	2.1	9.5	10.1	12.2	1.8
3	24.7	4.9	3.3	9.7	6.6	7.7	0.8
4	23.9	5.1	2.1	10.6	4.1	7.2	0.0
5	25.6	5.1	4.1	11.0	4.2	6.0	0.2

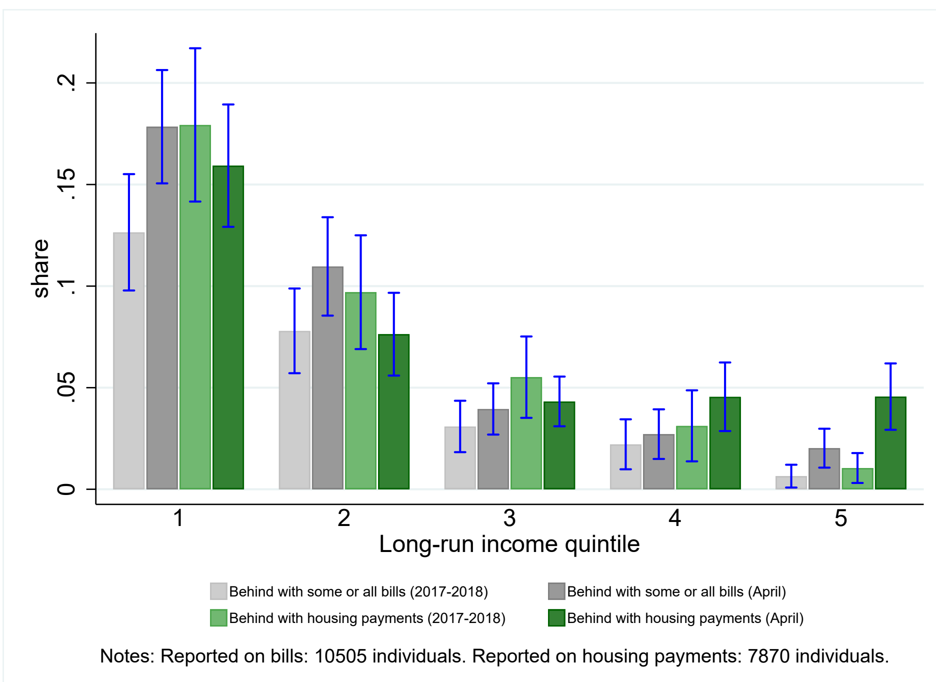
Notes: Each cell refers to a percentage of individuals experiencing a household earnings loss between April and February. Respondents can report multiple methods of mitigation. Sample size: 3345.

Figure 4: Spending Reductions by Household Earnings Loss



Notes: Sample is individuals who report positive household earnings in February 2020. 8,507 individuals.

Figure 5: Behind on Paying Bills and Rent/Mortgage



Notes: The COVID question provides more cues on the sorts of bills that may be included.

Table 8: Arrears (bills and housing), Hunger and Reduced Spending

	Behind with bills		Behind with housing			
	2017-18	April 2020	2017-18	April 2020	Hunger	Reduced spending
All	5.2	7.4	7.5	7.4	4.6	37.1
Gender:						
Men	4.1	6.4	7.2	7.0	4.5	36.4
Women	6.1	8.2	7.8	7.7	4.7	37.7
Ethnicity:						
Not BAME	4.7	6.6	7.0	6.4	4.4	36.5
BAME	10.6	15.8	12.4	16.7	6.4	43.6
Age:						
Age 20-29	5.4	8.4	10.4	10.0	10.4	41.2
Age 30-39	6.7	9.1	7.4	6.6	5.0	37.9
Age 40-49	5.4	8.2	6.8	8.0	3.4	39.0
Age 50-59	5.2	6.5	6.8	6.4	2.8	35.7
Age 60-65	2.4	4.0	6.0	5.1	1.6	30.1
Education:						
GCSE or lower	8.1	12.4	10.9	11.6	6.6	39.2
A-level	5.0	6.9	8.4	7.1	5.7	38.9
Degree	3.4	4.5	4.9	4.9	2.7	34.7
Household type:						
Single adult, no children	7.3	11.0	11.8	9.4	4.8	29.5
Single adult, children	14.0	19.6	17.7	12.6	5.9	39.5
Multiple adult, no children	3.5	4.7	6.3	6.8	4.5	35.3
Multiple adult, children	6.0	8.8	6.9	7.0	4.5	41.0
Long-run income quintile:						
1	12.6	17.8	17.9	15.9	7.7	44.6
2	7.8	11.0	9.7	7.6	7.4	41.6
3	3.1	4.0	5.5	4.3	3.4	36.3
4	2.2	2.7	3.1	4.6	3.1	33.0
5	0.6	2.0	1.0	4.6	1.5	30.3

Notes: Each cell refers to a percentage of the population. Hunger refers to individuals who report a time last week when they or others in their household were hungry but did not eat. Sample sizes (All): 10,505 (col 1-2), 7870 (col 3-4); 10,617 (col 5); 10,788 (col 6).

Table 9: Subjective Financial Situation: Past and Present

	Finding it difficult		Just about getting by		Living comfortably	
	2017-18	April 2020	2017-18	April 2020	2017-18	April 2020
All	8.4	7.8	23.2	20.3	68.4	71.9
Gender:						
Men	7.9	7.7	21.3	20.6	70.8	71.7
Women	8.9	8.0	24.8	20.0	66.3	72.0
Ethnicity:						
Not BAME	7.8	7.1	22.5	19.7	69.7	73.2
BAME	14.4	15.5	30.7	26.8	54.9	57.7
Age:						
Age 20-29	7.4	7.8	19.9	15.6	72.8	76.5
Age 30-39	9.6	9.2	25.5	19.5	64.9	71.3
Age 40-49	9.7	7.4	25.0	26.0	65.3	66.6
Age 50-59	8.7	8.1	23.6	21.4	67.7	70.5
Age 60-65	5.3	6.1	20.5	15.9	74.1	78.0
Education:						
GCSE or lower	11.6	11.5	27.6	28.1	60.7	60.4
A-level	8.4	8.4	23.3	20.2	68.3	71.4
Degree	6.3	5.3	20.5	15.5	73.2	79.2
Household type:						
Single adult, no children	13.0	11.6	28.7	24.2	58.3	64.1
Single adult, children	20.5	17.9	39.6	29.5	39.9	52.6
Multiple adult, no children	6.4	6.5	19.7	16.7	73.9	76.8
Multiple adult, children	8.9	7.8	25.1	23.3	66.0	68.9
Long-run income quintile:						
1	19.6	15.7	35.6	32.7	44.8	51.6
2	10.0	10.9	31.3	27.1	58.6	62.0
3	6.5	5.5	21.9	18.9	71.6	75.6
4	4.4	4.6	17.9	14.8	77.7	80.6
5	2.0	2.9	10.1	8.6	87.9	88.4

Notes: Each cell refers to a percentage of the population. The categories are derived from a question asking individuals how they are managing financially. Columns 1-2 refer to individuals 'finding it 'difficult' or 'very difficult'; columns 3-4 to those 'just about getting by'; and columns 5-6 to those 'living comfortably' or 'doing alright'. Sample size (All): 10,732.

Table 10: Changes in arrears, financial distress and spending

	Behind with bills	Behind with housing	Financial distress	Reduced spending
Constant	0.00	-0.01	-0.01	0.37***
	(0.02)	(0.04)	(0.03)	(0.04)
Gender:				
Male	ref	ref	ref	ref
Women	-0.00	0.00	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Ethnicity:				
Not BAME	ref	ref	ref	ref
BAME	0.03	0.05	0.02	0.06**
	(0.02)	(0.03)	(0.02)	(0.02)
Age:				
40-49	ref	ref	ref	ref
20-29	0.01	-0.02	0.03	0.04
	(0.02)	(0.03)	(0.02)	(0.02)
30-39	-0.00	-0.02	0.02	-0.01
	(0.01)	(0.02)	(0.02)	(0.02)
50-59	-0.01	-0.02	0.02	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)
60-65	-0.01	-0.03	0.03	-0.05*
	(0.01)	(0.02)	(0.02)	(0.02)
Education:				
A-level	ref	ref	ref	ref
GCSE or lower	0.03	0.02	0.00	0.02
	(0.01)	(0.02)	(0.01)	(0.02)
Degree	-0.01	0.01	-0.01	-0.04*
	(0.01)	(0.01)	(0.01)	(0.02)
Household type:				
Multiple adult, no children	ref	ref	ref	ref
Single adult, no children	0.02	-0.03	-0.01	-0.05*
	(0.02)	(0.03)	(0.02)	(0.02)
Single adult, children	0.04	-0.07	-0.02	0.03
	(0.04)	(0.04)	(0.04)	(0.04)
Multiple adult, children	0.01	-0.01	-0.01	0.05**
	(0.01)	(0.02)	(0.01)	(0.02)

Notes: Standard errors in parentheses. Dependent variables are the change from February to April. We count as in financial distress those reporting their subjective financial situation as 'finding it very difficult'. Sample sizes are: 10,393 (col 1), 7772 (col 2), 10,626 (col 3) and 10,674 (col 4).* p<0.05, ** p<0.01, *** p<0.001.

Table 11: Subjective Financial Situation: Future

	Next month Worse off	Next month About the same	Next month Better off
All	19.7	71.0	9.3
Gender:			
Men	19.0	71.1	9.9
Women	20.3	70.9	8.9
Ethnicity:			
Not BAME	19.2	71.5	9.3
BAME	24.7	65.5	9.8
Age:			
Age 20-29	16.0	68.1	15.9
Age 30-39	20.5	67.6	11.8
Age 40-49	22.1	69.3	8.6
Age 50-59	20.3	73.6	6.1
Age 60-65	18.2	77.2	4.6
Education:			
GCSE or lower	21.6	71.3	7.1
A-level	19.2	70.3	10.5
Degree	18.8	71.2	10.0
Household type:			
Single adult, no children	16.7	75.0	8.4
Single adult, children	25.8	67.3	6.9
Multiple adult, no children	18.2	72.4	9.4
Multiple adult, children	21.9	68.5	9.6
Long-run income quintile:			
1	24.0	67.9	8.1
2	23.4	67.9	8.8
3	18.3	73.3	8.4
4	16.4	72.1	11.5
5	16.8	73.5	9.8

Notes: Each cell refers to a percentage of the population. Sample size (All): 10,783.

Table 12: Statistical Testing of Survey Weights

	Wave 9	**Covid**			**Test Statistic**	
	Weighted	Unweighted	Basic weight	Refined weight	Basic	Refined
In refined weights only:						
Subjective financial situation:						
Living comfortably/doing alright	0.71***	0.76***	0.76***	0.72***	-0.04***	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.557)
Just about getting by	0.21***	0.18***	0.18***	0.21***	0.03***	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.382)
Finding it quite/very difficult	0.07***	0.06***	0.06***	0.07***	0.01***	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.901)
Housing tenure:						
Owned	0.65***	0.59***	0.59***	0.65***	0.06***	-0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.932)
Rented or mortgage	0.35***	0.41***	0.41***	0.35***	-0.06***	0.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.889)
In neither weighting model:						
Mental component summary	48.25***	49.06***	48.88***	48.27***	-0.62	-0.01
	(0.000)	(0.000)	(0.000)	(0.000)	(0.134)	(0.972)
Household net income	3365.95***	3706.34***	3583.01***	3546.84***	-217.05***	-180.89***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Receives core benefit	0.05***	0.03***	0.03***	0.04***	0.02***	0.01**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
Behind with council tax	0.06	0.03	0.04	0.05	0.02	0.01
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)

Notes: ‘Core benefits’ include Income Support, Job Seeker’s Allowance and Universal Credit. ‘Mental component summary’ is a validated mental health functioning score. It is derived from the short form 12-item Survey (SF-12) and takes values from 0-100 with a higher score indicating better functioning.

Appendix

Table 13: Summary Statistics

	Unweighted	Weighted
Men	0.400	0.456
BAME	0.132	0.086
Age	46.346	44.611
Highest Qualification:		
GCSE or lower	0.240	0.287
A-level	0.226	0.253
Degree	0.534	0.460
Household type:		
Single Adult, no children	0.083	0.090
Single adult, children	0.031	0.032
Multiple adult, no children	0.484	0.494
Multiple adult, children	0.402	0.384
Worker type:		
Fixed hours	0.676	0.670
Flexible hours	0.083	0.075
Employer sets (sure min.)	0.068	0.079
Employer sets (no sure min.)	0.024	0.029
Self-employed	0.150	0.147
Works at home:		
Sometimes or always	0.341	0.307
Never	0.659	0.693
Occupation:		
Elementary	0.069	0.090
Skilled trades	0.049	0.071
Sales, customer service	0.069	0.090
Process, plant, machine operatives	0.046	0.051
Caring, leisure, other service	0.094	0.098
Administrative, secretarial	0.130	0.120
Managers, directors	0.112	0.114
Associate professional, technical	0.185	0.165
Professional	0.245	0.200

Notes: 10,803 individuals aged between 20-65. Minimal item non-response. Occupation is recorded at wave 9 (2017-18).

Table 14: Shocks by industry

	(1) Employed (April)	(2) Positive hours (Feb)	(3) Positive hours (April)	(4) Hours (Feb)	(5) Hours (April)
Accommodation, Food Service	0.91	0.99	0.31	33.94	9.32
	(0.03)	(0.01)	(0.04)	(1.06)	(1.21)
Arts, other service	0.97	1.00	0.52	33.28	15.63
	(0.01)	(0.00)	(0.04)	(0.93)	(1.44)
Construction, Real Estate	0.96	1.00	0.56	38.90	18.81
	(0.01)	(0.00)	(0.03)	(0.71)	(1.26)
Wholesale, Retail Trade	0.96	0.99	0.60	33.79	19.91
	(0.01)	(0.00)	(0.02)	(0.56)	(0.86)
Transportation, Storage	0.98	1.00	0.64	39.27	24.48
	(0.01)	(0.00)	(0.04)	(0.72)	(1.51)
Administrative, Support Service	0.95	0.97	0.66	33.46	20.62
	(0.02)	(0.01)	(0.04)	(1.05)	(1.51)
Manufacturing, Agriculture,	0.97	0.99	0.67	39.29	25.23
Mining, Utilities	(0.01)	(0.00)	(0.02)	(0.41)	(0.98)
Education	0.97	0.99	0.73	33.02	20.18
	(0.01)	(0.00)	(0.02)	(0.56)	(0.69)
Professional, Scientific and Technical	0.99	1.00	0.79	35.64	27.47
	(0.01)	(0.00)	(0.02)	(0.47)	(0.97)
Information, Communication	0.95	0.99	0.80	36.45	29.54
	(0.02)	(0.00)	(0.03)	(0.60)	(1.38)
Human Health, Social Work	0.98	0.98	0.82	32.59	27.67
	(0.01)	(0.00)	(0.01)	(0.41)	(0.64)
Public Administration, Defence	0.98	0.99	0.86	34.89	29.67
	(0.01)	(0.01)	(0.02)	(0.47)	(0.81)
Financial, Insurance	0.98	0.99	0.87	36.77	32.45
	(0.02)	(0.00)	(0.03)	(0.68)	(1.20)

Notes: Sample of 7834 individuals who reported an industry at wave 9 (2017-18).
Standard errors in parenthesis.