The Income and Consumption Effects of Covid-19 and the Role of Public Policy

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Abstract

We provide empirical evidence on the labour market impacts of covid-19 in the UK and assess the effectiveness of mitigation policies. We estimate the relationship between employment outcomes and occupational and industrial characteristics and assess the effects on consumption. 70 percent of households in the bottom fifth of the income distribution must cut consumption within one week. Finally, we compare the effectiveness the UK's Coronavirus Job Retention Scheme to Economic Impact Payments in the US. The EIPs are more effective at mitigating consumption reductions as they have full coverage, depend on household structure and are higher for low-income workers.

Keywords: Covid-19, Consumption, Income, Household Structures, Mitigation Policy

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1 Introduction

Covid-19 has created new challenges for public policy. Measures introduced to curtail the spread of the virus come at potentially substantial economic cost. Importantly, many of these costs have been borne unequally, falling disproportionately on low income and younger workers. What explains the inequality in labour market impacts? Given assortative partnering, how well can households self-insure against the risks? And to what extent are the most affected households able to sustain consumption following any negative income shocks? The answers to these questions are crucial for designing and assessing policies to mitigate the economic costs of the pandemic.

In this paper, we use real-time nationally representative survey data from the UK to answer these questions. We analyse the source of observed inequalities in impacts of the pandemic by estimating the relationship between employment outcomes and three occupational and industry characteristics: *physical proximity* at the workplace, *location flexibility* of the job, and *industry exposure* to reduced demand. To the best of our knowledge, this is the first paper to quantify this relationship. We then compare the effects of the UK's Coronavirus Job Retention Scheme (CJRS) to an alternative relief program similar to the Economic Impact Payments in the US, taking into account labour market disruption associated with occupational characteristics, assortative partnering and differences in households' assets. Our findings shed important light on features of effective mitigation policy.

We document substantial variation in labour market outcomes across workers. The likelihood of labour market disruption (being laid-off or furloughed) falls over the income and asset distributions. Less educated workers, females, and those younger than 25 or older than 65 have also faced substantial disruption. At the household level the relationship between labour market impacts and income is qualitatively similar to the individual level. However, while 23 percent of singles in the bottom fifth of the income distribution are laid-off, only four percent of couples experience both partners being laid off; in the majority of cases, at least one partner either works as usual or is furloughed. This highlights the importance of partial insurance at the household level.

To understand sources of inequalities in the impact of the pandemic, we relate these outcomes to measures of physical proximity, location flexibility and industry exposure to reduced demand during the pandemic across occupations and industries. Lower earning workers are most likely to be in industries with reduced demand, and also have least flexibility to work remotely. This is also the case for lower educated, the youngest and the oldest workers. Females are more likely to have jobs requiring close physical proximity than males. At the household level, exposure to reduced industry demand falls in the top half of the income distribution, and work flexibility rises substantially across both the income and assets distributions. These risks are also highly correlated between spouses, particularly among low income households. This suggests that the occupational

and industrial characteristics are important determinants of labour market impacts across workers and and households.

We quantify this relationship directly by estimating a probit model of employment outcomes (either working, furloughed or separated) on the physical proximity, location flexibility and industry exposure of a worker's job. We find that all three factors matter for the likelihood of being laid-off, but only location flexibility and industry exposure are key predictors for being furloughed or working. This suggests that policy should target support to those with inflexible working arrangements and those in the most exposed industries.

We then conduct a quantitative analysis of the impacts of covid-19 on incomes and consumption. We show that, despite the support from CJRS, the reduction in labour income leads to a shortfall between income and expenditure for lower income households. Among these households, 70 percent have insufficient assets to maintain expenditure for even one week. Our findings imply that the labour market effects of the pandemic are likely to widen inequalities in consumption and savings since lower income household (1) experience a larger proportionate income reduction; (2) lower income households have a smaller buffer between usual income and expenditure, and make smaller savings during lockdown; and (3) hold insufficient liquid assets to sustain expenditure. These facts explain why savings rates fell among low-income households but rose among high-income households during the pandemic, (Haldane, 2020).

Finally, we compare the effectiveness of the UK's CJRS to the very different mitigation policy in the US. CJRS pays 80 percent of pre-pandemic earnings (up to a monthly cap) for furloughed workers.[1] The US policy instead provides a one-off payment to all tax-filing households. The size of the payment reduces in pre-pandemic earnings and takes into account household characteristics such as the number of children. We find that the US-style payment would better enable households to maintain usual expenditure. This is because (1) the payment has full coverage, while CJRS does not cover laid-off workers; (2) the payment has a higher replacement rate for low-income workers, unlike the flat 80 percent rate of CJRS (up to a cap); and (3) households with more children (who tend to be lower income) get higher payments.[2]

This paper is closely related to work studying heterogeneity in labour market impacts of lockdown measures. Much existing work uses occupational characteristics to study the possible effects of covid-19 on labour supply, focusing on income losses. Hicks et al. (2020) study physical proximity and Dingel and Neiman (2020) analyse work location flexibility, while Lekfuangfu et al. (2020) and Mongey et al. (2020) consider the interaction between these two factors. del Rio-Chanona et al. (2020) provide a quantitative prediction of both supply and demand across wage

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[1]The scheme has had substantial uptake, with over 30 percent of the workforce supported by the scheme by 31 May 2020 (HMRC, 2020).

[2]A key objective of CJRS was to keep workers with their existing employer. While it is not yet possible to assess its effectiveness in achieving this objective, retaining employment relationships is likely to generate longer-term benefits.

levels.[3] However, the relationship between these ordinal indices of occupational characteristics and labour market disruption remains unstudied, making it difficult to understand policy implications.

Using real-time and nationally representative survey data from the UK Household Longitudinal Study (UKHLS), we contribute to the literature in four ways. First, we provide new empirical evidence on heterogeneity in labour market disruption. In addition to gender and education, as documented in Adams-Prassl et al. (2020a), we analyse impact differentials by characteristics that typically determine eligibility for welfare programmes such as income, assets and household structure. Second, this is the first paper to quantify the relationship between labour market outcomes and indices of occupational and industrial characteristics. Third, we analyse the implications of the pandemic for consumption in addition to income, as this may better reflect the true impact on household welfare (Poterba, 1989; Cutler, 1992). Our findings can explain the inverse relationship between changes in savings rates and households' incomes in Haldane (2020). Finally, we provide a comparative assessment of flagship policies implemented in the UK and US to mitigate the impacts of the pandemic.

Additionally, our paper is related to the literature on household risk sharing and consumption (e.g. Attanasio et al., 2002; Heathcote et al., 2014; Blundell et al., 2008). These papers highlight the role of family labour supply as partial insurance for consumption against income shocks. We show that couples are less affected by the pandemic than singles. This is because correlation in the income shocks between partners is imperfect, providing for some partial insurance. However, the correlation between partners' labour market risks is highest for lower income households, making them least able to self-insure.

Overall, this paper highlights the importance of differences in households' ability to cushion negative income shocks and sheds light on features of effective pandemic-mitigation policy. Our results suggest that, to effectively reduce the negative and uneven consequences of covid-19 on household welfare, it is important to provide short-term liquidity (as the most affected households also have the lowest means to smooth consumption), and in the longer term, provide a combination of income and employment support to workers with least flexibility to work from home and in industries with most reduced demand. This is particularly the case as affected workers tend to be young—losing the opportunity to accumulate human and social capitals at work could have long term consequences for lifetime earnings.

2 Data Overview

Our main data are drawn from UKHLS, a nationally representative longitudinal survey of individuals in the UK. We focus on the most recent wave (wave 9), collected in 2017 and 2018, and merge

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[3]Their measure of demand shocks is based on pre-covid-19 estimates from an influenza pandemic.

in detailed data on assets from a specialist survey module administered during 2016 and 2017. We use additional information on labour market outcomes during the pandemic from the first UKHLS supplemental covid-19 module (collected at the end of April 2020).

We focus on individuals who were working and over the age of 16 at the time of their wave 9 interview. We define occupations using the three-digit Standard Occupation Classification code of their main job, and similarly define industries using top-level Standard Industrial Classification codes. We define earnings as net labour income in the month before the individual was interviewed in wave 9;[4] then we define total income, which adds to earnings any benefit or other income. Finally, we construct liquid assets as the sum of savings and any funds held in investment accounts.

The UKHLS data also include household expenditure on a small set of essential items in 2017 and 2018. To provide a more complete picture of household spending, we impute total household expenditure using detailed data on household spending drawn from the 2017-18 Living Costs and Food Survey (LCFS). We follow a similar imputation procedure as Blundell et al. (2008).

We drop workers who did not provide data on assets in wave 8 or have missing information about industry exposure. Our sample contains 13,225 residents in 9,639 households. We provide details on our data in Appendix A.

3   Labour Market Impacts of Covid-19

The pandemic has disrupted labour markets along multiple dimensions. Given worker heterogeneity across occupations and industries, the impacts are likely to be uneven. In section 3.1, we examine labour market outcomes at the individual and household levels. In section 3.2, we analyse the drivers of labour market outcomes. We relate outcomes to three labour market risks using a probit model. The first two—physical proximity and location flexibility—may lead to labour supply disruption. These have been used as possible predictors of labour market impacts of covid-19 in a number of papers (although the relationship to outcomes remains unquantified).[5] The third measure is associated with reduced labour demand. We find a clear relationship between these risks and labour market outcomes, underlining their importance in understanding the unequal impacts of the pandemic.

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[4]This includes usual pay from their main job, pay from any second jobs, and profits (or losses) from self-employment.

[5]For example, Dingel and Neiman (2020) for the location flexibility factor and Hicks et al. (2020) for the physical proximity factor.

3.1 Labour Market Outcomes

We use data from the UKHLS covid-19 module to study the labour market impacts of the pandemic. In addition to labour market status in April 2020, respondents provided their 'baseline' employment status in February 2020. We focus on people working at the baseline and identify those who, in April, were either working, furloughed on the CJRS, or no longer employed.

Figure 1 shows these outcomes across workers' time-invariant characteristics. Figure 1.a categorises by race in the left panel and by gender and education in the right panel. Black people are most likely to have kept their jobs (75 percent) and least likely to have been laid off (8.1 percent). This may be because a high proportion of black people are essential workers (Platt and Warwick, 2020). Asian people are half as likely to be furloughed as other races (11 percent vs. around 20 percent). However, Asian and mixed race people are over twice as likely as black people to be laid off. In the right panel, we show that low educated workers are more adversely affected than high educated workers.

Figure 1.b plots the outcomes by location (left panel) and age (right panel). Workers in London are least likely to have experienced labour market disruption, while those in the Midlands, Wales and Northern Ireland are most disrupted. There are polarized impacts across ages. The youngest (under 25 years) and the oldest (over 65 years) are the most likely to experience labour market disruption.

Figure 1.c shows the outcomes by individuals' incomes (left panel) and assets (right panel). Lower-income workers are much more affected than those with higher incomes. And workers with lower assets are also most likely to be disrupted. Finally, Figure 1.d shows the distribution of impacts at the household level by the income quintile of household heads, focusing on singles in the left panel and couples in the right. The relationship between labour market risk and income is qualitatively similar at the household level as it is at the individual level. However, while 23 percent of singles in the bottom fifth of the income distribution are laid-off, both partners are laid off in only 4 percent of couples.

Overall, these plots provide compelling evidence that workers at the bottom of both the earnings and asset distributions are most affected by labour market disruption caused by covid-19, particularly singles who have no household-level risk sharing. This is likely to have important implications for their ability to smooth consumption. We return to this point in section 4.

3.2 Sources of Outcome Differential

To analyse factors driving differences in labour market outcomes, we focus on three sources of risk. We adopt the physical proximity and location flexibility factors from Lekfuangfu et al. (2020) who construct these indices from O*NET using factor analysis (see Lekfuangfu et al. (2020) and

Appendix B for more details). The indices are continuous, reflecting that these features are unlikely to be binary (as also noted by Adams-Prassl et al. (2020b)). Our third measure is an index of industry exposure based on the economic impact survey of ONS (2020). We use the percentage of businesses reporting to have temporarily closed in each industry, defined by its top-level SIC code, as an indicator of industry exposure (see Table A.4 in Appendix C).[6] The measures of all three factors are standardised to have mean zero and standard deviation one.[7]

We first motivate our focus on these three factors. The top panel of Figure 2 shows how each of the risks varies across age groups, conditional on gender and education. While there is limited variation in physical proximity by age, location flexibility and industry exposure exhibit a U-shape and inverse U-shape, respectively. This implies that youngest and oldest workers may be most adversely affected by the pandemic due to the inflexibility of their jobs and demand disruption within their industries. And these undesirable characteristics of jobs are also most prevalent among low educated workers across all age groups.

The middle panel of Figure 2 shows the measures across earnings deciles. Physical proximity varies only modestly across the earnings distribution and types of workers. On the other hand, location flexibility and industry exposure vary substantially: lower earning workers (particularly low educated males) are most likely to be in industries exposed to demand reductions and with least flexibility to work remotely. This is consistent with with patterns observed in other countries.[8] Finally, the bottom panel of Figure 2 shows the measures along the distribution of liquid assets. Low educated workers are most exposed to negative demand shocks, and also have relatively low liquid assets (as indicated by the size of markers).

Assortative partnering between people with similar education levels further amplifies the unequal distribution of risks at the household level. As shown in Appendix D, these risks are positively correlated between spouses, particularly at the bottom of the income and asset distributions. Overall, these plots demonstrate that households at the bottom of both the earnings and asset distributions are most exposed to labour market risks.

To quantify the effects of these risks, we estimate the probability of three labour market outcomes—working as usual, being furloughed, or not working—as a function of the three risks using

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[6]Due to some industries having an insufficient number of firms responding to the ONS survey, this measure is available for only 12 of 21 top-level SIC codes, representing 82 percent of the UK workforce. We have dropped individuals whose industry is missing from the ONS survey from our analysis.

[7]Specifically, the measures have mean zero and standard deviation one across unweighed occupations and industries.

[8]E.g. Mongey et al. (2020) for the US, Saltiel (2020) and Lekfuangfu et al. (2020) for developing countries.

a multinomial probit model.[9] For each of the three labour market outcomes, we write

$$y_{ij} = \alpha_j \mathbf{f}_i + \beta \mathbf{x}_i + \xi_{ij} \tag{1}$$

where $j = \{\text{working}, \text{furloughed}, \text{separated}\}$, y_{ij} is the latent labour market outcome variable of worker i, $\mathbf{f}_i$ is a vector containing the three factors and their interactions based on the individual's occupation and industry in the pre-pandemic period, $\mathbf{x}_i$ contains individual's characteristics such as age, and $\xi_{ij} \overset{iid}{\sim} N(0,1)$ is an idiosyncratic shock.

Table 1 reports the estimated marginal effects of each factor, holding other variables at their means. The marginal effects are robust across specifications. On average, a one unit increase in physical proximity increases the probability of being laid-off by around four percentage points, but has no statistically significant impact on the probability of being furloughed. By contrast, a one unit increase in location flexibility reduces the lay-off and furlough probabilities by around 5.5 percentage points. Finally, a one unit increase in industry exposure increases the lay-off probability by around two percentage points, but increases the furlough probability by seven to eight percentage points.[10] Overall, workers with least location flexibility and in industries with most reduced demand are most likely to experience labour market disruption during the pandemic. Policy aimed at mitigating the impacts on incomes should therefore target these workers.

4 Effects on Income and Spending

We now consider the consequences of the labour market risks for income and consumption of households. To quantify these effects, we first calculate the expected income of each individual in a household during the pandemic, based on the estimated probabilities of labour market disruption.[11] For each individual in our sample, we calculate expected monthly labour earnings during the pandemic y_{covid} as

$$y_{\text{covid}} = \big(\Pr(\text{working}) \times y_{\text{pre}}\big) + \big(\Pr(\text{furloughed}) \times y_f\big) + \big(\Pr(\text{separated}) \times y_s\big),$$

where y_{pre} is earnings in the pre-pandemic period; y_f is earnings if furloughed; and y_s is earnings if separated.[12] We examine the effects of the pandemic on household income across the income distribution in section 4.1. Then, in section 4.2, we consider the extent to which reduced income

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[9]The net benefits of the employment outcomes to firms may not have global ordering. Therefore, we consider a multinomial probit to be more appropriate than an ordered probit model.

[10]We plot the distribution of these marginal effects in Figure A.2.

[11]We select model 3 from Table 1 as our preferred specification, based on its AIC and BIC.

[12]This approach allows us to include the full UKHLS wave 9 sample in our analysis, rather than the subset who responded to the covid-19 module.

affects households' ability to meet their expenditure requirements, and in section 4.3 we discuss households' ability to maintain expenditure using liquid assets.

4.1 Income

We assume that the earnings of individuals who continue working y_{pre} are unchanged compared to the pre-crisis period, as measured in wave 9 of UKHLS during 2017 or 2018. Earnings of separated workers y_s fall to zero, and earnings of furloughed workers y_f are supported by the CJRS, under which the government pays 80 percent of their usual earnings up to a cap of £2,500 a month before taxes (around £2,000 net). We then define total income as earnings plus other incomes. For couples, total household income is the sum of each individual's total income.[13] We allow for increases to Universal Credit—the main benefit supporting unemployed or low income households—if income falls. To reflect the typical minimum wait between claiming and receiving Universal Credit, we assume that households only receive additional payments after five weeks. We hold all other unearned income an individual received in 2017/18 fixed.

We show the impact of covid-19 on household income for couples in Figure 3.a, and for singles in 3.b. The green bars show median household income per person before the pandemic across quintiles of the income distribution; the red bars show expected household income during the pandemic before adjustments to Universal Credit; and the orange bars include any increased Universal Credit. For both couples and singles, the *absolute* reduction in per person household income is larger for higher-earning households. However, the *proportionate* reduction in income is highest for low-income households before adjustments to Universal Credit. For couples, median per person household income falls by 17 percent in the bottom earnings quintile compared with 13 percent in the top; similarly the reduction is 22 percent for singles in the bottom quintile and 14 percent for those in the top. This highlights that the labour market impacts of the pandemic fall disproportionately on low income households. And, while Universal Credit mitigates these unequal income effects, we show in section 4.2 that there remains inequality in the ability of households to absorb reduced income.

4.2 Expenditure

We now consider the effect of these income reductions on households' ability to finance expenditure from income.[14] We present expected gap between income and expenditure in Figure 3.c for couples and 3.d for singles. In these panels, we show 'short-term' income-expenditure gaps per

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[13]We drop households containing non-family members as they may not share resources within households and exclude children's earnings from household income.

[14]Expenditure includes all types of spending, reflecting that a households may have financial commitments in addition to spending on consumption items.

household member, before any additional support from Universal Credit.[15] The green bars show that the median gap before the pandemic is increasing in household income, suggesting that higher income households are better able to absorb a reduction in income.[16] The red bars show the expected income-expenditure gaps during the pandemic. For couples, the reduction in income increases the pre-existing income-expenditure deficit for those in the bottom quintile, and reduces the income-expenditure surplus over the rest of the distribution (although the gaps remain positive). For singles, the pre-existing income-expenditure deficits increase in the bottom 40 percent. Therefore, despite the support from CJRS, the labour market impacts of the pandemic jeopardise the ability of the lowest-income households to afford usual spending. And the effects are particularly severe for singles.

However, as a result of increased restrictions, household spending may have fallen during the pandemic. We construct a second measure of total expenditure which reduces spending on categories that are likely to have fallen as a result of lockdown measures.[17] We show the gap between household income during the pandemic and this reduced expenditure in the blue bars of Figures 3.c and 3.d. The income-expenditure gap returns to around the pre-pandemic level for couples and singles in the bottom 20 percent of the income distribution, and but fails to compensate reduced income for other groups. We note, however, that higher-income households make larger savings on usual expenditure during the pandemic since they spend more on expenditure items likely to be unavailable.

4.3 Using Assets to Maintain Expenditure

We now analyse the extent to which the households whose income-consumption gap becomes negative (or more negative) have sufficient savings to maintain spending.[18] We consider the three groups whose median income-expenditure gap becomes more negative as a result of the pandemic: couples in the bottom quintile of the earnings distribution, and singles in the first two quintiles. We calculate the number of weeks each household in these groups could finance the increase in the median income-consumption gap based on pre-pandemic expenditure using their liquid assets.[19]

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[15]These deficits become slightly smaller when we include Universal Credit (see Figure A.6 in Appendix D.3), but remain larger than before the pandemic.

[16]We also note that the pre-pandemic income-consumption gap is negative for lower-income households. The observation that median household income exceeds expenditure for the lowest income households is consistent with other studies e.g. Brewer et al. (2006) for the Britain and Pew Charitable Trusts (2016) for the U.S.

[17]We exclude any spending on restaurants, hotels and leisure activities, and reduce spending on transport by 80 percent reflecting that, across modes, transport use fell by between 70 percent (for car travel) 95 percent (for rail travel) (Cabinet Office, 2020).

[18]We summarise the distribution of liquid assets across income quintiles, separately for couples and singles, in Appendix Figure A.1.

[19]We take the median income-expenditure gaps based on pre-pandemic expenditure as a reference point for each income group, instead of the reduced lockdown expenditure, as the latter may understate households' actual expenditure

We incorporate an increase in income from Universal Credit after five weeks, reflecting the typical minimum wait between claiming and receiving Universal Credit. We focus attention on the number of households able to finance the median income-expenditure gap from liquid assets for (1) less than one week, (2) less than five weeks, (3) less than 12 weeks and (4) more than 12 weeks. Households in categories (1) and (2) are of particular policy interest, as these highly constrained households may not be able to sustain spending until receiving any increased benefit entitlement. We show the proportions of households in each of these categories in Figure 3.e.

Across all three groups, a substantial fraction of households have insufficient liquid assets to finance the median income-consumption gap for even one week. For couples in the bottom quintile of the income distribution, around 78 percent would be unable to maintain expenditure for the five weeks before receiving any increased benefit payments. The equivalent figures are 70 percent and 73 percent for singles in the first and second quintiles. This underlines that a substantial fraction of the households whose income falls below required expenditure are likely to need to reduce spending as a result.

In summary, the labour market effects of the pandemic are likely to widen inequalities in consumption and savings since lower income households (1) households experience a larger proportionate income reduction because of the types of jobs they do; (2) have a smaller buffer between usual income and expenditure, and make smaller savings during lockdown; and (3) do not hold sufficient assets to sustain expenditure. These results explain why savings rates fell among low-income households, but rose among high-income households, during the pandemic in the UK (Haldane, 2020).

5   Alternative Policy Response

5.1   US-style Economic Impact Payments

In this section we consider an alternative scheme, based on the Economic Impact Payments (EIPs) in the US. EIPs provide a one-off payment to all households who file a tax return, up to a maximum of $1,200 for each adult household member and $500 for every child. The payments are reduced at a rate of $5 for every $100 of income above a threshold which depends on household structure.

This policy has a number of important differences from the CJRS. First, the payments are a one-off transfer rather than a recurring income replacement. The generosity of the EIPs therefore falls over time. Second, the EIPs are available to all households, whereas CJRS is only available to furloughed workers—not those continuing to work, nor those who are laid off. Finally, the lowest

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needs: it simply removes some items without allowing households to substitute this consumption into other categories. While modelling consumption responses (which could depend on households' incomes, beliefs and preferences) would be an interesting extension, it is beyond the scope of this paper.

income households are entitled to the highest EIP, unlike the fixed at 80 percent replacement rate (up to a monthly cap) under CJRS.

We study the likely effects of an EIP-style payment in the UK. We set the maximum payment to £593 per adult and £247 per child. These amounts are equal to 1.0 and 0.4 times average weekly household expenditure in the UK, the same level as the EIPs relative to average household spending in the US (BLS, 2019). We then reduce the payments by 5 pence for every pound of gross household labour income above £4,031 a month for couples and £1,916 a month for singles. These are the 60th percentile of the household income distributions for couples and singles in our sample, corresponding to the approximate location of the EIP thresholds in the US income distribution.

Unlike the CJRS, EIPs do not provide firms with assistance in retaining workers.[20] In the absence of CJRS, it is likely that some furloughed workers would have lost their jobs. We consider three scenarios intended to capture the full range of potential outcomes: (1) all furloughed workers would have instead been laid off, (2) furloughed workers would have either separated or continued to work with equal probability, or (3) all furloughed workers would have continued to work. These represent worst-, mid- and best-case scenarios for the counterfactual outcomes of furloughed workers in the absence of CJRS.

5.2 Comparison Between US and UK-style Support

In Table 2, we show the impacts of the policies on households' ability to maintain expenditure. We also consider a 'No Policy' scenario, in which the labour market impacts are identical to the worst-case EIP scenario but workers receive no additional support from the government. Across all scenarios, households may also become entitled to additional support from Universal Credit after five weeks.[21]

In Panel A, we show the fraction of households which can sustain pre-pandemic expenditure using liquid assets for different lengths of time. With no policy intervention, 62 percent of households would retain income above required expenditure. However, over 18 percent would need to cut expenditure within one week.

CJRS partially mitigates the adverse effects. The fraction of households able to sustain expenditure indefinitely increases to 66 percent and the fraction needing to cut spending within one week falls to 16 percent. However, the EIP-style scheme is much more effective at supporting expenditure in the short term, reducing the fraction of households unable to sustain expenditure for

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[20]There is a small Employee Retention Credit available in the US, providing a credit of 50 percent of wages paid up to $10,000 from March to December 2020. However, the scheme is less generous than the UK's CJRS—particularly as it requires employers to continue paying wages.

[21]In response to the pandemic, the UK government introduced a system of Universal Credit 'advances' designed to reduce this wait period. However, only around one in five new claimants in March, April and May were received an advance payment (Department for Work and Pensions, 2020).

one week to almost zero across all three scenarios. This highlights the severity of liquidity constraints for the households most affected by the pandemic, which the EIP is effective at relaxing.

In Panel B, we consider the effects of the policies on average total expenditure per household member. We assume that households reduce expenditure if (1) their income falls below pre-pandemic expenditure (or any pre-existing income-expenditure deficit increases) and (2) their assets are insufficient to finance the shortfall for one, five or 12 weeks. We also report pre-covid average expenditure of £1,652 per household member.

While both CJRS and EIP mitigate the reduction, the EIP is most effective, at least in the short term. The worst case EIP scenario generates the same average expenditure reduction as CJRS after five weeks. In the best case scenario, expenditure is barely affected. This highlights the potentially substantial short-term benefits of providing constrained households with liquidity. However, over longer time horizons, the continued support provided by the UK's CJRS becomes increasingly beneficial: by 12 weeks, the consumption reduction under CJRS is similar to the mid-case EIP.

In Panel C we assess how each policy affects the pattern of consumption reductions over the income distribution. We report the estimated coefficient from a linear regression of the percentage reduction in household spending on pre-pandemic household income (expressed in logs).[22] A negative coefficient indicates that the percentage expenditure reduction is smaller for higher income households, while a positive coefficient indicates the opposite. Across all scenarios, the gradients become less negative (or more positive) over time. This reflects that the very short term effects on consumption are concentrated on the lowest income households because they have less of a buffer. And, at every point in time, CJRS mitigates the income gradient of consumption effects compared with the no policy scenario.

However, the EIP is more effective at eliminating the relationship between household income and the effect on consumption. In fact, after five and 12 weeks, the estimated relationship between consumption reductions and household income is positive. There are three main reasons for this. First, the EIP is highest for low income households; by contrast, CJRS pays a fixed proportion of income (up to a cap). Second, EIPs depend on household structure (including number of children) which is related to household income (see Figure A.5 in Appendix). Finally, all households are entitled to receive the EIP, including those with laid off workers, unlike CJRS.

Finally, in Panel D, we consider the cost per household of the CJRS and EIP payments. The cost of CJRS per household is higher than the EIP by 12 weeks. But, despite its cost, it does not perform substantially better at supporting consumption over this period. However, we note that CJRS may have longer-term benefits if it succeeds in helping workers retain their jobs.

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[22]We include all households in our sample, including those with no required spending reduction.

6 Conclusion

This paper assesses the implications of the labour market disruption caused by covid-19 for households in the UK. Workers with already low labour force attachment, such as those with lower education and females, are most adversely affected. The impacts are also concentrated on households at the bottom of the income and asset distributions. We provide evidence that occupational and industrial characteristics explain inequalities in income risk. These characteristics capture the impact of the pandemic on both labour supply (as measured by flexibility to work from home) and labour demand.

We then consider the consequences of this differential exposure for incomes and consumption. Lower income households experience the largest proportionate income reduction. This, along with a smaller buffer between usual income and expenditure, contributes to a shortfall between income and required expenditure for lower income households, but not for higher income households. Moreover, inequality in liquid wealth exacerbates inequality in the transmission of the income shocks to consumption. More than two thirds of households in the bottom fifth of the income distribution have insufficient assets to maintain expenditure for even one week. Finally, we compare the relative effectiveness of UK's CJRS to the US's EIPs. We find that the EIP would have been substantially better at helping households in the UK to maintain usual expenditure in the short term.

Overall, this paper highlights important differences in households' abilities to cushion negative income shocks. To effectively reduce the negative and uneven consequences of covid-19 on household welfare, it is crucial to both provide short-term liquidity (as the most affected households also have the lowest means to smooth consumption) and, in the longer term, provide a combination of income and employment support to those with lowest ability to work remotely and in industries with most reduced demand. This is particularly the case as affected workers tend to be young—for these workers, losing the opportunity to accumulate human and social capitals at work could have long term consequences for lifetime earnings.

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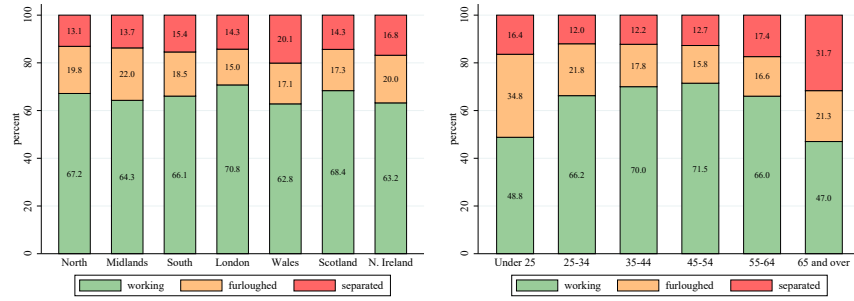
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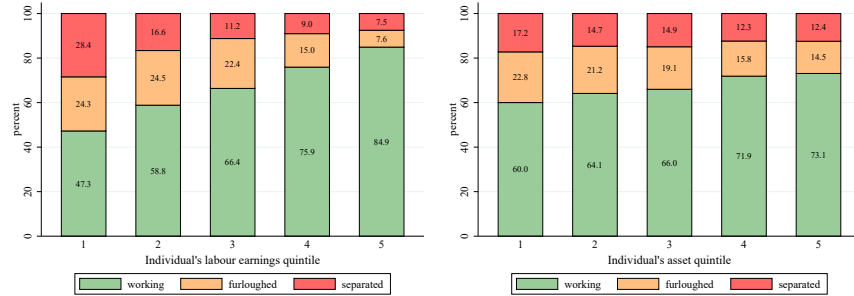
Figure 1: Heterogeneity in labour market outcomes

(a) Race (left) and gender-education (right)
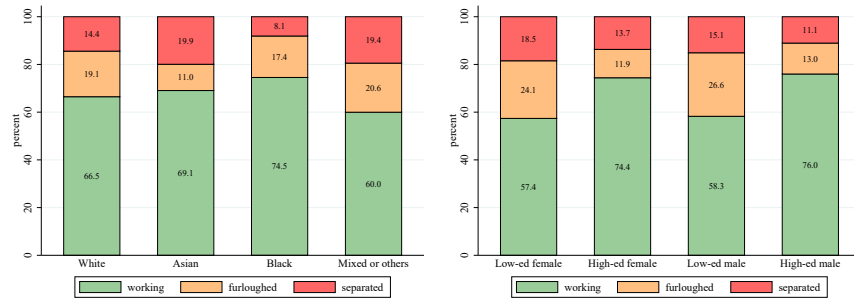
(b) Location (left) and age group (right)

(c) Earnings (left) and assets (right)

(d) Singles (left) and couples (right)
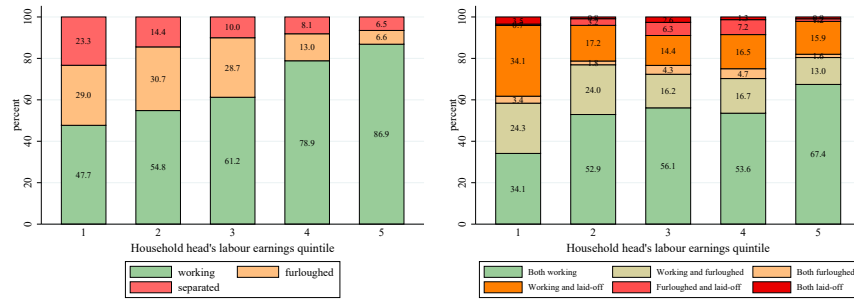
Notes: High education is defined as having a university degree or higher. Subfigures a-c include employed workers in the baseline period of the covid-19 supplementary sample. The right panel of subfigure d includes households with partners living together. Household head defined as the highest earning partner, and household head's labour earnings quantile is calculated from the unconditional individual earnings distribution, comparable to the individual-level labour income quantiles in subfigure c.

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Figure 2: Work Characteristics by Sex and Education

(a) Physical Proximity by Age Groups

(b) Industry Exposure by Age Groups

(c) Location Flexibility by Age Groups

(d) Physical Proximity by Labour Income

(e) Industry Exposure by Labour Income

(f) Location Flexibility by Labour Income

(g) Physical Proximity by Liquid Assets

(h) Industry Exposure by Liquid Assets

(i) Location Flexibility by Liquid Assets
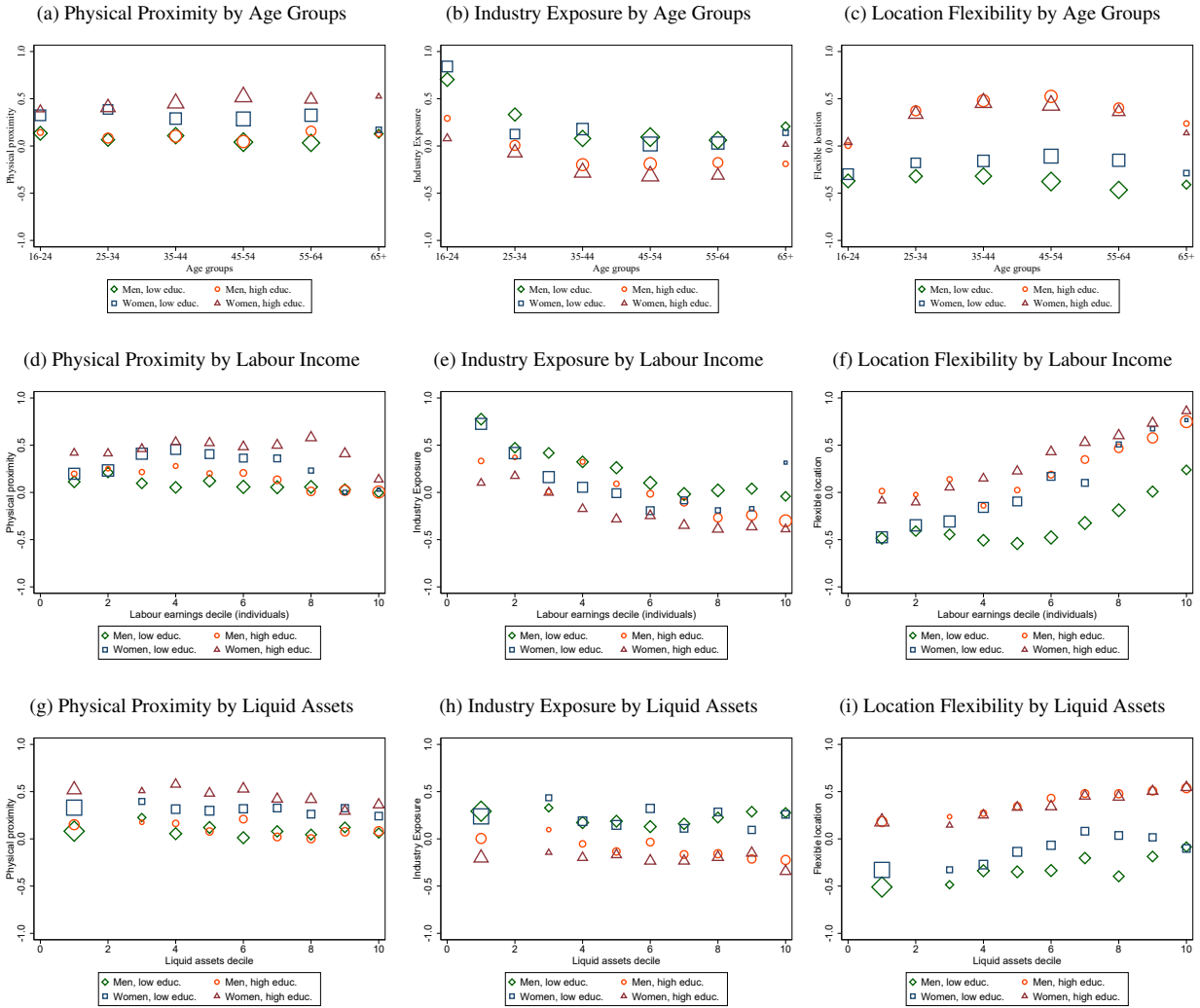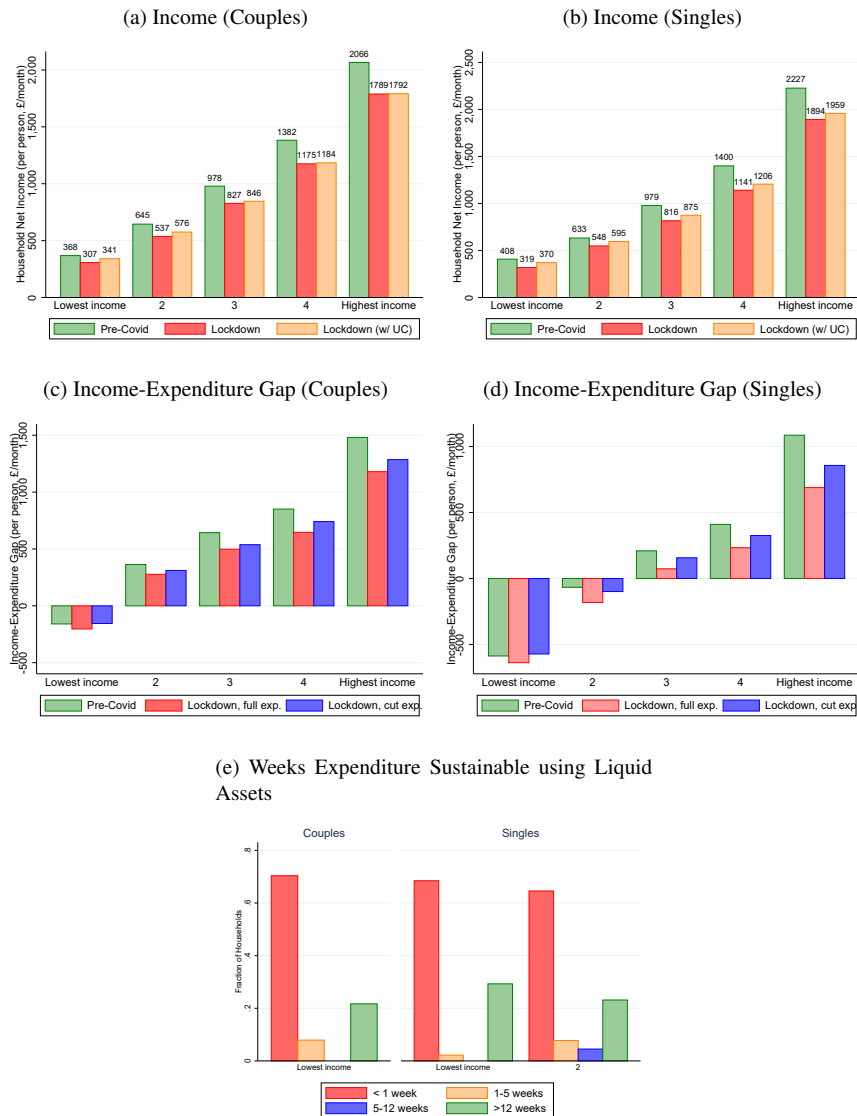
Notes: High education is defined as having a university degree or higher. Marker size reflects employment counts relative to the unconditional individual earnings distribution (meaning that sizes are comparable across subfigures). Sample includes all employed workers in the main UKHLS sample.

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Table 1: Marginal Effects

Marginal Effects	Model 1	2	3	4	5
Physical Proximity					
Working	-0.0253	-0.0285	-0.0251	-0.0255	-0.0248
	(-1.47)	(-1.62)	(-1.42)	(-1.45)	(-1.40)
Furlough	-0.0200	-0.0128	-0.0131	-0.0140	-0.0156
	(-1.42)	(-0.89)	(-0.91)	(-0.98)	(-1.07)
Laid-off	0.0452***	0.0413***	0.0382**	0.0395**	0.0404***
	(3.92)	(3.45)	(3.20)	(3.25)	(3.35)
Industry Exposure					
Working	-0.0987***	-0.0930***	-0.0900***	-0.0894***	-0.0907***
	(-7.83)	(-7.36)	(-7.16)	(-7.20)	(-7.31)
Furlough	0.0775***	0.0722***	0.0704***	0.0707***	0.0702***
	(7.75)	(7.23)	(7.09)	(7.18)	(7.09)
Laid-off	0.0211*	0.0208*	0.0195*	0.0187*	0.0205*
	(2.48)	(2.42)	(2.33)	(2.19)	(2.51)
Flexibility Location					
Working	0.111***	0.0882***	0.0848***	0.0843***	0.0783***
	(7.15)	(5.40)	(5.18)	(5.16)	(4.77)
Furlough	-0.0565***	-0.0327*	-0.0309*	-0.0314*	-0.0273*
	(-4.34)	(-2.37)	(-2.25)	(-2.28)	(-1.97)
Laid-off	-0.0542***	-0.0555***	-0.0538***	-0.0529***	-0.0510***
	(-5.05)	(-4.95)	(-4.78)	(-4.72)	(-4.53)
Controls:					
Male		✓	✓	✓	✓
High Education		✓	✓	✓	✓
Age and age squared			✓	✓	✓
Regional dummy				✓	✓
Race					✓
Sample size	3258	3258	3258	3258	3229
AIC	4894.7	4852.6	4827.4	4839.6	4770.4
BIC	4992.1	4974.3	4973.5	5131.8	5098.7

Notes: Marginal effects at means. Z-scores in parenthesis. ***, ** and * signify p-value <0.01, p-value<0.05 and p-value <0.1, respectively. Sample includes employed workers in the baseline period of UKHLS covid-19 module.

Figure 3: Effects on Income and Consumption

(a) Income (Couples)

(b) Income (Singles)

(c) Income-Expenditure Gap (Couples)

(d) Income-Expenditure Gap (Singles)

(e) Weeks Expenditure Sustainable using Liquid Assets

Notes: Panels (a) shows median per person net household total income for couples in each quintile of the (per person) household income distribution. Panel (c) shows the median gap between income and expenditure (per person) for couples, both in the pre-covid period and under the two scenarios described in the text. Panels (b) and (d) show the same statistics for singles. Panel (e) shows, for households in income quintiles with a negative median income-expenditure gap in our scenario, the lengths of time households could afford to maintain pre-crisis expenditure by using liquid assets. Specifically, it shows the distribution of household's liquid assets divided by the median income-expenditure gap for their income quintile and status as a couple or single, defined using the pre-pandemic expenditure measure (i.e. the red bars in panels (c) and (d)). For groups with a negative median income-expenditure gap before the pandemic, we instead divide liquid assets by the increase in the income-expenditure gap (i.e. the difference between the red and green bars in panels (c) and (d)).

Table 2: Effects on Expenditure

	No Policy (1)	UK CJRS (2)	US EIP Best case (3)	US EIP Mid case (4)	US EIP Worst case (5)
Panel A: Maintain exp. with liquid assets					
< 1 week	18.2%	15.9%	0.0%	0.0%	0.1%
1-5 weeks	2.9%	1.1%	0.2%	1.3%	4.0%
5-12 weeks	1.8%	1.5%	1.5%	5.5%	4.7%
> 12 weeks	14.6%	15.5%	29.8%	28.0%	27.7%
No exp. Gap	62.4%	65.9%	68.4%	65.1%	63.4%
Panel B: Average exp. (pre-covid mean = 1652)					
After 1 week	1593	1623	1652	1652	1651
After 5 weeks	1603	1629	1651	1644	1629
After 12 weeks	1595	1623	1647	1627	1611
Panel C: Income gradient of exp. reduction					
After 1 week	-1.987	-0.810	-0.007	-0.013	0.028
	(0.384)	(0.174)	(0.001)	(0.002)	(0.020)
After 5 weeks	-0.603	-0.330	0.047	0.270	0.559
	(0.264)	(0.133)	(0.010)	(0.094)	(0.195)
After 12 weeks	-0.444	-0.142	0.158	0.437	0.651
	(0.280)	(0.147)	(0.062)	(0.174)	(0.248)
Panel D: Cost per household					
After 1 week	0	100	913	913	913
After 5 weeks	0	499	913	913	913
After 12 weeks	0	1198	913	913	913

Notes: Table compares the effects of various policy options on households' ability to maintain expenditure during the covid-19 pandemic. In each column, we consider a scenario in which the labour market disruption a worker faces depends on their estimated probabilities of continuing to work, being furloughed, or separating from their employer. In all five columns, we assume workers also receive support from the UK welfare system after five weeks. See the text for details. Standard errors in parentheses in Panel C.

Online Appendix

A. Data

A.1 UKHLS: Employment and Income

The UKHLS is the largest nationally representative household panel survey in the UK, containing individual-level data on employment, income, assets and family characteristics for a panel of individuals. We focus on the wave 9 of the survey (the most recent), which contains data collected in 2017 and 2018. We merge in detailed data on liquid assets from a specialist survey module administered during wave 8 (in 2016 and 2017).

We focus on individuals who are employed or self-employed over the age of 16 at the time of their wave 9 interview. We define occupations using the three-digit Standard Occupation Classification (SOC) codes of their current main job, and similarly define industries using top-level Standard Industrial Classification (SIC) codes.[23]

We combine information on the labour market impacts of covid-19 from the supplementary module. In addition to labour market status in April 2020, sample respondents were asked to provide a recent 'baseline' employment status—specifically, their status in February 2020. We define 'remaining employed'workers as those who were receiving positive earnings both in the baseline and in April, and 'separated' if they were receiving positive earnings only in the baseline. We classify workers as furloughed if they were receiving positive earnings in the baseline and reported as furloughed on the CJRS in April.

We construct two measures of income. First, we define earnings as labour income in the month before the individual was interviewed in wave 9, net of taxes and national insurance contributions. This includes usual pay from their main job, pay from any second jobs, and profits (or losses) from self-employment. Second, we define total income which adds to earnings any benefit payments or income from investments, pensions, or other sources (such as from a family member).

Of the 36,055 individuals (from 20,510 households) in UKHLS wave 9, we drop 15,489 individuals who are not employed and a further 4,328 who did not provide data on assets in wave 8 (either because they missed their wave 8 interview or refused to respond to the assets questions). We also drop 3,013 individuals with missing information on industry exposure. Our final sample therefore contains 13,225 residents in 9,639 households.

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[23]Specifically, we use the SOC 2010 and the SIC 2007 classification systems.

A.2 UKHLS: Assets

We use detailed data on individuals' assets collected as part of a specialist question module in wave 8 of UKHLS (in 2016 and 2017). Individuals were asked whether they held savings or investments, either in their sole name or jointly with others, in any of (1) a savings or deposit account, (2) national savings account, (3) ISA (cash only) account, (4) ISA (investment: stocks and funds) account, (5) premium bonds or (6) other type of account. For each of these six types of account an individual reported holding, they were asked how much they held in total across all accounts of that type.

We construct two measures of assets from these data. Our measure of liquid assets (LA) is the sum of assets held across all six account types, while our measure of non-volatile liquid assets (NVLA) is the sum of amounts held in categories (1), (2), (3) and (6) only. The NVLA reflects assets the individual can access at short notice and costlessly smooth consumption. In particular, given the volatility in stock prices since the pandemic has begun, liquidating investments in funds and stocks may involve significant costs for some people; hence we make a distinction between NVLA and LA in our analysis. Further, neither measure includes non-liquid wealth held in housing or cars, available credit on credit cards, or any debts which may offset the gross asset holdings. This is because our main focus is on assets people could access at short notice and at relatively small transaction costs to smooth consumption in response to an unanticipated reduction in earnings.

In the benchmark analysis, we present results using LA. Our results are similar when we restrict the definition of assets to NVLA. We plot the distributions of LA separately for couples and singles in each income quintile, in Figure A.1.

A.3 LCFS: Expenditure Imputation

We use the 2017/18 release of LCFS to correspond with the timing of our UKHLS sample. Our imputation is similar to Blundell et al. (2008) and proceeds as follows. First, we estimate the demand for food (a consumption item available in both UKHLS and LCFS) as a function of total expenditure and household characteristics:

$$\ln f_{it} = \beta_0 \ln c_{it} + D'_{it}\beta_1 \ln c_{it} + X'_{it}\mu + \ln p'_t\theta + \varepsilon_{it}, \tag{2}$$

where $\ln f_{it}$ is the logarithm of food expenditure for individual i in year t, $\ln c_{it}$ is a measure of total expenditure, and $\ln p_{it}$ is the logarithm of food prices. X_{it} are household characteristics including household size, number of children, government office region, the age and birth cohort of the household head, and binary indicators for whether the household contains a couple and

Figure A.1: Liquid Assets
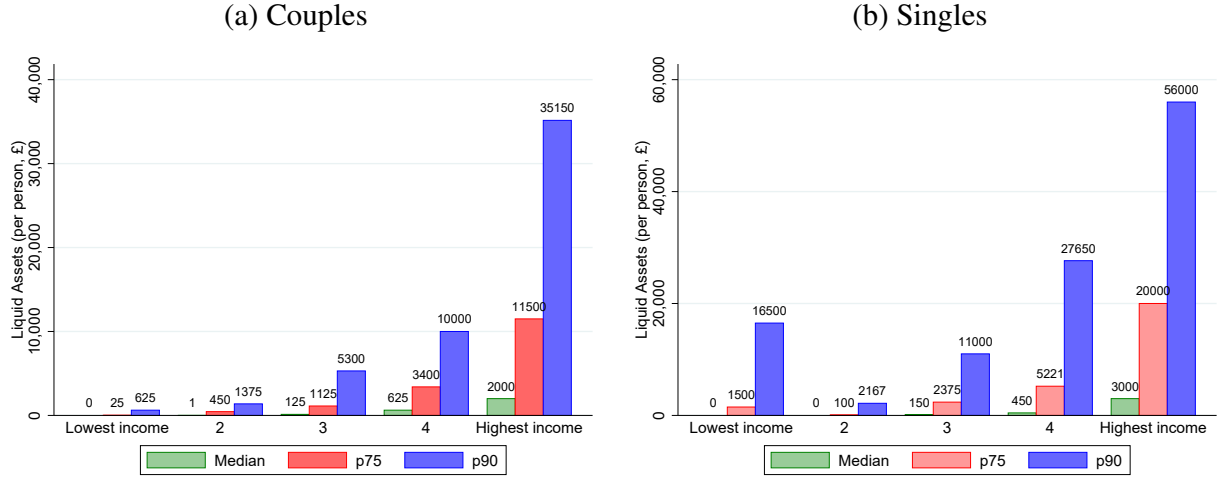
(a) Couples

(b) Singles

Notes: Figure shows the median, 75th and 90th percentiles total liquid assets per household member, separately for couples in panel (a) and singles in panel (b).

whether the household head has an undergraduate degree. Finally, D_{it} are household characteristics which we allow to affect the share of food expenditure in total consumption, including the number of children, whether the household head has an undergraduate degree and whether the household contains a couple. All measures are available in both UKHLS and LCFS except for total expenditure c_{it} which is available only in LCFS.

We consider two measures of expenditure c_{it}. The first is total household expenditure across all categories. However, as a result of reduced travel and increased restrictions, household spending may have fallen during the covid-19 pandemic. Our second measure attempts to reflect this by excluding or reducing spending on certain items, such as travel or eating in a restaurant.[24] These two measures are intended to place bounds on households' expenditure since the start of the pandemic: the first provides an upper bound as it does not account for spending reductions, while the second provides a lower bound as it does not allow for households to substitute their reduced spending with increases in other categories.

We estimate demand equation (2) for the measure of total expenditure c_{it} by OLS, then invert the equation to express c_{it} as a function of f_{it}, X_{it}, D_{it} and p_t. We then use this inverted equation to impute each measure of total expenditure for each household in UKHLS. We report the estimated coefficients for demand equation (2) in Table A.1. Additionally, we perform a validation exercise in which we estimate equation (2) on a randomly selected 90 percent subset of the LCFS sample and compare the actual and imputed total consumption measures for the remaining 10 percent.

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[24]In particular, it excludes entirely any spending on restaurants, hotels, leisure classes, and other miscellaneous activities such as visiting a museum, club or cinema, and reduces spending on transport by 80 percent

Overall, the imputed consumption measure is close to (but slightly lower than) the actual measures in LCFS, as shown in Table A.2.

We impute our measure of reduced expenditure into UKHLS following a two-step procedure. First, we construct the ratio r_{it} of reduced expenditure to total expenditure for each individual in LCFS and estimate the logistic transformation of this ratio as a function of food expenditure and other characteristics in LCFS:

$$\ln(\frac{r_{it}}{1 - r_{it}}) = \delta_0 \ln f_{it} + D'_{it} \delta_1 \ln f_{it} + X'_{it} \gamma + \ln p'_t \phi + v_{it}. \tag{3}$$

We show the estimated coefficients from this equation in Table A.3. We then impute the expenditure ratio into UKHLS, and compute for each individual $\tilde{c}^{\text{reduced}}_{it} = \tilde{r}_{it} \times \tilde{c}_{it}$, where the c_{it} is the measure of total expenditure and tildes denote that the variables are imputed measures in UKHLS. We show the distribution of the imputed ratio across households in the UKHLS sample in

B. Occupational Factors

The location flexibility and physical proximity factors are taken from Lekfuangfu et al. (2020). These factors are constructed from 24 task-based occupational variables from the O*NET data on 'Work Context' and 'Work Activities' for each of 900 detailed six-digit occupations using factor analysis (see Lekfuangfu et al. (2020) for more details). The O*NET measures are associated to occupations using US SOC codes. Unfortunately, there is no one-to-one mapping between the US SOC codes and the UK SOC codes provided in UKHLS. Therefore we manually assigned each 3-digit UK SOC code present in our data to one or more detailed US SOC codes, based on a close reading of the job requirements of each occupation. In cases where we assigned more than one US SOC code to a UK code (either because the lower detail of the UK codes in our data mean that they nest multiple more-detailed US codes, or because there is an imperfect equivalent between the two systems), we assign the average of the factors across US SOC occupations to the UK occupation.

C. Industry Exposure

We take the percentage of businesses reporting to have temporarily closed in each industry, defined by its top-level SIC code, from the economic impact survey of ONS (2020) on 7 May 2020. We interpret this as an indicator of negative demand shock and construct an index for industry exposure by standardising these fractions of bushinesses closing to have mean zero and standard deviation one, as shown in Table A.4.

Figure A.2: Predictive margins by risk factor
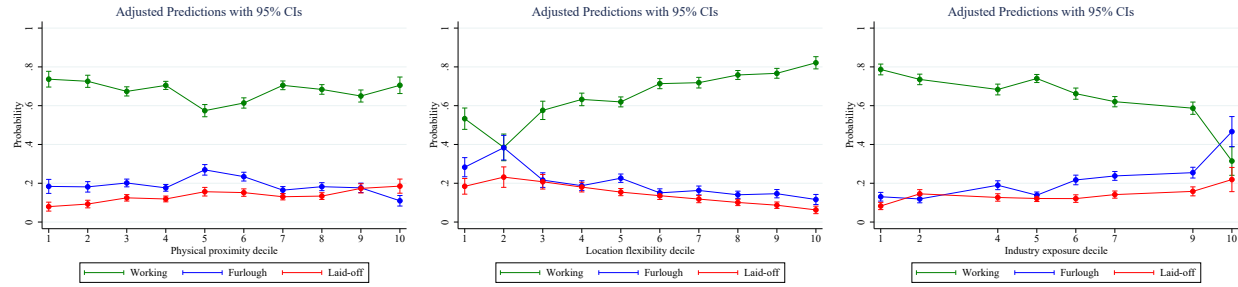
Notes: Predictive margins based on model 3 in Table 1. Probabilities calculated using all employed workers in UKHLS wave 9.

Figure A.3: Distribution of Imputed Ratio of Pre- to Post-covid Expenditure
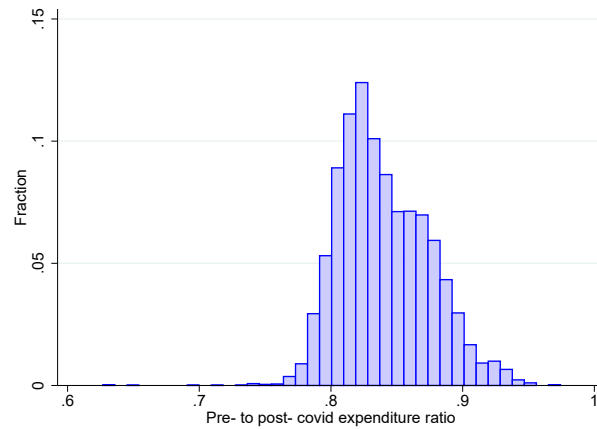
Notes: Figure shows shows the distribution of the imputed ratio of pre- to post-covid expenditure, $\tilde{r}_{it}$, across households in UKHLS. See text in Appendix A.3 for details.

D. Additional Results

D.1 Spouses' Occupational Sorting

To understand how assortative partnering may amplify the inequality in these risks, Figure A.4 shows the within-couple correlations of each factor (on the left vertical axis), and the average score of household head for a given factor (the right vertical axis).[25] The marker size in this figure represents the number of household heads in each decile of the individual earnings distribution. The top panel shows spousal correlations by the household head's earnings, and the bottom panel shows similar statistics along the distribution of household liquid assets.

While there is little difference in the average degree of physical proximity across the household head's earnings distribution, the average degree of work flexibility rises substantially in the top half of the distribution and the average degree of industry exposure declines gradually in income. That is, low earnings households are more likely to experience unfavourable shocks to labour supply and demand. Further, these risks are positively correlated between spouses because they tend to work in similar occupations and industries, particularly at the bottom end of the income distribution.

Additionally, the bottom panel in Figure A.4 shows that the average degree of the household head's physical proximity does not vary much by the household's liquid assets. However, the degree of industry exposure is slightly declining in the household's assets, with a higher positive correlation among spouses in wealthy families. The degree of work flexibility of household head is substantially lower at the bottom end of the asset distribution and it is more correlated between spouses than the other measures. Overall, these plots provide compelling evidence that households at the bottom of both the earnings and asset distributions are more at risk from disruption to their work caused by covid-19.
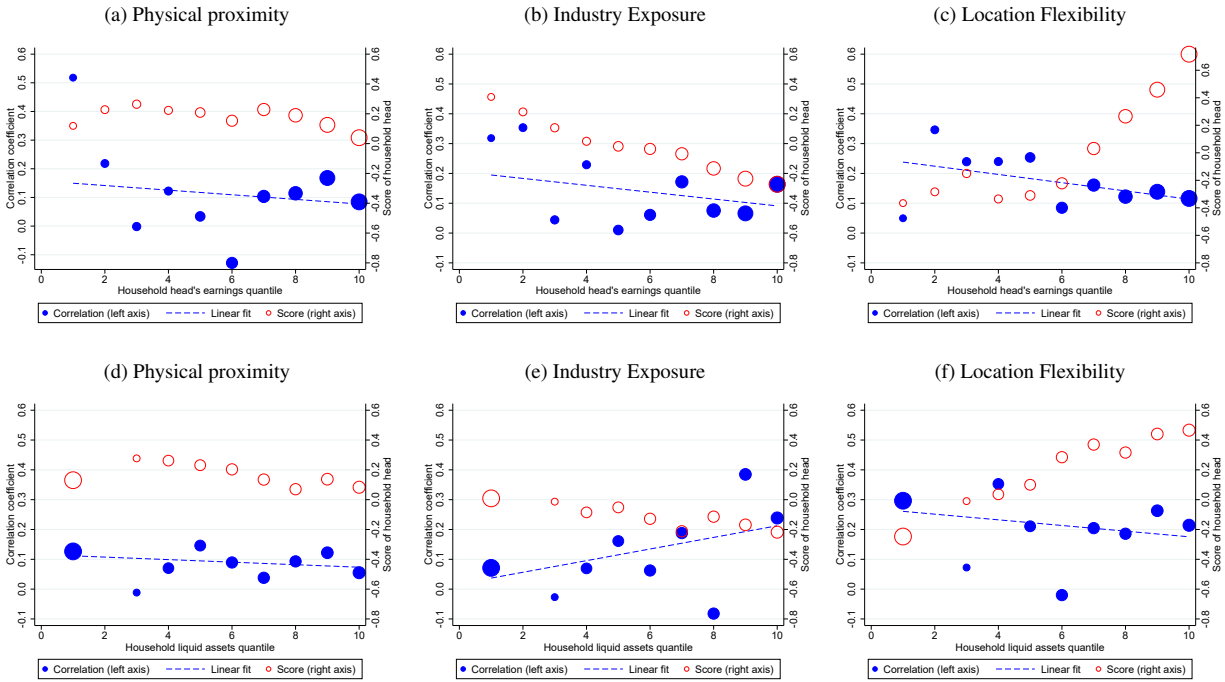
D.2 Family Characteristics

Figure A.5 shows the proportion of households who have children aged 13 or under at the time of their UKHLS wave 9 interview in 2017 or 2018 by quintiles of the household per person income distribution. Nearly 60 percent of households in the bottom quintile have children, and nearly 80 percent in the second quintile. This underlines that the lowest income household are also most likely to have children, meaning that the adverse labour market consequences of the pandemic are concentrated on households with children. This also makes the dependence of EIP on the number of children within a household a beneficial feature, and an important difference with CJRS (under which payments do not depend on household structure).

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[25]We designate the highest earning member of a cohabiting couple as the household head.

Figure A.4: Within-household correlation between exposure measures

(a) Physical proximity

(b) Industry Exposure

(c) Location Flexibility

(d) Physical proximity

(e) Industry Exposure

(f) Location Flexibility

Notes: Correlation between partners' values of each exposure measure (left axis) and score of the exposure measure for the household head (right axis). Household head defined as the highest earning partner. Marker size reflects number of household heads in each decile of the unconditional individual earnings distribution (including singles and partners of heads). Sample includes all employed spouses in the main UKHLS sample.

D.3 Income-Expenditure Gaps with Universal Credit

Figure A.6 shows the median gaps between per person income and expenditure within households, including allowance for increased Universal Credit payments following labour market disruption. The Figure is equivalent to panels (c) and (d) of Figure 3 in the main text; the only difference is that Figure A.6 allows for increased Universal Credit while Figure 3 does not. See the text in section 4.2 for more detail.

Allowing for Universal Credit makes the income-expenditure gaps become marginally more positive (or less negative) than is the case without. However, qualitatively the pattern of impacts is very similar with or without allowing for Universal Credit increases, and the main conclusions of section 4.2 on the distribution of the impacts are unchanged.

Figure A.5: Presence of Children by Income Quintile
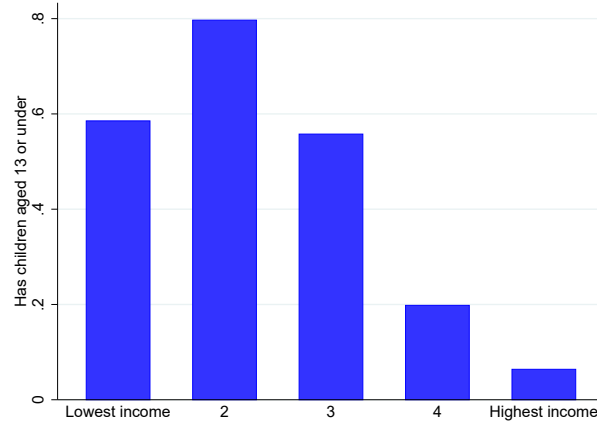
Notes: Figure shows proportion of households with children aged 13 or younger at the time of their wave 9 interview (in 2017 or 2018) by quintiles of the household per person income distribution.

Figure A.6: Income-Expenditure Gaps, Including Increased Universal Credit
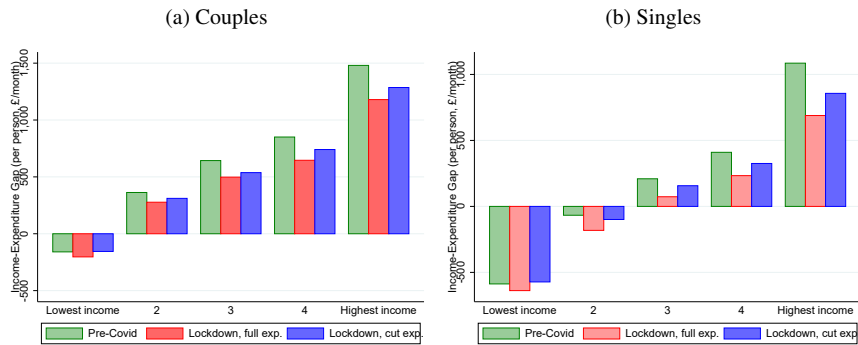
Notes: Panel (a) shows the median gap between income and expenditure (per person) for couples, both in the precovid period and under the two scenarios described in Section 4.2 in the text, including any increased entitlement to Universal Credit. Panel (d) shows the same statistics for singles.

Table A.1: Consumption Function Coefficients

	Total Expenditure
	(1)
$\ln c$	0.352***
	(0.0333)
Education	
University degree	-0.0958
	(0.218)
$\ln c \times$ university	0.0190
	(0.0337)
Family structure	
One child	0.0981
	(0.278)
Two children	-0.203
	(0.295)
Three children	-0.914
	(0.515)
$\ln c \times$ one child	-0.00906
	(0.0430)
$\ln c \times$ two children	0.0308
	(0.0445)
$\ln c \times$ three children+	0.135
	(0.0787)
Married	0.536*
	(0.235)
$\ln c \times$ married	-0.0625
	(0.0380)
HH size	0.178***
	(0.0172)
Characteristics of HH head	
Age	0.0119
	(0.0236)
$Age^2/1000$	-0.000235
	(0.247)
Region dummies	\checkmark
Cohort dummies	\checkmark
Ethnicity dummies	\checkmark
Other controls	
$\ln c \times$ year dummies	\checkmark
$\ln p_{food}$	-5.806
	(10.40)
Constant	27.35
	(47.92)
R^2	0.403
N	2920

Notes: Table shows coefficients of equation (2), estimated using LCFS data for 2017/18, for total household expenditure. Standard errors in parentheses. See the text in Appendix A.3 for further details.

Table A.2: Imputation Validation

	Total Expenditure Model	
	Mean	S.D.
True $\ln(c)$	6.19	0.73
Imputed $\ln(c)$	6.26	1.55
True c	626.6	487.9
Imputed c	539.7	1056.9
$N = 438$		

Notes: Table shows the results of a validation exercise for our imputation procedure. We randomly selected an approximate 90 percent subsample of the LCFS data and re-estimated (2). The table compares actual and imputed consumption for both our total and reduced expenditure measures in 10 percent subsample excluded from estimation.

Table A.3: Consumption Ratio Coefficients

	Expenditure Ratio (1)
$\ln f$	0.121*
	(0.0617)
Education	
University degree	-0.437
	(0.237)
$\ln f \times$ university	0.0769
	(0.0571)
Family structure	
One child	0.511
	(0.326)
Two children	0.404
	(0.372)
Three children	1.818**
	(0.667)
$\ln f \times$ one child	-0.0683
	(0.0780)
$\ln f \times$ two children	-0.0370
	(0.0847)
$\ln f \times$ three children +	-0.281
	(0.149)
Married	-0.0984
	(0.271)
$\ln f \times$ married	-0.0519
	(0.0692)
HH size	-0.123***
	(0.0319)
Characteristics of HH head	
Age	-0.00976
	(0.0432)
Age^2/1000	0.242
	(0.247)
Region dummies	✓
Cohort dummies	✓
Ethnicity dummies	✓
Other controls	
$\ln f \times$ year dummies	✓
$\ln p_{food}$	17.04
	(12.25)
Constant	-78.30
	(56.42)
R^2	0.081
N	2887

Notes: Table shows coefficients of equation (2), estimated using LCFS data for 2017/18, for total household expenditure. Standard errors in parentheses. See the text in Appendix A.3 for further details.

Table A.4: Industry Exposure Index

Industry	Percent temporarily closed	Index
Accommodation and food service	80.6	2.99
Arts and recreation	79.5	2.94
Construction	26.1	0.37
Wholesale and retail trade	24.3	0.29
Manufacturing	20.6	0.11
Education	12.6	-0.28
Utilities and waste management	10.0	-0.40
Administrative and support	8.1	-0.49
Transportation and storage	8.5	-0.47
Human health and social work	4.9	-0.65
Information And Communication	4.5	-0.67
Professional Scientific And Technical Activities	3.0	-0.74

Notes: Table shows percentage of businesses reporting to have temporarily closed in each industry from the economic impact survey of ONS (2020), and corresponding standardised index.