Economics Working Paper Series

2023/003

Health Risks and Labour Supply: Evidence from the COVID-19 Pandemic

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March 2023

Abstract:

In this paper, we explore the relationship between health risks from COVID-19 and UK labour supply. Using pre-existing conditions as the source of variation in COVID-19 health risks, we show that employment fell by 2 to 3 percentage points with each prior additional condition, after controlling for pre-pandemic labour supply and other relevant factors. These effects begin in April 2020 and persist through to September 2021, long after the pandemic's peak. Furthermore, these effects were concentrated in jobs difficult to perform remotely, are not driven by labour demand shocks, and similar relationships did not exist prior to the pandemic.

JEL classification: I12, J22, J40

Keywords: COVID-19; Labour supply; Health risks; Pre-existing conditions; Job separations

* I thank Pavel Chakraborty and participants in the Lancaster PhD workshop, alongside my supervisors Maria Navarro Paniagua and Ian Walker, for providing helpful comments and feedback. Data and code are available upon request and all errors that remain are my own. The *Understanding Society* COVID-19 Study is funded by the Economic and Social Research Council (ES/K005146/1) and the Health Foundation (2076161). Fieldwork for the survey is carried out by Ipsos MORI and Kantar. Understanding Society is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex. The research data are distributed by the UK Data Service.
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1 Introduction

As a novel infectious disease, COVID-19 increases the health risks associated with any in-person work. Because falling ill is undesirable, these health risks could increase the disutility of work and thus reduce labour supply. This would be consistent with the facts that job losses were concentrated in more exposed occupations (Adams-Prassl et al, 2020; Mongey et al, 2021; Finkelstein, et al 2022), job search efforts decreased (Hensvik et al, 2020; Balgova et al, 2022; Carrillo-Tudela et al, 2023), and so did estimates of labour supply itself (Brinca et al 2021; Faberman et al 2023). Nevertheless, alternative explanations for these phenomena, such as occupational health risks being correlated with labour demand shocks from government restrictions, are also possible.

Using pre-existing health conditions as a source of variation in health risks from COVID-19, we test whether these health risks affected labour supply during the pandemic. Using nine COVID-19 waves of Understanding Society, a panel survey of the UK population, we assess whether COVID-19 labour supply is related to pre-existing health conditions conditional upon a rich set of controls for pre-pandemic labour supply, occupation, and other relevant characteristics. We find that in most waves[1] the probability of working positive hours per week fell by 2 to 3 percentage points with each additional pre-existing condition among 25-64 year-olds. Typically, these results also represent a decrease in labour market attachment as there was not a correspondingly large effect on the probability of being furloughed[2]. These effects persist through to September 2021 despite all restrictions having been lifted and vaccinations were universally available. This result could be explained by persistence in COVID-19 risk attitudes (Barrero et al, 2022) or the separations having a scarring effect (e.g., Yagan, 2019). Furthermore, the changes in labour supply are concentrated on those whose pre-pandemic occupations were hard to perform at home and so were the most likely to be exposed to COVID-19 risk at work.

Investigating the robustness of these results, we test whether pre-existing health conditions predict labour supply the following year, conditional on the same controls, prior to the pandemic.

[1] Smaller and statistically insignificant effects are estimated in two months – July and September 2020 – when case rates were low and government restrictions were weak, which may have been interpreted as a signal of safety.
[2] Employers were able to place any employee not currently working onto a furlough scheme where the government would cover most of their wages and their current employment contract would be maintained.

This estimated effect is close to zero, precisely estimated, and statistically insignificant for the three most recent pre-pandemic waves.

Then, we conduct further robustness tests by: including additional controls; testing whether these changes represent labour demand shocks using a placebo test; and analysing whether health declines due to untreated conditions could explain the results. The results are robust to a variety of controls – for differences in worker productivity, geography, childcare responsibilities, home-working facilities, wealth, and having long COVID. Meanwhile, the placebo test demonstrates that pre-existing health conditions are uncorrelated with pure labour demand shocks, such as redundancy or a business being affected by lockdown restrictions, in April 2020. Finally, we argue that health declines are not a viable alternative explanation as they can neither explain the strong labour supply responses early in the pandemic, nor the fact that asthma, a highly manageable condition in adults, still has a negative effect on labour supply through to September 2021.

Furthermore, to determine whether individuals with pre-existing health conditions were indeed taking more precautions, we investigate whether other COVID-19 risk reducing strategies are related with pre-existing conditions. We find that those with pre-existing conditions have fewer different face-to-face social contacts and there are also some signs that they were more likely to download the NHS COVID-19 app, a potential proxy for compliance with government guidelines. These results are consistent with Eichenbaum et al (2020)'s finding that those with pre-existing conditions were more likely to cut back their consumption during periods of high COVID-19 risk, as well as mask wearing and social distancing being associated with higher levels of medical risk (Schoeni et al, 2021).

This paper extends our existing knowledge of COVID-19 health risks' effects on labour supply by providing a unique combination of internal and external validity. While employing a similar methodology to this paper and finding a null result[3], Agarwal and Bishop (2022) focuses

[3] It is also unclear whether these results are estimated with sufficient precision as no standard errors are provided. They do, however, also exploit sharp age cut-offs in vaccine eligibility to estimate the effects of COVID-19 risk on labour supply using a regression discontinuity. This specification also returns null results but the confidence intervals are wide enough to include economically significant effect sizes and the coefficient may have a different interpretation as this risk variation is foreseeably very temporary.

on Australian cities that experienced 100 cases per day. In contrast, the UK experienced 100 *deaths*/day at the height of the pandemic after scaling the populations to comparable sizes[4]. Meanwhile, Barrero et al (2022) show that significant proportions of the US population were still claiming that COVID-19 health risks curtailed their labour supply well into 2022, and that social distancing intentions correlated strongly with labour force non-participation. This paper contributes relative to Barrero et al (2022) by adding internal validity through being able to account for differences in pre-pandemic labour supply, having explanatory variables defined prior to the pandemic[5], and being less reliant upon self-reports. Nevertheless, their paper complements this one by documenting substantial persistence in social distancing attitudes and their relationship with labour supply long after the height of the pandemic, suggesting that these results could be relevant to understanding present labour market trends.

This research also contributes to the broader research agenda on labour markets during and after COVID-19, because health risks reducing labour supply can help explain many empirical results in this literature. These results range from increases in stated reservation wages (Faberman et al, 2023), retirements increasing (Forsythe et al, 2022), and reductions in job search effort (Hensvik et al, 2020; Balgova et al, 2022; Carrillo-Tudela et al, 2023). In turn, these factors can explain the unusual tightness of COVID-19 labour markets relative to previous recessions (Forsythe et al, 2020). Besides aggregate labour market effects, a labour supply response to health risks can also help explain the pandemic's unequal impacts. Both racial minorities and the economically disadvantaged were more likely to work in jobs exposed to high levels of COVID-19 risk (Adams-Prassl et al, 2020; Mongey et al, 2021; Finkelstein et al, 2022) and are more likely to have pre-existing health conditions (Wiemers et al, 2020). Correspondingly, these groups disproportionately faced income losses (Crossley et al, 2021). Finally, if these effects do persist through either persistent social distancing (Barrero et al, 2022) or scarring (Yagan, 2019), they are also relevant to more recent labour market trends. For instance, labour demand is outstripping labour supply at the bottom of the labour market (Autor

[4] For example, Melbourne has a population of around 5 million while the UK has a population of 67 million. The 7-day rolling average of deaths in the UK peaked at 1241 on 22nd January 2021. For data, see the UK Government's COVID-19 data dashboard: https://coronavirus.data.gov.uk/details/deaths/.

[5] It is plausible that not working could affect someone's social interaction, and thus their response to a question on social distancing, while it is much less likely that future work status will affect present health.

et al, 2023) and low skill occupations are both disproportionately exposed to infection risk and employ individuals in worse health.

The final contribution of this paper is to the literature on how labour supply responds to occupational health risks. In normal times, it is well documented that workers require additional compensation to accept jobs posing health hazards (Kniesner et al, 2012; Lavetti and Schmutte, 2018; Lee and Taylor, 2019; Lavetti, 2020), with the variation in risk usually coming from occupational accidents. However, existing research on risks from communicable diseases on labour supply has so far been limited to sex workers (Gertler et al, 2005; Shah, 2013) and this paper replicates such behaviour in a very different context.

2 Data

The data used in this paper come from *Understanding Society*, a longitudinal survey of households drawing its sample from the whole UK population, with approximately 20,000 households participating per year. We focus on the data from its nine COVID-19 waves, that were conducted between April 2020 and September 2021[6] to track labour supply throughout the pandemic, while drawing information on pre-existing health conditions and other covariates from the regular pre-COVID-19 waves. Individuals for whom a key outcome or independent variable from the main analysis was missing are dropped from the sample, alongside those aged under 25 or over 64. After these exclusions, we are left with sample sizes ranging between 5,934 to 10,869 individuals for each COVID-19 wave. So that these varying samples do not prohibit comparisons between waves, survey weights predicting non-response are applied to all analyses, making these data close to representative of the UK population[7]. The variables used as the basis for exclusions are described alongside the variables used for other analyses in Table A1.

One particularly important variable in this analysis is the number of pre-existing health conditions a respondent has. The number of pre-existing health conditions is defined from the following list of conditions that a respondent had pre-pandemic: asthma, angina, bronchitis,

[6] The surveys were conducted in the following months: April 2020, May 2020, June 2020, July 2020, September 2020, November 2020, January 2021, March 2021, and September 2021.

[7] The population ratios targeted are those from when the survey began, meaning there is some under sampling of ethnic minorities.

chronic obstructive pulmonary disease, coronary heart disease, diabetes, emphysema, hypertension, liver conditions, and being a stroke or heart attack survivor. These conditions were chosen as they are associated with a higher risk of severe disease from COVID-19 (Honardoost et al, 2021; Treskova-Schwarzbach et al, 2021). Moreover, they are not rapidly degenerative, so should not directly cause large declines in sufferers' future labour supply[8]. Detailed information on the prevalence of these conditions in the sample is in Table B1, with most of the variation coming from asthma, diabetes, and hypertension.

3 Descriptive Statistics and Background

The COVID-19 pandemic was associated with a large fall in labour supplied, as can be seen in the descriptive statistics presented in Table 1. Furthermore, this fall was concentrated in occupations where COVID-19 risks were highest (Adams-Prassl, 2020; Mongey et al, 2021), which is consistent with a fall in labour supply. This relationship also exists within this data set (Figure 1), where the measure of risk is the proportion of working people who shared their occupation pre-pandemic who report never working from home. The intuition behind this measure is that people from occupations that cannot be performed remotely, which is necessarily the lowest level of risk, will never be able to work from home. Although the relationship is particularly strong in April 2020, it still exists in September 2021 after lockdowns had been lifted, workplaces adapted to remote working, and the risks were genuinely lower due to widespread vaccination.

Although the correlation between an occupation's risk and its labour supply is likely confounded by labour demand shocks, similar patterns also exist between an individual level source of risk, pre-existing health conditions, and labour supply during the pandemic. Figure 2 documents this relationship, with workers suffering from a pre-existing conditions often being as much as eight percentage points less likely to work positive hours. A strong unconditional relationship is present for all but two waves (July 2020 and September 2020 which were spells with low case rates and few lockdown restrictions[9]), and appears to persist through to September

[8] The other way these health conditions could affect labour supply during the pandemic specifically is that, if they are caused by health behaviours, they could signal willingness to accept health risks. To the extent that this is true, it would make our estimates a lower bound of the true effect.

[9] Table A2 details the active government restrictions and programmes at the time of each wave alongside COVID-19 death rates.

Table 1: **Summary Statistics**

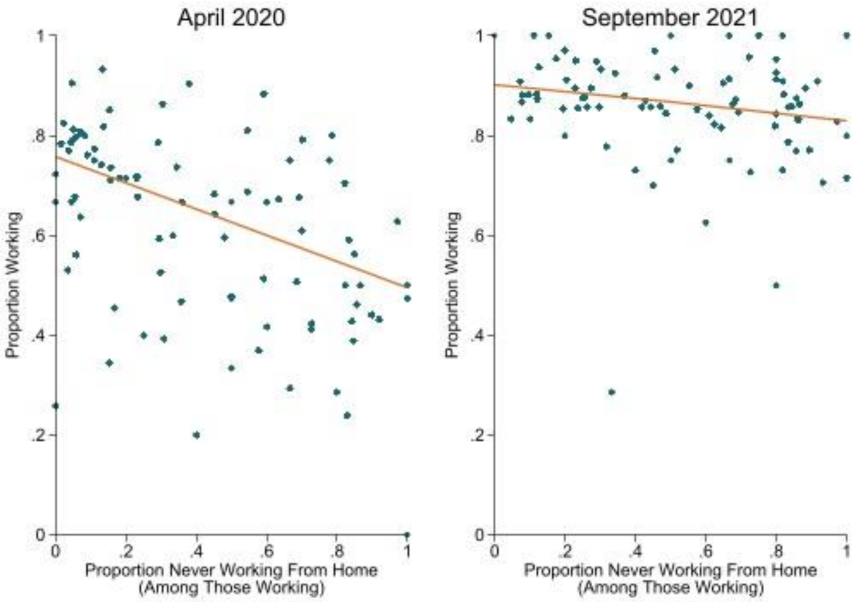
Wave:	April 2020		September 2020	
	Mean	Std. dev	Mean	Std. dev
Working	0.545	0.498	0.743	0.437
Hours worked (per week)	18.200	19.212	26.348	18.497
Female	0.535	0.499	0.550	0.498
Age	45.479	11.486	45.905	11.480
No. health conditions	0.539	0.856	0.546	0.886
Non-white	0.077	0.267	0.080	0.271
Working pre-pandemic	0.801	0.399	0.801	0.399
Pre-pandemic hours worked	27.212	16.733	27.115	16.491
Response lag (months)	6.789	4.018	6.750	4.018
Education				
No qualifications (reference)	0.028	0.166	0.036	0.187
GCSEs/O-Levels	0.205	0.404	0.195	0.396
Other qualifications	0.062	0.241	0.060	0.237
AS/A-Levels	0.217	0.412	0.214	0.410
Other degree-level qualification	0.126	0.332	0.126	0.332
Degree	0.361	0.480	0.368	0.482
Observations	10,869	10,869	7,731	7,731

Notes: Working is defined as working a positive number of hours per week. Hours worked includes those who are not working. Response lag is defined as how many months prior to March 2020 the person's last responded a main wave of Understanding Society. Anyone whose most recent response was before January 2018 was excluded from the sample.

2021. Furthermore, this difference widens for those whose occupations expose them to more risk (Figure 3), as a health risks explanation would predict.

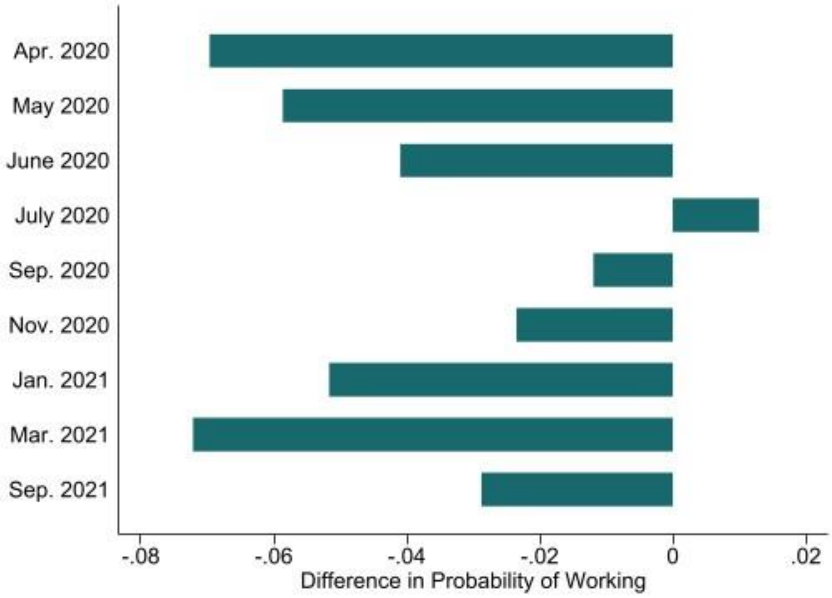
If these relationships are causal, we must consider workers' alternative options during this period in order to accurately interpret the results. This requires some knowledge of the UK labour market during this period. For example, it is possible that individuals not wanting to work during the pandemic were placed on the government furlough scheme at little cost to their employer, increasing any labour supply response. Alternatively, and more concerning for this analysis, some workers could have preferred being furloughed to working and employers gave priority to those with health conditions. We examine this issue in Appendix B and show that relationship between the probability of being furloughed and health conditions is notably smaller than any labour supply response and is typically statistically insignificant. The other government program that could affect the interpretation of these results is the shielding program that ran

Figure 1: **Proportion Working by Pre-Pandemic Occupation**



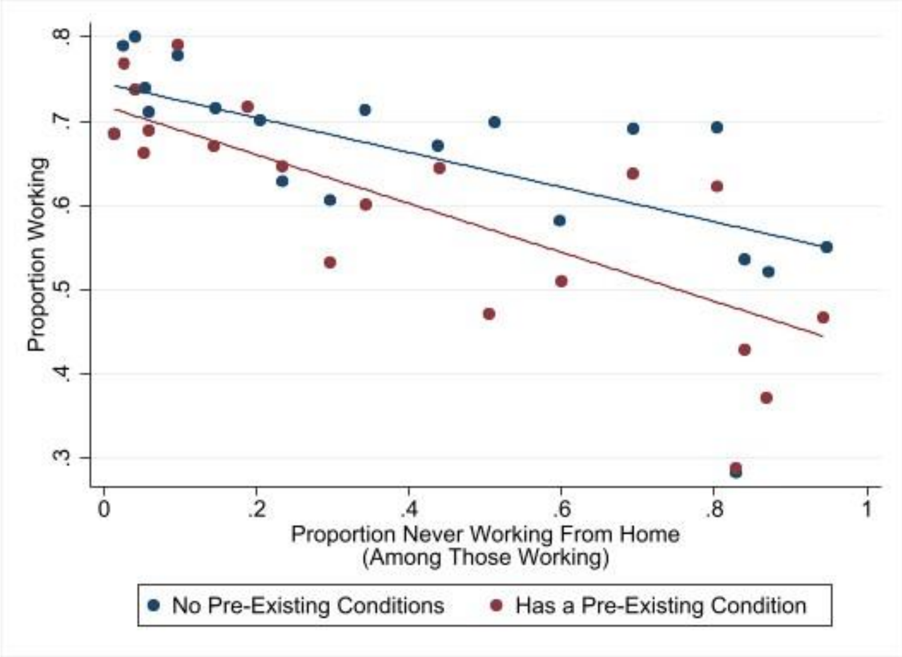
Notes: Occupation is defined at the three-digit level and proportion working is defined as the proportion of 25-64 year-olds working in that occupation prior to the pandemic who worked positive hours. The proportion never working from home is calculated for individuals who shared the same three-digit occupation prior to the pandemic. Source: Understanding Society.

Figure 2: **Difference in Probability of Working for Workers with a Pre-Existing Condition Versus Workers Without**



Notes: Statistics are weighted to be representative of the UK population aged 25-64 and are restricted to those who were working during the most recent pre-pandemic survey wave population. A respondent is defined as working if they worked positive hours that week. A negative number indicates that individuals with pre-existing conditions were less likely to be working. Source: Understanding Society.

Figure 3: **Proportion Working by Pre-Existing Conditions and Occupation (April 2020)**



Notes: Occupation is defined at the three-digit level and proportion working is defined as the proportion of 25-64 year-olds working in that occupation prior to the pandemic worked positive hours. The proportion never working from home is calculated for individuals who shared the same three-digit occupation prior to the pandemic. Source: Understanding Society.

up to April 2021, which advised individuals at the most risk from COVID-19 to take strong social distancing precautions. We include these individuals in the main analyses because removing anyone who is not working due to COVID-19 health risks would bias the results downwards. Additionally, a significant proportion of shielders who were working prior to the pandemic continued to attend in-person work during the pandemic (Table B2), so they were by no means prohibited from working. Nevertheless, we also re-run the main analyses excluding these individuals in Appendix B and the results are qualitatively unchanged, suggesting that these responses are not only attributable to specific government guidance.

4 Empirical Strategy

Identifying labour-supply responses to COVID-19 health risks from occupation alone would be confounded by contemporaneous labour demand shocks. Thus, we use a measure of individual risk, the number of pre-existing health conditions, as the source of identifying variation. Crucially, these health conditions also impact behaviour and risk perceptions; individuals with pre-existing conditions were both more likely to cut back their consumption during the pandemic

(Eichenbaum et al, 2020) and to engage in more self-protective behaviours such as masking (Schoeni et al, 2021). The intuition behind using health conditions is that, conditional on controlling for other factors affecting labour supply and demand, such as pre-pandemic labour supplied and occupation, these conditions should only have an additional effect through differences in COVID-19 risks. These pre-pandemic variables are defined using a person's most recent response to Understanding Society between January 2018 and February 2020, with most observations coming from February 2019 onwards. This motivates the following linear probability model, which we estimate separately wave-by-wave:

$$Working_{ij} = \alpha_0 + \alpha_1 HealthConditions_{ij} + \alpha_2 \boldsymbol{X}_{ij} + \mu_j + \varepsilon_{ij} \tag{1}$$

where $Working_{ij}$ is a dummy variable that equals 1 if person i, working in pre-pandemic occupation j, worked positive hours in the past week and zero otherwise. Meanwhile, $HealthConditions_{ij}$, the independent variable of interest, is a count of how many relevant pre-existing conditions a person suffered from pre-pandemic. Alongside these variables, we also add fixed effects for pre-pandemic occupation at the three-digit level (μ_j) to net out occupation-specific demand shocks. Finally, a vector of controls ($\boldsymbol{X}_{ij}$) is added to address factors that could represent labour demand or supply shocks from the pandemic and be correlated with health conditions. Among these controls, pre-pandemic employment status is particularly important as it separates out the employed and self-employed as well as those who are not working for different reasons, such as those who are long-term sick or caring from those who are temporarily unemployed, and likely have different employment transition probabilities from one another. The remaining controls cover basic demographic factors, indicators of productivity, measures of attachment to the labour market, pre-pandemic industry, and health factors that could affect labour supply through channels other than disease risk (pain and mental health). A full list of the controls and how they are specified in the regression is available in Table A1.

These regressions are estimated separately for each wave, rather than using pooled OLS or a difference-in-differences specification, to reflect the structural changes in the labour market that occurred after the pandemic, as well as between waves. Therefore, the appropriate values for coefficients on covariates coefficients may change between waves in a highly non-linear fashion, such as the effect of a specific occupation depending heavily on the presence of a lockdown. Consequently, estimating each cross-section separately is the most appropriate strategy, as it allows the covariates' effects to vary flexibly between waves alongside allowing us to track labour supply responses at different points in time[10].

In addition to predicting less labour supply among those most vulnerable to COVID-19, the health risks hypothesis also predicts that the effects of pre-existing conditions should be concentrated among those whose jobs expose them to higher levels of risk. To test his hypothesis, we interact $HealthConditions_{ij}$ with $\overline{NeverWFH}_j$, a variable defined as follows:

$$\overline{NeverWFH}_j = \frac{NumberNeverWFH_j}{NumberWorking_j} \tag{2}$$

where $NumberNeverWFH_j$ is the number of people who worked in occupation j pre-pandemic who are currently working and never do so from home, while $NumberWorking_j$ is the number of people from occupation j who are currently working. As working from home is necessarily the lowest level of risk, this should provide a good proxy for COVID-19 risks by occupation[11]. Adding a term interacting the number of health conditions with $\overline{NeverWFH}_j$ results in the following linear probability model, with all other variables taking on the same definitions as in equation (1):

$$\begin{aligned} Working_{ij} = \beta_0 + \beta_1 HealthConditions_{ij} + \beta_2 HealthConditions_{ij} * \overline{NeverWFH}_j \\ + \beta_3 \boldsymbol{X}_{ij} + \mu_j + \varepsilon_{ij} \end{aligned} \tag{3}$$

Finally, for α_1, β_1, or β_2 to be reflect responses to COVID-19 health risks, it is critical to assume that $HealthConditions_{ijkl}$ would not predict future labour supply in this specification without a pandemic. Consequently, we estimate both these labour supply specifications on the most recent pre-pandemic waves to test whether this assumption holds. This test has obvious similarities to testing for pre-trends in a difference-in-differences design.

[10] Technically, identical results could be achieved by estimating each wave together with wave fixed effects and interacting each explanatory variable with the wave indicators, but this would be far less parsimonious.

[11] This is preferred to measures based upon job tasks (e.g., Dingel and Neiman, 2020) as it directly reveals whether home working was an option available to workers in that occupation at that time, reducing measurement error.

5 Results

This section contains two main parts. First, we present our main results on the relationship between pandemic labour supply and pre-existing health conditions and how this varies by industry. Then, I proceed to conduct several robustness checks.

5.1 Main Results

Table 2 presents the results from the main analysis, showing that labour supply fell by three percentage points with each additional pre-existing condition during the initial wave of lockdown[12]. Once that lockdown is lifted and infection risks fell, the effect size falls, with the results no longer being statistically significant. Possible explanations for this include that the government's active efforts to get people to socialise, such as 'Eat Out to Help Out'[13], might have decreased risk perceptions or that social distancing decreases when case rates fall (Yan et al, 2021). However, once a new lockdown was implemented in response to a surge in cases by November 2020, statistically significant effects of around two percentage points per condition emerge. These effects persist through to September 2021, possibly due to long social distancing or hysteresis, by which time the risks were lower and most government COVID-19 programmes had ended. As the main reduction in risk by September 2021 stemmed from vaccination, this result may also align with the fact that vaccination did not have a significant effect on social distancing behaviour (Agrawal et al, 2022).

If these results are explicable by health risks from pre-existing conditions, the effects should be concentrated among those working in occupations that are difficult to perform remotely. This indeed is the case. In Table 3, we interact the number of pre-existing health conditions with $\overline{NeverWFH}_j$, clustering the standard errors at the occupation level[14], and the interaction term

[12] Similar results are obtained using a probit model, see Table B3. Furthermore, Table 3's results can also be replicated using a probit, as shown in Table B4. Alternatively, similar estimates can be obtained using hours worked as the outcome variable in a Tobit model (Tables B5 and B6). The extensive margin is preferred as it likely contains less measurement error, does not require imposing any restrictions on the error term's distribution, and is the most likely margin of adjustment due to the lack of open vacancies.

[13] This was a UK government scheme that provided very large subsidies to in-person dining in August 2020.

[14] This is done as the treatment is partially assigned at that level. Relatedly, non-interacted results are robust to clustering at that level (Table B7), although the standard errors slightly increase. However, robust standard errors

Table 2: **Relationship Between Probability of Working and Number of Health Conditions**

Wave:	Apr. 2020	May 2020	June 2020	July 2020	Sep. 2020
	(1)	(2)	(3)	(4)	(5)
No. health conditions	-0.032***	-0.029***	-0.025***	-0.002	-0.008
	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
Observations	10,869	9,105	8,638	8,373	7,821
R-squared	0.358	0.395	0.430	0.456	0.517
Proportion working	0.545	0.596	0.631	0.649	0.718
Controls	Yes	Yes	Yes	Yes	Yes
Wave:	**Nov. 2020**	**Jan. 2021**	**Mar. 2021**	**Sep. 2021**	
	(6)	(7)	(8)	(9)	
No. health conditions	-0.021**	-0.018**	-0.020***	-0.016**	
	(0.008)	(0.008)	(0.006)	(0.006)	
Observations	5,934	7,090	7,642	7,731	
R-squared	0.497	0.483	0.480	0.511	
Proportion working	0.703	0.683	0.697	0.743	
Controls	Yes	Yes	Yes	Yes	

Notes: Estimates come from a linear probability model. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description. *** p<0.01, ** p<0.05, * p<0.1

is statistically significant in the expected direction in several waves. Furthermore, the main effect completely disappears in all waves, suggesting that these health conditions have little direct effect for those in safer occupations.

These labour supply results should be interpreted primarily as separations from the labour market, rather than placement on the furlough scheme. The relationship between participation in the furlough scheme and pre-existing health conditions is consistently smaller than the direct labour supply response (Table B8), conditional on the same controls. Moreover, for the waves later in the pandemic with available data[15], the point estimates are very close to zero and precisely estimated. These furlough results may offer a partial explanation for why the main effects attenuated when risks decreased in June 2020, but not September 2021, as the effects

are preferred for that specification as treatment effect heterogeneity between clusters, which is present, biases the clustered standard errors (Abadie et al, 2023).

[15] There was no reliable data on furlough in the September 2020 and November 2020 waves.

Table 3: **Relationship Between Probability of Working and Number of Health Conditions by Ability to Perform Occupation from Home**

Wave:	Apr. 2020 (1)	May 2020 (2)	June 2020 (3)	July 2020 (4)	Sep. 2020 (5)
No. health conditions	0.004	0.010	0.020	0.020	0.015
	(0.013)	(0.020)	(0.017)	(0.023)	(0.024)
No. health conditions$*\overline{NeverWFH}_j$	-0.089***	-0.097**	-0.100**	-0.046	-0.044
	(0.027)	(0.046)	(0.045)	(0.057)	(0.042)
Observations	10,869	9,105	8,638	8,361	7,821
R-squared	0.359	0.396	0.432	0.458	0.517
Proportion working	0.545	0.596	0.631	0.649	0.718
Controls	Yes	Yes	Yes	Yes	Yes
Wave:	**Nov. 2020 (6)**	**Jan. 2021 (7)**	**Mar. 2021 (8)**	**Sep. 2021 (9)**	
No. health conditions	0.014	0.016	0.013	0.004	
	(0.023)	(0.020)	(0.017)	(0.020)	
No. health conditions$*\overline{NeverWFH}_j$	-0.072	-0.079*	-0.071**	-0.036	
	(0.050)	(0.045)	(0.033)	(0.042)	
Observations	5,934	7,090	7,642	7,731	
R-squared	0.498	0.484	0.481	0.511	
Proportion working	0.703	0.683	0.696	0.743	
Controls	Yes	Yes	Yes	Yes	

Notes: Estimates come from a linear probability model. The standard errors are in parentheses and clustered at the three-digit occupation level. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors measured before the pandemic's onset, such as mental health. See Table A1 for a complete description. *** p<0.01, ** p<0.05, * p<0.1

earlier in the pandemic were more likely to be offset by an increase in furlough rates, preserving job matches.

5.2 Test for Pre-Trends

If a similar relationship between pre-existing health conditions and future labour supply as in the main results would have occurred in the absence of a pandemic, then it would not be reasonable to attribute it to health risks from COVID-19. Therefore, I test whether pre-existing conditions predict future labour supply, conditional on the same controls drawn from the most recent prior wave, for the three most recent main waves[16]. Similarly, we also run the same tests

[16] These are the eighth, ninth, and tenth waves, which were in the field from 2016-18, 2017-19, and 2018-20 respectively. Any observations dated after February 2020 in wave ten, of which there were few, were discarded.

with the interaction term added, where $\overline{NeverWFH_j}$ takes on the same values as it does for occupation j in April 2020[17].

Results from the pre-trends tests are presented in Table 4. For all three specifications without an interaction term, the coefficients are statistically insignificant and estimated to a high degree of precision, suggesting that pre-trends are not a serious concern for this analysis. Similarly, none of the interaction terms are statistically significant at the five percent level either, with the point estimates pointing in the opposite direction to the main results estimated during the pandemic.

Table 4: **Relationship Between Probability of Working and Number of Health Conditions Pre-Pandemic**

Wave:	Wave 8		Wave 9		Wave 10	
	(1)	(2)	(3)	(4)	(5)	(6)
No. health conditions	-0.005	-0.009	-0.003	-0.004	0.001	-0.010
	(0.003)	(0.008)	(0.003)	(0.007)	(0.003)	(0.009)
No. health conditions$*\overline{NeverWFH_j}$		0.009		0.002		0.026
		(0.019)		(0.016)		(0.019)
Observations	17,037	17,037	17,106	17,106	16,449	16,449
R-squared	0.674	0.674	0.653	0.653	0.647	0.647
Proportion working	0.763	0.763	0.752	0.752	0.742	0.742
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates come from a linear probability model. The standard errors in parentheses. The standard errors in specifications (1), (3), and (5) are heteroscedasticity-robust, while in (2), (4), and (6) they are clustered at the three-digit occupation level are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. $\overline{NeverWFH_j}$ is defined using the proportion of individuals from occupation j who never worked from home in April 2020 among those who were working. The controls cover work history, demographics, and other factors measured as of the previous wave, such as mental health. See Table A1 for a complete description. *** p<0.01, ** p<0.05, * p<0.1

5.3 Robustness to Additional Controls

In this sub-section, we investigate whether specific factors that affect labour demand or supply during the pandemic could be correlated with pre-existing health conditions, and thus bias the results, by varying the set of controls used. To ensure comparability between the specifications, we drop all observations for which any control from another specification is missing. In Table 5,

[17] I have also estimated the results using September 2021 to define $\overline{NeverWFH_j}$, with the results being presented in Table B9. This specification produces very similar results, although statistically significant results are picked up in one specification. However, such incidences should sometimes occur by chance when testing multiple hypotheses and the direction of the effects are in the opposite direction to what would be required to confound the main results.

we present these results for September 2021. In principle, similar specifications could be presented for any wave, but September 2021's results are statistically significant and the most policy relevant. Nevertheless, the results are similar regardless of which wave is chosen[18] and whether an interaction term is included. For example, a similar degree of coefficient stability is shown for the interaction term specification using April 2020 data in Table B10.

Table 5: **Relationship Between Probability of Working and Number of Health Conditions with Varying Controls**

Dependent variable:	Probability of Working (September 2021)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. health conditions	-0.019***	-0.018***	-0.018***	-0.018***	-0.020***	-0.019***	-0.019***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Observations	7,459	7,459	7,459	7,459	7,459	7,459	7,459
R-squared	0.512	0.513	0.516	0.518	0.520	0.521	0.522
Controls bar education and wages	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education and wage controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	No	No	Yes	Yes	Yes	Yes	Yes
Caring controls	No	No	No	Yes	Yes	Yes	Yes
Work from home controls	No	No	No	No	Yes	Yes	Yes
Savings controls	No	No	No	No	No	Yes	Yes
Long COVID controls	No	No	No	No	No	No	Yes

Notes: Estimates come from a linear probability model. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The main controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description of the main controls and Table B11 for a complete description of the other ones. *** p<0.01, ** p<0.05, * p<0.1

The first regression in Table 5 demonstrates the effects of dropping the controls for wage and education, proxies for worker productivity, while the second represents the baseline specification. This is done to test whether workers are being laid off according to differences in productivity and this is then correlated with health. The coefficients remain highly stable upon removing the education and wage controls, which suggest that productivity differences are not confounding the results.

Another potential source of confounding is that there are significant health inequalities between UK regions (Marmot, 2010) and their economies may also have been affected differently by the pandemic. For example, the differing policy responses in Scotland and Wales' could have impacted labour markets, or urban areas might have been affected differently to rural ones.

[18] These results are available upon request.

Thus, we add a dummy for whether someone lived in an urban area prior to the pandemic alongside fixed effects for government office regions, such as Scotland and the North West, finding that these have little impact.

A separate group that was differentially affected by the pandemic was parents, as they may have been burdened with additional care responsibilities or found it harder to work when their children are at home. Indeed, mothers' labour supply was negatively affected relative to both other women and fathers (Couch et al 2021). To address this, we add controls for whether someone was a parent prior to the pandemic, allowing the effects to vary by both the youngest child's age[19] and the parent's gender. Additionally, we also control for whether someone was a carer prior to the pandemic, as they may also have been adversely affected[20]. Adding these controls also does not affect the results.

While remote work may have burdened parents, it also could have burdened those with few computer skills or whose homes are unsuitable for home working. Thus, we add a dummy variable for whether their household had a suitable home computer[21] pre-pandemic, self-reported frequency of internet use, and a dummy for whether their home had at least as many rooms as people. Regression 5 shows that these factors do not meaningfully change the main coefficient.

Instead of the ability to work from home, pandemic labour supply may be determined by the ability to not work. Specifically, wealthier workers may be more able to afford opting out of the labour force. Therefore, we add a dummy for whether an individual is an owner-occupier, a separate dummy for whether they own the house outright, and a control for investment and interest income. All of these should be good proxies of financial wealth and adding them does not substantially alter the results.

Finally, there is a risk that some of the later results could be driven not by fear of COVID-19, but its direct effects. As COVID-19 infections reduce labour supply (Goda and Soltas, 2022) and those with health conditions are at a greater risk of serious illness, long COVID-19 could push people with health conditions out of the labour force in later waves. To mitigate this

[19] The age categories are 0-5 years, 6-9 years, and 10-15 years. Anyone older is not treated as a child.
[20] Additionally, being a carer is a signal of family members' health, which could also affect social distancing.
[21] This could be a desktop, laptop, or netbook.

concern, we add a dummy representing whether a respondent had ever reported suffering from long COVID and another for whether they have lingering long COVID symptoms into Regression 7. The results of this exercise suggest that long COVID is not a significant factor in the relationship between pre-existing health conditions and labour supply.

5.4 Placebo Test

Interpreting these results as health risks causing a labour supply shock depends upon these health risks not being predictive of labour demand shocks. As Understanding Society asked participants in April 2020 for reasons why their working hours have decreased since the pandemic began[22], we can test whether reasons clearly related to labour demand are correlated with health conditions. For employed workers, these reasons are being laid off, being made redundant, and having their hours cut by their employer. Meanwhile, for self-employed workers, these reasons are their business facing a demand shock and their business being affected by government restrictions. Any worker who stated at least one of these reasons was coded as having faced a demand shock.

Regressing the labour demand shock dummy on health conditions and the controls shows that the correlation is a precisely estimated zero (Table 6), with the point estimate being the opposite sign to what would be expected from a demand shock. Similarly, there are no signs that these labour demand shocks increase with health conditions in occupations most exposed to COVID-19 either.

5.5 Health Conditions and Social Distancing

Although those with pre-existing health conditions are at greater risk of severe illness from COVID-19, this will only affect labour supply if they act upon this information. While Eichenbaum et al (2020) demonstrates that health conditions reduced risk taking in Portugal and Schoeni et al (2021) shows reduced risk taking in the US, it is not a perfect substitute for assessing whether those with health conditions are more cautious within this dataset. Consequently, we test whether those with pre-existing conditions are more cautious using

[22] This includes moves to zero hours of work. Unfortunately, no question on health risks was included here.

Table 6: **Relationship Between Labour Demand Shocks and Number of Health Conditions**

Dependent variable:	Probability of Facing a Labour Demand Shock	
	(1)	(2)
No. health conditions	-0.003	0.001
	(0.004)	(0.009)
No. health conditions$*\ \overline{NeverWFH}_j$		-0.010
		(0.020)
Observations	10,933	10,933
R-squared	0.235	0.235
Mean	0.118	0.118
Controls	Yes	Yes

Notes: Estimates come from a linear probability model. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as having faced a labour demand shock if they were made redundant, laid off, their employer cut their hours, their business lost trade (self-employed), or their business was affected by lockdown (self-employed). The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description. *** p<0.01, ** p<0.05, * p<0.1

Table 7: **Relationship Between Social Distancing and Number of Health Conditions**

Dependent variable:	Number of contacts		Has COVID-19 app	
Estimator:	Poisson		OLS	
Wave:	June 2020	Nov. 2020	Nov. 2020	Sep. 2021
	(1)	(2)	(3)	(4)
No. health conditions	-0.083***	-0.063**	0.020*	0.010
	(0.019)	(0.029)	(0.011)	(0.010)
Past number of contacts	0.057***	0.036***		
	(0.003)	(0.005)		
Past number of contacts^2/100	-0.047***	-0.037***		
	(0.005)	(0.010)		
No past contacts	-0.804***	-0.463***		
	(0.137)	(0.146)		
Observations	8,276	5,349	5,602	7,404
R-squared			0.122	0.084
Controls	Yes	Yes	Yes	Yes

Notes: Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Number of face-to-face contacts is defined as over the past month, while the past number of contacts was how many they recalled having in January and February 2020 when asked in the June 2020 wave. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description. *** p<0.01, ** p<0.05, * p<0.1

information on the number of different face-to-face social contact someone had in the past four weeks and whether they have installed the NHS COVID-19 app. The number of different contacts represents a measure of personal social distancing, while having the NHS app may signal compliance with government guidance.

To test whether pre-existing health conditions are related to caution with respect to COVID-19, we estimate regressions with a similar set of controls to the main specification. The difference in control variables stems comes from adding respondents' recollection of pre-pandemic social contacts as a control in some specifications to reduce bias from time invariant differences in socialising. As the face-to-face contacts model is count data and it is desirable for an increase in contacts from 1 to 10 to be treated as a bigger change than 91 to 100, we estimate that model using Poisson regression[23]. Meanwhile, we use a linear probability model to estimate the relationship between having the NHS app and pre-existing health conditions.

Table 7 shows that pre-existing health conditions do have the expected relationship with COVID-19 behaviours. Each pre-existing condition is related with 6-8% fewer face-to-face contacts and is also associated with higher downloads of the NHS COVID-19 app, albeit the latter association is only marginally statistically significant in one wave. Additionally, the relationship between health conditions and face-to-face contacts could be understated by this analysis, as both observations were taken during lockdowns (June 2020 and November 2020) and this makes large social gatherings more difficult, possibly reducing the number of contacts for those in the right tail of the distribution.

5.6 Additional Robustness Checks

In this sub-section, we discuss how likely the results are to be driven by alternative explanations. Namely, health declines among those with pre-existing conditions during the pandemic and government shielding advice.

One of the more serious threats to interpreting the results as health risks affecting labour supply preferences is that those with pre-existing health conditions may have seen their health

[23] Similar results are also garnered by a zero-inflated Poisson specification for the wave where the likelihood function converges. See Table B12.

decline and thus exited the labour force. However, several patterns in the data are at odds with this explanation. Most directly, this does not occur prior to the pandemic and the direct effects of long COVID-19 have already been ruled out. Nevertheless, the reduced availability of healthcare that could cause some long-term conditions to worsen and this in turn could affect labour supply. Three pieces of evidence suggest that this is unlikely: (i) labour supply responses are seen very early on in the pandemic before there was time for any health declines to occur and also change in a non-linear fashion; (ii) the effects appear entirely concentrated in jobs highly exposed to COVID-19 and this explanation would likely have some effect on those working any job; and (iii) very similar patterns are observed for health conditions that are unlikely to require intensive health treatment, with asthma alone having a strong statistically significant effect even in the later waves (Table B13). Similarly, the results cannot be driven solely by government shielding recommendations as the relationships survive shielders being excluded from the sample[24].

6 Conclusion

In this paper, we document that individuals at higher levels of health risk from COVID-19 became significantly less likely to work during the pandemic and this does not represent temporary placement on furlough. Furthermore, differences are driven by those whose jobs are difficult to perform from home and persist through to September 2021. As these effects appear uncorrelated with labour demand shocks and several pieces of evidence suggest that they are not driven by health itself, the most natural interpretation is that these results represent a labour supply response to occupational health risks.

The effects found in this paper are highly economically significant, with a back-of-the-envelope calculation suggesting a decline in labour supply from the effects of pre-existing conditions on health risks of 0.8 percentage points in September 2021[25]. This is likely a lower bound as some people without pre-existing health conditions may have reacted similarly and not

[24] See Tables B14 and B15

[25] The average survey participant has just over 0.5 health conditions and the coefficient on number of health conditions is -0.015.

all relevant health conditions were captured in the analysis. However, it should also be stressed that this is only a partial equilibrium result.

Nonetheless, a labour supply response to health risks can still help explain many important patterns in the labour market. Specifically, the heterogeneity in the pandemic's impacts and the unusual tightness of the labour market relative to typical recessions and their recoveries. Future research on this topic may wish to test for signs of persistence over even longer time spans, whether there is scarring from COVID-19 induced labour market separations, or to estimate how significant these effects are likely to be after accounting for general equilibrium responses.

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Appendix A

Table A1: **Main Variables List**

Variable	Functional Form
Controls from current wave	
Sex	Binary
Age	Quartic
Non-white	Binary
Controls from pre-pandemic waves	
Working	Binary
Hours worked	Quadratic
Wage	IHS
Wants a job (unemployed)	Binary
Looking for a job (unemployed)	Binary
Perceived probability of finding job (unemployed)	Categorical
Employment status fixed effects	Categorical
Occupation fixed effects (three digit)	Categorical
Industry fixed effects (two digit)	Categorical
Highest level of education	Categorical
Mental health affected accomplishment	Categorical
Mental health affected diligence	Categorical
Pain affected work	Categorical

Notes: Functional form refers to how the variable is entered into the regression. IHS refers to the inverse hyperbolic sine transformation. Unemployed means that this question was only asked of respondents who were not working at the time of the relevant survey.

Table A2: **Summary of Government Policies and COVID-19 Rates by Wave**

Wave	Lockdown	Schools closed	Furlough active	Death rate
April 2020	✓	✓	✓	840.0
May 2020	✓	✓	✓	252.0
June 2020	✓	✓^	✓	78.7
July 2020		✓^	✓	25.4
September 2020			✓^^	38.6
November 2020	✓		✓	412.6
January 2021	✓	✓	✓	1133.0
March 2021	✓		✓	74.7^^^
September 2021				95.9^^^

Notes: Death rates are 7-day rolling average of deaths across the UK as of the 24^{th} of that month, which was the typical start date for the survey, and are sourced from the UK COVID-19 data dashboard. ^ Partial closure. ^^ Employers had to make a small contribution. ^^^A sizeable portion of the vulnerable population is now vaccinated during this wave, so these represent far higher case rates, but there are signs that a change in risk from vaccination did not affect social distancing behaviour (Agrawal et al, 2022).

Appendix B (NOT FOR PUBLICATION)

Table B1: **Summary Statistics for Health Conditions**

	Obs.	Mean	Std. dev
	April 2020		
Has a pre-existing condition	10869	0.382	0.486
No. health conditions	10869	0.539	0.856
Asthma	10869	0.193	0.395
Bronchitis	10869	0.013	0.114
Chronic obstructive pulmonary disease	10869	0.013	0.113
Emphysema	10869	0.004	0.066
Angina	10869	0.011	0.105
Congestive heart failure	10869	0.001	0.031
Coronary heart disease	10869	0.014	0.117
Heart attack survivor	10869	0.013	0.112
Hypertension	10869	0.174	0.379
Stroke survivor	10869	0.013	0.113
Diabetes	10869	0.060	0.238
Liver disease	10869	0.031	0.172
	September 2021		
Has a pre-existing condition	7731	0.383	0.486
No. health conditions	7731	0.546	0.886
Asthma	7731	0.203	0.403
Bronchitis	7731	0.014	0.116
Chronic obstructive pulmonary disease	7731	0.014	0.119
Emphysema	7731	0.006	0.079
Angina	7731	0.011	0.105
Congestive heart failure	7731	0.001	0.029
Coronary heart disease	7731	0.012	0.110
Heart attack survivor	7731	0.012	0.110
Hypertension	7731	0.167	0.373
Stroke survivor	7731	0.017	0.131
Diabetes	7731	0.060	0.237
Liver disease	7731	0.028	0.165

Notes: All statistics are weighted using the non-response weights.

Table B2: **Work Location for Workers in April 2020 by Shielding Status**

	Mean	
	Non-shielders	Shielders
Not working	0.343	0.526
Never works from home	0.241	0.140
Sometimes works from home	0.063	0.014
Often works from home	0.060	0.035
Always works from home	0.290	0.284
Observations	8490	293

Notes: All statistics are weighted using the non-response weights. The sample is restricted to those who were working prior to the pandemic to make the two groups more comparable.

Table B3: **Relationship Between Probability of Working and Number of Health Conditions (Probit)**

Wave:	Apr. 2020	May 2020	June 2020	July 2020	Sep. 2020
	(1)	(2)	(3)	(4)	(5)
No. health conditions	-0.038***	-0.034***	-0.030***	-0.004	-0.012*
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
Observations	10,863	9,072	8,562	8,332	7,723
Mean	0.545	0.595	0.628	0.647	0.714
Controls	Yes	Yes	Yes	Yes	Yes

Wave:	Nov. 2020	Jan. 2021	Mar. 2021	Sep. 2021
	(6)	(7)	(8)	(9)
No. health conditions	-0.022***	-0.020***	-0.023***	-0.018***
	(0.008)	(0.007)	(0.007)	(0.006)
Observations	5,789	6,955	7,508	7,577
Mean	0.695	0.677	0.690	0.737
Controls	Yes	Yes	Yes	Yes

Notes: Estimates are average marginal effects from a probit regression. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.

*** p<0.01, ** p<0.05, * p<0.1

Table B4: **Relationship Between Probability of Working and Number of Health Conditions by Ability to Perform Occupation from Home (Probit)**

Wave:	Apr. 2020	May 2020	June 2020	July 2020	Sep. 2020
	(1)	(2)	(3)	(4)	(5)
No. health conditions	-0.012	-0.007	0.001	0.016	0.004
	(0.010)	(0.015)	(0.012)	(0.018)	(0.020)
No. health conditions$*\ \overline{NeverWFH}_j$	-0.063***	-0.063*	-0.067**	-0.040	-0.029
	(0.021)	(0.034)	(0.032)	(0.044)	(0.034)
Observations	10,863	9,072	8,562	8,332	7,723
Mean	0.545	0.595	0.628	0.647	0.714
Controls	Yes	Yes	Yes	Yes	Yes
Wave:	Nov. 2020	Jan. 2021	Mar. 2021	Sep. 2021	
	(6)	(7)	(8)	(9)	
No. health conditions	0.004	0.005	-0.001	-0.003	
	(0.016)	(0.014)	(0.014)	(0.017)	
No. health conditions$*\ \overline{NeverWFH}_j$	-0.050	-0.055*	-0.045*	-0.028	
	(0.032)	(0.030)	(0.025)	(0.033)	
Observations	5,789	6,955	7,508	7,577	
Mean	0.695	0.677	0.690	0.737	
Controls	Yes	Yes	Yes	Yes	

Notes: Estimates are average marginal effects from a probit regression. The standard errors are in parentheses and clustered at the three-digit occupation level. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors measured before the pandemic's onset, such as mental health. See Table A1 for a complete description.

*** p<0.01, ** p<0.05, * p<0.1

Table B5: **Tobit Regression of Hours Worked on Health Conditions**

Wave:	Apr. 2020	May 2020	June 2020	July 2020	Sep. 2020
	(1)	(2)	(3)	(4)	(5)
No. health conditions	-1.395***	-1.516***	-1.326***	-0.028	-0.508
	(0.330)	(0.364)	(0.381)	(0.345)	(0.373)
Observations	10,873	9,110	8,643	8,376	7,825
Mean hours worked	18.200	19.828	21.582	22.192	24.948
Controls	Yes	Yes	Yes	Yes	Yes
Wave:	Nov. 2020	Jan. 2021	Mar. 2021	Sep. 2021	
	(6)	(7)	(8)	(9)	
No. health conditions	-0.967**	-0.701*	-0.726**	-0.724**	
	(0.411)	(0.406)	(0.351)	(0.345)	
Observations	5,939	7,092	7,644	7,735	
Mean hours worked	24.610	24.082	24.453	24.669	
Controls	Yes	Yes	Yes	Yes	

Notes: Coefficients are average marginal effects. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.
*** p<0.01, ** p<0.05, * p<0.1

Table B6: **Tobit Regression of Hours Worked on Health Conditions by Occupational Ability to Work from Home**

Wave:	Apr. 2020	May 2020	June 2020	July 2020	Sep. 2020
	(1)	(2)	(3)	(4)	(5)
No. health conditions	-0.071	-0.164	-0.011	0.383	-0.064
	(0.439)	(0.543)	(0.535)	(0.801)	(0.842)
No. health conditions$*\overline{NeverWFH}_j$	-3.384***	-3.345*	-3.010*	-0.814	-0.855
	(1.100)	(1.729)	(1.675)	(2.141)	(1.592)
Observations	10,873	9,109	8,642	8,364	7,825
Mean hours worked	18.200	19.832	21.586	22.171	24.948
Controls	Yes	Yes	Yes	Yes	Yes

Wave:	Nov. 2020	Jan. 2021	Mar. 2021	Sep. 2021
	(6)	(7)	(8)	(9)
No. health conditions	0.471	0.439	0.320	-0.225
	(0.780)	(0.711)	(0.525)	(0.771)
No. health conditions$*\overline{NeverWFH}_j$	-2.995	-2.627	-2.239*	-0.941
	(1.898)	(1.883)	(1.243)	(1.664)
Observations	5,939	7,092	7,644	7,735
Mean hours worked	24.610	24.082	24.543	26.350
Controls	Yes	Yes	Yes	Yes

Notes: Coefficients are average marginal effects. Standard errors clustered at the three-digit occupation level are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.

*** p<0.01, ** p<0.05, * p<0.1

Table B7: **Relationship Between Probability of Working and Number of Health Conditions with Clustered Standard Errors**

Wave:	Apr. 2020	May 2020	June 2020	July 2020	Sep. 2020
	(1)	(2)	(3)	(4)	(5)
No. health conditions	-0.032***	-0.029**	-0.025***	-0.002	-0.008
	(0.009)	(0.014)	(0.008)	(0.006)	(0.010)
Observations	10,869	9,105	8,638	8,373	7,821
R-squared	0.358	0.395	0.430	0.456	0.517
Proportion working	0.545	0.596	0.631	0.649	0.718
Controls	Yes	Yes	Yes	Yes	Yes

Wave:	Nov. 2020	Jan. 2021	Mar. 2021	Sep. 2021
	(6)	(7)	(8)	(9)
No. health conditions	-0.021	-0.018*	-0.020***	-0.016**
	(0.013)	(0.010)	(0.007)	(0.008)
Observations	5,934	7,090	7,642	7,731
R-squared	0.497	0.483	0.480	0.511
Proportion working	0.703	0.683	0.697	0.743
Controls	Yes	Yes	Yes	Yes

Notes: Estimates come from a linear probability model. Standard errors clustered at three-digit occupation level are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.

*** p<0.01, ** p<0.05, * p<0.1

Table B8: **Relationship between Furlough Probability and Number of Health Conditions**

Wave:	Apr. 2020 (1)	May 2020 (2)	June 2020 (3)	July 2020 (4)	Jan. 2021 (5)	Mar. 2021 (6)	Sep. 2021 (7)
No. health conditions	0.013***	0.017***	0.008	0.000	0.002	0.001	-0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.001)
Observations	10,927	8,956	8,514	8,235	7,144	7,676	7,783
R-squared	0.226	0.183	0.165	0.159	0.222	0.228	0.123
Proportion furloughed	0.144	0.123	0.095	0.062	0.079	0.062	0.009
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimates come from a linear probability model. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.

*** p<0.01, ** p<0.05, * p<0.1

Table B9: **Relationship Between Probability of Working and Number of Health Conditions Pre-Pandemic with Occupation's Ability to Work from Home Measured Using September 2021 Data**

Dependent variable:	Probability of working		
Wave:	Wave 8	Wave 9	Wave 10
	(1)	(2)	(3)
No. health conditions	-0.013	-0.004	-0.026**
	(0.013)	(0.010)	(0.013)
No. health conditions$*\overline{NeverWFH}_j$	0.016	0.003	0.046**
	(0.022)	(0.018)	(0.022)
Observations	17,037	17,106	17,635
R-squared	0.674	0.653	0.640
Proportion working	0.763	0.752	0.743
Controls	Yes	Yes	Yes

Notes: Estimates come from a linear probability model. Standard errors clustered at the three-digit occupation level are in parentheses. $\overline{NeverWFH}_j$ is defined using the proportion of individuals from occupation j who never worked from home in April 2020 among those who were working. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover work history, demographics, and other factors measured as of the previous wave, such as mental health. See Table A1 for a complete description.
*** p<0.01, ** p<0.05, * p<0.1

Table B10: **Relationship Between Probability of Working and Number of Health Conditions by Occupational Risk with Varying Controls (April 2020)**

Dependent variable:	Probability of working					
	(1)	(2)	(3)	(4)	(5)	(6)
No. health conditions	0.004	0.007	0.007	0.006	0.007	0.007
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
No. health conditions$*\overline{NeverWFH}_j$	-0.095***	-0.098***	-0.097***	-0.095***	-0.095***	-0.094***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)	(0.027)
Observations	10,466	10,466	10,466	10,466	10,466	10,466
R-squared	0.353	0.362	0.363	0.364	0.366	0.366
Controls bar education and wages	Yes	Yes	Yes	Yes	Yes	Yes
Education and wage controls	No	Yes	Yes	Yes	Yes	Yes
Geographic controls	No	No	Yes	Yes	Yes	Yes
Caring controls	No	No	No	Yes	Yes	Yes
Work from home controls	No	No	No	No	Yes	Yes
Savings controls	No	No	No	No	No	Yes

Notes: Estimates come from a linear probability model. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The main controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description of the main controls and Table B11 for a description of the others.
*** p<0.01, ** p<0.05, * p<0.1

Table B11: **List of Additional Controls Drawn from Before the Pandemic**

Variable	Functional form
Geographic controls	
Urban	Binary
Government office region fixed effects	Categorical
Caring controls	
Parent (Under 6)	Binary
Parent (Under 10)	Binary
Parent (Under 16)	Binary
Mother (Under 6)	Binary
Mother (Under 10)	Binary
Mother (Under 16)	Binary
Carer	Binary
Hours spent caring	Linear
Work from home controls	
Frequency of internet use	Categorical
Suitable home computer	Binary
More rooms than people	Binary
Savings controls	
Owns home	Binary
Owns home outright	Binary
Savings and investment income	IHS
Long COVID controls (from current wave)	
Has had long COVID	Binary
Still has long COVID symptoms	Binary

Notes: Functional form refers to how the variable is entered into the regression. IHS refers to the inverse hyperbolic sine transformation.

Table B12: **Relationship Between Number of Face-to-Face Contacts and Number of Health Conditions in June 2020 (Zero Inflated Poisson)**

Dependent variable:	Number of contacts	
Estimator:	ZIP	Poisson
	(1)	(2)
No. health conditions	-0.078***	-0.077***
	(0.020)	(0.019)
Past number of contacts	0.064***	0.058***
	(0.004)	(0.003)
Past number of contacts^2/100	-0.056***	-0.050***
	(0.006)	(0.006)
No past contacts	-0.494***	-0.857***
	(0.112)	(0.118)
Observations	6,581	6,581
Controls	Yes	Yes

Notes: All reported results are semi-elasticities and heteroscedasticity-robust standard errors are in parentheses. ZIP stands for zero-inflated Poisson and the first stage was estimated using logistic regression. Observations dropped by the zero-inflated Poisson are also dropped in the Poisson specification for comparability. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Number of face-to-face contacts is defined as over the past month, while the past number of contacts was how many they recalled having in January and February 2020 when asked in the June 2020 wave. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B13: **Relationship Between Probability of Working and Asthma**

Wave:	Apr. 2020	May 2020	June 2020	July 2020	Sep. 2020
	(1)	(2)	(3)	(4)	(5)
Asthma	-0.047***	-0.052***	-0.034**	-0.006	-0.002
	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)
No. health conditions (other)	-0.025***	-0.020**	-0.021***	-0.000	-0.010
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Observations	10,869	9,105	8,638	8,373	7,821
R-squared	0.358	0.395	0.431	0.456	0.517
Proportion working	0.545	0.596	0.631	0.649	0.718
Controls	Yes	Yes	Yes	Yes	Yes

Wave:	Nov. 2020	Jan. 2021	Mar. 2021	Sep. 2021
	(6)	(7)	(8)	(9)
Asthma	-0.030*	-0.035**	-0.019	-0.025*
	(0.016)	(0.016)	(0.015)	(0.013)
No. health conditions (other)	-0.017*	-0.012	-0.021***	-0.012*
	(0.009)	(0.008)	(0.008)	(0.007)
Observations	5,934	7,090	7,642	7,731
R-squared	0.497	0.483	0.480	0.511
Proportion working	0.703	0.683	0.697	0.743
Controls	Yes	Yes	Yes	Yes

Notes: Estimates come from a linear probability model. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. No. health conditions (other) is the number of relevant pre-existing health conditions an individual has excluding Asthma. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.

*** p<0.01, ** p<0.05, * p<0.1

Table B14: **Relationship Between Probability of Working and Number of Health Conditions Excluding Shielders**

Wave:	Apr. 2020	May 2020	June 2020	July 2020
	(1)	(2)	(3)	(4)
No. health conditions	-0.030***	-0.027***	-0.023***	0.002
	(0.007)	(0.008)	(0.008)	(0.007)
Observations	10,385	8,689	8,230	7,977
R-squared	0.349	0.385	0.420	0.443
Wave:	**Sep. 2020**	**Nov. 2020**	**Jan. 2021**	**Mar. 2021**
	(5)	(6)	(7)	(8)
No. health conditions	-0.009	-0.018*	-0.018**	-0.019***
	(0.008)	(0.009)	(0.008)	(0.007)
Observations	7,459	5,653	6,798	7,381
R-squared	0.501	0.477	0.476	0.474

Notes: Estimates come from a linear probability model. Heteroscedasticity-robust standard errors are in parentheses. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors such as mental health. See Table A1 for a complete description.

*** p<0.01, ** p<0.05, * p<0.1

Table B15: **Relationship Between Probability of Working and Number of Health Conditions by Ability to Perform Occupation from Home Excluding Shielders**

Wave:	Apr. 2020	May 2020	June 2020	July 2020
	(1)	(2)	(3)	(4)
No. health conditions	-0.007	0.004	-0.001	0.006
	(0.010)	(0.017)	(0.015)	(0.019)
No. health conditions$*\ \overline{NeverWFH}_j$	-0.060**	-0.079**	-0.050	-0.009
	(0.024)	(0.039)	(0.037)	(0.047)
Observations	10,385	8,689	8,230	7,977
R-squared	0.349	0.385	0.420	0.443
Wave:	Sep. 2020	Nov. 2020	Jan. 2021	Mar. 2021
	(5)	(6)	(7)	(8)
No. health conditions	0.004	-0.004	0.024	0.014
	(0.025)	(0.022)	(0.020)	(0.020)
No. health conditions$*\ \overline{NeverWFH}_j$	-0.024	-0.029	-0.096**	-0.071*
	(0.047)	(0.050)	(0.044)	(0.043)
Observations	7,459	5,653	6,798	7,381
R-squared	0.501	0.477	0.477	0.474

Notes: Estimates come from a linear probability model. The standard errors are in parentheses and clustered at the three-digit occupation level. All regressions are weighted using non-response weights and are restricted to those aged 25-64. Individuals are classified as working if they report working a positive number of hours in the past week. The controls cover pre-pandemic work history, demographics, and other factors measured before the pandemic's onset, such as mental health. See Table A1 for a complete description.
*** p<0.01, ** p<0.05, * p<0.1