The Gender Gap in Mental Well-Being At the Onset of the Covid-19 Pandemic: Evidence from the UK*

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Abstract

We assess the decline in mental health after the onset of the Covid-19 pandemic in the UK. This decline was more than twice as large for women as for men. We seek to explain this gender gap by exploring gender differences in: family and caring responsibilities; financial and work situation; social engagement; health situation, and health behaviours, including exercise. We assess their quantitative relevance by applying standard decomposition methods. We find that compositional differences in family and caring responsibilities explain part of the gender gap, but more important are gender differences in social factors, particularly changes in loneliness. We explore this result further by analysing gender differences in personality traits. Even after controlling for all factors there remains a noticeable age-gender gradient, with young females suffering particularly badly.

JEL Classification: I10, I14, I18, I30

Keywords: Mental well-being, Mental health, Gender, Covid-19

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1 Introduction

The Covid-19 pandemic caused large disruption to much of the population across the globe, and along many dimensions. This disruption negatively and substantially affected mental well-being (e.g., Adams-Prassl et al. 2022; Banks and Xu 2020; Davillas and A. M. Jones 2021). A body of empirical evidence now clearly shows that the effects on well-being were felt unequally, with differential outcomes by several socio-economic characteristics such as age (Banks and Xu 2020; Daly et al. 2020; Davillas and A. M. Jones 2021; Zhou et al. 2020), gender (Banks and Xu 2020; Davillas and A. M. Jones 2021) and ethnicity (Proto and Quintana-Domeque 2021). In this paper, we focus on the gender gap in well-being that emerged after the onset of the pandemic. Investigating this gender gap is important not only for understanding the effect of pandemics and associated policies for similar future events, but also for understanding gaps in well-being by gender more broadly. We use rich representative data from the UK to explore potential reasons for this differential impact.

To illustrate the large decline in mental well-being, Figure 1 displays averages over time in the UK by gender, including after the start of the pandemic. It shows a large drop after onset, and, consistently with the existing evidence, a disproportionate effect on women, for whom the impact appears to be over twice as large.[1] In our analysis, we first document how well-being of women and men was related to a variety of factors that have been shown to be affected by Covid, such as economic situation, health outcomes and time use within the household. Building on the literature in psychology (see e.g. Holt-Lunstad et al. 2015, for a recent review), we additionally consider social circumstances such as friendships and loneliness. We then use a coherent framework to shed light on which particular aspect of disruption affected the gender gap in well-being to the largest degree. We find that social factors, and particularly increases in loneliness, are the most important factor, indicating a key role of social restrictions.

The UK is a particularly suitable setting for the analysis. During its first wave, the UK was one of the countries most affected by the pandemic. At its peak in mid-April, the 7-day moving average of official daily deaths was 950 (14 per million per day), among the highest rates in the world. Meanwhile, the data we examine were collected only a little afterwards, when the death rate was around 800 per day.[2] At this time the 'lockdown' was in full force, including strict social distancing measures.[3] Indicators of economic activity were sharply negative.[4] At the same time, the main policy tools relating to the economy, such as the UK Job Retention ('furloughing') Scheme, were already well established.[5]

[1] We base this claim on a comparison with average well-being over 2017-2019. Given largely similar profiles for men and women before 2020, controlling for trends has a negligible effect on this estimate.

[2] The data were collected from April 24th. See Section 2. Death rates obtained from https://www.worldometers.info/coronavirus/country/uk/, accessed on June 4th 2020.

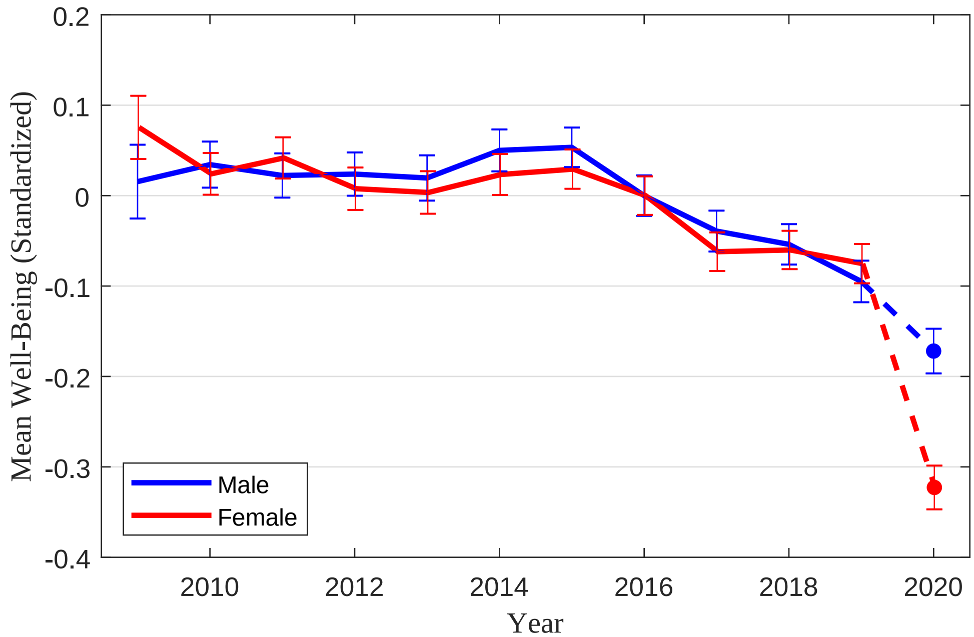
[3] See, for example, the cross-country tracker of policy responses in Hale et al. (2021).

[4] For example, over the weekend during which most of our data were collected the FTSE 100 stock market index stood at 5750 points, 25% below its level at the beginning of the year.

[5] The UK Job Retention Scheme was introduced on March 20, 2020.All the other main schemes were introduced at a similar time, including the Self-Employed Income Support and Mortgage Relief Schemes, among others.

Figure 1: Mental Well-Being by Gender, up to April 2020

Indexed to 2016 = 0



Notes: Data from UKHLS waves 1-10, 2019 wave and April 2020 Covid module. Figure shows standardized, seasonally-adjusted and inverted Likert score, obtained from 12 questions in the General Health Questionnaire. See section 2 for more details. Profiles indexed to 0 in 2016. Sample consists of all those responding to the Covid module, whether or not they responded to previous waves. Interviews binned according to the calendar year of the response rather than reference year of survey wave. Error bars show 95% confidence intervals.

The data we use come mainly from the UK Household Longitudinal Survey (UKHLS) Covid module, which contains rich, nationally-representative data on important individual characteristics and outcomes during the pandemic. The UKHLS has been used to investigate mental health during Covid-19 by a variety of studies.[6] We complement these data by also exploiting the UKHLS main survey going back a decade previously. Moreover, to build a comprehensive dataset that includes information on all relevant background factors, we additionally incorporate pre-pandemic data from the UK Time Use Survey (UKTUS).

We begin the analysis by systematically reviewing the associations between mental health changes and the range of relevant factors for women and men separately. For most factors, we find larger well-being decreases for women than for men. Regarding time-use, we document an association between mental well-being changes and pre-existing childcare responsibilities, and that these responsibilities fell more heavily on women. We document large associations between mental well-being and changes in financial situation, but that in fact *fewer* women faced a worse financial situation. In terms of the labour market, large declines in well-being were reported by those who had entirely lost their job. However, the size of this group was small, and dwarfed by the number of workers placed on furlough, for whom well-being was little affected. Consistently with the literature, we document

[6] Beyond the many examples cited elsewhere, see also Pierce et al. (2020) and Pierce et al. (2021).

that young women were much more negatively affected in general than older individuals. Most strikingly, we document a strong relationship between declines in well-being and social factors that differ by gender. The declines in well-being are particularly large for those who reported an increase in loneliness since their last pre-Covid interview. These correlations are larger for women, and women were more likely than men to report loneliness deteriorations.

Our main empirical exercise is to quantify these contributions using a standard Oaxaca-Blinder decomposition, that is usually applied to assess e.g. gender gaps in wages (Blinder 1973; Oaxaca 1973). Here we focus most on 'compositional' effects, which capture *differential exposures* across women and men. We find that domestic and time use factors play a significant, but relatively small role in explaining the gender gap across the population. However, as would be expected, this factor plays a substantially larger role when we examine those with children only. Health and medical factors also play a role, with a larger fraction of women reporting changes in their caring arrangements. In line with the discussion above, we find that changes in financial situation *narrowed* the gap, and that the relatively higher number of women reporting improvements in their financial situation is quantitatively relevant. In terms of explaining the gender gap, the most important role is played by the social factors: these explain around a quarter of the gap overall.

The framework we use allows for both dynamic factors that may have changed substantially at the onset of the pandemic, such as work status, as well as pre-existing exposures, such as the presence of children or being a recipient of care. Of course, the dynamic factors in particular may be endogenous to mental health changes themselves. In keeping with the standard use of decomposition methods, therefore, we refrain from giving our results a causal interpretation. Instead they provide 'bottom-line' indicators of the likely quantitative importance of different factors (see, for example, Fortin et al. 2011). However, we pursue our explanations further by seeking additional credible evidence from factors that are highly pre-determined. Specifically we focus on personality traits, which are measured around a decade before the pandemic, which have been shown to predict changes in mental well-being during Covid-19 (Proto and Zhang 2021) and which are consistently shown to differ by gender (Feingold 1994; Weisberg et al. 2011).

Our results for personality traits illuminate those from our main model. While quantitatively these explain little of the gender gap, composition effects arising from traits are statistically significant and coincide with the results discussed so far. Specifically, differences in extraversion, which is associated with an orientation towards social engagement (McCrae and Costa 1987) explain a portion of the gender gap: Women score more highly in this factor, and extraverts overall suffered larger well-being declines. In fact, the other personality traits together favoured women during the pandemic, such that the gender gap would have been wider if these traits were evenly distributed, although results for these are less significant.

Throughout our analysis we also discuss 'structural' components from the decomposition. These structural effects capture *differential responses* to the same exposure. For example, we document that women, but not men, suffered significantly larger well-being declines when working from home. Unfortunately, in the context of the full decomposition analysis, these structural components are estimated with too little precision to make strong inference. However, focussing on age, we find that the age-gender gradient in well-being declines remains noticeable across all specifications. This indicates that the factors we examine here provide only a partial explanation of why younger women in particular were so badly affected by the pandemic.

Our main analysis focuses on the immediate onset of the pandemic, in April 2020. This allows us to concentrate on the immediate effect of pandemic conditions. In addition, *a priori* interesting variables such as changes in receiving formal care and exercise are available in the April 2020 data only. However, for a more comprehensive view, we replicate our analysis as far as possible, and show that our conclusions are unchanged when including data from later in the first wave, collected in May and June 2020. In fact, Figure A.1 shows that the gender gap persisted not only during spring 2020, but also re-appeared, equally strongly, in the UK's second wave, during the winter of 2020-21. We therefore consider this large gender gap as a highly stable feature of the pandemic period that warrants detailed attention. Our analysis goes beyond existing papers examining the gender gap at the onset of the pandemic (Adams-Prassl et al. 2022; Banks and Xu 2020; Davillas and A. M. Jones 2021). We do this by using rich data both from before and during the pandemic from the UKHLS and UKTUS, that we analyse in a coherent framework, taking into account findings from both the economics and the psychology literature. This is our primary contribution.

This paper also contributes to the growing literature on gender inequality during Covid-19 more broadly (e.g. Alon et al. 2020). While most studies collect real-time data during the onset of the pandemic, they mostly rely on cross-sectional surveys with limited background characteristics of respondents (e.g. Adams-Prassl et al. 2020, 2022; Andrew et al. 2020; Sevilla and Smith 2020). To this literature we provide systematic and rich nationally-representative evidence on changes in the exposures faced by men and women. We then quantify their respective effects on well-being through a formal decomposition. Particularly relevant to this literature, we find limited evidence that the gender gap in well-being at the onset of the pandemic was driven by the increase in time spent on childcare, or differential labour-market outcomes.

Going beyond Covid-19, our work contributes to a longer-standing literature on the 'paradox' of declining female happiness relative to males, which can be contrasted with the increasing success of women across a range of economic and social spheres (Astbury 2001; Seedat et al. 2009; Stevenson and Wolfers 2009). Although not shown in this paper, we similarly find a persistent gender gap in the *level* of well-being scores across all waves of UKHLS. We contribute to this literature by gathering detailed evidence from the extra 'shock' of Covid-19. Overall, and in the context of this literature, our work is therefore informative about the role of differences in social needs and social engagement in the production of mental well-being across genders.

Finally, our analysis broadly relates to various strands of literature from economics and psychology that examine different correlates of well-being, both before and during the pandemic. We investigate employment-related and financial factors whose linkages to well-being economists have investigated extensively (e.g. Blanchflower and Oswald 2004; A. Clark and Oswald 1994; L. Winkelmann and R. Winkelmann 1998) and find comparable patterns during a large disruption of normal life. We investigate factors related to time use that have received special attention during the pandemic (e.g. Cheng et al. 2021; Xue and McMunn 2021). We also investigate social factors, making the distinction between perceived social disconnectedness (i.e., loneliness) and social (dis)connectedness in terms of number of friends.[7] We confirm previous results in psychology finding that perceived connections are more important than actual connections for well-being (e.g. Cornwell and Waite 2009; Coyle and Dugan 2012; Taylor et al. 2018).[8] Not only do we investigate all these factors separately, but we also quantify their respective importance in a representative sample for the gender gap in well-being at the onset of the pandemic. Our results highlight that social factors, in particular loneliness, are more important than economic factors in explaining the gap.[9]

2 Data

2.1 UK Household Longitudinal Survey

Our within-pandemic data come from the first wave of the Covid-19 module from the UK Household Longitudinal Survey (UKHLS) (University of Essex 2019). These data come from interviews conducted in the 7 days from Friday April 24, with 75% of responses completed by Sunday April 26. For information on the pre-pandemic period, we merge these with the '2019 wave' of the survey, a special release designed for Covid research taken from waves 10 and 11 of the parent UKHLS survey (also known as 'Understanding Society'). For additional background information, we also use data from waves 1-10 of the main UKHLS, which has been administered nationwide yearly from 2009.

The UKHLS Covid April wave was conducted entirely over the internet. The underlying sampling frame consists of all those who participated in the UKHLS main survey's waves 8 and 9 (conducted over 2016-2018). To adjust our analysis for non-response, we use the survey weights provided. In addition, to allow for the fact that many respondents are related either through primary residence

[7]Even though closely related, loneliness needs to be conceptually distinguished from social support networks (Golden et al. 2009). We thus include both the number of close friends as a proxy for social support networks and loneliness in our analyses.

[8]Regarding social factors, both objective isolation and its subjective perception (loneliness) can negatively impact mental health (J. Cacioppo et al. 2015, 2011; Holt-Lunstad et al. 2015; House et al. 1988). Focusing on subjective well-being specifically, loneliness has been shown to have a moderately strong association (VanderWeele et al. 2012).

[9]In this, we go beyond the analysis of studies investigating the relationship between well-being and loneliness at the onset of the pandemic. Economists have used google trends (Brodeur et al. 2021; Knipe et al. 2020; Tubadji et al. 2020) or helpline data (Armbruster and Klotzbuecher 2020; Brülhart and Lalive 2020) and are hence restricted in their scope of analysis.

or through the extended family, we cluster all regressions at the primary sampling unit level. For a further discussion of the Covid module and underlying UKHLS design see Social and Research (2020), ISER (2020).

The main variable of interest is mental well-being. Our measure is derived from the Likert index that sums 12 questions from the General Health Questionnaire (GHQ-12). The GHQ battery asks questions regarding, for example, the ability to concentrate, loss of sleep and enjoyment of day-to-day activities. Importantly, the questionnaire asks participants to evaluate their well-being with respect to 'usual' and thus induces a reference point against which respondents evaluate their current feelings. This feature distinguishes our measure from other measures of mental well-being such as the WHO 5-question module (used e.g. in Adams-Prassl et al. 2022) or the PHQ9 depression questionnaire (adopted e.g. in Fetzer et al. 2020) that ask about occurrence of specific feelings or behaviors over the last two weeks. While the latter measures have been shown to reflect the cognitive dimension of well-being, our measure captures affective well-being (see e.g. Diener et al. 1985). The GHQ-12 from this survey has been widely used, both in psychological (e.g. Bridger and Daly 2019) and other social sciences research (e.g. B. Clark et al. 2020; Davillas et al. 2016; Davillas and A. M. Jones 2021; Powdthavee et al. 2019). Importantly the GHQ questionnaire has been administered in all waves of UKHLS in exactly the same form. For precise details on the GHQ questionnaire see Appendix C.

Each item of the GHQ is answered on a 4-point Likert scale and can be scaled from 0 (least distressed) to 3 (most distressed). The 'Likert score' is obtained by summing these scores across the 12 items to yield a total score between 0 and 36. We standardize this score across all waves and invert it so that, in our analysis, lower scores indicate lower well-being. To remove seasonal effects in mood, we take account of month effects, adjusting all pre-Covid data to 'April equivalents'. To remove individual factors in reporting style, we use differences of the Covid-module measures from 2019. We treat all the 2019 data as uniformly 'pre-Covid' and, other than by the seasonal adjustment, do not adjust for differences in interview timing.

A key issue for our analysis is the comparability of GHQ scales across gender. A concern is that gender gaps reflect differences in reporting style rather than genuine differences in mental well-being. However, several studies investigating various measures of mental well-being conclude that the measured differences reflect true health states and are not driven by gender-related reporting bias (Drapeau et al. 2010; Galenkamp et al. 2018; Oksuzyan et al. 2019; Spitzer and Weber 2019). In the context of the UK, Griffith and K. Jones (2019) use data from UKHLS and find that the GHQ exhibits measurement invariance with respect to gender, and so measures the same concept in the same way for both women and men.

We make use of the extensive background information collected in the Covid April wave, as well as the prior UKHLS surveys. In the Covid module, participants were asked a battery of questions about their current experiences. These include questions on employment, on health, on caring responsibilities, on time use and childcare, as well as self-assessments of financial situation and feelings of loneliness. We mostly focus on changes in these variables from 2019 to April 2020 to examine dynamic impacts, or use the 2019 variables as lags. Most of our change variables are thus calculated as differences of the same variable measured at two points in time. In this, we differ from cross-sectional Covid studies that either compare a variable that is measured once contemporaneously and once with re-call, or rely on respondents directly reporting the differences. In addition to the 2019 data, we make use of a specific module conducted in wave 9 (i.e., mostly in 2017 and 2018) on social networks. This module contains detailed self-reports on the quantity, intensity and nature of friendships. We also use wave 3 data (from 2011-12) on personality traits, measured with the 10-item Big-5 inventory. Table A.1 presents summary statistics of the main variables.

Finally, although our main analysis focuses on data from April 2020, we report results using data from May and June 2020 for completeness. We focus on the earlier data in the main paper to examine the impact of the pandemic at onset, and because some of the factors we examine were not measured in these later waves. Parallel versions of all our main tables with all the available data, and showing similar results, are provided in Appendix B.

2.2 Distribution of Well-Being by Gender

To provide a graphical illustration of the main variable of focus, Figure 2 shows the distributions of standardized well-being scores across genders.[10] The left panel shows scores for women, where solid bars indicate values in 2020 and transparent bars show values in 2019. For both women and men, the left tail became fatter, suggesting that a wide spectrum of individuals was affected.

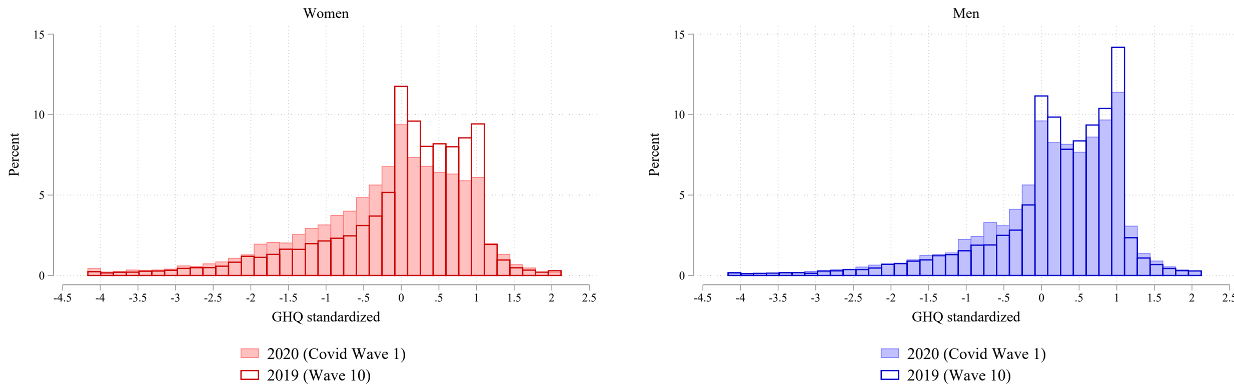
Examining within-individual changes (not shown here), we find that about 52 percent of respondents had worse mental well-being in April 2020 than in 2019. Fifty-seven percent of those were women. 12 percent saw no change (of those, 41 percent are women) and 36 percent had better well-being in 2020 (49 percent women). Within the group reporting a deterioration, women faced on average larger well-being drops: On the non-standardized GHQ-12 scale from 1 to 36, women's well-being decreased an average of 5.6 points, compared to an average 4.5 points for men.

2.3 Data on Childcare from the UK Time Use Survey

One of the main factors that changed during the pandemic was time spent with children and on childcare. Even early on, childcare was identified as a particularly important facet of gender inequalities (see, e.g., Andrew et al. 2020). While the UKHLS provides direct information on

[10] For the ease of exposition, this figure is not seasonally adjusted. In all of our regressions reported later, we control for seasonality.

Figure 2: Distributions of Mental Well-Being Before and During the Pandemic, by Gender



Notes: Data from UKHLS 2019 and Covid module. Figure shows standardized and inverted Likert score, obtained from 12 questions in the General Health Questionnaire.

time spent looking after children during the pandemic, unfortunately no comprehensive equivalent information can be found in previous waves.

To complete the picture of time use before the pandemic, we impute childcare information using data from the UK Time Use Survey (UKTUS, Gershuny and Sullivan 2017). The UKTUS is a comprehensive survey of a representative sample of the UK population covering 12 months from April 2014, eliciting time diaries for every adult household member surveyed. It combines this with detailed background information on demographics and household circumstance. See Fisher et al. (2015) for more information.

Specifically, we use the following time use item: 'childcare of own household members'. This item is composed of: 'unspecified childcare', 'physical care and supervision', 'teaching the child', 'reading, playing and talking with child', 'accompanying child', 'other specified childcare'. This definition lines up well with the corresponding item in the UKHLS Covid module, which is elicited from the question 'About how many hours did you spend on childcare or home schooling last week?'.

We use these data by first predicting time spent on childcare using a regression which includes full and flexible interactions of the following: gender; number of children under 4 years of age in the household; number of children between 5 and 10 years of age; the presence of a partner, and economic status (working, inactive, dedicated to care). Because all households complete the survey both for a day from the weekend and from mid-week, we use the survey weights to give an average at the individual level across a typical week. The results of the regression are given in appendix Table A.6, and come from a usable sample size of 14,688. Together these variables explain around 50 percent of variation in time spent on childcare in the UKTUS.

We then use the identical background variables in the UKHLS 2019 survey to impute predicted childcare in our baseline. Our approach therefore assumes that patterns of time spent with children are comparable across 2014 and 2019. Within this context, it should be noted that minor changes to shared parental leave rights were introduced in April 2015, between the two survey dates. However, our imputation conditions on economic status, including working/carer status, and so controls for subsequent changes to the distribution of childcare time to the extent that these changes occurred along this extensive margin.

The adjusted number of interviews in the UKHLS for which full information is available on all measures, including relevant measures from previous UKHLS waves and the imputed childcare hours for 2019, is 10,870.

3 Framework

We begin our formalization of the relationship between changes in mental well-being and explanatory factors using the following regression model:

$$\Delta ghq_{it} \quad = \quad \alpha + \beta\, Female_i + \delta_1^* \Delta Z_{1,it} + \delta_2^* Z_{2,it=2019} + \epsilon_{it} \tag{1}$$

where $Female_i$ is a binary dummy capturing the gender of individual i. Δx_t indicates a change in variable x at time t during the pandemic since the pre-Covid baseline ($t = 2019$), with Δghq_{it} therefore denoting the dependent variable of interest. These time subscripts are included for completeness and for ease of exposition even though in our main analysis we estimate the model using $t =$ April 2020 only.

As shown in model (1) we allow changes in mental health to depend not only on gender but a variety of other factors. We first isolate dynamic factors that may have worsened since before the pandemic, given by the vector Z_1. Examples of relevant variables here might be the presence of Covid symptoms or labour market status. We also consider, in Z_2, factors for which pre-existing exposure may be important. These may include, for example, the presence of young children in the household. In various specifications Z_2 also includes purely fixed factors such as year of birth, as well as highly durable factors such as personality traits. We allow vectors Z_1 and Z_2 to overlap: mental health changes might depend on pre-existing and continuing childcare obligations, as well as on changes in childcare brought about by school closures. In this model therefore, when Z_1 and Z_2 include all relevant factors, β captures the gender gap which remains after adjusting for composition differences in relevant exposures.

We explore gender differences in mental health further by examining an extension of model (1) as follows:

$$\Delta ghq_{it} \quad = \quad \alpha_g + \delta_{g1} \Delta Z_{1,it} + \delta_{g2} Z_{2,it=2019} + \epsilon_{it} \tag{2}$$

where $g(i) \in \{male, female\}$ and is written for simplicity as g. This model allows for gender differences in the effect of different exposures. For example we may expect men and women to react differently to the presence of children in the household.

Models (1) and (2) can be combined to provide the standard Oaxaca-Blinder (OB) decomposition framework, most commonly applied to differences in wages across gender or race. For notational convenience, we further combine Z_1 and Z_2 into Z and drop subscripts i and t. Then, letting $\overline{x}^g$ denote the population average of variable x for group g, the mean difference in mental health changes across genders can be written as:

$$\begin{aligned} \Delta\overline{ghq}^f - \Delta\overline{ghq}^m &= \delta^* \left(\overline{Z}^f - \overline{Z}^m\right) + \beta & (3) \\ &= \underbrace{\delta^* \left(\overline{Z}^f - \overline{Z}^m\right)}_{\substack{\text{composition} \\ \text{effect}}} + \underbrace{\left[(\delta_f - \delta^*)\,\overline{Z}^f + (\delta^* - \delta_m)\,\overline{Z}^m + \alpha_f - \alpha_m\right]}_{\text{structural/unexplained effect}} & (4) \end{aligned}$$

where, in line with the discussion in the Introduction, the composition effect captures differences in exposures across genders, and the structural effect captures differences in responses to those exposures. In the language of the OB literature, here we use the 'pooled' version of the decomposition, where we effectively weight (or 'price') differences in exposures at the average mental health change across genders. The composition effect can be estimated from model (1) alone, while the detailed 'structural' effect is obtained by estimating model (2) additionally.

Several aspects of the implementation of this framework require further discussion. First, many of the factors included in Z may be endogenous to mental health changes. In line with the standard use of the OB framework, we do not give our results a causal interpretation. Instead the effect sizes are interpreted as giving 'bottom line' indications on the likely importance of different factors. Second, and relatedly, we group together different bundles of explanatory factors according to how closely they are related to mental health changes. In particular we focus on two specifications: our main specification captures salient and relevant observable factors, many of which may be endogenous, such as labour market status or time spent on childcare in 2019; our additional specification is restricted to highly pre-determined factors which may provide underlying causal relevance - specifically personality traits. Third, while a detailed analysis of the composition effect for each explanatory factor is straightforward, it is well known that the structural effect is more difficult to interpret in detail. Just like the intercept in a standard regression, interpretation depends crucially on the choice of baseline categories (Fortin et al. 2011). In our discussion in Section 4 we describe in detail the interpretation of the structural effect whenever it is examined.

4 Results

4.1 Declines in Well-Being by Gender and by Salient Factors

We begin our analysis by presenting correlations of the change in subjective well-being at the onset of the pandemic with a variety of background characteristics/circumstances. We present these results separately by gender, to highlight differential responses to the circumstances that men and women face. As such, the Tables we present here correspond to univariate implementations of model (2) above. As discussed, our main analysis focuses on the immediate onset of Covid-19 and thus uses within-pandemic data from April 2020 only. In Appendix B, we provide results for the entire first Covid wave in the UK, including data from May and June 2020, yielding similar conclusions.

Time Use

We start with factors that relate to situation within the household. Alon et al. (2020) discuss that the closure of schools and daycare facilities affected women more than men in the U.S. and that the effects on time use were overall stronger than effects relating to employment. For the UK, Andrew et al. (2020) show that mothers in households with two opposite-gender parents bore a disproportionate share of household responsibilities. In line with the framework presented in Section 3 we therefore examine whether changes in well-being are related to changes in time spent on childcare, as well as pre-existing exposure to childcare duties. We also show the effects of changes in time spent doing housework.

Accordingly, Table 1 shows the change in well-being by gender and when individuals are grouped into coarse bins based on their exposure. Importantly, Table 1 includes all respondents, with and without children. Columns 1 and 4 show the correlation of changes in well-being with experienced changes in childcare duties. All of the three groups faced a decline in mental well-being on average in Spring 2020. Women who faced either no change or an increase in childcare duties were more affected than men in the same categories. However, there is no strong evidence that women with increases in childcare duties suffered substantially more than those whose duties changed little or had no children.

We show the proportions of the sample making up each category in Figure 3, which we use extensively to discuss differential exposure. Relating to the framework discussed in Section 3, this figure therefore captures Z^f and Z^m, used in equation (4) and later used to explain the gender gap in well-being in the aggregate. The top-left panel of the figure indicates that although more women faced an increase in childcare than men (17 percent compared to 15 percent), these differences are dwarfed by the approximately equal number facing no changes. This is due to the fact that most adults do not have young children. Therefore, to the extent that women faced some impact from increasing childcare duties, it seems unlikely that these changes alone contribute much to the gender gap overall.

Table 1: Well-Being by Gender: Time Use and Family Effects

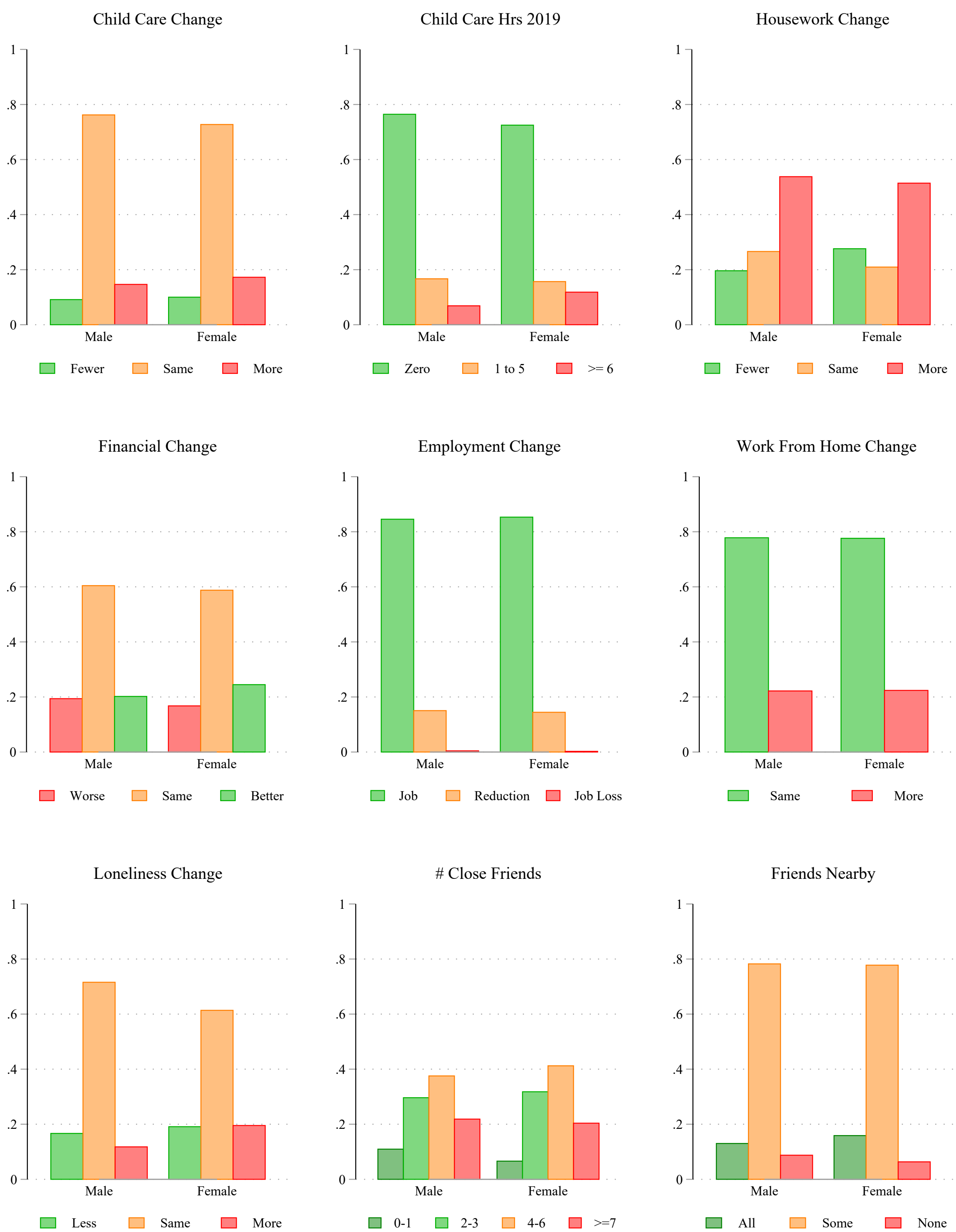
	Female	Female	Female	Male	Male	Male	Difference
Δ Childcare: Fewer hrs	-0.23***			-0.17**			[0.51]
	(0.05)			(0.08)			
Similar hrs	-0.22***			-0.06**			[0.00]
	(0.03)			(0.03)			
More hrs	-0.29***			-0.11*			[0.02]
	(0.05)			(0.06)			
Childcare in 2019: Zero		-0.22***			-0.06**		[0.00]
		(0.03)			(0.03)		
1 to 5		-0.18***			-0.09*		[0.19]
		(0.05)			(0.05)		
≥ 6		-0.36***			-0.17***		[0.01]
		(0.05)			(0.06)		
Δ House Work: Fewer hrs			-0.18***			0.04	[0.01]
			(0.05)			(0.06)	
Similar hrs			-0.29***			-0.11***	[0.01]
			(0.04)			(0.04)	
More hrs			-0.27***			-0.11***	[0.00]
			(0.03)			(0.03)	
Observations	6959	7015	6790	5077	5105	4890	
Adjusted R^2	0.045	0.047	0.052	0.007	0.007	0.011	

Notes: Data from UKHLS 2019 and Covid module. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. Changes in childcare and house work are computed based on self-reported time use in the previous week. Childcare levels in 2019 are imputed from UKTUS as explained in Section 2.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns 2 and 5 examine the role of pre-existing exposure to childcare, splitting respondents by weekly childcare hours in 2019. Both women and men who reported childcare duties of 6 hours or more per week before the pandemic faced on average the worst well-being at its onset.[11] While women with higher childcare duties suffered more, we also note a pronounced gender imbalance in exposure, with 12 percent of women in the higher childcare group compared to only 7 percent of men (top center panel in Figure 3). On these results, it seems that the more important predictor of well-being declines for women was not so much the increase in childcare at the start of lockdown, but the pre-existing exposure to children who required a high level of attention.

[11] All these results are in line with Xue and McMunn (2021) who report a negative correlation of child care and changes in well-being of women in the UKHLS and a negative, but not statistically significant relationship for men, but using the April 2020 data only. See also Cheng et al. (2021) and Chandola et al. (2020) for similarly consistent results.

Figure 3: Fraction of Women and Men facing a given Circumstance



Notes: Data from 2019 and Covid module, including survey weights. Variables are the same as those presented in Tables 1, 2 and 3. For each variable, the figure reports proportions of the sample taking each value, by gender.

To examine other aspects of time use, Columns 3 and 6 show the relationship between changes in well-being and changes in time spent on house work. Again, most groups faced on average worse mental health in Spring 2020. In terms of the proportions of men and women that fall into each of the three categories, we in fact find results that contrast with those for childcare, suggesting some substitutions in time use: A higher fraction of men reported increases in housework time (54 percent vs 51 percent for women, top right panel in Figure 3), with a higher fraction of women reporting decreases. These results indicate that this factor in particular is unlikely to account for the widening gender gap.

Economic Impacts

Much of the current literature on consequences of the pandemic has focused on economic impacts such as hours worked or facing financial difficulties. Accordingly, Table 2 shows the relationship of changes in well-being by gender and various indicators of economic position. Columns 1 and 4 show mean group effects for a change in a subjective measure asking how well respondents are getting by.[12] We use this measure as a summary of the complex impacts of loss of earnings and other incomes, as well as changes in expenditure patterns induced by the pandemic. Not surprisingly, we see a stronger average decline for those who report a worse subjective financial situation.[13] This effect is not significantly different for women and men. Only for those who see no change or an improvement in their financial situation are well-being changes for women significantly worse. For the majority of respondents, the financial situation does not change (59 percent of women and 60 percent of men; see middle left graph in Figure 3). However, it is noteworthy that more women report an improvement in their financial situation (24 percent vs 20 percent of men), indicating that compositional differences in this factor may, if anything, *narrow* the gender gap. Again, it is worth remembering, however, that this analysis is broad-brush and does not examine particular subgroups for which gender differences in financial outcomes may be different (see Andrew et al. 2020; Benzeval et al. 2020).

In Columns 2 and 5 we turn to furloughing and job loss, the latter of which is usually a strong predictor of subjective well-being (Blanchflower and Oswald 2004; A. Clark and Oswald 1994; L. Winkelmann and R. Winkelmann 1998). Those who lost their jobs fully saw large declines in well-being.[14] However, only less than 0.32 percent of the sample falls into this category, which implies

[12]Respondents are asked 'How well would you say you yourself are managing financially these days? Would you say you are...', and then given 5 options: 'Living comfortably'; 'Doing alright'; 'Just about getting by'; 'Finding it quite difficult', and 'Finding it very difficult'. We compare respondents' answers in 2019 and April 2020.

[13]This is consistent with Chandola et al. (2020) who use the 2020 data of this variable and report that those who find it quite or very difficult to get by are 2.4 times more likely to be classified as suffering from clinical mental distress than those who report living comfortably. See also Adams-Prassl et al. (2022) for the US.

[14]These findings are in line with the existing evidence pre-Covid documenting a negative relationship between unemployment and well-being. For example, A. Clark and Oswald (1994) use the first wave of BHPS (1991) and find that the unemployed have a 2 times larger GHQ score than the employed. See also, for example, Janke et al. (2020) and L. Winkelmann and R. Winkelmann (1998). While the difference is not significant, our point estimates suggest

that the explanatory power of job loss for the gender gap is likely to be limited. More usually, for roughly 15 percent of the sample, hours were cut or employees were furloughed. For these, the decline in well-being was not significantly different than for those who continued working as previously. Examining the fraction of women and men who faced these different working circumstances, we do not see a difference between gender (middle centre graph in Figure 3).

Table 2: Well-Being by Gender: Finances and Work

	Female	Female	Female	Male	Male	Male	Difference
Δ Finances: Worse	-0.49***			-0.37***			[0.17]
	(0.06)			(0.06)			
No change	-0.28***			-0.06**			[0.00]
	(0.03)			(0.03)			
Better	0.02			0.17***			[0.02]
	(0.04)			(0.05)			
Δ Employment: No change		-0.23***			-0.08***		[0.00]
		(0.02)			(0.02)		
Reduction		-0.27***			-0.03		[0.00]
		(0.05)			(0.05)		
Job Loss		-0.98***			-0.61*		[0.37]
		(0.25)			(0.33)		
Δ WFH: No change			-0.21***			-0.08***	[0.00]
			(0.03)			(0.03)	
More			-0.33***			-0.06*	[0.00]
			(0.03)			(0.04)	
Observations	7122	7136	7135	5154	5161	5159	
Adjusted R^2	0.070	0.047	0.049	0.039	0.007	0.006	

Notes: Data from UKHLS 2019 and Covid module. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. Change in finances is based on self-reports of the present financial situation, measured in 2019 and 2020: variable 'finnow'. Change in employment (no change, reduction in hours/furlough, job loss) comes from Covid wave 1. Changes in work from home are calculated based on self-reported work from home patterns for February 2020 and April 2020 (both measured in Covid wave 1).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To broadly assess the importance of the type of work and the way it can be done, we examine changes in working from home (WFH) patterns in Columns 3 and 6. All groups saw a decline in their well-being. On the one hand, the effect of increases in WFH on mental well-being declines was significantly stronger for women. On the other hand, there were no gender differences in frequencies of these categories: 22 percent of each gender worked from home more often (middle centre graph in Figure 3). This factor therefore provides an illustration of different explanations of the gender gap, aligning with the discussion in Section 3. As the frequencies of WFH were similar across gender, the

a higher impact of unemployment on women than men. In fact the literature usually finds a higher impact for men (Blanchflower and Oswald 2004).

role of compositional differences here are necessarily small. However, WFH was clearly associated with *structural* differences in well-being, with women who worked from home suffering more than men. We return to this discussion in Section 4.2.

Social Factors

One immediate consequence of the pandemic was social distancing induced by the lockdown policy. We therefore examine the role of social relationships and loneliness, which have been associated with subjective well-being in a predominantly psychological literature (for a review see e.g. J. Cacioppo et al. 2015). Table 3 shows social factors and their correlation with changes in well-being.

Table 3: Well-Being by Gender: Social Factors

	Female	Female	Female	Male	Male	Male	Difference
Δ Loneliness: Less	0.18***			0.29***			[0.17]
	(0.05)			(0.06)			
No change	-0.17***			-0.05**			[0.00]
	(0.03)			(0.02)			
More	-0.86***			-0.70***			[0.07]
	(0.04)			(0.08)			
Friends: 0-1		-0.13			0.03		[0.31]
		(0.12)			(0.10)		
2-3		-0.21***			-0.06		[0.01]
		(0.05)			(0.04)		
4-6		-0.28***			-0.09**		[0.00]
		(0.03)			(0.04)		
≥ 7		-0.25***			-0.11***		[0.01]
		(0.03)			(0.04)		
Friends nearby: All			-0.14*			-0.01	[0.11]
			(0.07)			(0.04)	
Some			-0.25***			-0.08***	[0.00]
			(0.02)			(0.02)	
None			-0.30**			-0.13	[0.35]
			(0.12)			(0.14)	
Observations	7131	7059	7131	5155	5076	5156	
Adjusted R^2	0.137	0.049	0.048	0.082	0.007	0.006	

Notes: Data from UKHLS 2019, Covid module and UKHLS wave 9. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. Change in loneliness is based on self-reports of the present frequency of feeling lonely, measured in 2019 and 2020. Number of close friends and fraction of friends living nearby are measured in UKHLS wave 9.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For changes in loneliness, we document strong effects. Those who were less lonely saw an *increase* in well-being, whereas those who were more lonely faced a large negative decline.[15] Women appear to be worse affected than men. Whereas the majority did not face changes in loneliness (61 percent of women and 72 percent of men), we see that more women than men reported an increase in loneliness (20 percent vs 12 percent; see also bottom left graph in Figure 3). This finding indicates that changes in loneliness potentially play an important role in explaining the gender gap.

To examine the role of social connectedness in more detail, we make use of a special module conducted in wave 9 that elicits the number of close friends. *A priori*, it is not clear how the number of friends would relate to subjective well-being during the pandemic and in particular the lockdown. On the one hand, one might hypothesise that a strong social network can help coping with such a difficult situation, thus leading to a positive correlation between number of friends and well-being changes. On the other hand, related to the above discussion of loneliness, being more connected might lead to increased feelings of loneliness during physical distance measures and lockdowns, as well as indicating a higher dependence on friendships in general. Columns 2 and 5 suggest that the latter explanation applies: individuals with more close friends faced somewhat larger declines in well-being.[16] This pattern is similar for women and men. Interestingly, and similarly to loneliness, the distributions across categories also display significant gender differences: only 7 percent of women fall in the category for whom outcomes were most favourable, reporting zero or one friend, as opposed to 11 percent of men (see bottom middle graph in Figure 3).

Pursuing this analysis further, we examine the role of *geographic proximity* to friends. Even though meeting friends was prohibited at the time we examine, outdoor exercise was allowed, and therefore social interaction with friends nearby was possible with only a minor infringement of the rules. We thus explore how well-being changes relate to the fraction of friends living close by. Those who have all of their friends living nearby saw smaller well-being declines than those with at least some friends living faraway.[17] In fact, composition effects for this variable are in favour of women, with a larger fraction of women appearing in the most advantaged category with all their friends nearby (16 vs. 13 percent; see bottom right graph in Figure 3). However, the differences across genders are small and it is unlikely that proximity of friends is important for the gender gap in aggregate.

[15] These correlations are in line with previous psychological studies reporting negative correlations between levels of loneliness and levels of mental health. For example, Coyle and Dugan (2012) find that older adults in the US who reported loneliness had a 17 percent higher change of having a mental health problem and Cornwell and Waite (2009) report a 60 percentage point lower likelihood of reporting very good or excellent mental health for those who feel extremely isolated (as compared to those who do not feel isolated). J. T. Cacioppo et al. (2006) use a within-participant design and hypnosis to vary feelings of loneliness in a small sample and find higher levels of anxiety for the high loneliness condition.

[16] When pooled across genders and including a gender dummy, the relationship between number of friends and the drop in well-being is significant at the 10% level (not shown). See also studies that find a positive correlation of number of friends and various cross-sectional outcomes such as mental health or life satisfaction. See, for example, Helliwell and Huang (2013), Ho (2016), and Lima et al. (2017).

[17] The difference between those with all friends nearby and those with only some nearby is also significant at the 10% level when pooling women and men.

Other Factors

We also investigate additional correlations of well-being changes with changes in medical and health factors, health behaviors and key demographics. These are presented in Appendix tables A.2, A.3 and A.4, respectively. Figure A.2 shows the proportion of women and men in the different categories. In sum, we find negative average changes in well-being for almost all groups. While patterns are largely similar across both genders, women in any given category are often worse affected.

Regarding medical (health) factors, we see that those who experienced Covid symptoms (11 percent of the sample) also experienced larger declines in well-being, with women more affected than men (see Table A.2).[18] Those who received more external help experienced larger well-being declines than those without a change and women in both categories saw larger declines than men.

Regarding health behaviors (shown in Table A.3), patterns differ more clearly between women and men. For example, men who exercised more during the pandemic did not face a change in their well-being and did significantly better than those who did not change their exercise level or those who exercised less. For women, changes in exercise show a less systematic relationship with well-being changes.

We present correlations with key demographics in Table A.4. Interestingly, only men appear to be negatively affected by the presence of children. Most notable are results by age (in line with Banks and Xu 2020; Davillas and A. M. Jones 2021). Young women (16–29 years old) faced substantially larger well-being declines than any other groups. This is particularly interesting as overall, the young appear to be comparatively more affected by the policy response to Covid than by Covid itself.

4.2 Decomposition Results

We turn now to the decomposition, formalized in Section 3. The results are presented in Table 4. The first column includes a full set of controls grouped into the six relevant factors discussed in Section 4.1: domestic and time-use; financial and work; social; health; health behaviours, and basic demographic.[19]

The first row of Table 4 shows the estimated raw gender gap, equaling 17.5 percent of a standard deviation in April 2020 compared to baseline. The top main panel of Table 4 then shows the

[18] The presence of symptoms and vulnerability only appear in the Covid data. However, we treat these as dynamic variables and impose their absence across the population in the pre-pandemic period.

[19] The allocation of controls to these factors is somewhat arbitrary, and, in some cases overlapping: For example, we include working from home status in 'financial and work' rather than 'domestic and time-use', while 'basic demographic' includes age, which is also strongly correlated with domestic and time use factors. This is why we also examine the most salient factors such as age and changes in childcare and house work separately in Table 4 and Table A.5, respectively.

Table 4: Decomposition of the Gender Gap

	(1)	(2)	(3)	(4)
Gender Gap	0.175***	0.175***	0.175***	0.149***
	(0.031)	(0.031)	(0.033)	(0.035)
Composition effect attributable to:				
1) Time use and family	0.015**	0.016**		
	(0.007)	(0.007)		
2) Finances and work	-0.017***	-0.018***		
	(0.005)	(0.005)		
3) Social factors	0.041***	0.039***		
	(0.009)	(0.010)		
4) Medical factors	0.011***	0.013**		
	(0.004)	(0.005)		
5) Health behaviors	0.000	-0.000		
	(0.003)	(0.003)		
6) Demographics (incl. age)	-0.000	0.002	-0.001	
	(0.005)	(0.006)	(0.005)	
Age only				0.000
				(0.003)
Extraversion				0.008**
				(0.004)
Other traits				-0.020*
				(0.012)
Total Composition Effect	0.050***	0.051***	-0.001	-0.012
	(0.014)	(0.015)	(0.005)	(0.012)
Structural effect attributable to:				
Groups 1) + 2)	-0.021	-0.021		
	(0.041)	(0.040)		
Groups 3) + 4) + 5)	-0.011	-0.010		
	(0.079)	(0.078)		
Group 6) Household composition	-0.065	-0.066	-0.057	
	(0.052)	(0.054)	(0.061)	
Group 6) Age	0.102	0.100	0.148**	0.124**
	(0.076)	(0.075)	(0.067)	(0.058)
Extraversion				0.004
				(0.048)
Other traits				0.103
				(0.105)
Constant	0.120	0.120	0.085	-0.070
	(0.120)	(0.120)	(0.091)	(0.131)
Total Structural Effect	0.126***	0.124***	0.177***	0.160***
	(0.029)	(0.030)	(0.032)	(0.035)
Observations	10870	10870	10870	9756

Notes: Data from UKHLS 2019, Covid module and UKHLS wave 9. Dependent variable is individual change in standardized inverted GHQ Likert score. See text for details. Standard errors clustered at the primary sampling unit and presented in parentheses. Columns 1, 3 and 4 show pooled specifications and Column 2 replicates Column 1 but evaluated at female prices. Columns 1 and 2 group variables of Table 1 in Group 1) Time use and family, variables of Table 2 in Group 2) Finances and work, variables of Table 3 in Group 3) Social factors, variables of Table A.2 in Group 4) Medical factors, variables of Table A.3 in Group 5) Health behaviors, variables of Table A.4 in Group 6) Demographics unless indicated otherwise. The lower panel groups several structural effects for the ease of exposition; all estimates are shown in Table A.7. The omitted categories are 'no change' for change variables or '0' for variables that take positive values. All variables that are originally continuous (time use variables, number of friends, change in exercise and kids) are included in their continuous version, together with its square. The sample in Column 3 is restricted to those who are also included in Columns 1 and 2. Column 4 uses Big-5 personality traits measured in UKHLS wave 3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

'composition' (or 'explained') effect, as discussed in Section 3. This panel therefore shows the importance of different exposures rather than differential responses to the same exposure. The first column shows the components when they are evaluated at the average effect of the exposures across women and men. Although not discussed formally in Section 3, we present results using the 'detailed decomposition', which is standard in the literature (Fortin et al. 2011).

Table 4 shows that significant fractions of the gap can be explained by social, time use and and health ('medical') factors. Of these the largest is social factors which explains around 4.1 percentage points of a standard deviation.[20] This factor includes reported change in loneliness as well as number of friends reported in 2019 and the proportion of friends living closely. Gender differences in time use and family are less important overall and explain around 1.5 pp. Health is less important still, explaining around 1.1 pp. Also noteworthy are financial and work factors which provide a *negative* contribution to the gap of 1.7 pp. This estimate implies that women reported *benefitting* from a better financial situation, and in fact the gender gap in mental well-being would have been even worse had this factor been equally distributed. Of the remaining groups, differences in health behaviours provide no contribution to the gender gap. Finally, that demographics do not contribute to this part of the gender gap is to be expected as basic characteristics (age, marriage and children) are roughly equally distributed across genders. In fact, however, demographics are relevant for the gender gap in other dimensions, as we discuss shortly.

The bottom main panel of Table 4 shows the 'structural' (or 'unexplained') effect, also described in Section 3. This shows the differential responses to the same exposures. Again as discussed in Section 3, this detailed decomposition can be difficult to interpret, and depends crucially on the omitted categories or bases of the included variables.[21] We use natural bases, which are typically 0 or 'same' on change variables, and 0 on variables that take positive values (such as time spent on childcare). Importantly, for age, we take as base those aged 70 and above. The results in the bottom panel therefore correspond to the increase in the size of the gender gap at the means of the relevant variables compared to these bases, with the precise quantitative results showing a net contribution, weighting for distribution and controlling for the other factors.

In the discussion in Section 4.1, we highlighted some noticeable structural differences between men and women. For example Table 2 showed that women experienced relatively worse outcomes when working from home. Unfortunately, in the context of the full decomposition analysis, the precision on the structural effects is typically lower than on the composition effects, and no factors are found to be significant. For this reason, here we combine several of the groups together. The disaggregrated results are shown in Table A.7. The factor showing the strongest influence is age (p-value of 0.18)

[20]The importance of social factors is broadly in line with Armbruster and Klotzbuecher (2020), who, for a different country and with very different data, discuss that the decline in mental health is not driven by financial worries or fear of the disease, but is due to higher levels of loneliness and anxiety.

[21]It is sometimes said that this detailed decomposition suffers from an identification problem (see, for example Oaxaca and Ransom 1999). In fact, as discussed by Fortin et al. (2011), the challenge is not one of identification, but of interpretation.

which accounts for over 80% of the unexplained effect. This estimate reflects the fact that the gender gap is far smaller for the over-70s than for younger groups, and shows the important interaction of age with gender (Banks and Xu 2020).

The second column of Table 4 is similar to the first, except the composition part is evaluated at the female effects (the female 'price' in the language of wage decompositions). The results here are virtually identical to those in the first column, with the composition effects only very slightly larger. All the components are also very similar when evaluated at the male effects (not shown).

The third column of Table 4 focuses on demographic factors only and removes all other controls. In this simple specification, the positive contribution of age to the structural effect (the interaction of age and gender) is more precisely estimated and significant at the 5-percent level. The point estimate of 0.148 is around 45% larger than that shown in the first column. This estimate indicates that the controls we include, such as time use and financial factors, explain some of this interaction, but not the majority of it.

The final column of Table 4 uses a largely different set of controls and shows the OB decomposition when we use pre-determined factors: the big-5 personality traits. We continue to control for age in this model because personality traits have been shown to follow age profiles (Roberts et al. 2006). Importantly in our context, several papers show that personality traits differ by gender (Feingold 1994; Weisberg et al. 2011). Building on the model shown in the first two columns, we focus in particular on extraversion, which is potentially related to social factors, and which we find to be higher in women in our sample.[22] Among composition factors, this final column shows that differences in extraversion explain around 0.8 percentage points of the gender gap. The small size of the effect itself is to be expected: it is *a priori* unlikely that large gaps in mental health outcomes would be explained substantially by questionnaires filled in a decade previously. Nevertheless we proceed with using the full apparatus of the decomposition analysis for comparison with our other results. Interestingly, when grouping together the other personality traits, they amount to 2.0 percentage points of the gender gap but in the *negative* direction. In other words, if women had the same levels of the other traits (agreeableness, conscientiousness, neuroticism and openness) as men, then the gender gap in mental health decline would be noticeably larger. For conscientiousness, for example, women score more highly in this trait, which is associated with better mental health outcomes during the pandemic.

The bottom panel shows the structural decomposition for this final specification. Compared to the third column, the point estimate on age is brought down slightly. The small point estimate on extraversion implies that the gender gap remains stable along the distribution of this trait. The

[22]More generally, gender differences in extraversion are nuanced. Weisberg et al. (2011) find that women score more highly in facets of extraversion related to enthusiasm, while men score more highly in facets related to social dominance. In labour economics, a recent literature has explored the idea that female comparative advantage in social skills – associated with extraversion – is important for explaining recent changes in the labour market (Borghans et al. 2014; Cortes et al. 2018).

point estimate on other traits is much larger, but is similarly imprecisely estimated. Overall, as with the specification in the first column, the most conclusive results from personality traits come from the analysis of the composition effect in the top panel, and show a clear role for gender differences in social factors.

To provide a graphical illustration of our main results, Figure 4 plots the estimates of the detailed composition effects as percentages of the total gender gap. The left bars show the contribution of the four main groups of variables either as factors that together explain the gender gap (shown as positive components above the horizontal axis), or as factors working in opposition (below the horizontal axis). Together, the positive components explain a little under 40 percent of the gap. As discussed previously, social factors are by far the most important. In fact of the three variables entering into this group, the change in loneliness explains the overwhelming majority.[23] Although the distribution of friends works qualitatively in the same direction, quantitatively it is not as important.[24]

The right bars of Figure 4 show the equivalent contributions for personality traits. As discussed above, differences in extraversion explain around 5 percent of the gender gap, while the other traits *widen* the gender gap by around 13 percent. Of the other traits, the most quantitatively important are conscientiousness and neuroticism, in both of which women score more highly, although no trait widens the gap significantly at the 5 percent level.

We finish our discussion by briefly investigating in additional detail the factors that have received the most attention in the literature: domestic and time-use (Andrew et al. 2020). As illustrated in Figure 4, we find that these factors have a modest joint effect on the gender gap for the population as a whole.

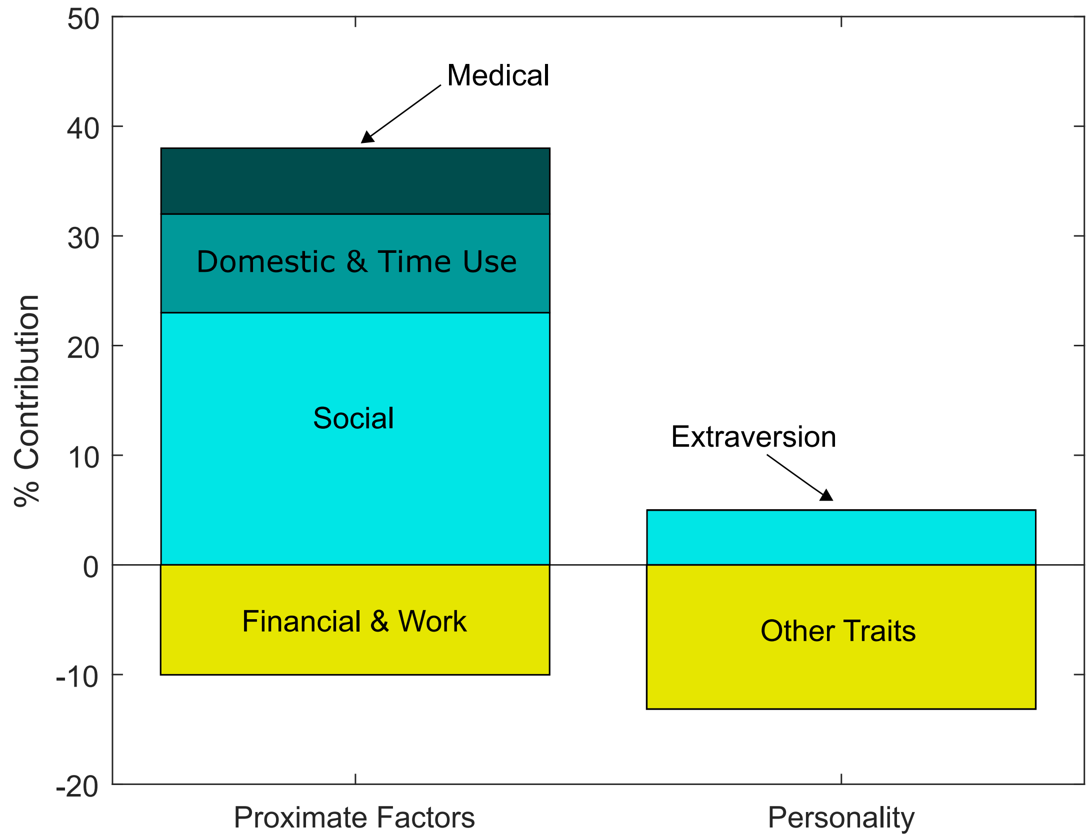
Table A.5 shows the percentage contribution to the overall gender gap for the three sub-factors factors we consider: pre-existing childcare, change in childcare, and change in housework. The results in the top row come from the same specification and sample as in Column 1 of Table 4. Although the detailed estimates are not precise, the point estimates are illuminating: In line with the discussion around Table 1, levels of childcare from 2019 seem to contribute more to the gender gap (5%), than do childcare changes (2%). Changes in house work also contribute a small amount to the gap at around 1.5%.[25]

[23]Chandola et al. (2020) report that feelings of loneliness are the most important predictor of overall changes in mental well-being (i.e., for both women and men). While they consider a smaller set of correlates and employ a different analysis, our results help interpret their findings.

[24]The importance of *feeling* lonely relative to the number of friends is in line with studies that find a stronger relationship between perceived isolation and mental health than between actual social disconnectedness and mental health (Cornwell and Waite 2009; Coyle and Dugan 2012; Taylor et al. 2018, all for older adults in the US). These findings also support the point of Golden et al. (2009) and Hughes et al. (2004) that loneliness and objective social isolation are two distinct concepts.

[25]P-values for childcare in 2019, changes in childcare and changes in house work are 0.13, 0.17 and 0.48, respectively.

Figure 4: Compositional Contributions To the Gender Gap



Notes: Figure shows components of the composition effect, shown in Table 4, as a percentage of the total gender gap. Areas above the axis are positive contributions to explaining the gap, areas below the axis are negative contributions. See Table 4 for more details on underlying calculations.

The bottom row shows the same decomposition, but restricts the sample to those with children only. As expected, the effects are much larger for this subsample and are in line with Andrew et al. (2020).[26] As shown in the second row of Table A.5, total time use factors now contribute 24% to the gender gap (p-value of 0.02). Again this contribution seems driven mainly by differential exposure to childcare levels, and less to childcare changes.[27]

Overall, Table A.5 illustrates the usefulness of representative samples that allow us to investigate effects for different subgroups as well as for the population as a whole. Not surprisingly, the choice of the sample influences the results. With our analysis, we can put findings of e.g. Andrew et al. (2020), who explicitly focus on mothers and fathers, into a broader perspective: Given that the majority of the population does not have young children, the gender gap in the overall population cannot be explained much by domestic and time use factors.

[26] The sample is reduced to 3,669 respondents, with a corresponding loss of power.

[27] P-values for childcare in 2019, changes in childcare and changes in house work are 0.12, 0.13 and 0.42, respectively.

5 Conclusion

Using rich longitudinal data from the UK, we assess the decrease in mental well-being at the onset of the pandemic that is particularly apparent for women. In April 2020, this extra gender gap in well-being amounted to 0.18 standard deviations in our representative sample. We explore possible explanations for this gap, examining a wealth of different factors, ranging from pre-existing domestic situation, to changes in work situation, to changes in loneliness and social factors. In our analysis, we distinguish between different circumstances faced by men and women and differential effects of the same circumstances on mental well-being.

We find that women were more exposed to domestic and time use factors that were associated with worse declines in well-being. For parents, these factors explain a noticeable fraction of the gender gap. However, we show that other factors that are more prevalent across the whole of the population played a larger role overall. Specifically, we document important gender differences in social factors, with women reporting substantially more increases in loneliness. Overall, our results suggest that the early impacts of lockdown on mental well-being of women worked less through its effect on time use or labour market, and more through the perceived loss of social interaction.

In terms of policy, our work has implications for strategies to tackle mental health in the later stages and immediate aftermath of the pandemic. We show that combating loneliness, particularly for women, will be paramount. This is especially true if social distancing continues in the medium term, perhaps mandated by policies necessary to tackle even more transmissible variants. However, even 'light touch' policies might be problematic for gender inequality given that women were found to be more cautious in their behavior at the onset of the pandemic (Galasso et al. 2020), consistent with the notion that women are more risk averse in many domains. This factor might imply that women are more likely to adopt behaviors that result in loneliness, even without the explicit policies such as those in place during the period of our study.

In line with the psychology literature that examines factors related to well-being in general, we emphasize the role of *perceived* isolation for both well-being declines and the gender gap. This finding poses interesting questions for policy and future research. For example, are there ways to reduce face-to-face interactions without increasing loneliness? Can access to new technologies and social media provide a solution?

Although not the focus of our analysis, we note that the gender gap in well-being grew equally large again in early 2021. Gender gaps in well-being are important not only in themselves, but also because they can exacerbate existing gender inequalities in other domains. For example, lower mental well-being can reduce productivity and hence impact current and future earnings, increasing the gender gap in pay. More generally, the age–gender gradient in well-being that we document is another example where preferences and/or needs of large parts of the population might be addressed more quickly or effectively if politicians reflected the diversity of the entire population.

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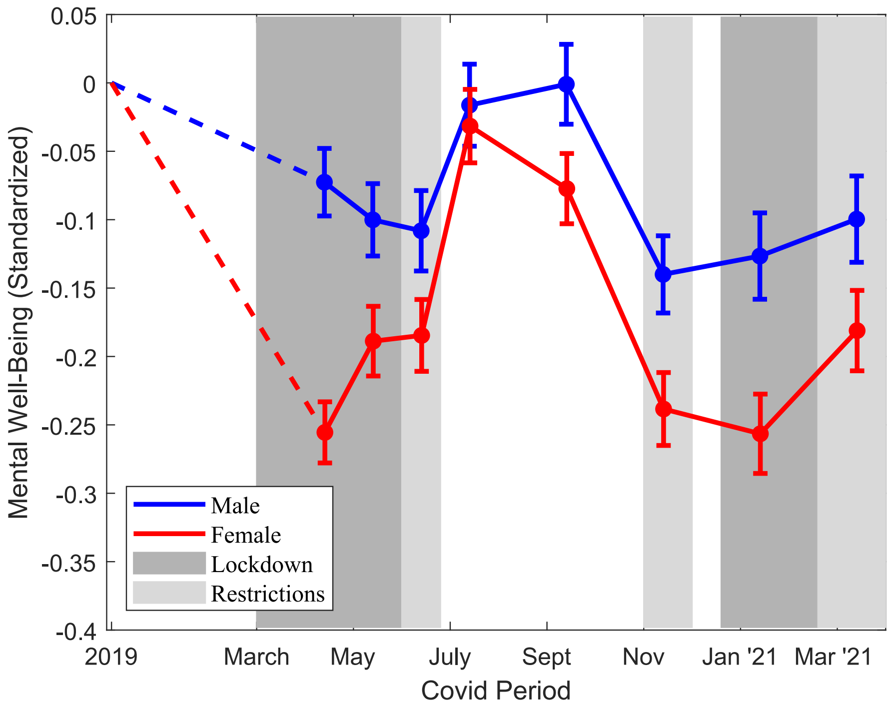
Appendix

A Additional Tables and Figures

Figure A.1: Mental Well-Being by Gender Across the First Year of the Pandemic

Indexed to 2019 = 0



Notes: Data from UKHLS 2019 wave and Covid module. Figure shows standardized, seasonally-adjusted and inverted Likert score, obtained from 12 questions in the General Health Questionnaire. See section 2 for more details. Profiles indexed to 0 in 2019. Sample consists of all those responding to each wave. Cross-sectional survey weights used. Error bars show 95% confidence intervals.

Table A.1: Summary Statistics of Main Variables

	Mean	SD	Min	Max	N
Well-being change	-0.16	1.02	-6.10	5.43	12,135
Female	0.52	0.50	0.00	1.00	13,775
Change in childcare (hrs)	2.83	11.29	-13.00	72.00	12,970
Childcare in 2019 (hrs)	1.49	4.23	0.00	37.00	13,065
Change in house work (hrs)	2.18	8.71	-21.00	30.00	12,578
Change in finances	0.04	0.64	-1.00	1.00	12,600
Employment	0.15	0.37	0.00	2.00	13,775
Change in WFH	0.21	0.41	0.00	1.00	13,769
Change in loneliness	-0.02	0.59	-1.00	1.00	12,862
Close friends	5.02	3.73	0.00	20.00	13,275
Friends nearby	1.93	0.47	1.00	3.00	13,271
Symptoms	0.12	0.32	0.00	1.00	13,775
Vulnerable	0.08	0.28	0.00	1.00	13,775
Change in help	0.13	0.49	-1.00	1.00	12,936
Change in alcohol	-0.19	0.44	-1.00	1.00	13,755
Change in exercise	0.04	0.86	-1.00	1.00	13,142
Change in smoking	-0.02	0.22	-1.00	1.00	13,255
Age	49.70	18.17	17.00	96.00	13,775
Couple	0.61	0.49	0.00	1.00	13,155
Children	0.33	0.47	0.00	1.00	13,317

Notes: Data from UKHLS main waves and Covid module 1. Table presents summary statistics using survey weights. Changes in finances, work from home, loneliness, help, alcohol, exercise and smoking are coded -1 for less, 0 for same and 1 for more in 2020. Employment takes the value of 1 for no change, 2 for a reduction in hours and 3 for job loss. Friends nearby takes the value 1 for all, 2 for some and 3 for none. Children is an indicator for children below the age of 16 in the household.

Table A.2: Well-Being by Gender: Medical/Health Factors

	Female	Female	Female	Male	Male	Male	Difference
Δ Symptoms: No	-0.22***			-0.07***			[0.00]
	(0.02)			(0.02)			
Yes	-0.39***			-0.14**			[0.00]
	(0.07)			(0.06)			
Δ Vulnerable: No		-0.23***			-0.07***		[0.00]
		(0.02)			(0.02)		
Yes		-0.30***			-0.11		[0.20]
		(0.11)			(0.09)		
Δ Receiving Help: Less			-0.33***			-0.23*	[0.54]
			(0.09)			(0.13)	
No change			-0.19***			-0.04	[0.00]
			(0.02)			(0.03)	
More			-0.35***			-0.18***	[0.03]
			(0.06)			(0.05)	
Observations	7136	7136	6846	5161	5161	5014	
Adjusted R^2	0.049	0.047	0.052	0.006	0.006	0.009	

Notes: Data from UKHLS 2019 and Covid module. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. 'Symptoms' comes from self-reported presence of symptoms since the onset of the pandemic. 'Vulnerable' takes value "yes" either if the individual has received an NHS letter requesting they should stay at home ('shielded') or the individual is pregnant. 'Help' is a self-report of whether the individual has received formal care and is measured twice in the Covid module, once for current help and once for help in 2019. Symptoms are vulnerable are reported for the Covid period only: we impose these variables as uniformly 0 in the pre-Covid period.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Well-Being by Gender: Health Behaviors

	Female	Female	Female	Male	Male	Male	Difference
Δ Alcohol: in 2019 only	-0.22***			-0.11			[0.20]
	(0.05)			(0.07)			
No change	-0.24***			-0.07***			[0.00]
	(0.02)			(0.02)			
in 2020 only	-0.45***			0.20			[0.01]
	(0.15)			(0.21)			
Δ Exercise: Less		-0.29***			-0.13***		[0.00]
		(0.04)			(0.04)		
No change		-0.20***			-0.12**		[0.27]
		(0.05)			(0.05)		
More		-0.23***			-0.00		[0.00]
		(0.03)			(0.03)		
Δ Smoking: in 2019 only			-0.41***			-0.25*	[0.45]
			(0.16)			(0.14)	
No change			-0.24***			-0.07***	[0.00]
			(0.02)			(0.02)	
in 2020 only			-0.17			0.29	[0.06]
			(0.13)			(0.20)	
Observations	7130	7054	7133	5158	5125	5161	
Adjusted R^2	0.047	0.047	0.047	0.006	0.009	0.008	

Notes: Data from UKHLS 2019 and Covid module. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. 'Alcohol' comes from self-report of whether respondent has drunk any alcohol in previous 4 weeks. 'Exercise' is based on self-report of whether the individual has either done moderate exercise or vigorous exercise on at least three days in the previous week. 'Smoking' is based on self-report of whether the individual smokes cigarettes. All variables are measured both in 2019 and 2020.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Well-Being by Gender: Demographic Factors

	Female	Female	Female	Male	Male	Male	Difference
Age: 16-29	-0.40***			-0.10			[0.00]
	(0.05)			(0.08)			
30-49	-0.29***			-0.07*			[0.00]
	(0.04)			(0.04)			
50-69	-0.18***			-0.04			[0.00]
	(0.03)			(0.03)			
Over 70	-0.14**			-0.11***			[0.65]
	(0.06)			(0.04)			
Couple: No		-0.26***			-0.06		[0.00]
		(0.04)			(0.05)		
Yes		-0.23***			-0.08***		[0.00]
		(0.02)			(0.02)		
Children: No			-0.24***			-0.05*	[0.00]
			(0.03)			(0.03)	
Yes			-0.25***			-0.11***	[0.00]
			(0.03)			(0.03)	
Observations	7136	7068	7024	5161	5129	5090	
Adjusted R^2	0.053	0.048	0.048	0.006	0.006	0.006	

Notes: Data from UKHLS 2019 and Covid module. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations.

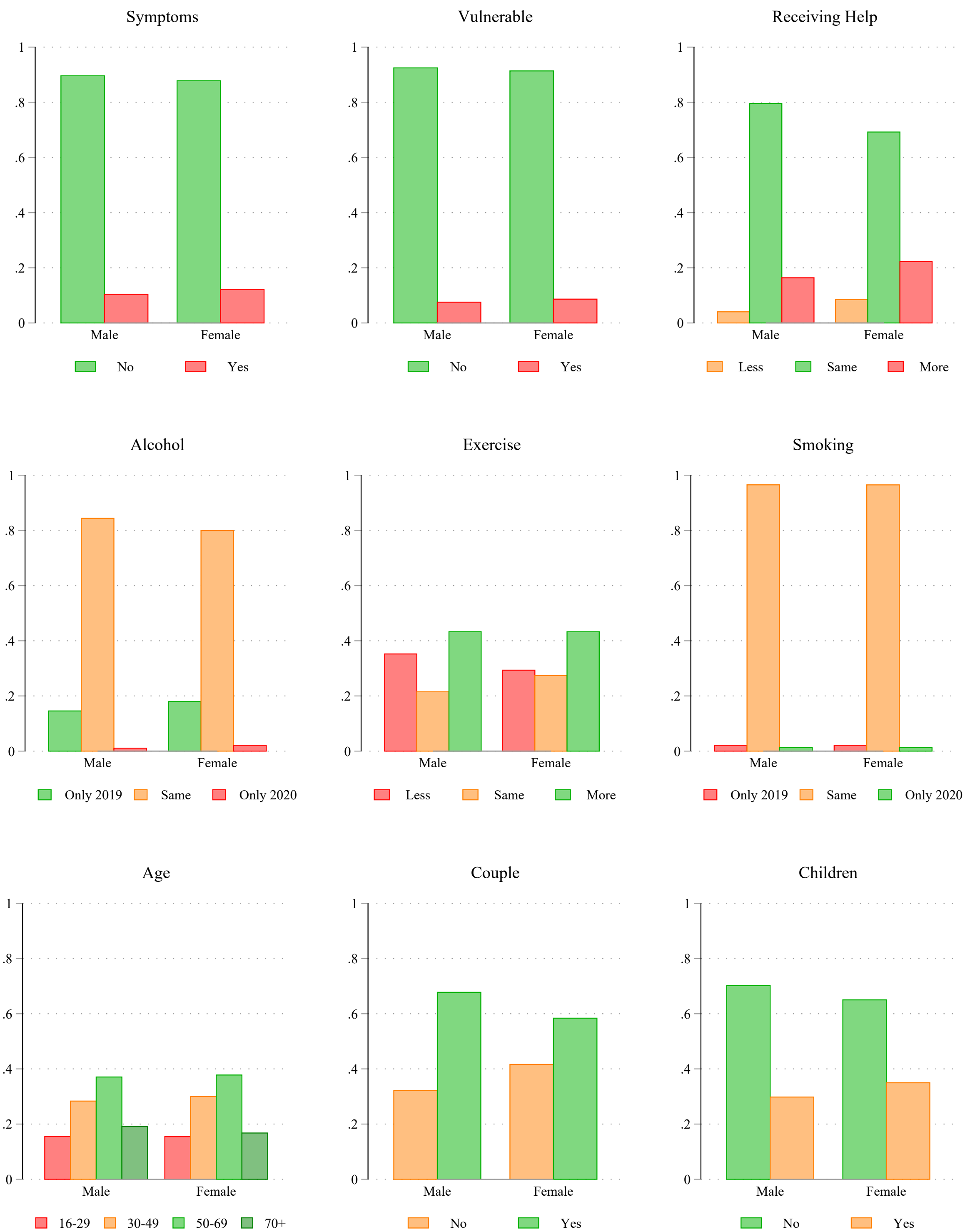
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Contributions to the Gender Gap (in %)

	Δ Childcare	Childcare 2019	Δ House work	Total time use
Entire Sample	2.12	4.73	1.54	8.38**
Those with Children	7.18	14.04	2.59	23.81**

Notes: The table shows the percentage that each time use variable contributes to the gender gap in terms of its composition effect. The first row includes the entire sample and thus expands Column 1 of Table 4. The second row shows results from a decomposition of the gender gap for those who have children. The total composition effect for those with children is 0.035 (SE = 0.029) and the gender gap amounts to 0.157 (SE = 0.049).

Figure A.2: Fraction of Women and Men facing a given Circumstance



Notes: Data from 2019 and Covid module, including survey weights. Variables are the same as those presented in Tables A.2, A.3 and A.4. For each variable, the figure reports proportions of the sample taking each value, by gender.

Table A.6: Time Spent on Child Care in the UKTUS (mins/day)

This Table shows results for a regression of time spent performing childcare on explanatory factors. The model is as follows. A two-part linear function for the number of children aged 4 and under (i.e. linear for one child and above) is interacted with gender, with marital status and a three-valued function for economic status: in work or otherwise occupied (such as being disabled), inactive with free time (unemployed, retired, or 'doing something else') or reporting being a dedicated carer (on maternity leave or 'looking after family or home'). A two-part linear function for the number of children aged 5-10 is interacted with the same variables and also included. The R-squared on this regression is 49% with $14,688$ observations. The columns of the table show the interaction with economic status, with the left-hand column being those in work or otherwise occupied. Standard errors are reported in parentheses.

Variable	Estimate	Variable	Estimate	Variable	Estimate
Constant (No kids,...	1.31	... * Inactive	-0.35	... * Dedicated	-1.31
Male, Single, In work)	(0.39)		(0.54)	Carer	(0.39)
Kids (0-4) > 0	119.87	... * "	67.36	... * "	159.65
	(46.71)		(121.40)		(87.63)
Number Kids (0-4)	-47.70	... * "	-46.39	... * "	-30.22
	(22.22)		(60.37)		(52.53)
Kids (5-10) > 0	-0.04	... * "	-74.45	... * "	38.87
	(11.23)		(61.26)		(56.11)
Number Kids (5-10)	0.64	... * "	57.69	... * "	4.95
	(9.93)		(64.87)		(53.38)
Female	1.84	... * "	-1.14	... * "	39.08
	(0.66)		(0.92)		(11.82)
Female * Kids (0-4) > 0	14.28	... * "	-22.81	... * "	-254.52
	(52.57)		(148.35)		(100.78)
Female * # Kids (0-4)	1.09	... * "	47.78	... * "	170.90
	(27.27)		(93.03)		(66.01)
Female * Kids (5-10) > 0	41.39	... * "	77.83	... * "	-47.05
	(15.94)		(71.63)		(53.49)
Female * # Kids (5-10)	-8.63	... * "	-55.18	... * "	-18.73
	(13.01)		(67.22)		(46.78)
Couple	3.00	... * "	-2.10	... * "	13.73
	(0.77)		(1.47)		(7.76)
Couple * Kids (0-4) > 0	-68.25	... * "	-93.10	... * "	0.58
	(47.75)		(132.24)		(185.59)
Couple * # Kids (0-4)	58.56	... * "	85.67	... * "	-13.61
	(23.31)		(77.15)		(104.17)
Couple * Kids (5-10) > 0	3.64	... * "	84.46	... * "	-19.22
	(13.30)		(69.83)		(60.78)
Couple * # Kids (5-10)	5.68	... * "	-64.92	... * "	-8.00
	(11.13)		(70.06)		(31.15)
Couple * Female	1.86	... * "	-3.15	... * "	-18.75
	(1.38)		(1.96)		(15.37)
Coup. * Fem. * Kids (0-4) > 0	-52.60	... * "	185.00	... * "	171.71
	(56.89)		(167.18)		(194.52)
Coup. * Fem. * # Kids (0-4)	80.13	... * "	-211.79	... * "	-156.71
	(32.43)		(108.10)		(114.03)
Coup. * Fem. * Kids (5-10) > 0	-45.04	... * "	-63.99	... * "	14.17
	(20.07)		(87.71)		(57.03)
Coup. * Fem. * # Kids (5-10)	23.35	... * "	69.38		
	(15.70)		(75.51)		

Table A.7: Decomposition of the Gender Gap

	(1)	(2)	(3)	(4)
Gender Gap	0.175^{***}	0.175^{***}	0.175^{***}	0.149^{***}
	(0.031)	(0.031)	(0.033)	(0.035)
Composition effect attributable to:				
1) Time use and family	0.015^{**}	0.016^{**}		
	(0.007)	(0.007)		
2) Finances and work	-0.017^{***}	-0.018^{***}		
	(0.005)	(0.005)		
3) Social factors	0.041^{***}	0.039^{***}		
	(0.009)	(0.010)		
4) Medical factors	0.011^{***}	0.013^{**}		
	(0.004)	(0.005)		
5) Health behaviors	0.000	-0.000		
	(0.003)	(0.003)		
6) Demographics: HH characteristics	0.000	0.001	-0.001	
	(0.005)	(0.005)	(0.005)	
6) Demographics: Age	-0.001	0.001	-0.000	0.000
	(0.002)	(0.003)	(0.002)	(0.003)
Extraversion				0.008^{**}
				(0.004)
Other traits				-0.020^{*}
				(0.012)
Total Composition Effect	0.050^{***}	0.051^{***}	-0.001	-0.012
	(0.014)	(0.015)	(0.005)	(0.012)
Structural effect attributable to:				
1) Time use and family	-0.013	-0.014		
	(0.023)	(0.021)		
2) Finances and work	-0.008	-0.007		
	(0.032)	(0.032)		
3) Social factors	-0.027	-0.025		
	(0.080)	(0.078)		
4) Medical factors	0.017	0.016		
	(0.023)	(0.020)		
5) Health behaviors	-0.001	-0.000		
	(0.023)	(0.023)		
6) Demographics: HH characteristics	-0.065	-0.066	-0.057	
	(0.052)	(0.054)	(0.061)	
6) Demographics: Age	0.102	0.100	0.148^{**}	0.124^{**}
	(0.076)	(0.075)	(0.067)	(0.058)
Extraversion				0.004
				(0.048)
Other traits				0.103
				(0.105)
Constant	0.120	0.120	0.085	-0.070
	(0.120)	(0.120)	(0.091)	(0.131)
Total Structural Effect	0.126^{***}	0.124^{***}	0.177^{***}	0.160^{***}
	(0.029)	(0.030)	(0.032)	(0.035)
Observations	10870	10870	10870	9756

Notes: Data from UKHLS 2019, Covid module and UKHLS wave 9. Dependent variable is individual change in standardized inverted GHQ Likert score. See text for details. Standard errors clustered at the primary sampling unit and presented in parentheses. This table shows the details of Table 4. See table notes of this table for a more detailed description.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Results for the entire first Covid-19 Wave (April – June)

In this section, we present results for the entire first Covid-19 wave in the UK, making use of UKHLS Covid waves 1–3. Waves 1 and 2 fall into the lockdown, whereas during wave 3, restrictions were still in place (see also Figure A.1). Except for financial situation, receiving help, exercise, smoking and alcohol consumption, all variables that we include in our main analysis are also contained in waves 2 and 3. The data now constitute an unbalanced panel.

The structure of this section follows our main analysis: we first present differential responses to same exposures, where Table B.1 replicates the analysis of domestic and time use factors shown in Table 1, Table B.2 mirrors Table 2 in analysing financial factors and Table B.3 repeats the analysis of social factors shown in Table 3. The overall pattern of results is largely similar. While several associations became stronger for men, the gender difference in responses to similar exposures remains in most cases. This is also true for medical factors and demographics, which we analyse in Tables B.5 and B.6, respectively.

We present decomposition results in Table B.4. Since we have to exclude the variables that are not measured in both waves 2 and 3, we start with presenting the decomposition with the reduced set of variables for wave 1 only in Column 1. This allows us to show to what extent the omitted variables were important in our main analysis before examining all three waves. Comparing Column 1 to our main analysis, we note two points. First, the importance of social factors and time use for the composition effect remains. Second and not surprisingly, leaving out the most important variables of financial and medical factors (financial situation and change in receiving external help) implies that these groups are not longer important for explaining the gender gap. Columns 2 and 3 include all three waves and present estimates of the pooled and the female-priced specification, respectively (similar to Columns 1 and 2 of Table 4). Adding waves 2 and 3 to our analysis reduces the estimate of the gender gap, consistent with Figure A.1. The importance of social and time use factors relative to the size of the gap thus increases. Columns 4 and 5 replicate Columns 3 and 4 of Table 4 (see also Table A.7 for better comparability). The structural effect of age is less important when considering UKHLS Covid waves 1–3. This can be explained with stronger declines for men in most age categories, as shown in Table B.6. Lastly, the effect of extraversion becomes smaller and statistically insignificant ($p = 0.12$).

Table B.1: Well-Being by Gender: Time Use and Family Effects (Waves 1-3)

	Female	Female	Female	Male	Male	Male	Difference
Δ Childcare: Fewer hrs	-0.23***			-0.20***			[0.66]
	(0.04)			(0.06)			
Similar hrs	-0.22***			-0.11***			[0.00]
	(0.02)			(0.02)			
More hrs	-0.29***			-0.16***			[0.01]
	(0.04)			(0.04)			
Childcare in 2019: Zero		-0.22***			-0.11***		[0.00]
		(0.02)			(0.03)		
1 to 5		-0.19***			-0.17***		[0.72]
		(0.04)			(0.04)		
≥ 6		-0.35***			-0.21***		[0.04]
		(0.05)			(0.05)		
Δ House Work: Fewer hrs			-0.19***			-0.00	[0.00]
			(0.03)			(0.04)	
Similar hrs			-0.25***			-0.17***	[0.07]
			(0.03)			(0.03)	
More hrs			-0.27***			-0.17***	[0.01]
			(0.02)			(0.03)	
Observations	19550	19687	19114	14150	14228	13679	
Adjusted R^2	0.047	0.047	0.051	0.019	0.019	0.025	

Notes: Data from UKHLS 2019 and Covid modules 1–3. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. Changes in childcare and house work are computed based on self-reported time use in the previous week. Childcare levels in 2019 are imputed from UKTUS as explained in Section 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Well-Being by Gender: Finances and Work (Waves 1-3)

	Female	Female	Female	Male	Male	Male	Difference
Δ Finances: Worse	-0.48***			-0.42***			[0.46]
	(0.05)			(0.06)			
No change	-0.25***			-0.10***			[0.00]
	(0.02)			(0.02)			
Better	-0.03			0.14***			[0.00]
	(0.04)			(0.04)			
Δ Employment: No change		-0.23***			-0.14***		[0.00]
		(0.02)			(0.02)		
Reduction		-0.27***			-0.04		[0.00]
		(0.05)			(0.05)		
Job Loss		-0.77***			-0.52*		[0.49]
		(0.27)			(0.27)		
Δ WFH: No change			-0.20***			-0.12***	[0.02]
			(0.02)			(0.03)	
More			-0.32***			-0.14***	[0.00]
			(0.03)			(0.03)	
Observations	13693	20028	19321	9868	14386	13859	
Adjusted R^2	0.065	0.048	0.048	0.050	0.019	0.018	

Notes: Data from UKHLS 2019 and Covid modules 1–3. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. Change in finances is based on self-reports of the present financial situation, measured in 2019 and 2020: variable 'finnow'. Change in employment (no change, reduction in hours/furlough, job loss) comes from Covid wave 1. Changes in work from home are calculated based on self-reported work from home patterns for February 2020 (measured in Covid wave 1) and the reports in April, May and June. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Well-Being by Gender: Social Factors (Waves 1-3)

	Female	Female	Female	Male	Male	Male	Difference
Δ Loneliness: Less	0.22***			0.24***			[0.72]
	(0.04)			(0.06)			
No change	-0.18***			-0.10***			[0.00]
	(0.02)			(0.02)			
More	-0.87***			-0.76***			[0.24]
	(0.04)			(0.08)			
Friends: 0-1		-0.14			-0.08		[0.61]
		(0.10)			(0.08)		
2-3		-0.21***			-0.11***		[0.04]
		(0.04)			(0.04)		
4-6		-0.27***			-0.16***		[0.00]
		(0.03)			(0.03)		
≥ 7		-0.24***			-0.14***		[0.06]
		(0.03)			(0.05)		
Friends nearby: All			-0.17***			-0.07*	[0.14]
			(0.05)			(0.04)	
Some			-0.24***			-0.12***	[0.00]
			(0.02)			(0.02)	
None			-0.30***			-0.25**	[0.75]
			(0.10)			(0.12)	
Observations	20011	19817	20014	14373	14136	14367	
Adjusted R^2	0.147	0.049	0.048	0.098	0.019	0.020	

Notes: Data from UKHLS 2019, Covid modules 1–3 and UKHLS wave 9. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. Change in loneliness is based on self-reports of the present frequency of feeling lonely, measured in 2019 and 2020. Number of close friends and fraction of friends living nearby are measured in UKHLS wave 9. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Decomposition of the Gender Gap (Waves 1-3)

	(1)	(2)	(3)	(4)	(5)
Gender Gap	0.165***	0.102***	0.102***	0.102***	0.105***
	(0.031)	(0.027)	(0.027)	(0.028)	(0.031)
Composition effect attributable to:					
1) Time use and family	0.012*	0.013**	0.016***		
	(0.006)	(0.005)	(0.006)		
2) Finances and work	-0.001	-0.000	-0.000		
	(0.001)	(0.001)	(0.001)		
3) Social factors	0.045***	0.034***	0.034***		
	(0.010)	(0.009)	(0.009)		
4) Medical factors	0.001	0.001	0.001		
	(0.001)	(0.001)	(0.001)		
6) Demographics: HH characteristics	-0.001	0.002	0.003	0.003	
	(0.005)	(0.004)	(0.004)	(0.004)	
6) Demographics: Age	-0.001	-0.001	-0.002	0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Extraversion					0.005
					(0.003)
Other traits					-0.016*
					(0.009)
Total Composition Effect	0.056***	0.048***	0.052***	0.003	-0.011
	(0.012)	(0.011)	(0.011)	(0.004)	(0.010)
Structural effect attributable to:					
1) Time use and family	-0.011	-0.002	-0.005		
	(0.023)	(0.018)	(0.016)		
2) Finances and work	0.030	0.027*	0.027*		
	(0.022)	(0.015)	(0.015)		
3) Social factors	0.014	-0.035	-0.035		
	(0.074)	(0.073)	(0.071)		
4) Medical factors	0.007	-0.002	-0.002		
	(0.015)	(0.010)	(0.010)		
6) Demographics: HH characteristics	-0.049	-0.062	-0.063	-0.060	
	(0.054)	(0.046)	(0.047)	(0.055)	
6) Demographics: Age	0.092	-0.033	-0.033	0.027	0.001
	(0.073)	(0.056)	(0.055)	(0.056)	(0.048)
Extraversion					0.010
					(0.041)
Other traits					0.063
					(0.095)
Constant	0.025	0.161	0.161	0.131	0.031
	(0.114)	(0.102)	(0.102)	(0.080)	(0.112)
Total Structural Effect	0.109***	0.054**	0.050*	0.099***	0.116***
	(0.030)	(0.026)	(0.026)	(0.028)	(0.032)
Observations	11457	30771	30771	30771	27544

Notes: Data from UKHLS 2019, Covid modules 1–3 and UKHLS wave 9. Dependent variable is individual change in standardized inverted GHQ Likert score. See text for details. Standard errors clustered at the primary sampling unit and presented in parentheses. This table uses UKHLS Covid waves 1–3 and replicates Table A.7. The following variables are only contained in wave 1 and have thus been omitted from the analysis presented in this table: health behaviors and change in receiving external help. Column 1 presents results for wave 1 only for comparability. Columns 2 and 3 include all three waves. Columns 1, 2, 4 and 5 show pooled specifications and Column 3 replicates Column 2 but with evaluated at female prices. See Table 4 for further notes.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Well-Being by Gender: Medical/Health Factors (Waves 1-3)

	Female	Female	Female	Male	Male	Male	Difference
Symptoms: No	-0.23***			-0.13***			[0.00]
	(0.02)			(0.02)			
Yes	-0.35***			-0.14***			[0.01]
	(0.06)			(0.05)			
Vulnerable: No		-0.23***			-0.12***		[0.00]
		(0.02)			(0.02)		
Yes		-0.21***			-0.20**		[0.93]
		(0.07)			(0.09)		
Δ Receiving Help: Less			-0.33***			-0.23*	[0.54]
			(0.09)			(0.13)	
No change			-0.19***			-0.04	[0.00]
			(0.02)			(0.03)	
More			-0.35***			-0.18***	[0.03]
			(0.06)			(0.05)	
Observations	20028	20028	6846	14386	14386	5014	
Adjusted R^2	0.048	0.048	0.052	0.018	0.018	0.009	

Notes: Data from Covid modules 1–3. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. 'Symptoms' comes from self-reported presence of symptoms since the onset of the pandemic. 'Vulnerable' takes value "yes" either if the individual has received an NHS letter requesting they should stay at home ('shielded') or the individual is pregnant. 'Help' is a self-report of whether the individual has received formal care and is measured twice in the Covid module, once for current help and once for help in 2019. This variable only exists in Covid wave 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Well-Being by Gender: Demographic Factors (Waves 1-3)

	Female	Female	Female	Male	Male	Male	Difference
Age: 16-29	-0.35***			-0.21***			[0.08]
	(0.05)			(0.07)			
30-49	-0.27***			-0.15***			[0.03]
	(0.03)			(0.04)			
50-69	-0.18***			-0.09***			[0.02]
	(0.03)			(0.03)			
Over 70	-0.19***			-0.11***			[0.14]
	(0.04)			(0.03)			
Couple: No		-0.28***			-0.14***		[0.02]
		(0.03)			(0.05)		
Yes		-0.20***			-0.12***		[0.00]
		(0.02)			(0.02)		
Children: No			-0.23***			-0.12***	[0.00]
			(0.02)			(0.03)	
Yes			-0.24***			-0.17***	[0.08]
			(0.03)			(0.03)	
Observations	20028	19843	19724	14386	14314	14206	
Adjusted R^2	0.051	0.049	0.048	0.020	0.018	0.020	

Notes: Data from UKHLS 2019 and Covid modules 1–3. Table reports grouped means of outcome variable, which is the individual change in standardized, seasonally-adjusted and inverted GHQ Likert score. Standard errors clustered at the primary sampling unit and presented in parentheses. The last column presents p-values testing the difference in female vs male means. Covid survey weights used in all computations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Description of GHQ-12 Questionnaire

As discussed in section 2 our measure of mental well-being comes from the Likert scale derived from the 12-question GHQ questionnaire. The GHQ questions are listed below. The Likert scale is obtained by recoding so that the scale for individual variables runs from 0 to 3 instead of 1 to 4, and then summing, giving a scale running from 0 (the least distressed) to 36 (the most distressed). The questionnaire is administered to everyone.

In our analysis we standardize this variable across gender and wave to have a mean of zero and a standard deviation of one. We then multiply by -1 to obtain a scale that runs from negative (more distressed) to positive (less distressed).

Wording of the questions:

ghqa [GHQ: concentration]: The next questions are about how you have been feeling over the last few weeks. Have you recently been able to concentrate on whatever you're doing?
1. Better than usual 2. Same as usual 3. Less than usual 4. Much less than usual

ghqb [GHQ: loss of sleep]: Have you recently lost much sleep over worry?
1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

ghqc [GHQ: playing a useful role]: Have you recently felt that you were playing a useful part in things?
1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual

ghqd [GHQ: capable of making decisions]: Have you recently felt capable of making decisions about things?
1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less capable

ghqe [GHQ: constantly under strain]: Have you recently felt constantly under strain?
1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

ghqf [GHQ: problem overcoming difficulties]: Have you recently felt you couldn't overcome your difficulties?
1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

ghqg [GHQ: enjoy day-to-day activities]: Have you recently been able to enjoy your normal day-to-day activities?
1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual

ghqh [GHQ: ability to face problems]: Have you recently been able to face up to problems?
1. More so than usual 2. Same as usual 3. Less able than usual 4. Much less able

ghqi [GHQ: unhappy or depressed]: Have you recently been feeling unhappy or depressed?
1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

ghqj [GHQ: losing confidence]: Have you recently been losing confidence in yourself?
1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

ghqk [GHQ: believe worthless]: Have you recently been thinking of yourself as a worthless person?
1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual

ghql [GHQ: general happiness]: Have you recently been feeling reasonably happy, all things considered?
1. More so than usual 2. About the same as usual 3. Less so than usual 4. Much less than usual