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Parental labour market instability and children's mental health during the pandemic

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Parental Labour Market Instability and Children's Mental Health During the Pandemic *

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Abstract

Childhood is a critical period for development of mental health: episodes of mental illness during this time often recur in adulthood but early intervention can be highly effective at reducing this persistence. Understanding determinants of child mental health is therefore key for the design of timely effective interventions. In this paper we study the impact of the COVID pandemic on the mental health of school-age children in England. We focus on how the significant pandemic induced disruptions to parental employment affected children and through what mechanisms, using unique nationally representative data we collected. We estimate an augmented Value Added model accounting for potential measurement error in child mental health scores. We find that changes in parental labour market circumstances over the course of the pandemic had a significant and negative impact on children's mental health of around 9% of a standard deviation equivalent to around 30% of the total average decrease in mental health in our sample over the course of the pandemic. Granular data on labour market experiences over the pandemic shows that it was *stability* of parental labour market trajectories that was key for child well-being. Mechanisms for the adverse impact of disruptions are likely to include negative impacts on actual and expected household economic situation as well as on parental psychological well-being.

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1 Introduction

Childhood is a critical period for mental health: among those experiencing mental ill health in adulthood, a third experienced initial symptoms before the age of 14 and a half by the age of 18 (Solmi et al., 2022). Mental health disorders experienced during childhood have wide-range associations with academic achievement, school engagement as well as adult mental health and economic outcomes (Case and Kraftman, 2022). There is also agreement that early intervention at the time of the first onset of symptoms is more effective than at later stages (Correll et al., 2018). In many countries, children and young people's mental health was deteriorating and of growing concern before the pandemic. Given the importance of stable and nurturing environments for child development, it is no surprise that the pandemic exacerbated these concerns.

Recent empirical studies confirm that children's mental health may have deteriorated during the pandemic (Ezpeleta et al., 2020; Ford, John and Gunnell, 2021; Guzman Holst et al., 2023; Waite et al., 2021). The COVID-19 pandemic disrupted children and families' lives in a myriad of ways that could have affected children's mental health. To date however, little is known about the exact factors that drove this deterioration in mental health. This is important for designing and appropriately targeting early interventions that are so critical for preventing life-long mental health problems and the wider set of challenges that accompany these.

In this paper we focus on one aspect of disruption brought about by the pandemic, namely the shocks to parental employment and economic circumstances. We ask what impact these shocks had on children's mental health and through which mechanisms these impacts occurred. A handful of pre-COVID studies suggest that parental employment-to-unemployment transitions can have detrimental impacts on children's mental health and behaviour, especially when these transitions are involuntary (Hill et al., 2011; Johnson, Kalil and Dunifon, 2012). These studies all focus on US samples of low-income families in the 1990s. Several features of the pandemic context suggest that impacts could have been different from those documented in the literature to date. For example, the generous employment insurance ('furlough') scheme buffered (at least for some time) much of the income losses that generally accompany transitions out of employment. Moreover, children were out of school for long periods of time, so spells out of employment may have provided opportunities for parents to better care for their children relative to parents in employment.

To assess the link between shocks to parental employment circumstances and child mental health, this paper exploits a unique bespoke dataset, which includes parental report on children's mental health and monthly histories of parental labour market circumstances during the first year of the pandemic in a representative sample of 6000 families with school aged children in England. To our knowledge, no dataset includes measures of children's mental health alongside such granular information on parental labour market transitions during the pandemic. Using those data, we show that, relative to the year before COVID, during the first year of the pandemic there was a lot more variation in the number and type of transitions that households experienced and these transitions were more evenly distributed across the socio-economic distribution. We also confirm emerging findings from the literature of a worsening of parental reports of children's emotional and behavioural development during COVID (Guzman Holst et al., 2023).

As in the wider literature on child development, we face two main challenges to identifying the causal impact of changes to parental labour market circumstances on children's mental health. First, we cannot observe all the factors that affect children's mental health. This creates a risk that any impacts we identify may suffer from endogeneity bias. We address this problem by exploiting measures of children's mental health before COVID, as recalled by the responding parent at the time of the interview, alongside a rich set of socio-economic characteristics in order to proxy for omitted inputs and unobserved child traits within a Value Added (VA) model (Keane, Krutikova and Neal, 2022; Todd and Wolpin, 2003). We also show that the VA model estimates are robust to measures of children's exposure to school closures and their network's exposure to the COVID-19 virus we collected information about in our survey.

The second identification challenge arises if the measures of children's mental health contain measurement error. This is a concern because child mental health is difficult to measure. As in most of the related literature, we capture it through questions administered to the child's parent about the child's behaviour and emotions at the time of the interview. Additionally, we ask parents to respond to these questions with reference to the pre-COVID time (February 2020). We construct our benchmark measures of child mental health as the sum of the respondent's answers to these 13 questions in each time period. Even if measurement error was random, the inclusion of the pre-COVID measure on the right-hand side of our VA model could create another endogeneity bias in our parameter of interest. Furthermore, the reliance on self-reported measures and on recall measures creates the risk that the respondents' answers are affected by their experiences of the pandemic, which could then lead to the additional problem that measurement error in the dependent variable is non-classical.

To address these issues, we explicitly model the measurement error contained in parents' answers to the 13 questions about their child's mental health. Exploiting the fact that we have multiple measures of the same skill, we estimate a flexible linear latent factor model that allows for measurement error to be possibly correlated with disruptions to parental labour market circumstances (our treatment variable). This approach, which is the focus of Heckman et al. (2022), has been used in a number of papers evaluating the impact of interventions on child skills where the measurement may be affected by the intervention (Attanasio et al., 2020; Heckman, Pinto and Savelyev, 2013). In our context, we find that measurement error is unlikely to be a source of bias in our main estimates by showing that estimates based on the benchmark measure of child socio-emotional skill are very similar to those based on richer and more flexible measurement models allowing for non-classical measurement error.

Our first key finding is that changes in parental labour market circumstances over the course of the pandemic had a significant and negative impact on children's mental health. Conditional on pre-pandemic levels of mental health and socio-economic characteristics, children living with parent(s) who experienced one or more labour market status change, such as becoming unemployed, going on furlough, taking on a job, or some combination of these experienced a reduction in mental health of around 9% of a standard deviation relative to those whose parents' labour market status did not change. This is equivalent to around 30% of the total average decrease in mental health in our sample over the course of the pandemic.

Furthermore, we see important heterogeneity in this impact. While the wider literature tends to find that interventions aiming to boost child development have stronger effects on children from economically disadvantaged families (Duncan et al., 2022), we find that the negative effect of changes in parental labour market circumstances during COVID was significantly stronger for children from more economically advantaged families. In fact, we do not see a significant impact on children from less economically advantaged families. This finding is consistent with wider evidence that unemployment has more detrimental effects on the psychological well-being of those with less prior experience of it (Clark, 2001).

We explore the mechanisms underlying the impacts that we find. The granular data that we collect on labour market trajectories of parents over the course of the pandemic allow us to investigate whether there were particular types of changes that were especially detrimental to children. We create a typology of parental labour market experiences using sequence analysis, a machine learning method to cluster discrete longitudinal data, and study how being in families across the different clusters affects children's mental health. From this analysis we conclude that it was the *stability* of parental labour market circumstances that was most conducive to mental health of children during the pandemic rather than a particular state, such as being employed, unemployed, or on furlough.

Using measures on a wider set of household economic circumstances, parental expectations, and parental well-being, we show that, at least in part, the adverse impact of instability of parental labour market circumstances on children was driven by its impact on actual and expected earnings, as well as parental well-being. Descriptive mediation analysis suggests that these factors could mediate around 40% of the adverse impact.

Our paper contributes first and foremost to the literature looking at the impacts of parental labour market status on children's mental health. To date, most of the literature has focused on the impact of parental job loss on children's outcomes in adulthood (Huttunen and Riukula, 2019; Oreopoulos, Page and Stevens, 2008), school outcomes (Di Maio and Nistico, 2019; Hilger, 2016; Rege, Telle and Votruba, 2011), and physical health (Lindo, 2011; Liu and Zhao, 2014). To our knowledge, only a handful of papers focus on the impact of parental job transitions on children's mental health. Hill et al. (2011) and Johnson, Kalil and Dunifon (2012), for example, study this in US samples of low-income families in the 1990s. Our paper exploits the large variation in parental job transitions during the pandemic to assess the intergenerational consequences of job instability on children's mental health across the whole socio-economic distribution. Our findings of stronger impacts on children in the more economically advantaged group show that broadening focus to children outside the low-income group can yield important new insights.

Second, the paper speaks to the literature on the determinants of mental health and socio-emotional development in childhood and adolescence. Within this literature, several papers attempt to model the dynamic process of development in this domain using rich data on relevant inputs (Del Bono, Kinsler and Pavan, 2022; Moroni, Nicholetti and Tominey, 2019), emphasising the crucial role that parental mental health, parenting style and household routines play. Our results shed light on the detrimental effect that economic instability has on child mental health, including via some of these channels - parental well-being, for example. These results are particularly notable as the disruptions to parental labour market circumstances took place in a context of great instability but one where huge policy efforts went into designing an insurance system to protect family incomes from the pandemic induced economic volatility.

Finally, we also contribute to the literature studying the effect of COVID pandemic on children which has predominantly focused on children's cognitive skills and learning losses (Andrew et al., 2021; Grewenig et al., 2021). As flagged in a recent Lancet commentary, the study of the well-being effects of the pandemic is dominated by work looking at the effects on adult rather than children (Newlove-Delgado et al., 2021). A small number of recent papers broadly suggests that in several countries, including the UK, there was a worsening in children's emotional and behavioural difficulties over the course of the pandemic (Ezpeleta et al., 2020; Ford, John and Gunnell, 2021; Waite et al., 2021). The deterioration in children's socio-emotional well-being and mental health has been linked to school closures (Blanden et al., 2021; Gassman-Pines et al., 2022), as well as factors such as lack of contact with friends (Theberath et al., 2022) and lower quality parental time investments due to job loss (Hupkau et al., 2023). Our study provides new evidence on how COVID-induced changes in the labour market affected children's mental health.

The rest of this paper is organised as follows. Section 2 provides some background on the course of the pandemic and policy response to it in the UK. We then describe the data that we collected and use in this analysis in Section 3 and key measures - parental labour market experiences and children's mental health for the pre-COVID and COVID periods - in Section 4. Section 5 sets out our empirical methodology and our main results are presented in Section 6. We explore potential mechanisms in Section 7 and conclude in Section 8.

2 The COVID-19 pandemic in England

We start by providing some background on the experience of the COVID-19 pandemic in England. In common with many other countries, the UK government imposed severe restrictions on schools, businesses, and individuals to help control the spread of the COVID-19 virus. There were three national lockdowns in England, shown in grey in Figure 1. While each lockdown came with different rules, all involved the closure of many 'non-essential' businesses; stay-at-home orders making it an offence to leave home without an 'reasonable excuse'; and restrictions on social gatherings. The first and third lockdowns also involved school closures and a shift to home learning for the majority of pupils. And even outside of national lockdowns, the UK government imposed a variety of restrictions at a local level.

2.1 Economic impacts

National lockdowns, local restrictions and social distancing rules reshaped economic activity in the UK. With the introduction of the first national lockdown on March 23rd, 2020, entire sections of the economy were ordered to shut down to prevent the virus from spreading. As in many other countries, these included all non-food, non-pharmaceutical retail; hotels and restaurants; and arts and leisure services. Passenger transport was also greatly reduced due to stay-at-home orders that made it an offence to leave home without a 'reasonable excuse'. Overall, Google mobility data suggests that on-site working fell to about a third of its pre-pandemic level.

The furlough programme Despite the severe economic disruption resulting from business closures and stay-at-home orders, Figure 1 shows that redundancies during the first lockdown increased only slightly. Instead, employees were insured through a novel government 'furlough' programme. [1] Furloughed workers did not carry out work tasks, but they remained employed and continued to receive up to 80% of their regular wages, paid by the government. (Employers could, but were not required to, top up these furlough payments to increase the replacement rate further.)

The aim of the furlough programme was to make it costless to employers to keep on workers, even if government regulations or wider economic uncertainty meant that their business would otherwise not be able to support these jobs.[2] While it was initially intended as a short-term measure to insure households and to preserve worker-firm matches, as the pandemic continued both the generosity and the duration of the furlough scheme changed frequently, often with little notice. During autumn 2020, the government began to require employers to contribute towards

[1]Information relating to the furlough scheme comes primarily from the House of Commons Library Briefing Paper (Francis-Devine, Powell and Clark, 2021).

[2]Furlough was limited to employees. Self-employed workers instead received government help through the Self Employment Income Support Scheme (SEISS), which offered grants worth up to 80% of average trading profits.

the 80% replacement rate; the impact of rising employer contributions can be seen in Figure 1 as a drop in furloughed employments and a rise in redundancies in early autumn 2020. With the second national lockdown in November 2020, the government returned to covering the full 80% of wages.

Families and employers also faced considerable uncertainty about the duration of support through the furlough scheme. Initially, the programme was due to end on 1 June 2020. It was subsequently extended five times, in one case just one day before support was set to expire. These frequent and often last-minute extensions added to uncertainty about what support would be available, particularly as Figure 1 suggests that reductions in furloughed employments were often correlated with increases in redundancies.

2.2 School closures

In addition to shutting down large segments of the economy, to minimise the spread of the virus, the government also instructed all schools in England to close several times during the pandemic. The first period of school closure started on 23rd March 2020, with all but the most vulnerable children and those with 'key worker' parents required to learn at home. As Figure 1 shows, only around 2% of students attended school each day in April and May.

Over June/July 2020, the government ran a staggered re-opening of schools (starting with primary school children in 'priority' year groups), followed by a full return to school from September 2020. As COVID cases peaked again that winter, the government instructed another period of full school closures, between January 2021 and March 2021. All in all, some children in England lost out on 26 weeks of in-person instruction; those who were subject to local restrictions or frequent rounds of self-isolation spent substantially longer away from school.

3 Survey of parents with school-age children

This paper uses data from a bespoke online survey that we administered to 6,095 parents with children age 4-16 and living in England in February 2021. The survey (henceforth, Covid survey) was implemented at the tail end of England's third national lockdown and second national school closure, a time of substantial disruption for families. The survey aimed to capture the economic situation of families with children during the pandemic, how these families were adjusting to changes brought about by the pandemic, as well as their well-being. The responding parent was asked questions about themselves, their partner (if they had one) and their child. If families had more than one child in the 4-16 age range, one was selected at random as the focal child in the survey. In this paper we utilise data on parental labour market circumstances and expectations, parental well-being, and the mental health of their child. We describe these measures in detail in the next section.

The sample was stratified based on respondent gender, location, educational qualifications, employment and marital status. In order to further improve the national representativeness of our data, we constructed balancing weights using the Labour Force Survey (LFS), the UK's largest household study used for providing official figures on employment. Following the same procedure as that in Andrew et al. (2022), we selected a sub-sample of households in the LFS using similar criteria to our sampling framework and constructed the weights using parental education, pre-lockdown working status, income, industry and occupation, and region of residence.[3] In Table A1, we compare the means of the variables used to construct the weights in the unweighted and weighted COVID samples to the LFS sample. The comparison of means across all three columns indicates that the weights are successfully balancing the sample to look similar to the LFS across a range of characteristics.

Table 1 presents the (weighted) means and standard deviations of some basic characteristics of the sample that we use in our analysis. After removing observations with missing or unreliable information for key analysis variables this sample consists of 5,039 households.[4] Almost 70% of nuclear families have a female survey respondent. Families have between two and three children on average, and mothers and fathers are similar in terms of age and level education. The sample is balanced with respect to the gender of the randomly selected focal child. Average age of children in the sample is around 10 years.

[3]We provide further details about the weighting procedure in Appendix subsection A.1.

[4]We consider data unreliable when respondents gave the same answer to all questions about the child's socio-emotional well-being

4 Measurement of key variables

The key variables in our analysis are child mental health and parental labour market experiences. In this section we discuss how these are captured in the survey, present summary statistics for each, and describe how the data collected is used to construct the measures used in the analysis.

4.1 Child mental health

The key outcome in this paper is children's mental health during COVID. It was captured by asking the responding parent 13 questions about the focal child. Each question makes a statement about a particular emotional or behavioural difficulty (e.g. "is easily scared", "is constantly fidgeting or squirming", "is generally obedient") and asks the parent whether the statement is "not true", "somewhat true", or "certainly true" in relation to the child (see Appendix Table A.2 for the complete list of statements). For each question, the parent was asked to provide a response for two reference periods: "Now, Feb 2021" and "Before first lockdown, Feb 2020". These questions were based on a subset of statements relating to externalising and internalising behaviours comprising the Strengths and Difficulties Questionnaires (SDQ), a widely used and validated psychometric scale of children's mental health (Goodman and Goodman, 2009; Goodman, 1997). Externalizing behaviours refer to problems that occur in interaction with others - such as aggression, impulsivity and hyperactivity - while internalizing problems are focused on one-self, including, for example, anxiety, depression, emotional problems and withdrawal (Nikstat and Riemann, 2020).

In line with recommendations by the developers of the SDQ, our benchmark measure of mental health is constructed by summing up responses to the 13 questions (0 for "Certainly true", 1 for "Somewhat true", and 2 for "Not true"), so that the total score ranges from 0 to 26. We re-code responses so that a higher number always refers to a higher level of mental health. We construct a score for mental health during COVID by summing up responses for the "Now, Feb 2021" period and for the pre-COVID period by summing up responses for the period "Before first lockdown, Feb 2020". We discuss possible sources of measurement error in the way we are capturing children's mental health, how this scoring method handles these and present alternative scoring strategies in our empirical strategy section below (Section 5).

We selected a subset of questions rather than administering the full SDQ scale in order to reduce the length of the survey, thereby minimising respondent burden and preserving data quality. We selected the 13 questions using data collected in a survey conducted earlier in the pandemic on a similar sample of parents. In that survey we administered all 20 statements of the SDQ which capture externalising and internalising behaviours. We used that data to implement latent factor analysis and select items with a high signal-to-noise ratio (results available upon request).

Although we are drawing on a well-established and validated scale in this process, we still need to check the validity of the new 13 question scale that we construct. We do this in several steps in line with recommendations in the literature (Fernald et al., 2017). First, we analyse its internal consistency: the degree of inter-relatedness among the questions, which indicates whether the different questions map onto one or several summary scores. We estimate a Cronbach's Alpha of 0.83, which is above the threshold of 0.7 commonly used to indicate a satisfactory level of internal consistency. Furthermore, an exploratory factor analysis reveals that all but one question have high factor loadings (above 0.4, relative to the highest loading equal to 0.64) (see Table A3) and there is one eigenvalue above 1 (see Table A4). This gives us confidence that it is appropriate to aggregate the responses to the questions into a uni-dimensional latent score.

Next, we assess concurrent validity - the extent to which the scale correlates with a validated measure of children's mental health. Here we leverage the availability of another nationally representative data-set which contains measures of children's mental health. This is the ongoing UK Household Longitudinal Study called Understanding Society (USoc). [5] USoc collects mental health measures for primary school age children using the complete 20 question of the SDQ focusing on internalising and externalising behaviours.[6] We use the USoc data to construct a score based on all 20 questions of the SDQ and another score based on the 13 questions we administered in our survey. The correlation between the two is 0.963 suggesting a very close mapping between the validated longer scale and the our shortened version.

We also utilise the USoc data to assess the convergent validity of our scale i.e. whether it is associated with the factors that are expected to be related to it. We study associations with child gender, age, ethnicity, whether the child lives in a one or two-parent household, the mother's

[5] General information about this study can be found here: https://www.understandingsociety.ac.uk/.

[6] The SDQ also includes five more questions about prosocial behaviour. Given that our 13 item scale does not incorporate any items about prosocial behaviours, we compare it to the 20 questions of the SDQ focusing on internalising and externalising behaviours. Scores on these 20 items are often reported separately from the score on the prosocial behaviour items and referred to as a total difficulties score.

and father's highest educational qualification, household earnings, and parental well-being (see Table notes for details of measures used). We start by comparing associations between these characteristics and the 20 versus the 13 statement versions of the mental health score in USoc data. The results are presented in Table 3. Each row of the table shows a separate regression of the mental health score on the characteristic in that row. Columns 1 and 2 show that the pattern of associations between mental health and child characteristics is almost identical for the version of mental health score constructed using 20 statement and that using 13 statements in USoc. This is further evidence that the 13 statement scale is capturing the same or a closely related construct to the 20 statement validated SDQ scale.

Next we regress the 13 statement score from our survey on the same set of socio-economic characteristics as those we analysed in the USoc data (Table 3, Column 3).[7] Reassuringly there is strong correspondence between the pattern of results in our survey and USoc. As in USoc, we see a significant positive correlation between child mental health and being female, living in a better off family and with parents who have higher levels of well-being. Additionally, we see a positive significant correlation between child mental health and maternal education in our data which is not as pronounced in the USoc data. Finally, while in both the USoc and our data-sets the coefficient on living in a lone parent family is negative, it is only statistically significant in our data.

The high Cronbach's Alpha of our measure of child mental health, its strong correlation with a validated scale, and the similarity of association between our measure and other factors relative to a validated scale are all consistent with the validity of our outcome variable. As noted above, we also aimed to capture pre-COVID child mental health by asking parents to respond to the same set of 13 statements but in relation to February 2020. As explained in more detail in the next section, we use this recall measure in our analysis to address concerns about endogeneity. Concurrent and recall measures may behave differently so we conduct additional validity checks on the recall measure.

First, the Cronbach's Alpha for this measure is very similar to that for the concurrent one. Additionally, we are able to leverage the availability of an earlier round of USoc data from 2020 to compare correlations of our recall measure with child characteristics to a concurrent measure from the same pre-COVID period. Columns 4 and 5 show that the significant positive correlation

[7]The sample size is smaller because we restrict it to children age 5-11 to make it comparable to the USoc sample as during the COVID round of the USoc study mental health questions were only administered to this age-group.

between household income and maternal education is evident in both surveys also during the pre-COVID period. There are positive coefficients for parental well-being in both surveys, though only statistically significant for our measure. Finally, there is stronger evidence of a positive correlation with paternal education in both surveys for the pre-COVID period than we saw for the COVID period. Again, this analysis is consistent with the validity of our recall mental health measure.

A concern might be that parents answer the same thing for the current and recall questions. However, a correlation of 0.76 between the two scales suggests that this is not the case, as does a comparison of the two distributions shown in Figure 3(a) which plots the histogram of child mental health scores before lockdown in February 2020 and during lockdown in February 2021. The figure shows that children's mental health worsened over the COVID period with the distribution shifting to the left and an average decline in mental health of 0.30 SD. It is worth noting that in line with Guzman Holst et al. (2023), this average worsening masks an improvement for a non-negligible minority (15%) of children (Figure 3(b)).

4.2 Labour market experiences

We are interested in the impact of pandemic induced disruptions to parental employment and economic situation on child socio-emotional well-being. In order to capture the labour market experience of the parents in our sample over the first year of the pandemic, we collected detailed, monthly employment histories. Specifically, the survey asked the respondent to report, for themselves and for their partner (if any), whether they were working for pay full or part-time, on furlough, on paid or unpaid leave (not furlough), or had no job in each of the 13 months between February 2020 and February 2021.

This data allows us to visualise the trajectories of households through the first year of the pandemic. In each month between February 2020 and February 2021, we categorise households into one of four mutually exclusive states: both parents employed; one parental employed and one unemployed; both parents unemployed; at least one parent on furlough.[8] Using a different colour for each of these four states, Figure 2 shows the employment trajectories of all households in the sample across the 13 months stacked on top of each other. Each horizontal line represents the

[8]This way of defining states 'prioritises' putting households experiencing furlough into their own category; two-parent households in this group could have a second parent either employed or unemployed.

experience of a particular household between February 2020 and February 2021, where the colours correspond to the state that the household is in in each month.

There was substantial heterogeneity in labour market experiences of parents in our sample over the first year of the pandemic. Labour market trajectories over this period differed in both the range of states that households experienced (furlough, unemployment, employment) and the duration of each state. Table 2 presents descriptive statistics on each of these dimensions. Around a third of our sample saw at least one of the parent going on furlough while half experienced unemployment of at least one parent over this period. On average, households spent about half of the 13 months covered by our data with both parents employed, 13% with at least one parent on furlough and just under a fifth of the time with both parents unemployed. The bottom panel of Figure 2 shows the distribution of households in each category in each month. The proportion of households who experienced furlough increases and decreases during the first year of the pandemic, while the proportion of households experiencing some unemployment remains fairly constant during this period.[9] A defining feature of the pandemic is that households changed labour market status more frequently than they would have in normal times. While over half (46% weighted) of our sample experience at least one change over the COVID period, this was the case for only 12% of a comparable sample of parents in the Understanding Society data over the year preceding the pandemic. Interestingly, however, only 10% of households reported seeing their earnings fall during this period - attesting to the importance of furlough for buffering incomes in the face of such significant volatility.

The main "treatment" indicator in our analysis is whether the household experienced a change to their labour market status over the pandemic period. In studying potential mechanisms we then leverage the granularity of the data to construct measures of different types of trajectories families experienced. We discuss how we do this in Section 7.

[9]To check the reliability of this data we compare the proportion of individuals in our sample who report being on furlough in each month between February 2020 and February 2021 with official government data (from HM Revenue Customs) and show that our data align well with national records (see Figure C1 in the Appendix).

5 Empirical strategy

We now turn to our empirical strategy for identifying the causal impact of changes in parental labour market circumstances on children's mental health during the COVID pandemic.

Denote θ_{it} child i's mental health in period t measured by variable Y_{it}, and D_{it} a dummy for our main treatment variable - a measure of disruption to labour market circumstances during the pandemic. For simplicity, we assume that our treatment variable D_{it} is binary, but the same arguments would apply should the treatment be multi-valued, a refinement that we consider in our empirical results section.

In this paper, our aim is to identify the causal effect of D_{it} on θ_{it}, holding everything else constant. For child i, we define θ^1_{it} as the child's mental health if the household is in state $D_{it} = 1$ and θ^1_{it} as child's mental health if the household is in state $D_{it} = 0$. With this notation, we can define the individual treatment effect as $\theta^1_{it} - \theta^0_{it}$. As we never observe child i in both states, we cannot identify the individual treatment effect and therefore our discussion here focuses on the conditions under which we can identify the Average Treatment Effect (ATE) as the difference between the average (or conditional average) of child mental health in the households that experienced $D_{it} = 1$ and the average (or conditional average) of child mental health in the households that experienced $D_{it} = 0$. That is, we aim to explicitly lay out the conditions under which we can state that $E(\theta^1_{it}) = E(\theta_{it}|D_{it} = 1)$ and $E(\theta^0_{it}) = E(\theta_{it}|D_{it} = 0)$ so that

$$ATE = E(ATE_i) = E(\theta_{it}|D_{it} = 1) - E(\theta_{it}|D_{it} = 0)$$

There are two types of identification challenges to consider. The first one arises if there are omitted variables, while the second one arises if mental health is measured with error. We discuss each of these challenges and our proposed strategy to circumvent them in turn.

5.1 Omitted variables

Suppose we assume that θ_{it} is an additive separable function of the treatment and unobserved terms, μ_i and ρ_{it}, which capture time-invariant and time-varying unobserved determinants of child mental health at time t. We can write the following model for θ_{it}:

$$\theta_{it} = \beta D_{it} + \mu_i + \rho_{it} \tag{1}$$

Assuming (for now) that we have an error-free measure of child mental health θ_{it}, estimation of the ATE as the OLS estimate of β in the equation 1 would require that $E(\mu_i + \rho_{it}|D_{it}) = 0$. This is problematic because children whose parents had particularly types of labour market experienced during the pandemic are likely to have other characteristics that are correlated with their mental health. For example, children of parents who became redundant during the pandemic are likely to come from more deprived families (Blundell et al., 2022). These families may also experience other challenges, such as poor parental mental health or poor inter-parental relationships, which past studies have shown to be strongly associated with poor child mental health (e.g. Butikofer et al., 2023). If this is the case, the conditional orthogonality assumption underlying the identification of ATE as $\beta^{\hat{OLS}}$ in regression (1) would be violated.

To deal with this endogeneity issue, we propose to control for the child's lagged mental health measured for the pre-COVID period, which we refer to as $\theta_{i,t-1}$. We refer to this specification as Value-Added (VA) specification, which we write as:

$$\theta_{it} = \beta D_{it} + \gamma\theta_{i,t-1} + \epsilon_{it} \tag{2}$$

where ϵ_{it} is the error term. To the extent that $\theta_{i,t-1}$ is determined by the same time-invariant unobservables μ_i as those determining $\theta_{i,t}$, the inclusion of $\theta_{i,t-1}$ will control for this unobserved fixed endowment so it is more than likely that $E(\epsilon_{it}|D_{it}, \theta_{i,t-1}) = 0$ holds in the VA model.

However, $\theta_{i,t-1}$ will not capture any unobserved time-varying factors or shocks which might affect the child's mental health over the period between $t-1$ and t. This is problematic if these are correlated with D_{it} resulting in a correlation between D_{it} and ϵ_{it}. This is particularly concerning in the context of the COVID pandemic during which the labour market shock was accompanied by health and education shocks, both of which may have had independent impacts on children's mental health. Specifically, the risk is that β confounds the impact of disruptions to parental labour market circumstances with the impact of these additional shocks if they are correlated with D_{it}.

This could happen, for example, if households which experienced more disruption to their labour market circumstances were also more vulnerable to catching COVID and/or if their children's schools were more likely to close or provide worse support during periods of closures.

To address this issue, we estimate an augmented VA model, which we refer to as VA+, in which we control for a set of additional co-variates pertaining to characteristics of the child and their family. That is, we estimate:

$$Y_{it} = \beta D_{it} + \gamma Y_{i,t-1} + X'\delta_i + \epsilon_{it} \tag{3}$$

Importantly, the vector X_i includes pre-COVID characteristics of the family, including the family's income, parental education, as well as three variables which measure what are thought to be three important inputs for child mental health: a measures of parental mental health, parenting practices and inter-parental conflict, all measured for the February 2020 (pre-COVID) period (see Section 7 for a discussion of these measures). Furthermore, we exploit additional data collected as part of the same survey, about the household's exposure to the COVID virus and about actions taken by the child's school during periods of closures, to construct additional controls for exposure to shocks over the pandemic period and test robustness of our findings to the inclusion of these.

5.2 Measurement error

The discussion so far has assumed that we have access to an error-free measure of child mental health. Child mental health is inherently difficult to measure however, and it is important to consider the implications of measurement error in θ_{it} for our estimates of the treatment parameter β. As discussed in Section 3 above, we do not have a single measure of child mental health, but rather follow the standard approach in the literature (also recommended by the SDQ developers) of summing up responses to multiple questions asking about emotional and behavioural difficulties to create a measure of children's underlying mental health. We denote Y_{it} and $Y_{i,t-1}$, the sum of responses to the 13 questions about child emotional and behavioural difficulties in periods t and $t-1$, i.e. as recalled in February 2020 and in February 2021 respectively.

These measures likely capture θ_{it} and $\theta_{i,t-1}$ with some error, which we refer to as υ_{it} and $\upsilon_{i,t-1}$.

Assuming additive separability in measurement error so that $Y_{it} = \theta_{it} + \upsilon_{it}$, model VA+ becomes:

$$Y_{it} = \beta D_{it} + \gamma Y_{i,t-1} + X'\delta_i + \epsilon_{it} + \upsilon_{it} - \gamma \upsilon_{it-1} \tag{4}$$

We first consider the case where measurement error is classical. Measurement error in Y_{it} does not introduce bias, but the inclusion of $Y_{i,t-1}$ on the right hand side of the equation in the VA and VA+ models creates an endogeneity issue. This is because $Y_{i,t-1}$ is, by definition, correlated with $\upsilon_{i,t-1}$ unless the degree of serial correlation in measurement error is exactly equal to the persistence in child mental health measured by γ (in which case $\upsilon_{it} = \gamma\upsilon_{it}$)). This endogeneity issue implies that the OLS estimate of γ is biased in model (4). And because D_{it} is likely to be correlated with $Y_{i,t-1}$, the OLS estimate of β is also biased.

If measurement error is i.i.d, the estimate of γ will be downward biased given the necessarily positive correlation between the lagged score measure $Y_{i,t-1}$ and its measurement error. However, in our case, measurement error is likely to be serially correlated given that both sets of questions are administered to the same respondent during the same interview. In this case, the endogeneity bias will arise not only because $E(\upsilon_{it-1}|D_{it}, Y_{i,t-1})$ but also because $E(\upsilon_{it}|D_{it}, Y_{i,t-1})$ (unless υ_{it} and $\gamma\upsilon_{i,t-1}$ exactly cancel each other out).

In order to tackle the issues arising from classical measurement error, we propose to introduce some structure on the underlying measurement error model and to exploit the fact that we have several items in our instrument for child mental health to purge our underlying measures of mental health at t and $t-1$ from measurement error. Specifically, we assume that the measurement error model is a linear latent factor model, whereby each of the 13 statements is related to underlying mental health θ_t in the following way:

$$M_{i,j,t} = \alpha_j + \lambda_j \theta_{i,t} + \xi_{i,j,t} \tag{5}$$

where all notations is similar as above where the parameter α_j is referred to as an intercept and λ_j as a factor loading. $\xi_{j,t}$ is the measurement error contained in $M_{i,j,t}$.

The scoring procedure whereby the aggregate score is obtained by summing up the 13 items correspond to a measurement model where all factor loadings are imposed to equal to each other.

Following standard identification results for latent factor models, it is, however, possible to relax the assumption of equal factor loadings and identify non-parametricallly the distribution of $\theta_{i,t}$ under a location and scale normalisation and as long as have at least three measures of $\theta_{i,t}$ (which is the case, since $J = 13$). As is standard in the literature, we normalise the location of the factor by assuming $E(\theta_0) = 0$ and by normalising one factor loading, say λ_1, to 1. We estimate the factor model above and use the regression method to predict a factor score $s_{i,t}$ as an estimate of the error-free latent factor $\theta_{i,t}$ for each child. Incorporating this measurement model in the analysis, our VA+ model becomes model VA+/ME:

$$s_{it} = \beta D_{it} + \gamma s_{i,t-1} + X'\delta_i + \upsilon_{it} \tag{6}$$

where we have replaced Y_{it} and $Y_{i,t-1}$ by the factor scores s_{it} and $s_{i,t-1}$, which measures error-free child mental health $\theta_{i,t}$ and $\theta_{i,t-1}$ under the measurement model (5). [10]

Consider next the case where measurement error in Y_{it} is non-classical and correlated with the treatment variable D_{it}. This is a particular concern in our context as our measure of child mental health is reported by the respondent, and this report may be affected by the respondent's experience of the pandemic (and the emotional consequences it will have had on them). This in turn would create a correlation between υ_{it} and D_{it}, which would violate the assumptions under which an OLS estimate of β is the ATE in the model in equation 3. Del Bono, Kinsler and Pavan (2022), for example, shows that measures of children's socio-emotional and behavioural problems tend to be affected by the respondent's (generally a parent or a teacher) characteristics and traits.

The inclusion of $Y_{i,t-1}$ on the right hand side in the VA and VA+ model would only solve this issue insofar as the degree of serial correlation is exactly equal to γ. Under any other scenario, the inclusion of $Y_{i,t-1}$ would likely exacerbate measurement error biases as the variance of the error would likely increase as a result.

We address this possibility by building a rich measurement model, which allows parents with different values of T_{it} to report their child mental health in different ways. Consider the most flexible version of the measurement error above where we now allow all parameters to depend on

[10] As mentioned above, T_{it}, the sum of respondent responses across our instrument items, is the score that one would estimate under a strong version of the measurement system above, where all factor loadings are imposed to be equal to each other.

the realised value d of treatment D_{it}:

$$M^d_{i,j,t} = \alpha^d_j + \lambda^d_j \theta_{i,t} + \xi^d_{i,j,t} \tag{7}$$

By allowing intercepts to depend on d, the model depicted in (7) allows an intercept-shift between respondents with different values of treatment. This intercept-shift would allow us to capture, for example, the possibility that respondents who experienced some change to their labour market conditions during the pandemic systematically see their child's behaviour as worse than it. In addition to an intercept-shift, the measurement model above also allows factor loadings to depend on d, hence allowing such misreporting to vary with the level of child mental health. This nuance could be important because there may be more scope of misreporting child mental health when children have worse behaviours or display more negative emotions than when children do not display much difficulty. Finally, the model also allows the variance of measurement error $xi^d_{i,j,t}$ to vary between respondents with different values of treatment.

While the model above is identified within each group, the distribution of latent factor $\theta_{i,t}$ that would be identified may not necessarily be comparable since the two measurement error models are identified under different scale and location normalisations. And this would be problematic since our estimate of the ATE relies on comparing conditional means between the two groups. This issue, which is referred to in the psychometrics literature as measurement invariance, is discussed at length in Heckman et al. (2022).

For the two distributions to be comparable, the measurement models models need to share at least one intercept and one factor loading so that they have equal location and scale. This condition is not a given, and must be tested following procedures outlined in the psychometrics literature. Our data is consistent with a form of measurement invariance that is sufficient for identifying distributions of latent skill that can be compared to each other. We estimate this model and predict factor scores as estimates of $\theta_{i,t}$ and $\theta_{i,t-1}$, which we denote $\tilde{s}_{i,t}$ and $\tilde{s}_{i,t-1}$. In our robustness section, we show the estimates of our VA+ model using these factors scores. We refer to this model as model VA+/ME+, specified as follows:

$$\tilde{s}_{i,t} = \beta D_{it} + \gamma \tilde{s}_{i,t-1} + X'\delta_i + \upsilon_{it} \tag{8}$$

As we discuss in the next section, the estimates of β are not only very robust across the VA and VA+ models, but also across models VA+/ME and VA+/ME+. We take this as strong evidence that we are dealing with those major sources of potential bias in our estimates of the ATE of interest.

6 Impact of changes in parental labour market circumstances on child mental health

6.1 Benchmark results

We start our analysis by estimating the relationship between change to parental labour market circumstances over the pandemic and children's mental health in February 2021. We define children as having experienced change in parental labour market circumstances if in February 2021 the responding parent reports any changes relative to the pre-pandemic labour market status of either parent (see Section 3 for description of this variable). The results are presented in Table 4. Column 1 shows our most "naive" estimates - that is a specification which includes only the "any change" indicator and controls for basic demographic characteristics of the child including child age and gender, as well as parental ethnicity, age, education, pre-COVID earnings per equivalent household member, number of children in the household and lone parent status. Columns 2-4 then show results of our Value Added approach (see discussion in Section 5) where we include controls for lagged (pre-COVID) mental health. Column (4) shows results for our preferred augmented Value Added specification (VA+) which, additionally, includes controls for parental pre-COVID labour market status, well-being and family processes.[11] Finally, in Column 5 we show the results if we use a factor score rather than a raw score - that is for each child in the sample, we use the estimates of the measurement systems described in equation (5) as the measure of mental health and estimate the VA+/ME model described in Section 5.

Column 1 shows that children whose parents had experienced changes in labour market circumstances, on average, had nearly a fifth of a standard deviation (SD) worse mental health skills in February 2021 than children with similar demographic characteristics but who did not experience such changes. Adding a control for pre-pandemic mental health in Column 2 shows that some of

[11] See table notes for details on these variables

these differences pre-date the pandemic. However, even among children with similar demographic characteristics, who entered the pandemic with similar levels of mental health, we see that change in parental labour market circumstances resulted in a mental healthdeterioration of around 0.08SD. An overall effect size of 0.08 of a standard deviation is non-negligible. It is equivalent to just under 30% of the total average decrease in the mental health of children in our sample over the COVID period.

Adding controls for parental pre-COVID labour market characteristics in Column 3 (including dummies for parental occupation and controls for tele-workability of those occupations), as well as controls for parental well-being in Column 4 (parental well-being, inter-parental relation shop and parenting quality) [12], we see a slight increase in the coefficient to 0.09 in our preferred specification (Column 4). Furthermore, we see that the inclusion of additional controls beyond lagged child mental health does not affect the estimates of coefficient on the lagged mental health. We take this as evidence strongly suggesting that the lagged measures is effective at capturing relevant unobservables (i.e. unobservables correlated with disruption to the household's labour market circumstances). Finally, column 5 shows that we find very similar size effects using a factor score rather than raw score for mental health, which suggests that our benchmark estimates of the impact of changes to parental labour market circumstances on child mental health are unlikely to be biased due to classical measurement error. We return to the issue of measurement error in Section 6.2.

The last two columns of Table 4 further suggest that the effect of change in parental labour market circumstances reflects similar size impacts across the two key sub-domains of mental health that are captured by our measure - externalizing and internalizing behavioural problems - rather than a large impact in one specific area. We see significant negative effects of change in parental labour market experience on both of these domains (which are coded in reverse so that a higher score indicates fewer problems). While the coefficient on any change is greater in the externalizing rather than the internalizing behaviors specification, the difference between the coefficients is not statistically significant.

[12] We explain how these are measured in the next section.

6.2 Validity of identification strategy

Before turning to considering what might be driving the impacts that we find, we examine the robustness of our identification strategy in several ways.

6.2.1 Scoring

First we return to the issue of how we construct our main outcome - the mental health measure. It is reassuring that the main estimates remain very similar when we use a measure of mental health scored according to guidance by test publishes and one scored using a measurement model (see results in Table 4). We now explore whether the estimates are sensitive to the assumption that measurement error is non-classical. In particular, we consider the case where measurement error in Y_{it} is correlated with the treatment variable D_{it}. This is a particular concern in our context where child mental health is reported by the respondent, and this report may be affected by the respondent's experience of the pandemic. If the 13 mental health questions relate to mental health differently depending on treatment status then there would be a correlation between υ_{it} and D_{it}, which would violate the assumptions under which an OLS estimate of β is the ATE in the model in equation 3.

As explained in Section 5, we propose to address this possibility by estimating a measurement model which allows for the possibility that parents with different values of T_{it} reported on their child mental health differently. We estimate this measurement model and use the factor score that we predict for the pre-COVID period and for the COVID period as lagged outcome and as outcome, respectively. Column (2) of Table 5 reports the estimates of this model. The estimated impact of change in parental labour market status is just under 10% of a standard deviation, which is very similar to our benchmark estimate of 0.09 SD, suggesting that this estimate is unlikely to be biased due to this type of non-classical measurement error.[13]

[13] The assumption of measurement invariance is also relevant when comparing the distributions of mental health over time, as we do in Section 4. In order for this comparison to be valid, we must assume that the way respondents' answers to the 13 questions relate to the underlying construct that the questions aim to measure does not vary between periods. An obvious reason why this may not be the case is because one set of questions is based on recall from a year ago, while another set of questions refers to the current period. We test whether the measurement system for the two time periods are invariant between the time periods and find that a weak form of partial invariance can be obtained though only one item has equal intercept and factor loading in both groups. As with the main measure, we see the distribution of child mental health scored using a measurement model which allows for reporting to differ between the two time-periods shifting to the left, thus indicating a deterioration. However, on average, according to this measure, child mental health worsened by 0.15 SD, a smaller change than the one estimated with the measure

Another possibility is that while the 13 questions relate to the underlying construct in the same way when reported by those affected by labour market changes and those not affected, those in the former group perceive their children to have systematically worse mental health than those in the latter group. If this were the case our OLS estimates of β would just be picking up impacts on perceived but not actual mental health. In order to investigate this we leverage the feature that we construct the labour market change variable using reports by the respondent regarding their own labour market experience as well as that of their partner. We can, therefore, check whether there is s systematic difference in reported child mental health between children where the responding parent is also the one affected by labour market changes and those where it is the partner of the responding parent who is affected. If experiencing labour market changes has a negative impact on parents' perception of child mental health we would expect a significant negative association between an indicator of responding parent being the one affected by labour market changes and child mental health. Appendix Table C8 shows that this is not the case. Column 2 shows that these is no significant impact of responding parent being the one experiencing change in labour market circumstances on child mental health in the sub-sample of 1,128 children who had only one parent experience such a change. Furthermore, results in Column 3 show that, in fact, in two parent families, the adverse impact of changes in parental labour market circumstance is driven by families in which *both* parents were affected. Having either the responding parent or their partner affected on their own does not have a significant impact on the child's mental health.

6.2.2 Omitted Variables

A key threat to our findings is that the VA model does not adequately control for relevant unobserved inputs, shocks, and household and child characteristics so that our main estimates suffer from endogeneity bias. For example, a concern may be that the "any change" variable is picking up the effects of a COVID related health or school closure shocks. To the extent that these shocks affect children's mental health and are correlated with parents' labour market experiences, they may bias our estimates of the impact of the latter on the former.

To assess the extent to which these other shocks influence our results, we construct measures

which assumes strong measurement invariance. Therefore, while we can be relatively confident that the distribution of children's mental health worsened on average, our estimates of the exact magnitude of the average change should be treated with caution.

of children's exposure to school closures and of their network's exposure to the COVID-19 virus. For school closures, we use measures (collected from our survey) of whether the child attended school in person in Summer 2020 (May-July) and in Winter 2021. To capture any effects of in-person schooling on the intensive margin, we use the number of (parent-reported) weekly hours of in-person schooling that children were receiving in Winter 2021, at the time of our survey (and during the second period of national school closures).

To measure health shocks, we use three questions from our survey, capturing how often children were absent from school in Autumn 2020 due to (i) their own case of (known or suspected) COVID-19; (ii) a classmate or schoolmate's case of COVID; and (iii) a case of COVID among their household or non-school contacts.

We incorporate these measures of school closures and health impacts as controls in our main specification, presenting the results in columns (3) and (4) of Table 5. Our results are highly robust to these additional control variables, suggesting that differential exposure to the virus is not driving our conclusions. (We also show a range of additional results, with alternative measures of health and schooling shocks, in Appendix Tables C6 and C5.)

7 Mechanisms

Why did changes in parental labour market circumstances over the COVID period have such a pronounced impact on children's mental health? In this section we explore potential mechanisms using more granular data on how parental labour market circumstances changed over the COVID period, as well as on a wider set of household circumstances and expectations. We start by trying to pin down the specific features of changes in parental labour market circumstances that affected children's mental health.

7.1 Distinguishing between different types of of labour market disruptions

The results presented so far compare households which experienced *some* change to parental labour market circumstances to those who experienced *no* change. The latter group is comprised of households in which parents were employed at the start of the pandemic as well as those in which parents were unemployed. It may well be that despite experiencing no change during the pandemic, the children of those two groups fared differently. We start by checking whether this is the case. To this end we re-estimate our main model, but with an additional indicator for households which experienced no change but had at least one parent unemployed at the start of the pandemic. In this model, the "any change" coefficient is now to be interpreted relative to households with all parents continuously employed between February 2020 and February 2021. The results presented in Appendix Table C2 show that children whose parents experienced no disruption to their labour market circumstances fared similarly, whether their parents were employed or unemployed prior to the pandemic (as evidenced by the insignificant coefficient on the "No change" and "at least one parent unemployed" indicators) . This is in line with our focus on the effects of disruption to parental labour market circumstances rather than a particular labour market state.

Building on this evidence, we next utilise the rich information we have on labour market trajectories of the parents (see Section 4 for details) to create a typology of labour market experiences using sequence analysis - a machine learning procedure - which clusters observations based on their similarity in terms of discrete time series data (in our case, households' monthly histories of labour market status between February 2020 and February 2021). This method consists of two steps. First, we use an algorithm to calculate the distance or dissimilarity between the trajectory of any pair of households in the sample. Second, using this dissimilarity matrix, we cluster household labour market trajectories using a non-hierarchical clustering algorithm (in our case, the Ward method). We present greater details about these steps in Appendix Section B.

Importantly, because we are interested in characterising the heterogeneity in those households that experienced some disruption to their pre-COVID labour market circumstances, we only apply this algorithm to the sub-sample that experienced some change. To facilitate interpretation of these results, we split the group that experienced no change into the group of households in which parents stayed employed throughout the pandemic and that in which parents stayed unemployed throughout the pandemic; we refer to these as Cluster 1 and Cluster 2 respectively.[14]

Figure 5 displays the full set of labour market trajectories from Figure 2, now grouped into six clusters (the four clusters determined by the clustering algorithm, and the two pre-defined Clusters 1 and 2 discussed above). The first and second (pre-defined) clusters include households that have

[14]Note that Cluster 2 contains two groups of families: those with both parents unemployed throughout and those where one parent was unemployed while the other was employed throughout. Below we show that our main findings are robust to splitting Cluster 2 into two separate clusters for the two types of families.

experienced no change to their labour market circumstances during the period. Clusters 3 and 4 are characterised by frequent spells of unemployment; in Cluster 3 this is the case for both of the parents most of the time, while in Cluster 4 this is the case for one of the parents, while the other is employed. In both clusters there is some churn with periods of frequent transitions between different states. Cluster 5 is defined by the sustained periods of furlough, with short spells of both parents being in employment. Finally, the households in Cluster 6 experienced prolonged periods of employment punctuated by shorter periods of furlough. We provide summary statistics on the characteristics and COVID experiences of households in each of these clusters in Appendix Tables C3 and C4.

We now examine whether the impact of any change in labour market circumstances that we find in our main analysis differs across the different *types* of changes in parental labour market circumstances captured by the clusters. To this end we repeat the main analysis presented in Table 4, but replacing the binary indicator for whether any change occured with indicators for the cluster that the child is in. The omitted category for the clusters is Cluster 1, which includes children with both parents (or the single parent in single-parent families) employed throughout the study period. The results are presented in Table 6.

Findings in the first column suggest that children of parents who were employed throughout the period were significantly better off than children of parents with any other labour market trajectory. However, this is not the case when we look at *change* in mental health over the COVID period. Controlling for pre-COVID mental health shows that being in Clusters 2 and 3 was *not* more detrimental to children's mental health over the COVID period than being in Cluster 1. That is, having experienced no change in parental employment status even if that means having both or one parent unemployed over the whole period, or having parents who spent a large proportion of the COVID period unemployed (Cluster 3), was not more detrimental for mental health than having parents employed the whole time for children who entered the COVID period with the same level of mental health.

This is not the case for the children in the remaining three clusters. The significant negative coefficients for these clusters in Columns (2)-(6) of Table 6 suggest that, even conditional on having the same level of mental health before the onset of the pandemic, these children suffered significantly worse adverse consequences of the employment situation of their parents during the COVID period for their mental health. Estimates using our preferred specification, which contains the most complete set of controls, are presented in Column 4. Being in Clusters 4-6 compared to Cluster 1 has an impact of around a 10% of an SD reduction in mental health.

As discussed above, Clusters 4-6 are characterised by more disrupted parental employment trajectories than Clusters 1 and 2. However, the type of disruption differs. The similarity across these clusters is that each contains a "dominant" state but, unlike in Clusters 1 and 2, this state is interrupted from time to time with alternative states. What the dominant state is differs across Clusters 4-6 in ways that we may, a-priori, think would affect children differently. For example, having at least one parent furloughed versus both parents employed. In spite of this, our estimates suggest that, in fact, being in Clusters 4, 5 and 6 had a very similar impact - the three coefficients are similar in magnitude (at around 0.1SD) and not statistically different from each other.

One interpretation of the similarity of impacts across Clusters 4, 5, and 6, as well as the significant difference in the way that living in Cluster 1 and 2 families affected children compared to living in Clusters 4-6 families is that what was conducive to child mental health during the pandemic was the stability of parental labour market circumstances rather than a particular state, such as being employed or unemployed. This is consistent with the lack of difference between Clusters 1 and 2 which contain families with very different circumstances but united in the complete stability in these.

7.2 Quality of the home environment

We continue our analysis of the mechanisms through which disruptions to parental labour market circumstances affected children's mental health by asking how changes in parental labour market circumstances affected dimensions of children's home life that are important for their mental health? Children's development is impacted by the direct material and time investments of parents, as well as the broader home environment (Attanasio et al., 2020). We, therefore, consider how instability in parental labour market circumstances may have impacted the quality of each of these inputs.

We do not have direct measures of inputs or the broader home environment but we do have measures which may be reasonable proxies of these. Our data captures changes in parental earnings over the COVID period, as well as expectations regarding future earnings. These may directly impact the material investments in children but also, potentially, indirectly affect the quality of the time that parents spend with their children through any impacts this has on parental well-being. We have several further measures which may proxy for the quality of the time that parents spend with their children. The first of these is a direct measure of parenting quality (see Appendix Section A for a description of the measure), as reported by the responding parent for the "current" and pre-COVID period. However, since measurement of parenting quality is notoriously challenging without the use of sophisticated direct observation methods (Smith, 2011), we also included measures of parental well-being, which has been shown to significantly influence quality of parental time investments (Newland (2015), Ramchandani et al. (2008)). Specifically, we include measures of own well-being using the Short Warwick Edinburgh Mental Wellbeing Scale (SWEMWBS) and three questions from the General Anxiety Disorder (GAD) scale and, for two-parent households, quality of relationship with partner using a subset of the Dyadic Adjustment Scale (see Appendix Section A for details). For both of these, we asked respondents to report in reference to the present time and February 2020, just before the start of the pandemic.

We start by showing that in our data the associations between these measures and children's mental health are consistent with the proposition that they capture variation in dimensions of the home-environment that impact children's mental health. Table 8 reports results of regressing our measure of children's mental health on each of these proxies for the quality of the home environment and investment in the child, alongside the full set of controls that are included in our preferred specification in Column 4 of the benchmark results in Table 4. We include each indicator individually and then all simultaneously. In order to look at the association with change in earnings flexibly, we include separate dummies for whether earnings fell or increased over this period.

We see that, relative to no change in earnings, a decrease in earnings is associated with a deterioration in mental and there is no significant association with an earnings increase. Next we look at earnings expectations - again by including dummies for whether the respondent reports an expectation that earnings will increase or decrease in the next 6 months. The results suggest that there is a negative association between expectations of earnings change and children's mental health. However, the negative association with expected *decreases* in earnings is larger and more statistically significant than that with increases in earnings. The remaining three columns in the table show that, in our sample, children's mental health is significantly and positively associated with parental well-being, quality of the relationship of the responding parent and their partner, as well as our measure of parenting quality. Column (6) shows that most of these significant associations persist once we include all of the indicators that are available for all families in one model (i.e.excluding parent relationship quality which is only available for couples). The exception to that is parenting quality.[15]

Having established the relevance of our measures of potential mechanisms for children's mental health, we now explore whether whether they are associated with changes in parental labour market status over COVID - our "treatment". Table 8 shows that this is the case for all of the earnings-related variables. Experiencing changes in labour market status is positively associated with both actual and expected decreases in earnings. This experience is also negatively associated with parental well-being but it is not correlated with our measures of quality of parenting and of the relationship between the partners.

To sum up, our analysis of potential mechanisms suggests that at least in part changes in parental labour market circumstances over the COVID period impacted children's mental health through their impact on actual and expected earnings, as well as parental well-being. Table 9 presents mediation analysis implemented using this set of mediators. It shows that the impact of changes in parental labour market circumstances decreases by 44% from over 9% SD to 5% SD when we add the mediators and that this reduction is effect size is statistically significant. It is important to note, however, that this analysis should not be interpreted causally. While it is illustrative of possible mechanisms underlying the main effects that we identify, we would need to tackle likely endogeneity of the mediators in order to draw more firm conclusions from it.

7.3 Heterogeneity Analysis

Before concluding, in Table 10 we check whether we can detect any significant heterogeneity in the main impacts and mechanisms. We start by looking at differences in the impact of any change in parental labour market circumstances by gender, parental earnings pre-COVID, baseline level of child mental health, and whether children are living in a one or two parent household.

We find little evidence of differences in impact sizes for most of these groups. Columns 1 and 2 in Table 10 show that effects are very similar for boys and girls. We also find similar effects when

[15] In the final column (7), where we only look at couples in order to include the control for parent relationship, expectation of a decrease in future earnings also loses significance, though the coefficient size goes down only slightly.

we split the sample by whether children's pre-covid mental health was above or below the median. Finally, while effects appear to be larger for children living in lone parent families compared to those living in two-parent families, the difference between the coefficients is not statistically significant.

The result that stands out in this analysis is the significant difference in impacts on children from families with above median pre-COVID earnings compared to those from families with below median pre-COVID earnings (Table 10, Columns 3 and 4). We capture pre-COVID earnings using the main respondent's recall of what these were. We see that parental labour market changes had *no* significant impact on children from families with below median household income. However, there is a pronounced and statistically significant impact of 13% SD on children from above median income households, which is significantly different from the null effect on the more disadvantaged children.

This pattern aligns closely with heterogeneity in the effect of change in parental labour market situation on the key mediators identified above - actual or expected fall in earnings and reduction in parental well-being. Appendix Table C7 shows that the negative impacts of labour market disruptions on reported earnings and parental well-being were significantly stronger for families with above median pre-COVID incomes.

While it has been repeatedly found that children from more disadvantaged households are more susceptible to shocks to their home environment (see the review in Duncan et al. (2022)), our results are consistent with evidence that adverse psychological well-being effects of labour market disruptions are lower for those who have experienced more unemployment in the past (Clark, 2001). There is ample evidence that lower income families face greater job insecurity. In USoc data, we can see that lower income families were more likely to have experienced labour market changes over the year before COVID. On average, therefore, the COVID induced labour market disruptions are likely to have been a more alien experience for higher compared to lower income families, with the latter group being more psychologically resilient in light of past experience.

8 Conclusion

The COVID-19 pandemic disrupted children and families' lives in a myriad of ways that could have affected children's mental health. But while much of the focus post-pandemic has been on children's academic skills and how best to support children to catch up on 'lost learning', the impacts on children's mental health and wider wellbeing have received much less attention.

While some children saw their mental health improve over the first year of the pandemic, many more had the opposite experience. In line with emerging findings from other studies (e.g. Guzman Holst et al., 2023), we estimate that nearly half of children had a lower level of mental health in February 2021 than they had had a year earlier. School closures, health shocks, the loss of time socialising with friends and extended family, and high levels of uncertainty are all likely to have played a role in this.

In this paper, we show the important role that parents' labour market experiences played in determining children's mental health during the pandemic. Our results suggest that, at least during the pandemic, transitions and instability in parents' labour market experiences mattered for children's mental health, regardless of what states the transitions were from and to.

The intergenerational effects of economic instability we document in this report are particularly notable as they happened in a context where huge efforts were made to absorb a large component of the economic uncertainty created by the pandemic through the furlough scheme. Indeed, the policy offered workers much higher levels of financial insurance and support than would typically be available through the UK's system of out-of-work benefits. While furloughed workers received up to 80% of their typical earnings, a single parent with two children would lose half of their net household income if they lost their job; a couple each earning the average wage would lose 40% of household income if one parent lost their job.

While much of the research and debate around out-of-work benefits has focused on the generosity of this 'replacement rate', our results suggest that policymakers should also consider the role played by economic instability and uncertainty. Over and above actual earnings losses, both the expectation of future earnings loss and lower parental wellbeing were associated with larger falls in mental health during the pandemic. This suggests that periods of significant economic turbulence, as well as policies that inadvertently raise uncertainty and/or stress for parents can have high human capital and well-being costs not only on the directly affected adults but also on their children.

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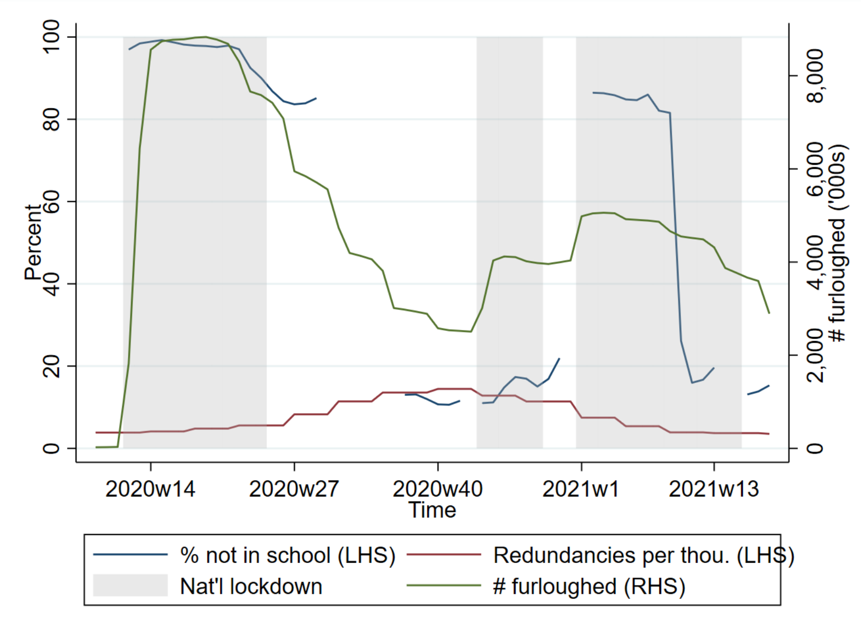
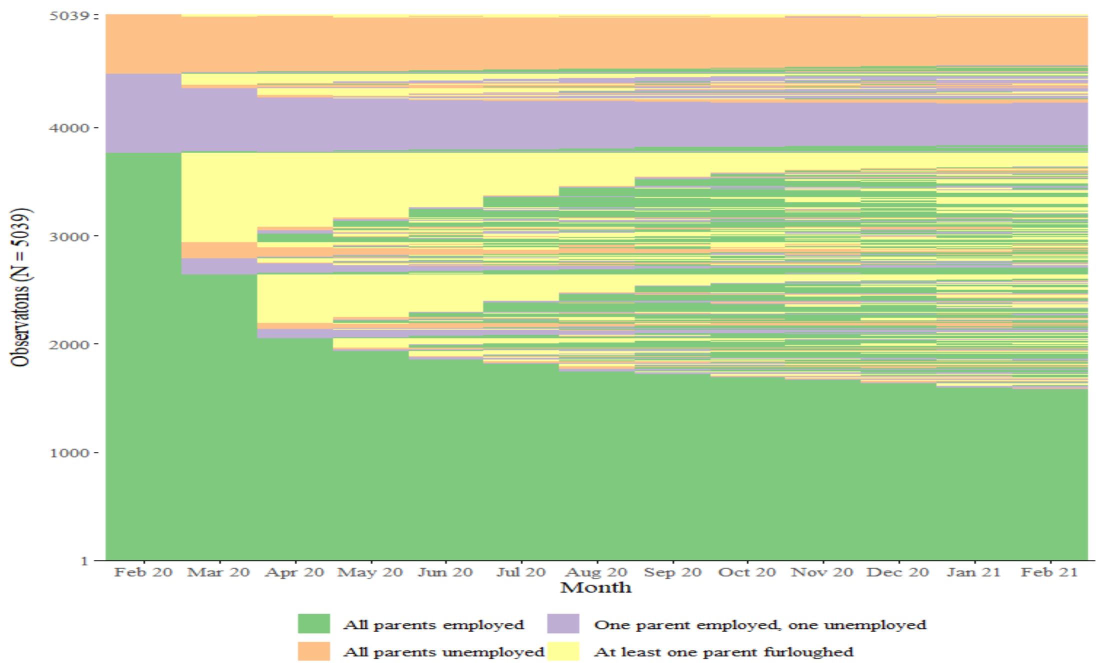
Figure 1: Timeline of COVID-19 pandemic in England



Note: Series for not in school is shown during term-time only. Source: Information on school attendance comes from Department for Education statistics. Furlough data comes from HMRC statistics. Data on redundancies come from the Office for National Statistics.

Figure 2: Household labour market trajectories between February 2020 and February 2021

(a) Household trajectories, stacked by initial state in February 2020



(b) Monthly distribution of households in each four states

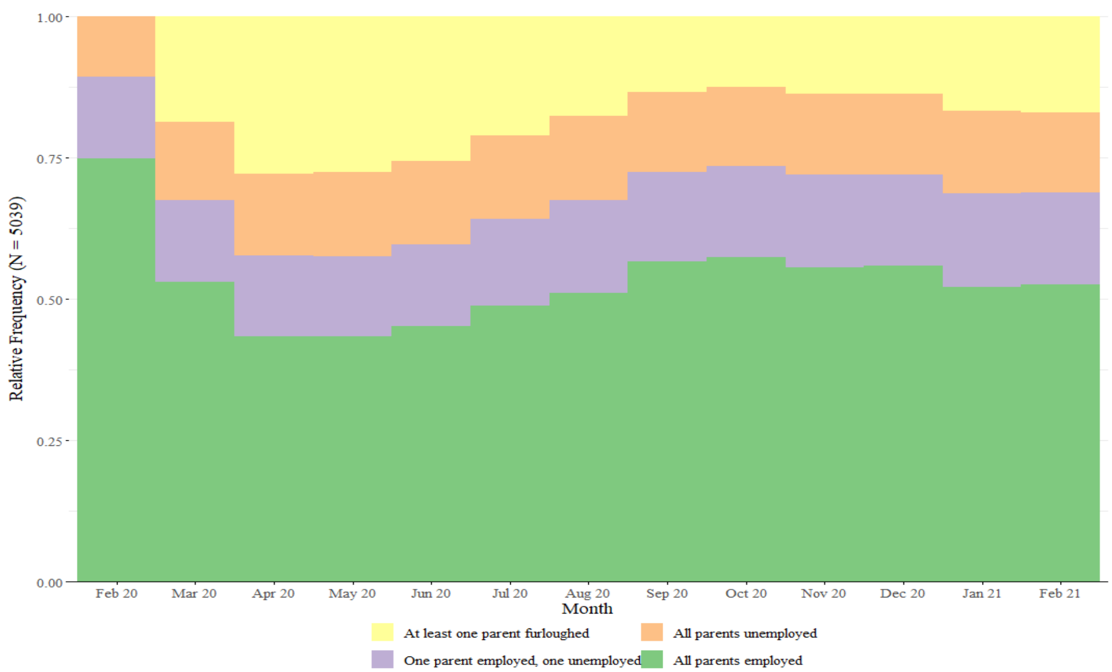
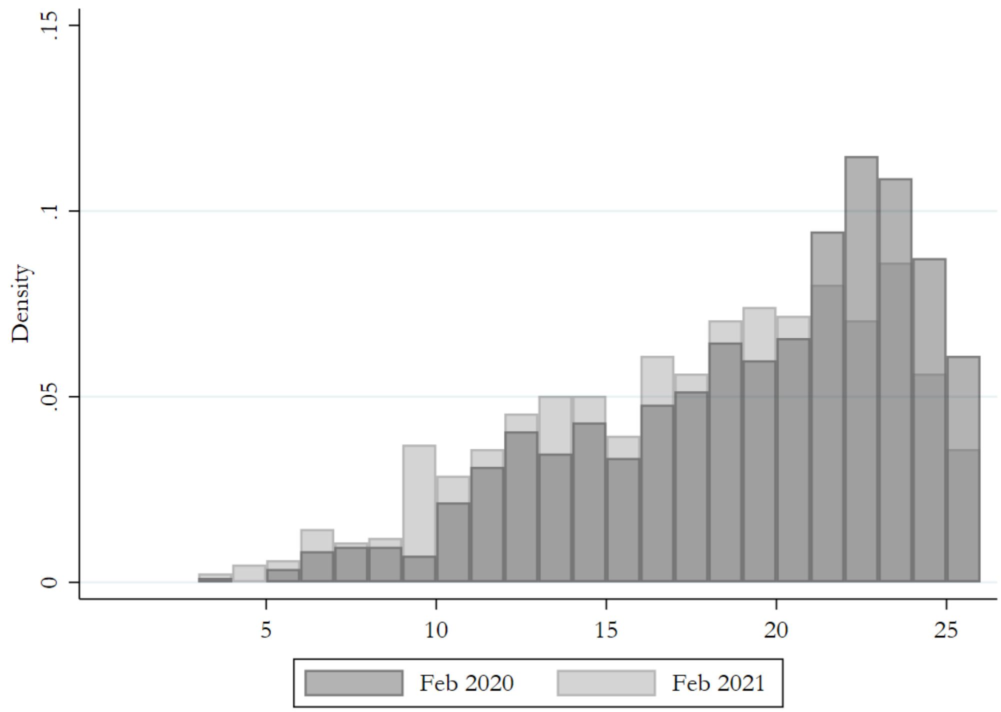


Figure 3: Change in child mental health during the first year of the pandemic

(a) Change in distributions



(b) Individual changes

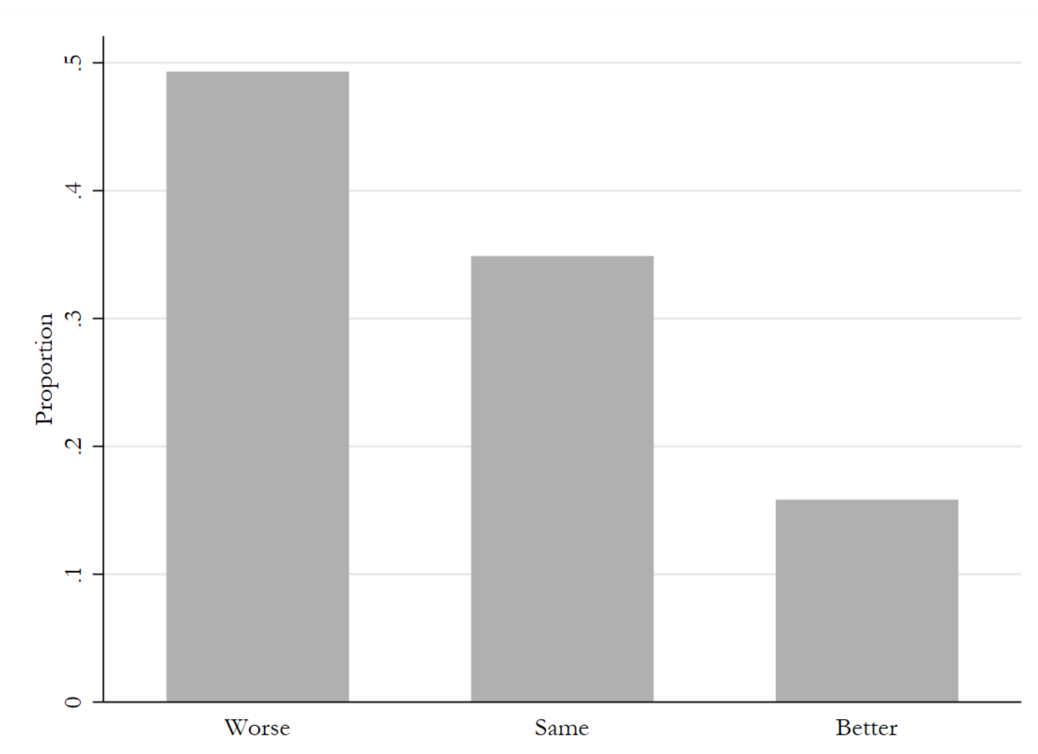


Figure 4: Distribution of mental health in Feb 2020 and Feb 2021, using a latent factor approach

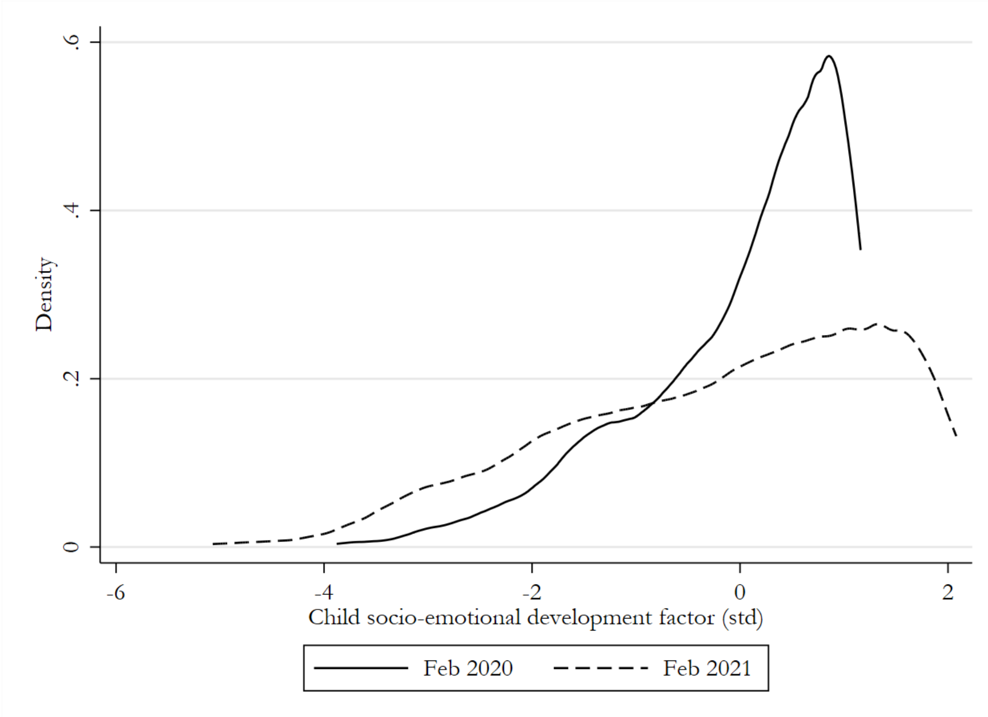


Figure 5: Typology of household labour market trajectories

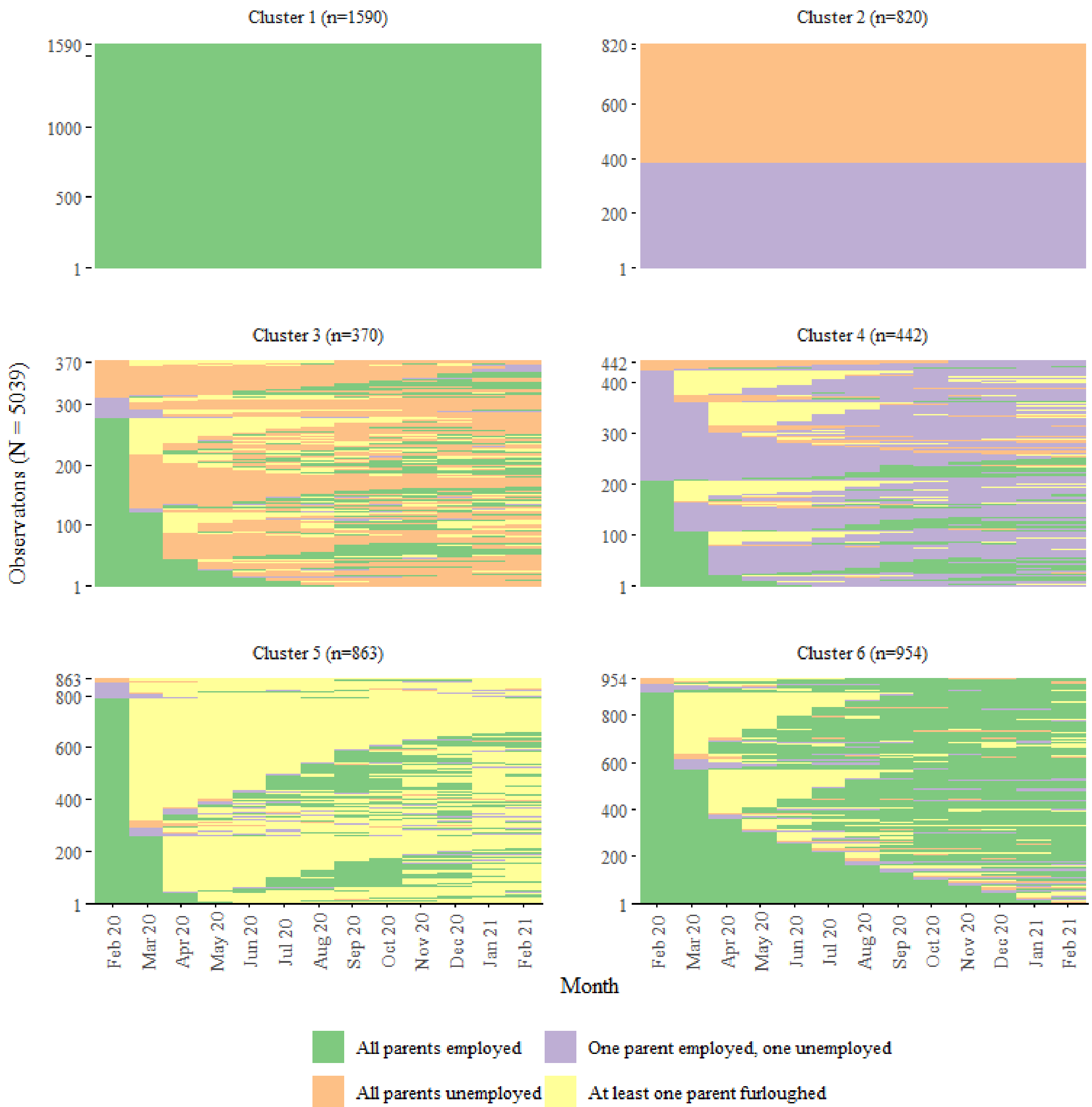


Table 1: Summary Statistics for the Whole Sample - Characteristics

	Mean	SD
Household Characteristics		
Two Parents	0.69	
Single Mother	0.29	
Single Father	0.02	
Number of Children	2.56	(1.06)
Father's Age	37.33	(8.93)
Mother's Age	37.31	(8.93)
Not White	0.17	
Father has Degree	0.37	
Mother has Degree	0.37	
Live in London	0.12	
Earnings (Equivalised)	1252.55	(1024.26)
Randomly Selected Child Characteristics		
Female	0.52	
Age	9.69	(3.52)
Mental Health 2020	0.03	(0.98)
Mental Health 2021	-0.27	(1.07)
Sample Size	5039	

Table 2: Summary Statistics for the Whole Sample - Labur Market Experiences

	Mean	SD
Parental Labour Market Experiences Feb 2020 - Feb 2021		
Any Change in Labout Market Experience	0.46	
Number of Transitions (both parents)	1.58	(2.57)
Either parent experienced furlough	0.33	
Either parent experienced unemployment	0.52	
Months both parents employed	6.57	(5.49)
Months both parents unemployed	2.39	(4.64)
Months one parent employed, one unemployed	2.25	(4.31)
Months at least one parent furloughed	1.79	(3.15)
Earnings of either parent fell	10.48	
Earnings of either parent increased	10.43	
Sample Size	5039	

Table 3: Concurrent validity of measure of child mental health in IFS Covid Survey

	(1)	(2)	(3)	(4)	(5)
		During Covid		Pre-Covid	
	USOC 20	USOC 13	IFS	USOC 13	IFS
Child is Female	0.025*	0.029*	0.174***	0.188*	0.064
	(0.015)	(0.017)	(0.052)	(0.097)	(0.093)
Child's Age	-0.005*	-0.005	0.012	0.027	-0.076
	(0.003)	(0.004)	(0.013)	(0.098)	(0.090)
Non-white Respondent	0.042*	0.044*	0.112*	0.102	0.070
	(0.022)	(0.024)	(0.065)	(0.142)	(0.121)
Lone Parent Family	-0.037	-0.040	-0.149***	-0.127	-0.164
	(0.024)	(0.028)	(0.055)	(0.136)	(0.100)
Second Tercile of Earnings	0.029	0.025	-0.052	0.111	0.087
	(0.018)	(0.021)	(0.061)	(0.131)	(0.113)
Thid Tercile of Earnings	0.044**	0.043*	0.149**	0.377***	0.265**
	(0.019)	(0.023)	(0.060)	(0.117)	(0.108)
Parent Wellbeing	0.042***	0.048***	0.175***	0.080	0.184***
	(0.007)	(0.009)	(0.028)	(0.073)	(0.052)
Maternal education = 2, A-level	0.001	0.004	0.052	0.096	0.219*
	(0.023)	(0.026)	(0.063)	(0.196)	(0.118)
Maternal education = 3, Higher	0.022	0.016	0.108*	0.232*	0.204*
	(0.019)	(0.023)	(0.061)	(0.119)	(0.114)
Paternal education = 2, A-level	0.050	0.054	-0.005	-0.062	0.254**
	(0.035)	(0.038)	(0.076)	(0.290)	(0.115)
Paternal education = 3, Higher	0.030	0.027	0.077	0.510***	-0.006
	(0.024)	(0.027)	(0.067)	(0.128)	(0.124)
Observations	851	851	2,842	765	847

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Sample sizes differ according to who the SDQ questions were asked of in Understanding Society. In the COVID waves children aged 11-15 were asked, whilst pre-COVID only children aged 5 and 8 were asked. This means that the Child's Age coefficient in the table above relates to a continous variable for during COVID and a dummy variable for columns (4) and (5).

Table 4: Impact of disruption to parental labour market circumstances during COVID on child mental health

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Raw Score				Internalising	Externalising
Any Change	-0.189***	-0.076***	-0.089***	-0.088***	-0.087***	-0.059**	-0.087***
	(0.037)	(0.025)	(0.027)	(0.027)	(0.025)	(0.030)	(0.025)
Baseline Outcome		0.816***	0.812***	0.812***	0.778***	0.756***	0.841***
		(0.014)	(0.014)	(0.015)	(0.014)	(0.016)	(0.013)
(5) vs (6)						0.277	
Observations				5,039			
R-squared	0.051	0.582	0.589	0.590	0.611	0.497	0.650
Pre-COVID child and family characteristics	X	X	X	X	X	X	X
Pre-COVID labour market characteristics			X	X	X	X	X
Pre-COVID parental wellbeing and family processes				X	X	X	X

Notes:OLS regression estimates for a standardised count measuring child socio-emotional development in February 2021 on an indicator for whether the household experienced any disruption to their labour market circumstances of February 2020 during the first year of the pandemic. All models control for a set of demographic characteristics, which includes child gender, child age and age squared, parent ethnicity, parent age and age squared, respondent gender, family structure (e.g. lone parent status and number of children), parental education level, pre-Covid earnings per equivalent household member, and region of residence. Column 2 includes a standardised count measuring socio-emotional development in February 2020. Column 3 adds controls for characteristics of parents' labour market circumstances before COVID, which include dummies for parental occupation and controls for the teleworkability of that occupation. Column 4 includes three variables measuring family processes in February 2020: well-being, quality of inter-parental relationship, and parenting quality. The inter-parental relationship variable is only relevant for two-parent household, so it is imputed to an arbitrary value for one-parent household and interacted with an indicator for two-parent household. In Columns 5 and 6, the same model is estimated, this time with a measures of internalising and externalising behaviours as outcomes respectively. Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Robustness checks: Measurement error and correlated shocks

	(1) Benchmark	(2) VA + / ME+	(3) Health shocks	(4) In-person School
Any Change	-0.088***	-0.096***	-0.087***	-0.086***
	(0.027)	(0.026)	(0.027)	(0.027)
Lagged outcome	0.812***	0.755***	0.814***	0.816***
	(0.015)	(0.016)	(0.015)	(0.015)
Observations		5,039		
R-squared	0.590	0.555	0.591	0.590

Note: The Raw Total outcome is the total of all mental health questions, standardised relative to pre-COVID variable. Column (1) shows estimates from the benchmark model for which estimates are reported in Table 4. Column (2) corresponds to the augmented VA model where there dependent variable and the lagged outcome are measured by a factor score estimated from a linear latent factor model where some parameters are allowed to differ between those who experienced some changes to pre-COVID labour market status and those who did not. The factor scores are standardised to have mean 0 and sd 1 in each period. Column(3) returns to the benchmark model and adds controls for measures of COVID-19 exposure, as measured by absences due to the child's own COVID case, a COVID case in the classroom, or a case among other household contacts (see Table C5 for full set of estimates). All models include the same controls as those included in the benchmark model (see notes to Table 4 for full list). Robust standard errors in parentheses; *** p$\leq 0.01, **p \leq 0.05, *p \leq 0.1$

Table 6: OLS Regression Results for Child Mental Health

	(1)	(2)	(3)	(4)
Reference Category = No Changes Employed				
Group 2 - No Changes Unemployed	-0.105*	-0.034	-0.024	-0.026
	(0.058)	(0.037)	(0.060)	(0.059)
Group 3 - Chaotic Unemployment (both parents)	-0.273***	-0.053	-0.055	-0.052
	(0.081)	(0.060)	(0.062)	(0.062)
Group 4 - Chaotic Unemployment (one parent)	-0.243***	-0.108**	-0.112**	-0.114**
	(0.071)	(0.049)	(0.052)	(0.052)
Group 5 - Sustained Furlough	-0.302***	-0.121***	-0.117***	-0.117***
	(0.063)	(0.043)	(0.043)	(0.043)
Group 6 - Short Furlough	-0.163***	-0.074**	-0.089**	-0.088**
	(0.054)	(0.036)	(0.036)	(0.036)
Baseline Outcome		0.815***	0.812***	0.812***
		(0.014)	(0.014)	(0.015)
Observations			5,039	
R-squared	0.053	0.582	0.589	0.590
Pre-COVID child and family characteristics	X	X	X	X
Pre-COVID labour market characteristics			X	X
Pre-COVID parental wellbeing and family				X

Notes: OLS regression estimates where the dependent variable is a standardised count measuring child mental health in February 2021 on a series of indicators for household labour market trajectories between February 2020 and February 2021. Explanatory variables include indicators for households being in one of the five clusters described in subsection 7.1. All models control for a set of demographic characteristics, which includes child gender, child age and age squared, parent ethnicity, parent age and age squared, respondent gender, family structure (e.g. lone parent status and number of children), parental education level, pre-covid earnings per equivalent household member, and region of residence. Column 2 includes a standardised count measuring socio-emotional development in February 2020. Column 3 adds controls for characteristics of parents' labour market circumstances before COVID, which include dummies for parental occupation and controls for the teleworkability of that occupation. Column 4 includes three variables measuring family processes in February 2020: well-being, quality of inter-parental relationship, and parenting quality. The inter-parental relationship variable is only relevant for two-parent household, so it is imputed to an arbitrary value for one-parent household and interacted with an indicator for two-parent household. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: OLS Regression Results for Child Mental Health on the Home Environment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Child Mental Health			
Earnings Fell	-0.096***					-0.065*	-0.106***
	(0.033)					(0.034)	(0.039)
Earnings Increased	-0.015					-0.015	-0.006
	(0.038)					(0.038)	(0.041)
Expects to Earn Less in 6 Months		-0.157***				-0.076*	-0.065
		(0.040)				(0.042)	(0.050)
Expects to Earn More in 6 Months		-0.051*				-0.044	-0.039
		(0.029)				(0.030)	(0.035)
Parent Well-being			0.194***			0.184***	0.147***
			(0.015)			(0.015)	(0.019)
Parenting Quality				0.073***		0.033	0.025
				(0.028)		(0.029)	(0.033)
Parent Relationship					0.181***		0.111***
					(0.028)		(0.028)
Baseline Outcome	0.804***	0.816***	0.802***	0.813***	0.824***	0.791***	0.814***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.017)	(0.015)	(0.018)
Observations	4,734	4,865	5,039	5,039	3,618	4,579	3,355
R-squared	0.587	0.592	0.615	0.590	0.613	0.615	0.627
Pre-COVID child and family characteristics	X	X	X	X	X	X	X
Pre-COVID labour market characteristics	X	X	X	X	X	X	X
Pre-COVID parental well-being and family	X	X	X	X	X	X	X

Notes: OLS regression estimates of a standardised count measuring child mental health in February 2021 on a range of variables relating to the home environment. These include whether earnings fell or increased between February 2020 and February 2021 or whether they increased over the same period, each relative to whether they stayed the same; expectations of earnings in the future - i.e. whether household members expect to be earning more or less relative to earnings expected to remain the same; and three family well being and process measures, relating to February 2021, which include respondent well-being quality of inter-parental relationship, and parenting quality. The inter-parental relationship variable is only relevant for two-parent household, so it is imputed to an arbitrary value for one-parent household and interacted with an indicator for two-parent household. All models control for a set of demographic characteristics, which includes child gender, child age and age squared, parent ethnicity, parent age and age squared, respondent gender, family structure (e.g. lone parent status and number of children), parental education level, pre-covid earnings per equivalent household member, and region of residence. Each model also controls for a standardised count measuring mental health in February 2020; characteristics of parents' labour market circumstances before COVID, which include dummies for parental occupation and controls for the teleworkability of that occupation; and also the three variables measuring family processes, but relating to February 2020, rather than February 2021. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8: OLS Regressions of Home Environment on Changes in Labour Market Experiences

	(1) Earnings Fell	(2) Expect to Earn Less	(3) Well-being	(4) Parenting Quality	(5) Parent Relationship
Any Change	0.291***	0.082***	-0.103***	-0.009	-0.011
	(0.015)	(0.013)	(0.035)	(0.022)	(0.031)
Observations	4,734	4,865	5,039	5,039	3,618
R-squared	0.214	0.061	0.209	0.642	0.599
Pre-COVID child and family characteristics	X	X	X	X	X
Pre-COVID socio-emotional development	X	X	X	X	X
Pre-COVID labour market characteristics	X	X	X	X	X
Pre-COVID parental wellbeing and family	X	X	X	X	X

Notes: OLS regression estimates where outcomes are aspects of the home environment, regressed on a binary indicator that equals 1 if there has been any change in parental labour market circumstances and 0 if no change. The home environment outcomes are whether earnings fell or increased between February 2020 and February 2021 or whether they increased over the same period, each relative to whether they stayed the same; expecations of earnings in the future - i.e. whether household members expect to be earning more or less relative to earnings expected to remain the same; and three family well being and process measures, relating to February 2021, which include respondent wellbeing quality of inter-parental relationship, and parenting quality. All models control for a set of demographic characteristics, which includes child gender, child age and age squared, parent ethnicity, parent age and age squared, respondent gender, family structure (e.g. lone parent status and number of children), parental education level, pre-covid earnings per equivalent household member, and region of residence. Each model also controls for a standardised count measuring socio-emotional development in February 2020; characteristics of parents' labour market circumstances before COVID, which include dummies for parental occupation and controls for the teleworkability of that occupation; and three variables measuring family processes in February 2020, which include respondent wellbeing quality of inter-parental relationship, and parenting quality. The inter-parental relationship variable is only relevant for two-parent household, so it is imputed to an arbitrary value for one-parent household and interacted with an indicator for two-parent household. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 9: Mediation Effect of the Home Environment

	(1)	(2)
	Child Mental Health	
Any Change	-0.088***	-0.053*
	(0.027)	(0.028)
Earnings Fell		-0.032
		(0.032)
Expect to Earn Less		-0.096**
		(0.040)
Parent Well-being		0.189***
		(0.015)
Baseline Outcome	0.812***	0.799***
	(0.015)	(0.015)
Test (1) vs (3)		0.003
Observations	5,039	5,039
R-squared	0.590	0.617
Pre-COVID child and family characteristics	X	X
Pre-COVID labour market characteristics	X	X
Pre-COVID parental wellbeing and family	X	X

Notes: OLS regression estimates of a standardised count measuring child mental health in February 2021 on a binary indicator for whether the household experience changes in labour market status over the first year of the pandemic as well as a range of variables relating to the home environment. These include whether earnings fell or increased between February 2020 and February 2021 or whether they increased over the same period, each relative to whether they stayed the same; expectations of earnings in the future - i.e. whether household members expect to be earning more or less relative to earnings expected to remain the same; and three family well being and process measures, relating to February 2021, which include respondent wellbeing quality of inter-parental relationship, and parenting quality. The inter-parental relationship variable is only relevant for two-parent household, so it is imputed to an arbitrary value for one-parent household and interacted with an indicator for two-parent household. All models control for a set of demographic characteristics, which includes child gender, child age and age squared, parent ethnicity, parent age and age squared, respondent gender, family structure (e.g. lone parent status and number of children), parental education level, pre-covid earnings per equivalent household member, and region of residence. Each model also controls for a standardised count measuring mental health in February 2020, characteristics of parents' labour market circumstances before COVID, which include dummies for parental occupation and controls for the teleworkability of that occupation; and also the three variables measuring family processes, but relating to February 2020, rather tha February 2021. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 10: OLS Regressions Examining Heterogeneity in Effects on Mental Health

	(1) Male	(2) Female	(3) Below Median Pre COVID Earnings	(4) Above Median Pre COVID Earnings	(5) Below Median Pre Covid Development	(6) Above Median Pre COVID Development	(7) Coupled Parents	(8) Lone Parent
Any Change	-0.091**	-0.082**	-0.035	-0.134***	-0.082*	-0.105***	-0.079**	-0.142***
	(0.042)	(0.039)	(0.044)	(0.036)	(0.045)	(0.034)	(0.032)	(0.055)
Baseline Outcome	0.828***	0.809***	0.771***	0.849***	0.676***	0.908***	0.821***	0.799***
	(0.021)	(0.023)	(0.022)	(0.019)	(0.030)	(0.048)	(0.017)	(0.028)
P-value	0.878		0.068		0.667		0.336	
Observations	2,270	2,270	2,355	2,684	2,263	2,776	3,618	1,421
R-squared	0.619	0.594	0.597	0.607	0.364	0.265	0.601	0.590
Pre-COVID child and family characteristics	X	X	X	X	X	X	X	X
Pre-COVID labour market characteristics	X	X	X	X	X	X	X	X
Pre-COVID parental well-being and family	X	X	X	X	X	X	X	X

Notes: OLS regression estimates of a standardised count measuring child mental health in February 2021 on a binary indicator that equals 1 if there has been any change in parental labour market circumstances and 0 if no change. All models control for a set of demographic characteristics, which includes child gender, child age and age squared, parent ethnicity, parent age and age squared, respondent gender, family structure (e.g. lone parent status and number of children), parental education level, pre-covid earnings per equivalent household member, and region of residence. Each model also controls for a standardised count measuring mental health in February 2020, characteristics of parents' labour market circumstances before COVID, which include dummies for parental occupation and controls for the teleworkability of that occupation. The first 6 models also include three variables measuring family processes in February 2020, which include respondent wellbeing quality of inter-parental relationship, and parenting quality. The inter-parental relationship variable is only relevant for two-parent household, so it is imputed to an arbitrary value for one-parent household and interacted with an indicator for two-parent household. Models 7 and 8 exclude this final variable. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

A Data Appendix

A.1 Survey weights and representativeness

To make our samples as representative as possible, we first imposed a series of quotas based on the characteristics of the respondent. Our aim was to use these quotas to ensure a broadly representative mix of parents.

To probe the effectiveness of this, we compared our unweighted samples and the nationally representative 2019 Labour Force Survey (LFS). From the LFS, we constructed a subsample roughly equivalent to the population targeted by our surveys: households with at least one child between the ages of 3 and 15. We then compared the extent to which our survey sample differed from the LFS across a range of key characteristics, such as respondent earnings, education and family structure. Columns (1) and (3) of Table A1 show these comparisons.

To further improve the representativeness of our data, we re-weighted our sample to achieve a closer match to the distribution of characteristics observed in the LFS. In particular, we reweighted on: family structure, parents' education, parents' pre-COVID earnings, geographic region, whether parents worked in industries likely to be locked down, and whether they worked in occupations amenable to home working.[1] The second column of Table A1 shows that, after the reweighting, the characteristics of our sample look very similar to the nationally representative LFS sample.

[1]The sample sizes of the LFS and our own survey, while large, are not large enough to allow us to re-weight on individual industries or occupations without over-fitting the data. We therefore focus on these broad characteristics of parents' jobs, in order to approximate how they might have been affected during the pandemic.

Table A1: Comparison of means of variables used in the creation of sampling weights in Labour Force Survey, unweighted and weighted COVID survey sample

	(1) Covid Survey Unweighted	(2) Covid Survey Weighted	(3) Labour Force Survey
Family Structure			
Single Mother	0.215	0.282	0.222
Single Father	0.062	0.021	0.017
Couple	0.723	0.697	0.761
Father's Education			
GCSE or Less	0.324	0.392	0.416
A Levels	0.256	0.232	0.229
University Degree	0.420	0.376	0.354
Mother's Education			
GCSE or Less	0.317	0.371	0.367
A Levels	0.269	0.254	0.249
University Degree	0.415	0.374	0.384
Single Mother's Education			
GCSE or Less	0.416	0.495	0.495
A Levels	0.281	0.271	0.272
University Degree	0.303	0.234	0.233
Pre-crisis Employment			
Mothers	0.800	0.735	0.745
Fathers	0.914	0.909	0.935
Single Mothers	0.764	0.671	0.678
Father's Pre-crisis Earnings (monthly)			
<£1000 per month	0.308	0.166	0.150
£1000 - £2500 per month	0.489	0.478	0.449
£2500 - £3500 per month	0.115	0.195	0.219
£3500	0.089	0.161	0.182
Mother's Pre-crisis Earning (monthly)			
<£1000 per month	0.551	0.532	0.542
£1000 - £2500 per month	0.362	0.351	0.353
£2500	0.087	0.116	0.105
Working in an industry more than 50% locked down			
Fathers	0.363	0.293	0.264
Mothers	0.340	0.260	0.231
Working in occupation where 0-15% of workers report being able to work from home			
Fathers	0.389	0.376	0.362
Mothers	0.354	0.351	0.327
Single Mothers	0.363	0.405	0.392
Working in occupation where 15.1-75% of workers report being able to work from home			
Fathers	0.269	0.210	0.192
Mothers	0.231	0.222	0.237
Single Mothers	0.247	0.275	0.300
Working in occupation where 75.1-100% of workers report being able to work from home			
Fathers	0.343	0.414	0.445
Mothers	0.414	0.427	0.436
Single Mothers	0.390	0.320	0.309
Region of Residence			
Greater London	0.159	0.122	0.118
South East	0.158	0.215	0.235
South West	0.105	0.102	0.097
West Midlands	0.118	0.104	0.107
North West	0.146	0.140	0.136
North East	0.069	0.068	0.061
Yorkshire & Humber	0.081	0.104	0.113
East Midlands	0.077	0.093	0.092
East of England	0.086	0.053	0.041

A.2 Measures of child mental health

Figure A1: Screenshot of questions about child socio-emotional development in the COVID survey

Q42 Please state how true each statement is of ${Q19/ChoiceTextEntryValue/5} as best you can even if you are not absolutely certain or the item seems daft.

	Now, Feb 2021			**Before first lockdown**, Feb 2020		
	Not true (1)	Somewhat True (2)	Certainly true (3)	Not true (1)	Somewhat True (2)	Certainly true (3)
${Q19/ChoiceTextEntryValue/5} has many fears, is easily scared (1)						
${Q19/ChoiceTextEntryValue/5} is constantly fidgeting or squirming (2)						
${Q19/ChoiceTextEntryValue/5} is restless, overactive, cannot stay still for long (3)						
${Q19/ChoiceTextEntryValue/5} is easily distracted, concentration wanders (4)						
${Q19/ChoiceTextEntryValue/5} is generally liked by other children (6)						
${Q19/ChoiceTextEntryValue/5} is nervous or clingy in new situations, easily loses confidence (8)						

Page Break

Table A2: Child Mental Health Questions

Question	Sub-domain	
Often lies or cheats.	Conduct	Externalising
Often fights with other children or bullies them.	Conduct	
Often has temper tamtrums or hot tempers.	Conduct	
Is generally obedient, usually does what an adult requests.	Conduct	
Steals from home, school, or elsewhere.	Conduct	
Is constantly fidgeting or squirming.	Hyperactivity	
Is restless, overactive, cannot stay still for long.	Hyperactivity	
Is easily distracted/concentration wanders.	Hyperactivity	
Has many worries/often seems worried.	Emotional	Internalising
Has many fears/is easily scared.	Emotional	
Is nervous or clingy in new situations, easily loses confidence.	Emotional	
Often unhappy, downhearted or tearful.	Emotional	
.	Peers	

Note: Questions are scored from 0 to 2 at point of collection, before being recoded so that a higher score is better for each question.

Table A3: Exploratory factor analysis of child mental health measures: Factor loadings and Uniquenesses

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Often unhappy, downhearted or tearful	0.5887	0.1627	-0.1921	0.0899	-0.0695	0.5771
Often fights or bullies other children	0.6304	0.3409	0.0897	-0.0689	-0.0044	0.4735
Often has temper tantrums or hot tempers	0.5923	-0.0079	0.0702	0.0475	-0.0845	0.6347
Is generally disobedient	0.0593	0.1202	0.2521	0.2518	0.0245	0.8545
Has many worries/often seems worried	0.5519	0.0306	-0.2823	0.0756	-0.0455	0.607
Often lies or cheats	0.6401	0.2982	0.0985	-0.1192	0.0214	0.477
Steals from home, school, or elsewhere	0.6086	0.4024	0.0527	-0.1434	0.0461	0.4421
Has many fears/is easily scared	0.5416	-0.1312	-0.2713	0.0559	0.0611	0.609
Is constantly fidgeting or squirming	0.6086	-0.3837	0.1616	0.0068	0.0153	0.456
Is restless, overactive, cannot stay still for long	0.5655	-0.386	0.234	-0.0507	-0.0158	0.4736
Is easily distracted/concentration wanders	0.5065	-0.4026	0.0989	-0.0157	-0.001	0.5714
Is generally disliked by other children	0.1868	0.272	0.1566	0.2395	0.0312	0.8082
Is nervous or clingy in new situations	0.4634	-0.1941	-0.2211	0.0578	0.0795	0.689

Table A4: Exploratory factor analysis of child mental health measures: Eigenvalues

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.67296	2.67674	0.8539	0.8539
Factor2	0.99622	0.55294	0.2316	1.0855
Factor3	0.44328	0.2576	0.1031	1.1885
Factor4	0.18569	0.15693	0.0432	1.2317
Factor5	0.02876	0.05854	0.0067	1.2384
Factor6	-0.02978	0.04034	-0.0069	1.2315
Factor7	-0.07013	0.03256	-0.0163	1.2152
Factor8	-0.10269	0.03548	-0.0239	1.1913
Factor9	-0.13817	0.00669	-0.0321	1.1592
Factor10	-0.14486	0.02423	-0.0337	1.1255
Factor11	-0.16909	0.00795	-0.0393	1.0862
Factor12	-0.17704	0.0166	-0.0412	1.045
Factor13	-0.19364	.	-0.045	1

A.3 Measures of parental well-being and family functioning

Parental Wellbeing To measure parental wellbeing we use two scales. The first scale is an adapted version of the short Warwick-Edinburgh Mental Wellbeing Scale (Tennant et al., 2007). The respondent was asked to respond to seven statements with either "None of the time or rarely", "Some of the time" or "Most of the time or always about pre-lockdown, as well as over the last few weeks. The second scale measures parental anxiety using a modified version of the Generalized Anxiety Disorder scale (GAD-7) (Spitzer et al., 2006). Respondents are asked to respond to three statements with either "None of the time or rarely", "Some of the time" or "Most of the time or always", once for pre-lockdown (in Feb 2020) and once for the past two weeks. See in Table A5 for the list of statements.

Parental relationship Parental relationship quality was measured with an adapted version of the Dyadic Adjust Scale (DAS, Spanier (1976)). This has two components. The first component asks about the frequency of knowledge sharing and working together between couples, asking the respondent in the past two weeks and pre-lockdown (Feb 2020). The second section corresponds to the overall health of the relationship. Respondents are asked several statements about their relationship as it is now, during lockdown, and before lockdown in Feb 2020 with the following options "Never or rarely", "Some of the time", or "Most of the time or always". See in Table A5 for the exact list of questionos.

Positive parenting Positive parenting is measured using a series of questions relating to parental activities with children, before lockdown (Feb 2020) and during lockdown (June 2020). These questions are similar to those included in several UK household surveys, such as Understanding Society. The list of questions is shown in Table A5.

Table A5: Parental well-being and anxiety and family functioning questions

Parental Well-being Questions (SWEMWBS)
I've been feeling optimistic about the future.
I've been feeling useful.
I've been feeling relaxed.
I've been dealing with problems well.
I've been thinking clearly.
I've been feeling close to other people.
I've been able to make up my own mind about things.
Parental Anxiety Questions (GAD)
I've been feeling nervous, anxious, or on edge.
I've not been able to stop worrying.
I've been becoming easily annoyed or irritable.
Parenting Quality
How often do you spend time together on leisure activities?
How many times in a typical week do you eat together?
How often do you talk to your child about things that matter?
How often do you allow your child to set rules?
How often do you praise your child?
How often do you cuddle your child?
Parental Relationship Questions (Dyadic Adjustment Scale)
How often do you have a stimulating exchange of ideas?
How often do you work together on a project?
How often do you discuss or consider divorce?
How often do you regret that you married or lived together?
How often do you and your partner quarrel?
How often do you and your partner get on each other's nerves?
How often do you kiss your partner?
How often do you and your partner engage in hobbies or outside interests together?

Note: Well-being and anxiety questions are on a 1 to 3 scale (None of the time/rarely, some of the time, most of the time/always); parenting questions are on a 1 to 4 scale (never, seldom, sometimes, often), and parental relationship questions are on 1 to 3 Scale (Once a week or less, several times a week, at least once a day).

Table A6: Child and Household Characteristics for the Whole Sample and by Cluster

	C1	C2	C3	C4	C5	C6
Household Demographics						
Nuclear Family	0.71	0.6	0.28	1	0.79	0.73
Lone Mother	0.27	0.39	0.68	0	0.2	0.25
Lone Father	0.03	0.01	0.05	0	0.01	0.02
Total Number of Children	2.43	2.79	2.7	2.75	2.48	2.41
	(0.95)	(1.15)	(1.36)	(1.04)	(1.02)	(0.95)
Father's Age	38.55	37.59	32.87	38.71	36.22	36.61
	(8.52)	(9.26)	(9.87)	(7.73)	(9.37)	(8.37)
Mother's Age	38.54	37.51	32.83	38.71	36.25	36.6
	(8.56)	(9.23)	(9.94)	(7.74)	(9.31)	(8.37)
Not White	0.17	0.16	0.26	0.1	0.18	0.18
Father Has Degree	0.46	0.29	0.23	0.3	0.36	0.39
Mother Has Degree	0.49	0.2	0.27	0.35	0.36	0.44
Lives in London	0.13	0.08	0.16	0.08	0.15	0.12
Randomly Selected Child Demographics						
Child is Female	0.54	0.49	0.52	0.46	0.53	0.54
Child Age	9.86	9.47	9.83	8.94	9.87	9.89
	(3.5)	(3.5)	(3.42)	(3.5)	(3.57)	(3.54)
Mental Health 2020	0.17	0	-0.29	0.01	-0.11	0.03
	(0.93)	(0.95)	(1.05)	(0.94)	(1.06)	(1.01)
Mental Health 2021	-0.11	-0.25	-0.52	-0.34	-0.45	-0.3
	(1.03)	(1.06)	(1.08)	(1.04)	(1.12)	(1.08)

Table A7: Household Labour Market Circumstances Before and During the Pandemic for the Whole Sample and by Cluster

	C1	C2	C3	C4	C5	C6
Pre-COVID Labour Market Characteristics						
Pre-COVID Earnings	1763.28	529.33	633.34	1191.19	1264.11	1546.25
	(1068)	(594.43)	(517.24)	(801.97)	(913.25)	(1036.41)
At least one parent working in industry more than 50% locked down	0.33	0.42	0.5	0.48	0.62	0.4
At least one parent working in occupation 0-15% teleworkable	0.47	0.43	0.51	0.5	0.57	0.5
At least one parent working in occupation 15-75% teleworkable	0.23	0.05	0.21	0.14	0.23	0.18
At least one parent working in occupation 75-100% Teleworkable	0.41	0.08	0.26	0.28	0.33	0.49
Household Labour Market Experiences Feb 2020 - Feb 2021						
Any Change in Labour Market Experiences	0	0	1	1	1	1
Number of Transitions HH Level	0	0	3.74	2.6	4.59	2.99
	(0)	(0)	(2.99)	(1.84)	(3.72)	(2.01)
Any HH member ever furloughed	0	0	0.48	0.48	1	0.71
Any HH member ever unemployed	0	1	1	1	0.39	0.51
Months all parents employed	13	0	3.49	2.24	3.47	9.33
	(0)	(0)	(2.52)	(2.62)	(2.33)	(1.93)
Months all parents unemployed	0	7.5	7.41	0.75	0.3	0.41
	(0)	(6.43)	(2.86)	(1.86)	(1)	(0.96)
Months one parent employed, one unemployed	0	5.5	0.43	8.07	0.64	0.89
	(0)	(6.43)	(1.05)	(2.43)	(1.21)	(1.53)
Months at least one parent furloughed	0	0	1.66	1.94	8.59	2.37
	(0)	(0)	(2.19)	(2.48)	(2.34)	(2.06)
Earnings Fell	10.82	4.28	29.34	7.23	11.42	11.87
Earnings Increased	10.87	4.3	29.2	7.03	11.22	11.76
Sample size	*1590*	*820*	*370*	*442*	*863*	*954*

B Typology of labour market trajectories using Sequence Analysis

B.1 Description of the methodology

This methodology, pioneered by Abbott and Forrest (1986), aims to construct dissimilarities between sequences which allow for similar trajectories to be clustered. The most common method for estimating distances between discrete time series is 'Optimal Matching' (OM) which provides a measure of 'edit distance' between each pair of trajectories. Its distinguishing feature (compared to other forms of sequence analysis) is its use of "edit distance" as a measure of dissimilarity between sequences. The edit distance between two individual sequences is the minimum total cost of operations (insertions, deletions, and substitutions) required in order to convert one into another. For example, editing the sequence "C B A" to become "A B B C" requires one insertion and two substitutions. If the cost of each operation is set to unity, the edit distance between the two sequences is 3.[2]The set of individual sequences, combined with this characterisation of substitution costs, thus permits us to derive a dissimilarity matrix that quantifies the relative distances between each pair of sequences. Using this dissimilarity matrix, it is then possible to cluster life trajectories using any standard clustering algorithm. For this purpose, we employ the "Ward's Method" algorithm, a form of hierarchical clustering.[3]

The algorithm proceeds as follows: we begin with n clusters (with each sequence in a cluster of its own), and then identify the two "closest" clusters, and merge these into a single cluster; there are now $n-1$ clusters. Identifying the two closest clusters consists of computing the merging cost of all possible cluster-mergers. The merging cost of any two clusters, A and B, is then simply the increase in the sum of squares caused by the merge. We repeat this process until only a single cluster remains, which contains all n observations.

We run this procedure on households that have experienced some change in labour market trajectories, as we impose that those who haven't are split between two groups - cluster 1, composed of

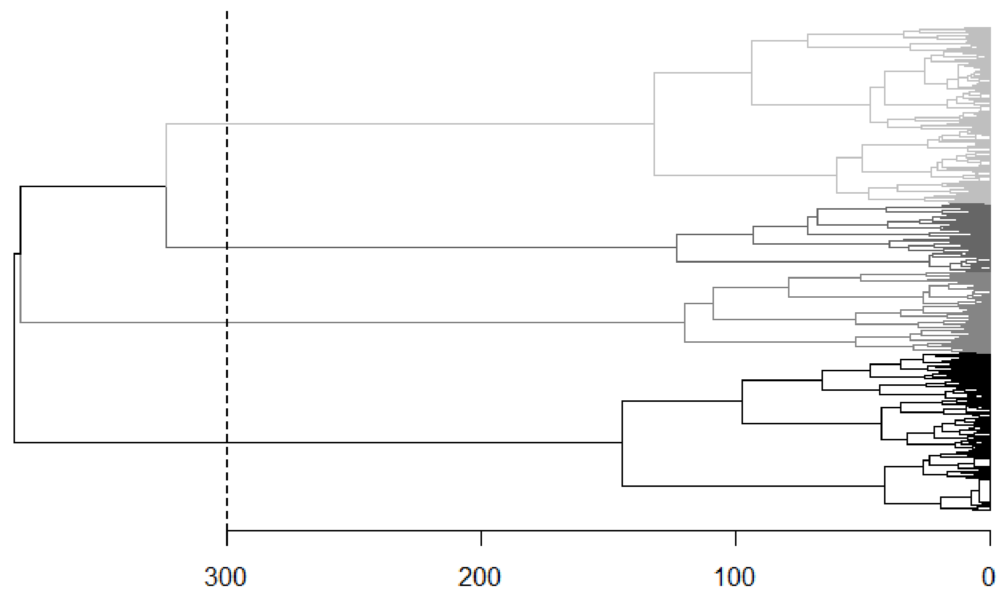
[2]Computing the dissimilarity between two such sequences thus requires us to specify the costs of these operations. In practice, these decisions are shaped by the question of which aspect of the empirical trajectories we consider to be relatively more important: in particular, setting 'indel' (insertion and deletion) costs high relative to substitution costs puts greater weight on the *timing* of spells, while the reverse weighs spell duration relatively heavily. In our balanced-panel setting, all sequences are of equal length; thus, substitutions are the only relevant operation to consider, and we set the indel cost to 1.

[3]We favour this over, for instance, a k-means algorithm, for two reasons: firstly, the flat partitions generated by the latter make it relatively difficult to determine visually the optimal number of clusters, compared to the dendrogram produced by the hierarchical method; and secondly (and relatedly), the k-means algorithm requires ex ante knowledge of the empirical cluster structure - by contrast, hierarchical clustering more readily permits this decision to be empirically led.

households where all parents were employed in each month of the retrospective panel, and cluster 2, composed of households where all parents were unemployed in each month of the panel.

Hierarchical clustering applied to the rest of the sample produces a tree of nested clusters. The dendrogram (Figure B1) shows the resulting clusters; the dashed line indicates where the cut is ultimately made, as outlined below - at four clusters. To inform this choice, we consider a range of diagnostics and measures of cluster quality; these are summarised in below.

Figure B1: Dendrogram Resulting from Ward's Method of Heirarchical Clustering



Note: the chart shows the arrangement of clusters resulting from the hierarchical clustering method. The different shades indicate membership of one of the four clusters, whilst the dashed line indicates the point above which the groupings are used. I.e. new branches below the line are ignored, with those groups being included in the relevant node above the line.

B.2 Diagnostics and quality measures for sequence analysis

We consider a range of diagnostics and cluster quality measures to inform our choice of the number of clusters to define. Figure B2 shows these statistics, each of which has been centered, for a range of clusters (from two to six).

- The Average Silhouette Width (or ASW on the chart) measures coherence of clustering by using the average distance between each observation in a cluster and both its own and the nearest other cluster. A higher number indicates that an observation is well clustered.

- The Calinsky-Harabasz Index (CH) is a pseudo F statistic that is the ratio of between- and within-cluster variance - higher is better.

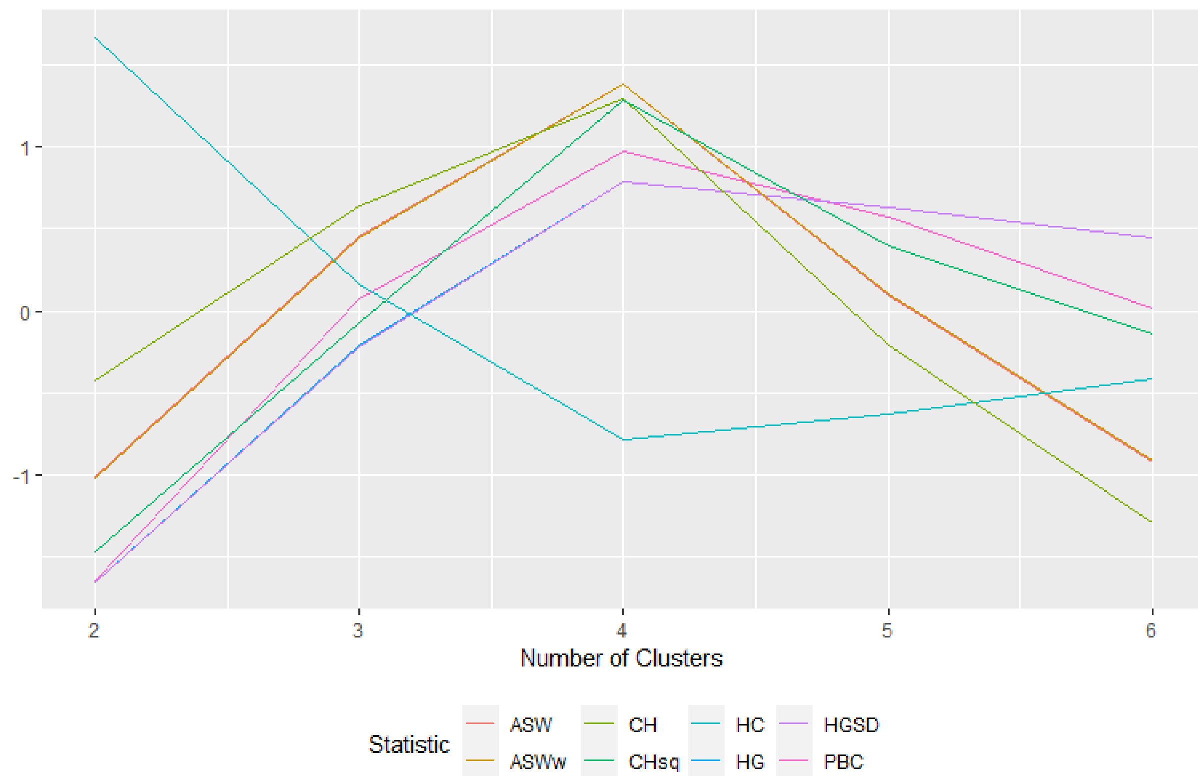
- Hubert's C (HC) computes the gap between the current split in the dendrogram and the best theoretical split given the number of clusters and the distance matrix that has been computed. This is the only one of the measures in the figure that is better if it is lower.

- Finally, Hubert's Gamma (HG), the point biserial correlation (PBC), and Hubert's Somers D (HGSD) are all correlation based measures that measure the capacity of the clustering analysis to reproduce the original distance matrix. The higher the correlation between the original distance matrix and the new distance, the better.

Each of these measures peaks (or in the case of the HC, troughs) at four clusters - indicating that this is the best choice to make. These four clusters are added to the two pre-specified clusters to make six clusters in total.

Analysis is conducted in R using the `TraMineR`, `WeightedCluster`, and `ggseqplot` packages, as well as the `hclust` command from the `stats` package that is bundled with R. The statistics outlined above are are easily computed from the output of the `as.clustrange` command.

Figure B2: Cluster Quality Statistics



Note: Each statistic is centred using the `scale` command in R. The Average Silouhette Width (ASW) measures coherence of clustering by using the average distance between each observation in a cluster and both its own and the nearest other cluster. The Calinsky-Harabasz Index (CH) is a pseudo F statistic. Hubert's C (HC) computes the gap between the current split in the dendrogram and the best theoretical split given the number of clusters and the distance matrix that has been computed. Hubert's Gamma (HG), the point biserial correlation (PBC), and Hubert's Somers D (HGSD) are all correlation based measures that measure the capacity of the clustering analysis to reproduce the original distance matrix. In each case other than the HC we are interested in where the measure peaks. For the HC, lower is better.

B.3 Differences in household characteristics between clusters

These clusters were created using only information on households' labour market circumstances during the first year of the pandemic. However, the different clusters vary along other key dimensions, including a) their demographic characteristics, b) their economic circumstances, including earnings before COVID, earnings change during COVID, and their expectations of change in the future, and c) the wellbeing of their members.

To understand better the differences between these groups, the final columns in **??** and **??** report the means of key variables for each of the six groups. Unsurprisingly, families in Cluster 1 (always employed) are in the most secure economic position, with the highest pre-COVID earnings. These families are generally headed by parents who are somewhat older and more likely to be educated to degree level than the average in our sample. Their children also had the highest level of baseline socio-emotional development.

The households in Cluster 6 (largely employed but with short periods of furlough or other disruption) look similar to Cluster 1 in many demographic characteristics, and on average both parents are employed for 9.33 of the 13 months in our panel. But over half of these families experienced furlough over the first year of the pandemic, and roughly half had experienced at least one month of unemployment.

Cluster 2 combines two types of 'stable' households, with no transitions: those where all parents are unemployed for the full 13 months, and those with one parent employed and one unemployed for the full period. These households had the lowest earnings of our six clusters, but also the most stable earnings: fewer than 5% saw their earnings fall during the first year of the pandemic.

Cluster 3 is characterised by many short transitions, particularly between unemployment and employment. These families are the most socio-economically disadvantaged in our survey: families in this cluster are much more likely to be headed by a lone parent[4], to have low levels of qualifications, and to have low earnings. Children in this cluster had the lowest level of baseline socio-emotional skill.

Cluster 4 is the most stable of the clusters defined by the algorithm, with on average 2.6 transitions over the 13-month period. This cluster is entirely comprised of dual-parent families. Like Cluster 3, the primary states for families in this cluster are employment and unemployment (rather than furlough).

Finally, Cluster 5 is distinguished by long spells of furlough, including a substantial minority who were furloughed for the entire first year of the pandemic. The average family in this cluster spent over 6 months with one parent on furlough. Despite this, families in Cluster 5 had the most transitions on average.

[4]This is partly mechanical, since at the household level it is easier to fall into the 'all parents employed' or 'all parents unemployed' states when there is only one parent in the family.

C Additional tables and figures

Table C1: Child and Household Characteristics by Direction of Change in Mental Health Feb 2020 to Feb 2021

	Worse	Same	Better
Household demographics			
Lone Mother	0.29	0.27	0.33
Lone Father	0.02	0.02	0.03
Nuclear Family	0.7	0.71	0.64
Total Number of Children	2.55	2.57	2.61
	(1.04)	(1.07)	(1.19)
Father's Age	36.55	39.04	35.22
	(8.75)	(8.61)	(9.71)
Mother's Age	36.53	39.03	35.12
	(8.73)	(8.65)	(9.6)
Not White	0.16	0.14	0.28
Father Has Degree	0.39	0.34	0.39
Mother Has Degree	0.42	0.32	0.33
Lives in London	0.12	0.1	0.16
HH Earnings (Equivalised)	1288.8	1226.83	1172.57
	(1027.49)	(1005.35)	(1029.77)
Child characteristics			
Child is Female	0.54	0.49	0.5
Child Age	9.42	9.86	10.12
	(3.53)	(3.52)	(3.46)
Mental Health 2020	0.1	0.23	-0.8
	(0.91)	(0.88)	(1.1)
Mental Health 2021	-0.72	0.23	-0.18
	(1.06)	(0.88)	(0.97)
Household labour market experiences between Feb 2020 - Feb 2021			
Number of Transitions HH Level	1.77	1.11	2.21
	(2.7)	(1.87)	(3.36)
Any HH member ever furloughed	0.35	0.26	0.4
Any HH member ever unemployed	0.53	0.51	0.56
Months all parents employed	6.51	6.48	6.16
	(5.39)	(5.67)	(5.45)
Months all parents unemployed	2.15	2.55	2.5
	(4.39)	(4.89)	(4.59)
Months one parent employed, one unemployed	2.2	2.4	1.75
	(4.24)	(4.52)	(3.7)
Months at least one parent furloughed	1.88	1.45	2.13
	(3.16)	(2.97)	(3.37)
Earnings Fell	9.83	10.86	11.51
Earnings Increased	9.75	10.82	11.52
Sample size	*2588*	*1863*	*978*

Table C2: Impact of disruption to parental labour market circumstances relative no disruption with and without some unemployment

	(1)	(2)	(3)	(4)
Any change	-0.229***	-0.090***	-0.096***	-0.095***
	(0.044)	(0.030)	(0.030)	(0.030)
No change and at least one parent unemployed	-0.097*	-0.033	-0.027	-0.028
	(0.058)	(0.037)	(0.056)	(0.056)
Baseline Outcome		0.815***	0.812***	0.812***
		(0.014)	(0.014)	(0.015)
Observations		5,039		
R-squared	0.052	0.582	0.589	0.590
Pre-COVID child and family characteristics	X	X	X	X
Pre-COVID mental health		X	X	X
Pre-COVID labour market characteristics			X	X
Pre-COVID parental wellbeing and family processes				X

Notes: OLS regression estimates of a standardised count measuring child mental health in February 2021 on a series of indicators for household labour market trajectories between February 2020 and February 2021. Panel B includes only one binary indicator that equals 1 if there has been any change in parental labour market circumstances and 0 if no change , as well as an indicator that equals 1 is there has been no change and at least one parent was unemployed prior to the pandemic. All models control for a set of demographic characteristics, which includes child gender, child age and age squared, parent ethnicity, parent age and age squared, respondent gender, family structure (e.g. lone parent status and number of children), parental education level, pre-covid earnings per equivalent household member, and region of residence. In column 2, the model also controls for a standardised count measuring mental health in February 2020. In column 3, the models also control for characteristics of parents' labour market circumstances before COVID, which include dummies for parental occupation and controls for the teleworkability of that occupation and the proportion of the parents' industry that are impacted by shutdowns. In Column 4, the models also include three variables measuring family processes in February 2020, which include respondent wellbeing quality of inter-parental relationship, and parenting quality. The inter-parental relationship variable is only relevant for two-parent household, so it is imputed to an arbitrary value for one-parent household and interacted with an indicator for two-parent household. Robust standard errors in parentheses; *** p¡0.01, ** p¡0.05, * p¡0.1

Table C3: Child and Household Characteristics for the Whole Sample and by Cluster

	C1	C2	C3	C4	C5	C6
Household Demographics						
Nuclear Family	0.71	0.6	0.28	1	0.79	0.73
Lone Mother	0.27	0.39	0.68	0	0.2	0.25
Lone Father	0.03	0.01	0.05	0	0.01	0.02
Total Number of Children	2.43	2.79	2.7	2.75	2.48	2.41
	(0.95)	(1.15)	(1.36)	(1.04)	(1.02)	(0.95)
Father's Age	38.55	37.59	32.87	38.71	36.22	36.61
	(8.52)	(9.26)	(9.87)	(7.73)	(9.37)	(8.37)
Mother's Age	38.54	37.51	32.83	38.71	36.25	36.6
	(8.56)	(9.23)	(9.94)	(7.74)	(9.31)	(8.37)
Not White	0.17	0.16	0.26	0.1	0.18	0.18
Father Has Degree	0.46	0.29	0.23	0.3	0.36	0.39
Mother Has Degree	0.49	0.2	0.27	0.35	0.36	0.44
Lives in London	0.13	0.08	0.16	0.08	0.15	0.12
Randomly Selected Child Demographics						
Child is Female	0.54	0.49	0.52	0.46	0.53	0.54
Child Age	9.86	9.47	9.83	8.94	9.87	9.89
	(3.5)	(3.5)	(3.42)	(3.5)	(3.57)	(3.54)
Mental Health 2020	0.17	0	-0.29	0.01	-0.11	0.03
	(0.93)	(0.95)	(1.05)	(0.94)	(1.06)	(1.01)
Mental Health 2021	-0.11	-0.25	-0.52	-0.34	-0.45	-0.3
	(1.03)	(1.06)	(1.08)	(1.04)	(1.12)	(1.08)

Table C4: Household Labour Market Circumstances Before and During the Pandemic for the Whole Sample and by Cluster

	C1	C2	C3	C4	C5	C6
Pre-COVID Labour Market Characteristics						
Pre-COVID Earnings	1763.28	529.33	633.34	1191.19	1264.11	1546.25
	(1068)	(594.43)	(517.24)	(801.97)	(913.25)	(1036.41)
At least one parent working in industry more than 50% locked down	0.33	0.42	0.5	0.48	0.62	0.4
At least one parent working in occupation 0-15% teleworkable	0.47	0.43	0.51	0.5	0.57	0.5
At least one parent working in occupation 15-75% teleworkable	0.23	0.05	0.21	0.14	0.23	0.18
At least one parent working in occupation 75-100% Teleworkable	0.41	0.08	0.26	0.28	0.33	0.49
Household Labour Market Experiences Feb 2020 - Feb 2021						
Any Change in Labour Market Experiences	0	0	1	1	1	1
Number of Transitions HH Level	0	0	3.74	2.6	4.59	2.99
	(0)	(0)	(2.99)	(1.84)	(3.72)	(2.01)
Any HH member ever furloughed	0	0	0.48	0.48	1	0.71
Any HH member ever unemployed	0	1	1	1	0.39	0.51
Months all parents employed	13	0	3.49	2.24	3.47	9.33
	(0)	(0)	(2.52)	(2.62)	(2.33)	(1.93)
Months all parents unemployed	0	7.5	7.41	0.75	0.3	0.41
	(0)	(6.43)	(2.86)	(1.86)	(1)	(0.96)
Months one parent employed, one unemployed	0	5.5	0.43	8.07	0.64	0.89
	(0)	(6.43)	(1.05)	(2.43)	(1.21)	(1.53)
Months at least one parent furloughed	0	0	1.66	1.94	8.59	2.37
	(0)	(0)	(2.19)	(2.48)	(2.34)	(2.06)
Earnings Fell	10.82	4.28	29.34	7.23	11.42	11.87
Earnings Increased	10.87	4.3	29.2	7.03	11.22	11.76
Sample size	*1590*	*820*	*370*	*442*	*863*	*954*

Table C5: OLS Regression Results for Child Mental Health: Robustness to measures of COVID-19 exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Any change	-0.088***	-0.090***	-0.086***	-0.088***	-0.089***	-0.087***
	(0.027)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)
Baseline outcome	0.812***	0.816***	0.810***	0.812***	0.813***	0.814***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
COVID exposure measures						
# absences: Child's own COVID		0.030***				0.043***
		(0.011)				(0.014)
# absences: Classmate's COVID			-0.012			-0.026**
			(0.011)			(0.013)
# absences: Household's COVID				0.005		-0.001
				(0.014)		(0.017)
# COVID-related absences					0.003	
					(0.005)	
Observations	5,039	5,039	5,039	5,039	5,039	5,039
R-squared	0.590	0.590	0.590	0.590	0.590	0.591

Table C6: OLS Regression Results for Child Mental Health: Robustness to measures of in-person schooling

	(1)	(2)	(3)	(4)	(5)
Any change	-0.088***	-0.088***	-0.086***	-0.086***	-0.087***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Baseline outcome	0.812***	0.812***	0.816***	0.816***	0.813***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
School absence measures					
In-person school: Summer 2020		0.018		0.011	
		(0.026)		(0.026)	
In-person school: Winter 2021			0.057*	0.056*	
			(0.031)	(0.031)	
Weekly hours in person: Winter 2021					0.001
					(0.002)
Observations	5,039	5,039	5,039	5,039	5,039
R-squared	0.590	0.590	0.590	0.590	0.590

Table C7: Heterogeneity in Effects of Any Change on Mediators by Income

	(1)	(2)	(3)	(4)	(5)	(6)
	Earnings Fell		Expect to Earn Less in 6 Months		Parent Wellbeing	
	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median
Any Change	0.214***	0.353***	0.089***	0.079***	0.010	-0.171***
	(0.020)	(0.022)	(0.023)	(0.016)	(0.057)	(0.044)
P-value of T-test	0.000		0.704		0.010	
Observations	2,282	2,452	2,270	2,595	2,355	2,684
R-squared	0.228	0.220	0.081	0.079	0.214	0.236
	X	X	X	X	X	X
	X	X	X	X	X	X
	X	X	X	X	X	X

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; all controls.

Table C8: Regression Results According to Which Household Member is Impacted by Changes to Labour Market Status

	(1) Main Estimate	(2) HH with Only One Parent Impacted	(3) Which HH Member Impacted
Any Change	-0.081**		
	(0.032)		
Respondent Impacted		-0.006	-0.051
		(0.047)	(0.038)
Partner Impacted			-0.038
			(0.042)
Both Impacted			-0.163***
			(0.051)
Mother Impacted			
Father Impacted			
Both Impacted			
Baseline Outcome	0.824***	0.814***	0.821***
	(0.017)	(0.026)	(0.017)
Observations	3,618	1,128	3,618
R-squared	0.602	0.648	0.603

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

Figure C1: Comparison of furlough rates in survey with governmental data