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Ethnicity and health at work during the COVID-19

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ABSTRACT

This paper explores how health-work-related illnesses and injuries have changed during the COVID-19 pandemic for different ethnic groups and by gender. We find that not all groups were affected in the same way. While almost all men in all ethnic groups were on average less likely to work during the pandemic period, women were more likely to work. We also find that Mixed Ethnic and Pakistani women who reported a higher probability of working in the reference week had a higher risk of illness/injuries at work. Meanwhile, White men and Other ethnic groups with a reduced probability of working during the pandemic had a lower risk of illness/injuries at work. Long-term illness varied by ethnicity and gender, with men experiencing a reduction and women an increase in physical and mental health issues. This research provides valuable insights into the multifaceted impact of the COVID-19 pandemic on the health and work patterns of different ethnic groups and gender. Understanding and identifying these disparities is crucial for formulating targeted policies aimed at mitigating adverse effects and promoting equitable outcomes in regional studies and urban economics.

1. Introduction

It is widely acknowledged that work is associated with certain illnesses and accidents (Takala et al., 2017; Losina et al., 2017; Echeverri et al., 2017, among others). According to the International Labour Organization (ILO), over two million women and men worldwide suffer from work-related accidents or diseases annually, incurring substantial costs. Annually, there are approximately 340 million occupational accidents and 160 million victims of work-related illnesses. Addressing this concern, one of the primary priorities of the European Commission is to support the prevention of work-related diseases, aiming to enhance the well-being of individual workers and reduce the financial burden associated with work-related illnesses and fatalities.

Leveraging the unprecedented COVID-19 pandemic shock in 2020, which significantly reduced employment activity, presents a unique opportunity to assess the impact of lockdown periods on workers' health outcomes. The main hypothesis of this study is that the reduction in work-related activities during lockdowns may have implications for employees' health issues and injuries at work. To test this hypothesis, we explore the heterogeneity across ethnic groups and gender, aiming to uncover any differential effects experienced by various demographic categories.

People of different ethnic groups tend to work in different occupations, which can have a different impact on their health. This is because different occupations have different levels of exposure to hazards, such as physical hazards, chemical hazards, and psychosocial hazards.

The task-specialization literature suggests that natives and migrants possess distinct comparative advantages in occupations characterized by different levels of abstraction and physical intensity (d'Amuri et al., 2010; Ottaviano and Peri, 2012; Peri and Sparber, 2009) . Due to limited institutional knowledge and language-specific skills, migrant workers with low education often tend to concentrate on physically intensive occupations (Hargreaves et al., 2019); Perez et al., 2012). In response to an increased supply of migrant labour, native workers may be incentivized to shift toward jobs with higher institutional-specific content (Foged and Peri, 2016), leading to reduced exposure to injury risks (Giuntella et al., 2019). Newly arrived migrants may opt for hazardous tasks due to differences in risk perception (Jaeger et al., 2010), positive selection based on initial health endowments (commonly known as the "healthy immigrant effect") (Kennedy et al., 2015; Chiswick and Miller, 2008), and limited outside options (Orrenius and Zavodny, 2009; Orrenius et al., 2012). As a consequence of migrant workers taking up riskier tasks, the exposure to severe impairments for native workers may decrease.

There is a growing body of evidence that supports the concept of occupational disparities in health outcomes. For example, a study by

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Giuntella et al. (2019) found that migrant workers in the UK were more likely to be exposed to hazardous working conditions than native workers. Another study, by Alacevich and Nicodemo (2019), found that ethnic minority workers in Italy were more likely to be employed in low-paying and insecure jobs. A more recent study, by Fasani and Mazza (2020), found that ethnic minority workers in Europe were more likely to be exposed to psycho-social hazards, such as job insecurity and discrimination.

Using data from the UK Labour Force Survey (UKLFS) between January 2018 and January 2021, we descriptively explored health-related issues and work accidents among ethnic groups before and after the pandemic. The main objective was to assert whether there were varying health outcomes before and after the pandemic, with some ethnic groups experiencing improvements, while others faced more challenges. For this purpose, we rely on the UK Labour Force Survey (UKLFS), which represents the largest household study in the UK and provides official measures of employment, unemployment, as well as employment-related health and well-being conditions. One of the primary advantages of this dataset, in comparison to other UK surveys, is that its large sample size enables the exploration of heterogeneities in health and employment conditions, allowing for the differentiation of specific migrants and ethnic groups rather than using macro-aggregated categories. This capability should facilitate the design of targeted interventions aimed at reducing health disparities and promoting well-being among diverse communities.

The Sewell Report (2021) on race and ethnic disparities in the UK labor market reveals significant disparities in pay, employment, and unemployment between ethnic minorities and white individuals. These differences can partly be attributed to the clustered distribution of ethnic groups in various sectors. For instance, 43% of Black individuals are employed in public, education, and health sectors, while 30% of Pakistani and Bangladeshi individuals work in hotel and restaurant sectors. Such patterns contribute to the observed disparities in the labor market.[1]

Our study contributes to the urban economics literature by examining how the concentration of ethnic minorities in specific sectors and occupations affects their health outcomes. Recent research in urban economics has shown that ethnic minorities tend to be concentrated in frontline occupations in urban areas, which affected their exposure to health risks during COVID-19 (Almagro et al., 2020). This occupational segregation, combined with the ethnic wage gaps documented by Ananat et al. (2018), suggests that ethnic minorities might face different health risks through both their type of work and their working conditions. The spatial organization of urban labor markets further compounds these effects, as ethnic minorities often face constraints in job accessibility (Andersson et al., 2018) and tend to be concentrated in specific urban sectors (Holzer and Neumark, 2021). Our analysis of health outcomes across ethnic groups during COVID-19 provides new evidence on how these established patterns of urban occupational segregation translate into differential health risks.

As the main empirical strategy, we employed a Linear Probability Model to analyze changes in specific work-related illnesses and injuries during the lockdown period. In particular, we focus on the following variables:

(i) Whether the respondent engaged in paid work during the reference week. (ii) Whether the respondent took days off from work due to sickness or work-related injuries. (iii) Whether the respondent had health problems lasting or expected to last over 12 months, which could limit the type of paid work they can perform.

For those who reported having health problems, we further examined the type of illness or issue, including respiratory, mental health, back/neck, limb, digestive, cardiovascular, sensory (eyes, hands, and mouth), progressive, and skin-related problems.

The pandemic lockdown yielded varied effects on workers, and our findings unveiled persistent ethnic and gender discrepancies in both employment and health outcomes. While the majority of male ethnic groups exhibited a decreased likelihood of working during the pandemic, women from White British, Mixed, Indian, Pakistani, as well as other Asian and Black backgrounds demonstrated an elevated tendency to work. Interestingly, an augmented probability of work correlated with an elevated risk of illness and injuries.

Therefore, this study aims to shed light on the relationship between economic activity and the health status of employees, thereby facilitating the development of improved health policies to ensure safer work environments. Additionally, by examining the performance of specific ethnic groups during the COVID period, we gain valuable insights into the inequalities faced by certain immigrant communities. This understanding will inform the formulation of targeted policies aimed at addressing these disparities and promoting a more equitable society.

The paper is divided into four sections: Section 2 provides the theoretical framework, Section 3 presents the empirical analysis, Section 4 outlines the results, and, finally, Section 5 offers concluding remarks and implications.

2. Data

Our analyses are based on the Quarterly Labour Force Survey (UKLFS), a comprehensive, repeated cross-sectional household survey covering adults aged 16 and above. This survey extensively captures various aspects of paid work, including employment status, occupation, industry, working hours, and earnings. Additionally, it collects valuable information on health, education, training, and family and household composition. Over a period of 36 months, from 1st January 2018 to 1st January 2021, we observe the data cross-sectionally, providing a robust foundation for our research.

The initial sample includes all respondents aged 16 and above. Subsequently, we focus on health outcomes among those who participated in the UKLFS employment and health module. This module is applicable only to individuals who reported that health or disability problems currently limit the type of paid work they can engage in at the time of the interview. In total, we gathered 759,995 observations, with 12% representing individuals from non-White British backgrounds (N=75,378). These respondents reported their employment status and indicated whether they experienced health issues that prevented them from working over a 36-month period. One pivotal feature of the UK Labour Force Survey (UKLFS) is its substantial large sample size, which enables the study of ethnic minorities at a more granular level than any other survey accessible in the UK.

Table 1 in the Appendix provides descriptive statistics for the sample mean, minimum, and maximum values for each variable considered in our analysis before (January 2018 to February 2020) and after (March 2020 to January 2021) the lockdown period. This table offers crucial insights into any potential changes in the composition of the workers' sample during these two periods.

Significantly, the data indicates that there were no noteworthy shifts in the composition of the workers' sample concerning ethnicity and gender following March 2020. This stability implies that our study is suitably poised to investigate the effects of the lockdown on health outcomes, unaffected by socio-demographic factors tied to alterations in sample characteristics and composition.

However, there are a couple of noteworthy observations. First, the proportion of respondents with a university degree increased slightly in the second period, rising from 0.259 to 0.284. This may reflect changes in the workforce or educational patterns during the pandemic.

Secondly, there was an increase in the number of respondents participating in the telephone survey due to mobility limitations during the pandemic. This shift in data collection methods may have implications for response biases and warrants consideration in our analysis.

Nevertheless, overall, the sample appears to be comparable across the two periods, providing a robust foundation for our investigation into the workers' health changes during the pandemic.

[1] For more details see: https://www.ethnicity-facts-figures.service.gov.uk/work-pay-and-benefits/employment/employment-by-sector/latest

Table 1
Summary statistics before/after March 2020.

	(1) Before March 2020			(2) After March 2020		
	mean	min	max	mean	min	max
White	0.881	0	1	0.889	0	1
Mixed	0.011	0	1	0.012	0	1
Indian	0.024	0	1	0.024	0	1
Pakistani	0.016	0	1	0.013	0	1
Bangladeshi	0.007	0	1	0.006	0	1
Chinese	0.005	0	1	0.005	0	1
Any other Asian background	0.011	0	1	0.010	0	1
Black/African/Caribbean/Black British	0.029	0	1	0.027	0	1
Other ethnic group	0.016	0	1	0.013	0	1
Age of respondent	47.9	16	99	48.2	16	99
Female	0.511	0	1	0.511	0	1
Degree or equivalent	0.259	0	1	0.284	0	1
Higher education	0.073	0	1	0.071	0	1
GCE A level or equivalent	0.188	0	1	0.186	0	1
GCSE grades A*-C or equivalent	0.172	0	1	0.168	0	1
Other qualification	0.070	0	1	0.061	0	1
No qualification	0.071	0	1	0.063	0	1
No Religion	0.392	0	1	0.418	0	1
Christian (all denominations)	0.521	0	1	0.503	0	1
Budhist	0.004	0	1	0.004	0	1
Hindu	0.014	0	1	0.014	0	1
Jewish	0.005	0	1	0.005	0	1
Muslim	0.040	0	1	0.033	0	1
Sikh	0.006	0	1	0.006	0	1
Any Other Religion	0.018	0	1	0.017	0	1
Single, never married	0.350	0	1	0.359	0	1
Married, living with spouse	0.486	0	1	0.478	0	1
Married separated from spouse	0.022	0	1	0.022	0	1
Divorced	0.078	0	1	0.078	0	1
Widowed	0.062	0	1	0.058	0	1
Currently or previously in civil partnership	0.002	0	1	0.005	0	1
Lone parent with dep. children	0.053	0	1	0.051	0	1
Household with dep. children	0.280	0	1	0.270	0	1
Over 65	0.161	0	1	0.164	0	1
North-East	0.040	0	1	0.040	0	1
North-West	0.110	0	1	0.108	0	1
Yorkshire and Humberside	0.082	0	1	0.082	0	1
East Midlands	0.072	0	1	0.073	0	1
West Midlands	0.088	0	1	0.089	0	1
East of England	0.093	0	1	0.094	0	1
London	0.133	0	1	0.132	0	1
South-East	0.137	0	1	0.137	0	1
South-West	0.085	0	1	0.085	0	1
Wales	0.048	0	1	0.048	0	1
Scotland	0.084	0	1	0.084	0	1
Northern Ireland	0.027	0	1	0.027	0	1
Keyworkers	0.134	0	1	0.133	0	1
Telephone	0.525	0	1	0.571	0	1
Face-to-face	0.475	0	1	0.429	0	1
Observations	**571,858**			**188,137**		

Quarterly UKLFS Jan. 2018–Jan. 2021; weighted data

3. Empirical strategy

Our analysis centers around various dichotomous outcomes to investigate the impact of work-related factors on employees' health. Specifically, we examine the following:

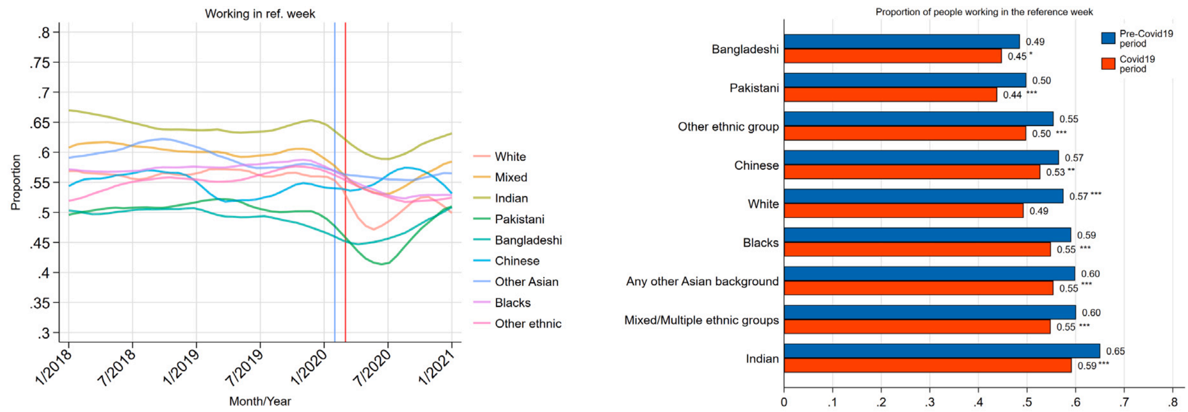
(a) Whether the respondent was engaged in paid work during the reference week. This variable allows us to understand the labor force participation and employment patterns during the study period.

(b) The probability of not working due to work-related injuries or illnesses. This variable represents the likelihood that individuals are not working due to injuries or illnesses associated with their employment, allowing us to explore the incidence of work-related health issues and their impact on work absence.

(c) Whether respondents reported having a longstanding health problem that prevented them from working. This variable provides insights into the prevalence of persistent health conditions that affect individuals' ability to participate in the workforce.

(d) We also investigate the specific types of health issues respondents faced, categorizing them into nine distinct categories. These health issues include respiratory, mental health, back/neck, limb, digestive, cardiovascular, diabetes, sensory (eyes, hands, and mouth), progressive, and skin problems. By examining these health conditions, we can identify patterns and understand the distribution of health issues among workers.

By focusing on these dichotomous outcomes, we aim to gain a comprehensive understanding of the interplay between work-related factors and employees' health outcomes, contributing valuable insights to inform policy interventions aimed at promoting a safer and healthier work environment.



(a) Working in the reference week over time (b) Proportion of people working in the reference week

Fig. 1. Trends over time and changes before/during COVID-19 period.
Note: (a) blue line represents 1st of February and red line 1st of March; (b) *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$, T-test: White diff = .082, Z = 60.2, p-val =0.000; Mixed diff = .521, Z = 3.92, p-val = 0.000; Indian diff = .0585, Z = 6.56, p-val = 0.000; Pakistani diff = .0599, Z = 4.90, p-val = 0.000; Bangladeshi diff = .037, Z = 1.88, p-val = 0.060; Chinese diff = .038, Z = 1.98, p-val = 0.048 Any other Asian background diff = .0447, Z = 3.25, p-val = 0.001 Blacks diff = .0417, Z = 4.62, p-val = 0.000 Other ethnic group diff = .056, Z = 4.49, p-val = 0.000; weighted data.

As the primary model specification, we employed a Linear Probability Model (LPM) stratified by ethnicity (j) to describe the changes following the first lockdown implementation, which we assumed marked the beginning of COVID-19's impact in the UK (March 2020). This approach allowed us to assess how various ethnic groups were affected by the pandemic and lockdown measures, providing valuable insights into the differential impacts on different communities. Formally, we have:

$$y^j = \beta_0^j + \beta_1^j(\mathrm{L}) + \beta_2^j(\mathrm{W}) + \beta_3^j(\mathrm{L} * \mathrm{W}) + \beta_4^j(\mathrm{year\backslash month}) + \sum \beta_5^j \mathrm{controls} + \varepsilon^j \tag{1}$$

Where β_1 is a dummy variable indicating the period before the lockdown, Jan. 2018–Feb. 2020 (0) and the one after, Mar. 2020–Jan. 2021 (1), Additionally, we consider the gender factor using the dummy variable β_2, which takes the value 1 for women. To understand how the lockdown effect varies by gender, we introduce the interaction term β_3.

To capture any underlying time-related trends, we include the variable β_4 as a time trend. Our model also accounts for several control variables denoted as β_5, which encompass age, age squared (age2), an over 65 dummy, religion, education, marital status, whether the respondent is in a union with dependent children, or a lone parent with dependent children, Government Office Region fixed effects, type of interview (telephone vs. web), and the quarter when the household entered the survey.

To account for potential heterogeneity across different time periods and individuals, we employ clustered standard errors at the month/year level and incorporate individual survey weights in our analysis. The inclusion of clustered standard errors allows us to account for potential correlations within the same month/year, while the use of survey weights ensures our results are representative of the target population.

We run separate models for each ethnic group. Our key parameters of interest are the before/after lockdown dummy and its interaction with gender. More precisely, our primary objective is to estimate whether there have been significant changes before and after the pandemic and whether there are potential gender differences across nine distinct ethnic groups: white British, mixed, Indian, Pakistani, Bangladeshi, Chinese, Other Asian, Blacks, and Other ethnic groups. Given the consideration of interaction effects, we opted for a Linear Probability Model (LPM) instead of logit or probit models. Notably, all coefficients presented in our analysis can be interpreted as discrete changes on the probability scale.[2]

4. Results

To initiate our analysis, we examine the trends over time in the probability of being employed during the reference week of the interview (Fig. 1, panel a) and the total average change between the pre-COVID-19 period and the COVID-19 period (Fig. 2, panel b) by each ethnic group. To capture the nuances in these trends, in panel a, we utilize a local polynomial regression stratified by ethnic group. By employing local polynomial regressions, we can discern more intricate patterns that might not be apparent in a simple linear analysis. This approach allows us to gain a deeper understanding of the dynamics at play and facilitates a more accurate interpretation of the trends over time. Overall, we observe the presence of significant ethnic heterogeneity concerning employment probability across ethnic groups, being Indians followed by mixed ethnic groups those with the highest share of employment, and Pakistani and Bangladeshi those with the lowest. The plot also illustrates a consistent reduction in the labor supply for all ethnic groups during the COVID-19 period between early 2020 and August 2020, with a recovery by the end of 2020 and January 2021. This probably reflects the lockdown restriction imposed in March 2020 and relaxed between June and July 2020.

In subsequent sections, we delve into the specific findings and implications of our analysis, shedding light on the factors influencing employment, days off due to illness or injuries, and long-term illness within different ethnic groups. This descriptive exercise will contribute to a more comprehensive understanding of the dynamics of employment and health outcomes in diverse communities in the UK.

Following the initial exploration of trends, we employ Linear Probability Models (LPMs) to investigate changes in employment and health conditions across different ethnic groups and genders during the pandemic period. This analysis will help us understand the nuanced impacts of the pandemic on employment and health conditions, particularly as they relate to the diverse experiences of different ethnic and gender groups. We hypothesize that the observed disparities in health problems across ethnic groups may be influenced by several mechanisms, including differences in socioeconomic status that affect

[2] As a robustness check, we also run a logit model and calculated average marginal effects. The results from the logit model are available upon request.

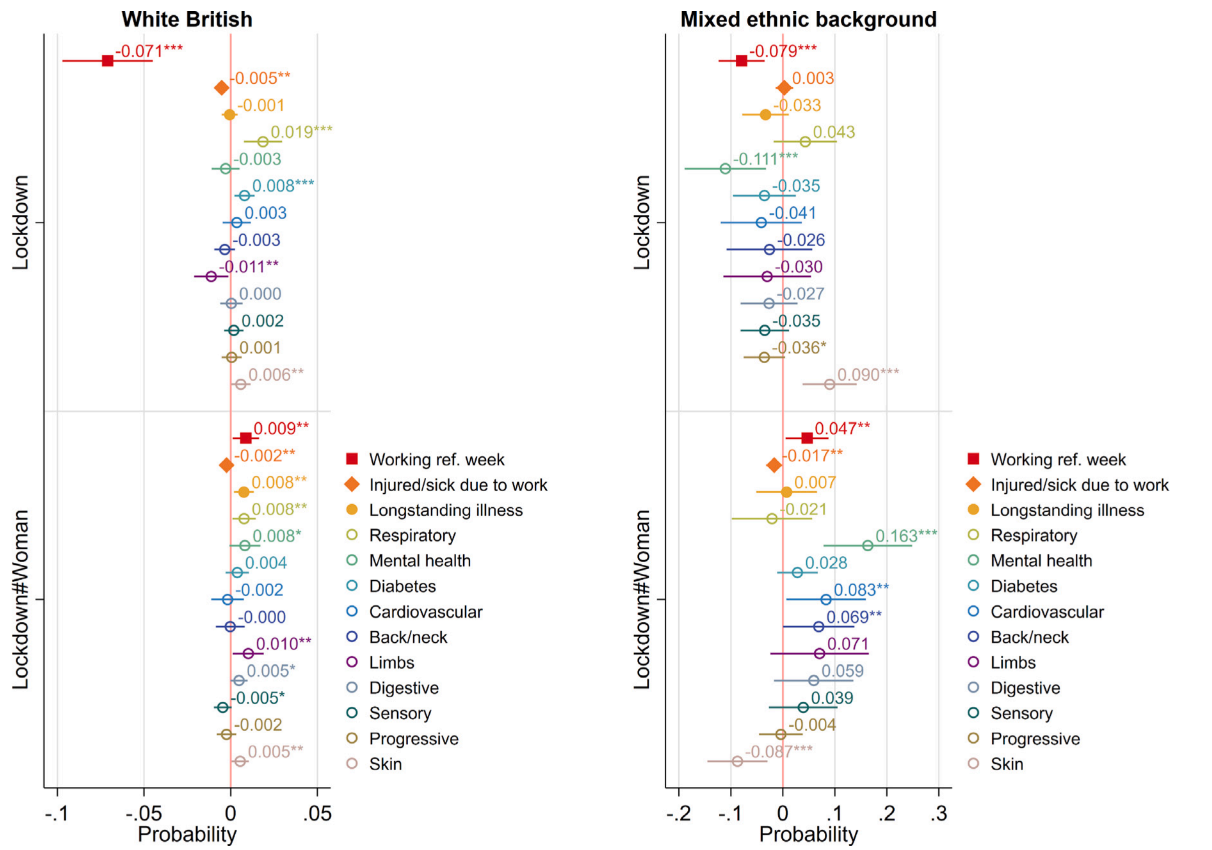


Fig. 2. LPM coefficients for White and mixed ethnic background. Note: stars denote the following p-values: *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$; weighted data.

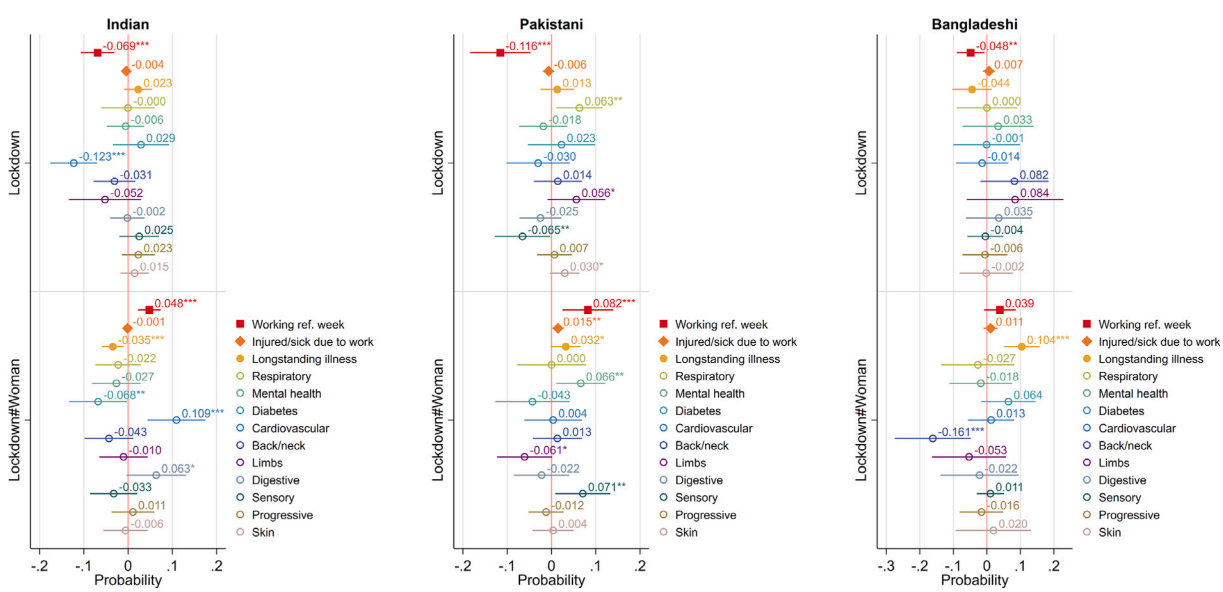


Fig. 3. LPM coefficients for South Asian. Note: stars denote the following p-values: *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$; weighted data.

access to healthcare and resources, occupational exposure risks associated with essential work, and varying cultural attitudes toward health and wellbeing, which could impact health-seeking behavior and the management of chronic conditions. Figs. 2–5 present the main coefficients of interest: the lockdown dummy and its interaction with a gender dummy (man = 0; woman = 1), for each ethnic group. In total, we report 26 coefficients for 13 different outcomes, including working in the reference week, risk of illness/injuries, long-standing illness (represented by full markers), and 10 types of health problems (represented by empty markers). Each coefficient includes 95% confidence intervals and denotes the level of significance. All the models included survey weights.

Regarding employment probability, our findings align with the previously observed trends. White British, Mixed ethnic background,

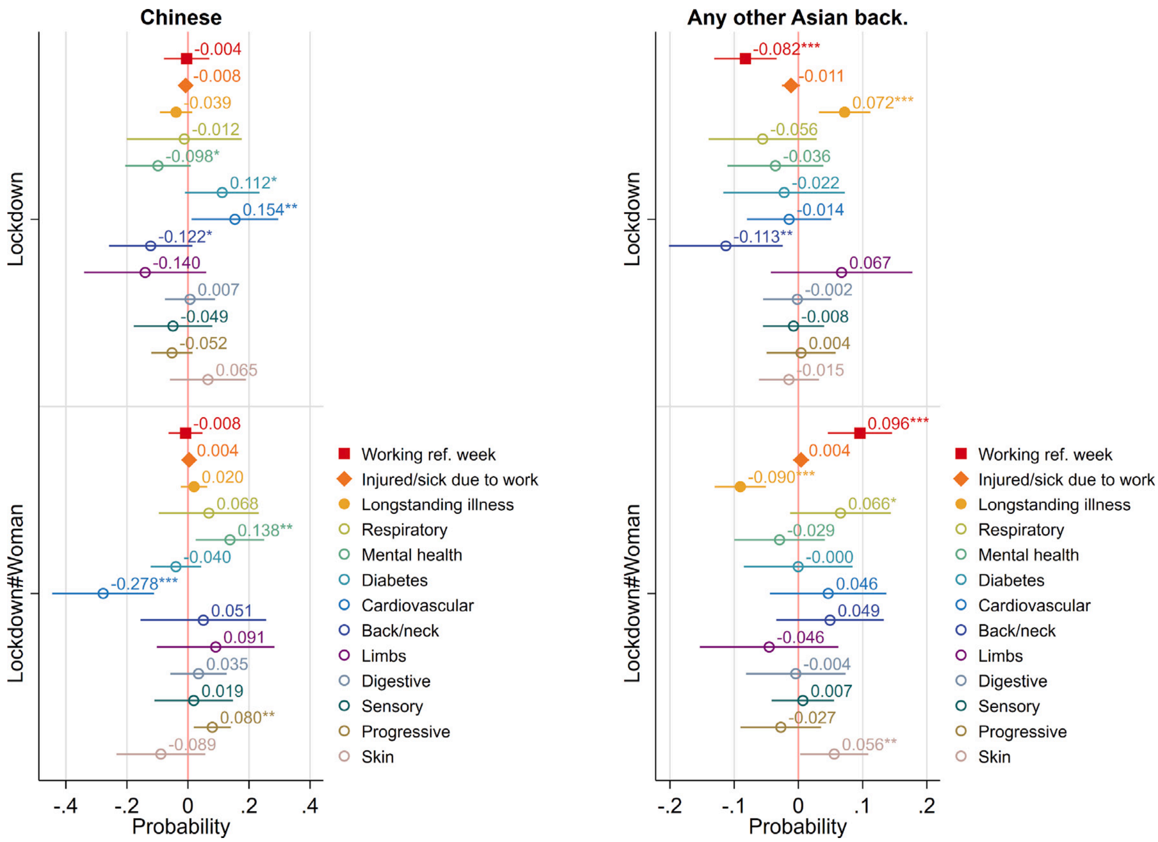


Fig. 4. LPM coefficients for Chinese and other Asian. Note: stars denote the following p-values: *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$; weighted data.

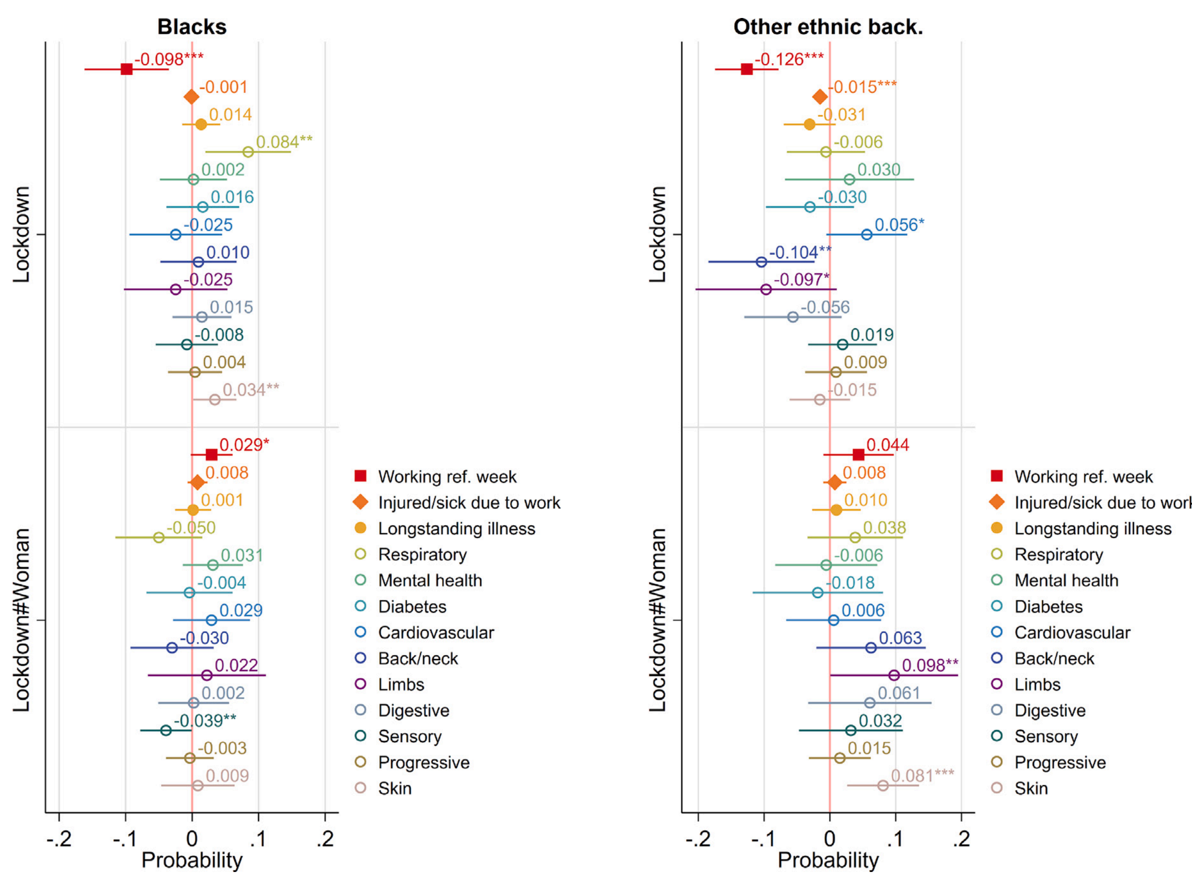
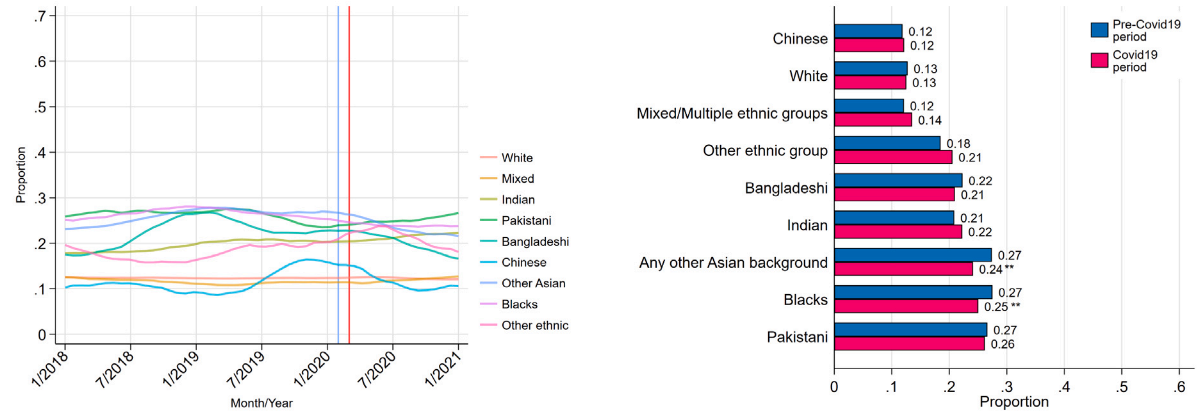
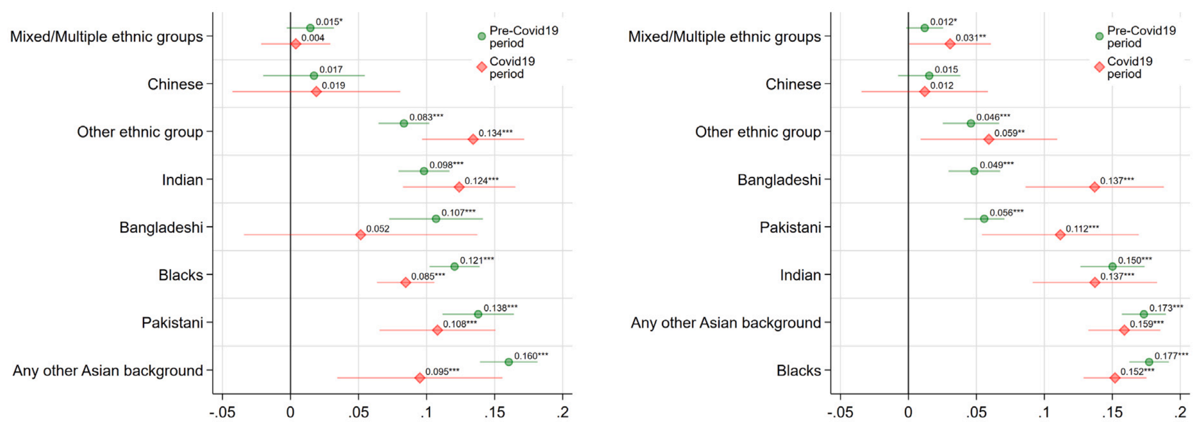


Fig. 5. LPM coefficients for blacks and other ethnic. Note: stars denote the following p-values: *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$; weighted data.



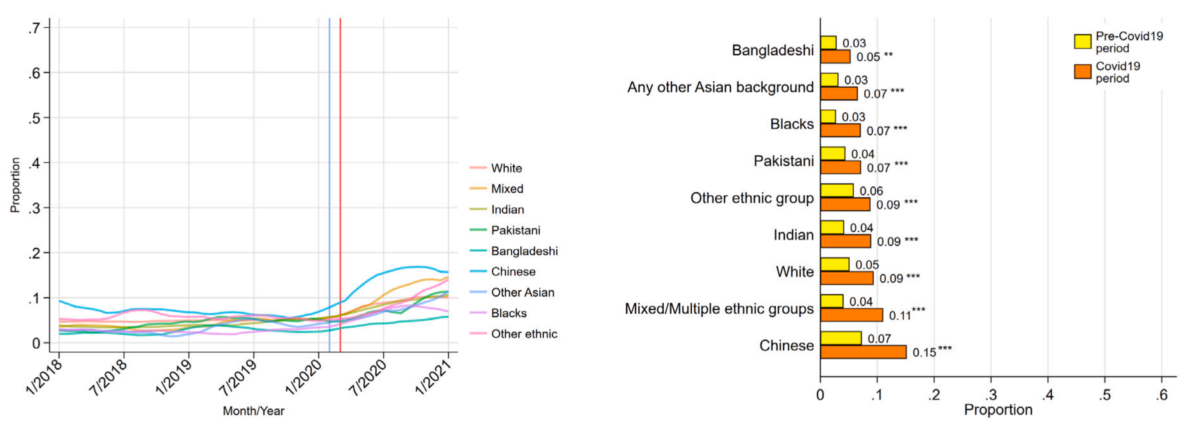
(a) Essential/key workers over time (b) Proportion of essential/key workers by ethnicity

Fig. 6. Essential and key workers.
Note: (a) blue line represents 1st of February and red line 1st of March; (b) *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$, T-test: White diff = .002, Z = 1.91, p-val = 0.056; Mixed diff = −.014, Z = −1.30, p-val = 0.193; Indian diff = −.0137, Z = −1.51, p-val = 0.130; Pakistani diff = −.004, Z = 0.30, p-val = 0.766; Bangladeshi diff = .0133, Z = 0.60, p-val = 0.550; Chinese diff = −.0027, Z = −0.17, p-val = 0.863; Any other Asian background diff = .0327, Z = 2.15, p-val = 0.032; Blacks diff = .025, Z = 2.46, p-val = 0.014; Other ethnic group = −.0207, Z = −1.63, p-val = 0.103; weighted data.



(a) Man (b) Woman

Fig. 7. Probability of working as an essential and Key worker. Note: stars denote the following p-values: *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$; weighted data.



(a) People working from home over time (b) Proportion of people working from home by ethnicity

Fig. 8. Essential and key workers.
Note: (a) blue line represents 1st of February and red line 1st of March; (b) (b) *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$, T-test: White diff = −.042, Z = −49.9, p-val =0.000 Mixed diff = −.07, Z = −8.94, p-val = 0.000; Indian diff = −.048, Z = −9.53, p-val = 0.000; Pakistani diff = −.028, Z = −3.82, p-val = 0.000; Bangladeshi diff = −.025, Z = −2.52, p-val = 0.012; Chinese diff = −.078, Z = −5.46, p-val = 0.000; Any other Asian background diff = −.034, Z = −5.07, p-val = 0.000; Blacks diff = −.043, Z = −10.25, p-val = 0.000; Other ethnic group diff = −.029, Z = −3.69, p-val = 0.000; weighted data.

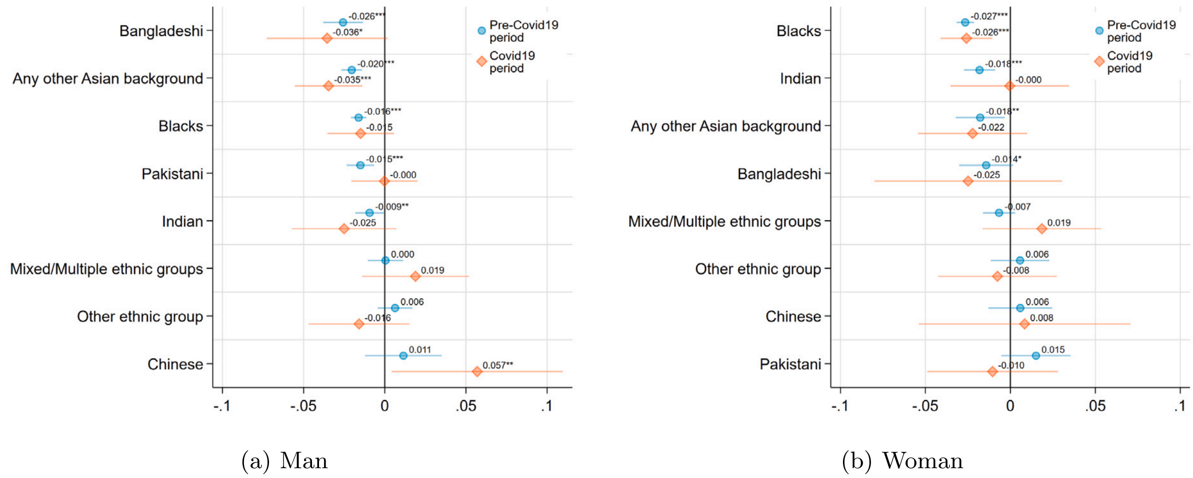


Fig. 9. Probability of working from home. Note: stars denote the following p-values: *** $p < 00.1$; ** $p < 0.05$; * $p < 0.10$; weighted data.

Indian, Pakistani, Bangladeshi, Other Asian, Blacks, and Other ethnic group men have a significantly lower probability of being employed during the pandemic period. Conversely, White British, Mixed, Indian, Pakistani, and any other Asian women show a higher probability of working during the pandemic period.

Further analysis reveals that among men who experienced reduced employment probability during the pandemic, the risk of having days off due to illness/injuries at work is only reduced for White British and Other ethnic groups. For women, however, Mixed ethnic and Pakistani individuals, who reported a higher probability of working in the reference week, also exhibit a higher risk of illness/injuries at work.

Regarding the probability of having a long-term illness, changes are relatively limited among men. The coefficient increases significantly only for any other ethnic group category. For women, the results are mixed: White British, Pakistani, and Bangladeshi have a positive and significant coefficient, while Indian and any other Asian women have a negative coefficient.

As mentioned earlier, it is essential to analyze whether the composition and type of health problems have changed during the pandemic. Therefore, our focus now shifts to individuals who previously reported having a longstanding illness or health issue.

Among men, White British, Pakistani, and Blacks individuals, and among women, White British and any other Asian individuals, experienced a higher prevalence of respiratory issues compared to the rest of the population. Notably, mental health issues saw an increase, especially among Mixed, Pakistani, and Chinese women. These findings are consistent with recent evidence from Proto and Quintana-Domeque (2021), who also highlighted the significant deterioration in mental health among South Asian women. However, due to sample sizes, they were not able to look at single ethnic groups and had to aggregate them into macro categories. Surprisingly, we found that Mixed men experienced a reduction in mental health issues during the pandemic period. In addition to mental health, we also observed some gender differences in physical health problems. For instance, among White British, men experienced a reduction in limb issues, while women reported an increase in these problems. Among other ethnic groups, men had a lower probability of back/neck and limb issues, while women experienced an increase in these conditions. Similarly, Pakistani men experienced a reduction in sensory issues, while women experienced an increase.

Furthermore, among Indians, we observed a decrease in cardiovascular issues among men, while women experienced an increase in these problems. Conversely, Chinese men had higher cardiovascular issues, while women experienced a reduction in these health concerns. These findings highlight the diverse impact of the pandemic on different ethnic and gender groups, underscoring the need for targeted healthcare interventions and support to address the specific health challenges faced by each subgroup.

4.1. Potential mechanisms

As a second step, and in order to understand potential mechanisms that could explain the observed differences in health among different ethnic groups we explored the probability of being an essential worker and the probability of working from home. Essential workers, also referred to as key workers, were defined by the UK government as a category of workers of primary importance and necessity for society and were therefore not subject to the lockdown restrictions. Both factors could influence the health of workers. In the first case, essential workers were more at risk of contracting COVID-19 and experiencing higher stress while those who were able to stay and work from home were to some extent more protected against these issues.

In the case of essential workers, following the approach of Fasani and Mazza (2020), we classified employed respondents into two categories: essential workers and non-essential workers using the SOC 3-digit information on occupations.[3] In total 13% (66,213 observations) of our sample had an essential job in the study period. Fig. 6 displays the proportion of essential workers over time among the 9 ethnic groups (panel a) and the proportion of essential workers before and during the pandemic (panel b). As expected, compared to Whites, the majority of the ethnic minorities in the UK are more likely to be employed in essential jobs. Notably, we do not see significant changes in the proportions of these workers over time, with the exception of a minor difference for Blacks and Other Asians, which is significant only at the 0.05 level of confidence. As expected, the vast majority of essential workers carried on with their duties without interruption during the COVID-19 pandemic.

Moreover, we run an LPM regressing the probability of working as an essential working on ethnicity, controlling for the same set of covariates of Eq. (1), and stratifying the model by gender and a before/during the COVID-19 period dummy. The purpose of this exercise was to assess the changes in the probability of being an essential worker during the pandemic taking as a reference category the White ethnic group. In total, only 6% (29,273 observations) reported having worked from home during the study period. Fig. 7 reports the coefficients for men (panel a) and women (panel b) where green circles indicate the pre-pandemic period (Jan 2018–Feb 2020) and red diamonds the

[3] In the Appendix section, Table A.1, we provide a full list of jobs included in the essential worker category.

Table A.1
List and distribution of essential jobs, UKLFS, Feb. 2018–Jan. 2021.

SOC Code and Occupation (main job)	Freq.	Percent	Cum.
1181 'Health servcs and public health	1,161	1.75	1.75
1241 'Health care practice mngrs'	384	0.58	2.33
2139 'IT and telecommunications profes	2,751	4.15	6.49
2211 'Medical practitioners'	4,220	6.37	12.86
2213 'Pharmacists'	1,028	1.55	14.41
2217 'Medical radiographers'	514	0.78	15.19
2218 'Podiatrists'	198	0.30	15.49
2219 'Health professionals n.e.c.'	1,083	1.64	17.13
2231 'Nurses'	10,582	15.98	33.11
3131 'IT operations technicians'	1,631	2.46	35.57
3132 'IT user support technicians'	1,493	2.25	37.82
3213 'Paramedics'	418	0.63	38.46
3217 'Pharmaceutical technicians'	463	0.70	39.16
3218 'Medical and dental technicians'	588	0.89	40.04
3219 'Health associate professionals n	949	1.43	41.48
3312 'Police officers (sergeant and be	2,332	3.52	45.00
3313 'Fire service officers (watch man	658	0.99	45.99
3314 'Prison service officers (below p	635	0.96	46.95
3315 'Police community support officer	226	0.34	47.29
3567 'Health and safety officers'	971	1.47	48.76
5235 'Aircraft maintenance and related	422	0.64	49.40
5242 'Telecommunications engineers'	868	1.31	50.71
5245 'IT engineers'	568	0.86	51.57
5431 'Butchers'	482	0.73	52.29
5432 'Bakers and flour confectioners'	508	0.77	53.06
6142 'Ambulance staff (excluding param	408	0.62	53.68
6145 'Care workers and home carers'	11,754	17.75	71.43
6146 'Snr care workers'	1,332	2.01	73.44
6147 'Care escorts'	238	0.36	73.80
6232 'Caretakers'	1,069	1.61	75.41
7114 'Pharmacy and other dispensing as	1,187	1.79	77.21
8111 'Food, drink and tobacco process	1,957	2.96	80.16
8124 'Energy plant operatives'	125	0.19	80.35
8126 'Water and sewerage plant operati	191	0.29	80.64
8212 'Van drivers'	4,055	6.12	86.76
8213 'Bus and coach drivers'	1,840	2.78	89.54
8214 'Taxi and cab drivers and chauffe	3,042	4.59	94.14
8233 'Air transport operatives'	212	0.32	94.46
8234 'Rail transport operatives'	199	0.30	94.76
8239 'Other drivers and transport oper	337	0.51	95.27
9119 'Fishing and other elementary agr	336	0.51	95.77
9211 'Postal workers, mail sorters, ms	2,374	3.59	99.36
9232 'Street cleaners'	138	0.21	99.57
9271 'Hospital porters'	286	0.43	100
Total	**66,213**	**100**	

pandemic period (Mar 2020–Jan 2021). From this figure, it becomes apparent that, among men, Indians and other ethnic groups witnessed an uptick in the likelihood of engaging as essential workers throughout the pandemic period. Meanwhile, Bangladeshi individuals (though not statistically significant in the COVID-19 period), Blacks, Pakistanis, and those with any other Asian background experienced a marginal decrease in the probability of working as essential workers. However, it is noteworthy that this probability consistently remained higher than that of Whites. Furthermore, in the case of women, our models reveal that, in comparison to the pre-pandemic period, Bangladeshi and Pakistani women encountered elevated probabilities of engaging as essential workers throughout the pandemic. Conversely, Indians, individuals from any other Asian background, and Blacks exhibited slightly diminished probabilities. Crucially, it is essential to note that for women, nearly all non-white ethnic groups displayed higher probabilities of working as essential workers than Whites across both periods under consideration.

We now move to analyzing the probability of remote work. Similar to the previous analysis, we begin by outlining the temporal trends and shifts that occurred before and during the pandemic. Subsequently, we apply the same LPM model, this time employing the probability of remote work as the primary outcome variable. Fig. 8 panel a shows the trends over time in the probability of working from home while panel b shows the differences between before and during pandemic periods for each ethnic group. As anticipated, all ethnic groups underwent a certain degree of rise in the likelihood of remote work due to the enforced lockdown measures during the pandemic period. Notably, the Chinese group displayed the most substantial increase, while the Bangladeshi group exhibited the lowest change, which was nearly negligible.

The results of the LPM of working from home on different ethnic groups are displayed in Fig. 9 for men (panel a) and women (panel b), respectively. Blue circles represent the coefficients of the pre-pandemic period while the orange triangles are those of the pandemic period. Regarding men, our model reveals that both Bangladeshi and individuals from any other Asian background exhibit lower probabilities of remote work in both periods. Conversely, Chinese men have a higher probability of remote work during the pandemic period compared to Whites. On the other side, only Black women seem to have a lower probability of working from home in both periods than White women.

These results warrant further investigation, as there might be a selection process influencing employment and type of work among different ethnic groups and genders.

The role of essential workers during the pandemic has been crucial, and understanding the impact of their employment on health outcomes is of great importance. While our initial findings do not reveal distinct patterns, a deeper analysis is needed to account for potential confounding factors and selection biases in the employment choices of various demographic groups. Further research in this area could provide valuable insights into the health implications of different job types during challenging times.

5. Conclusions and discussion

The COVID-19 pandemic has brought about significant disruptions to the economy and labor market, impacting employees and their health in various ways. In this study, we utilized quarterly UKLFS data from 2018 to 2021, combined with a more granular ethnicity breakdown, to investigate changes in employment and health conditions in the UK population following the outbreak of COVID-19. Our focus was to understand how lockdown measures, which led to fluctuations in labor supply for certain ethnic groups, affected their health outcomes.

Our findings reveal several ethnic and gender differences in the probability of working, which appear to be associated with varying risks of suffering from illness or injuries at work and other health conditions. Specifically, we observed that men who reduced their labor supply during the lockdown experienced improvements in their health conditions. Conversely, women who increased their labor supply were likely to face higher risks of illness or injuries and reported worse health conditions. These outcomes further vary among different ethnic groups, suggesting complex interactions between employment, health, and ethnicity.

Furthermore, we examined the distinction between essential and non-essential workers, but we did not identify any consistent patterns in the health outcomes. Notably, ethnic minorities were found to be more likely to work on the front-line during the COVID-19 pandemic, exposing themselves to a higher risk of worse health conditions. This emphasizes the need for targeted policies and interventions to protect the health and well-being of vulnerable communities.

While our study provides valuable insights into the relationship between employment, health, and ethnicity during the pandemic, it is essential to acknowledge that the data are based on self-reported responses, which may be subject to reporting biases. Therefore, it is important to acknowledge that our findings likely represent a lower bound of the true health impacts across ethnic groups during the COVID-19 pandemic. The self-reported health measures we use may be affected by reduced healthcare access during this period, as documented by several studies (Mansfield et al., 2021; Warner et al., 2021). The widespread cancellation of routine screenings, delayed laboratory tests,

Table A.2a
Linear probability model results for working.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	−0.071***	−0.078***	−0.070***	−0.116***	−0.042**	−0.003	−0.079***	−0.102***	−0.124***
	(0.013)	(0.022)	(0.019)	(0.034)	(0.020)	(0.036)	(0.025)	(0.031)	(0.024)
Female	−0.078***	−0.094***	−0.163***	−0.345***	−0.336***	−0.123***	−0.200***	−0.095***	−0.222***
	(0.001)	(0.010)	(0.008)	(0.008)	(0.014)	(0.013)	(0.015)	(0.008)	(0.009)
Gender*Lockdown	0.009**	0.043**	0.050***	0.082***	0.035	−0.008	0.095***	0.033**	0.044
	(0.004)	(0.020)	(0.012)	(0.028)	(0.023)	(0.029)	(0.025)	(0.016)	(0.026)
N	684 617	7179	15 501	10 623	3907	3529	7361	17 722	9556

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2b
Linear probability model results for ill/injured at work.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	−0.005**	0.003	−0.005	−0.007	0.006	−0.007	−0.011	−0.001	−0.014***
	(0.002)	(0.008)	(0.004)	(0.007)	(0.009)	(0.007)	(0.007)	(0.005)	(0.005)
Female	0.005***	0.007	0.006**	−0.001	−0.008	0.002	0.006	0.001	0.006**
	(0.000)	(0.005)	(0.003)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)	(0.003)
Gender*Lockdown	−0.002**	−0.017**	−0.001	0.015**	0.013	0.004	0.003	0.008	0.006
	(0.001)	(0.008)	(0.004)	(0.006)	(0.011)	(0.006)	(0.006)	(0.007)	(0.009)
N	434 923	4761	11 047	5758	2078	2177	4818	11 674	5816

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2c
Linear probability model results for lnglst.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	−0.001	−0.032	0.022	0.012	−0.048	−0.043	0.072***	0.015	−0.033
	(0.002)	(0.022)	(0.016)	(0.018)	(0.029)	(0.027)	(0.020)	(0.014)	(0.019)
Female	0.023***	0.055***	0.029***	0.028***	−0.054***	−0.022	0.003	0.038***	0.040***
	(0.001)	(0.015)	(0.006)	(0.009)	(0.013)	(0.015)	(0.009)	(0.006)	(0.011)
Gender*Lockdown	0.008**	0.008	−0.035***	0.031*	0.106***	0.026	−0.088***	0.001	0.009
	(0.003)	(0.028)	(0.012)	(0.017)	(0.026)	(0.022)	(0.019)	(0.013)	(0.018)
N	681 760	7184	15 424	10 588	3882	3509	7340	17 657	9487

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2d
Linear probability model results for cardiovascular.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	0.003	−0.039	−0.126***	−0.034	−0.020	0.147**	−0.002	−0.028	0.055*
	(0.004)	(0.038)	(0.026)	(0.034)	(0.040)	(0.070)	(0.032)	(0.035)	(0.032)
Female	−0.070***	−0.006	−0.085***	−0.050***	−0.016	0.051	−0.057**	0.014	−0.009
	(0.002)	(0.014)	(0.020)	(0.018)	(0.029)	(0.042)	(0.026)	(0.014)	(0.017)
Gender*Lockdown	−0.002	0.081**	0.114***	0.003	0.014	−0.264***	0.038	0.035	0.008
	(0.005)	(0.037)	(0.033)	(0.031)	(0.037)	(0.086)	(0.044)	(0.029)	(0.036)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

and postponed specialist visits during lockdowns likely led to underdiagnosis of various health conditions (Lai et al., 2020). This issue may be particularly relevant for ethnic minority groups who historically face greater barriers in accessing healthcare services. While our data

Table A.2e
Linear probability model results for respiratory.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	0.019***	0.055*	−0.003	0.061**	−0.015	−0.041	−0.061	0.088***	−0.008
	(0.005)	(0.029)	(0.030)	(0.025)	(0.046)	(0.098)	(0.042)	(0.032)	(0.029)
Female	−0.007***	0.043**	−0.031*	−0.003	0.032	−0.048	−0.015	0.023	0.008
	(0.002)	(0.017)	(0.015)	(0.016)	(0.024)	(0.042)	(0.019)	(0.015)	(0.016)
Gender*Lockdown	0.008**	−0.039	−0.025	−0.002	−0.021	0.096	0.066*	−0.056*	0.043
	(0.003)	(0.038)	(0.025)	(0.037)	(0.053)	(0.084)	(0.039)	(0.031)	(0.037)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group.
The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2f
Linear probability model results for diabetes.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	0.008***	−0.039	0.027	0.021	−0.005	0.114*	−0.029	0.021	−0.030
	(0.003)	(0.030)	(0.032)	(0.039)	(0.051)	(0.060)	(0.045)	(0.028)	(0.033)
Female	−0.050***	−0.031**	−0.058***	−0.072***	−0.002	0.029	−0.086***	−0.025	−0.088***
	(0.002)	(0.013)	(0.018)	(0.017)	(0.024)	(0.024)	(0.020)	(0.022)	(0.019)
Gender*Lockdown	0.004	0.032	−0.076**	−0.043	0.084*	−0.046	0.011	−0.009	−0.024
	(0.003)	(0.021)	(0.030)	(0.041)	(0.043)	(0.048)	(0.041)	(0.033)	(0.049)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group.
The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2g
Linear probability model results for backneck.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	−0.004	−0.030	−0.026	0.014	0.072	−0.148*	−0.111**	0.013	−0.110***
	(0.003)	(0.040)	(0.023)	(0.028)	(0.053)	(0.074)	(0.045)	(0.029)	(0.039)
Female	0.062***	−0.023	0.095***	0.022	0.010	0.037	0.038	0.106***	0.092***
	(0.002)	(0.021)	(0.013)	(0.022)	(0.029)	(0.043)	(0.029)	(0.015)	(0.021)
Gender*Lockdown	−0.000	0.072**	−0.043	0.010	−0.175***	0.072	0.049	−0.035	0.072*
	(0.004)	(0.032)	(0.027)	(0.027)	(0.059)	(0.108)	(0.042)	(0.031)	(0.042)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group.
The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2h
Linear probability model results for skin.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	0.006**	0.098***	0.014	0.023	0.000	0.060	−0.018	0.036**	−0.016
	(0.003)	(0.028)	(0.015)	(0.017)	(0.039)	(0.060)	(0.024)	(0.016)	(0.023)
Female	0.006***	−0.015	0.010	0.026**	−0.017	−0.015	0.015	−0.005	−0.012
	(0.001)	(0.010)	(0.012)	(0.010)	(0.020)	(0.029)	(0.014)	(0.008)	(0.012)
Gender*Lockdown	0.006**	−0.096***	−0.006	0.004	0.018	−0.067	0.064**	0.007	0.078***
	(0.002)	(0.028)	(0.024)	(0.023)	(0.054)	(0.071)	(0.027)	(0.027)	(0.026)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group.
The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2i
Linear probability model results for digestive.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	0.000	−0.031	−0.003	−0.020	0.027	0.006	0.002	0.013	−0.063
	(0.003)	(0.025)	(0.019)	(0.023)	(0.048)	(0.040)	(0.027)	(0.022)	(0.038)
Female	0.014***	0.032*	0.007	0.086***	−0.114***	−0.028	0.004	0.013	−0.047**
	(0.002)	(0.018)	(0.014)	(0.014)	(0.026)	(0.033)	(0.016)	(0.011)	(0.023)
Gender*Lockdown	0.005*	0.062*	0.064*	−0.027	−0.020	0.014	−0.012	0.005	0.062
	(0.002)	(0.036)	(0.034)	(0.032)	(0.058)	(0.048)	(0.038)	(0.026)	(0.048)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2j
Linear probability model results for progressive.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	0.001	−0.033*	0.021	0.007	0.000	−0.048	0.004	0.002	0.008
	(0.003)	(0.019)	(0.018)	(0.019)	(0.033)	(0.032)	(0.028)	(0.020)	(0.023)
Female	−0.002	0.036***	0.004	0.001	0.021	−0.034*	0.001	−0.009	0.022
	(0.001)	(0.012)	(0.008)	(0.011)	(0.019)	(0.019)	(0.022)	(0.010)	(0.015)
Gender*Lockdown	−0.002	−0.008	0.010	−0.011	−0.023	0.069**	−0.027	−0.001	0.012
	(0.003)	(0.020)	(0.024)	(0.019)	(0.032)	(0.030)	(0.031)	(0.018)	(0.023)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2k
Linear probability model results for mental.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	−0.003	−0.114***	−0.001	−0.019	0.039	−0.113**	−0.029	0.002	0.027
	(0.004)	(0.040)	(0.021)	(0.026)	(0.054)	(0.051)	(0.039)	(0.025)	(0.050)
Female	0.058***	0.076***	0.025	0.026	0.069**	0.027	0.096***	0.031***	0.058***
	(0.003)	(0.019)	(0.018)	(0.018)	(0.032)	(0.025)	(0.021)	(0.011)	(0.016)
Gender*Lockdown	0.008*	0.172***	−0.029	0.067**	−0.027	0.149***	−0.037	0.030	−0.004
	(0.004)	(0.042)	(0.026)	(0.027)	(0.050)	(0.050)	(0.039)	(0.022)	(0.039)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

Table A.2l
Linear probability model results for sensory.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	0.002	−0.035	0.026	−0.067**	−0.007	−0.062	−0.009	−0.008	0.014
	(0.003)	(0.022)	(0.022)	(0.030)	(0.027)	(0.057)	(0.024)	(0.023)	(0.025)
Female	−0.011***	0.014	−0.000	−0.025*	−0.059***	0.090***	−0.036**	0.030**	0.007
	(0.002)	(0.012)	(0.012)	(0.014)	(0.015)	(0.030)	(0.017)	(0.012)	(0.017)
Gender*Lockdown	−0.005*	0.041	−0.035	0.070**	0.009	0.022	0.008	−0.039**	0.033
	(0.003)	(0.032)	(0.026)	(0.030)	(0.020)	(0.055)	(0.026)	(0.018)	(0.040)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

cannot directly measure the extent of foregone care, the documented disparities in healthcare disruption across ethnic groups suggest our estimates may be conservative, particularly for minority populations.

In conclusion, our study sheds light on the differential impact of the COVID-19 pandemic on employment and health outcomes among various ethnic and gender groups in the UK. These findings underscore the importance of targeted policies to address disparities and promote the well-being of vulnerable populations during challenging times. Future research should continue to explore these relationships with more sophisticated methodologies to gain a deeper understanding of

Table A.2m
Linear probability model results for limbs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown	−0.011**	−0.029	−0.047	0.058*	0.077	−0.125	0.067	−0.024	−0.102*
	(0.005)	(0.041)	(0.041)	(0.033)	(0.073)	(0.094)	(0.056)	(0.038)	(0.053)
Female	0.069***	0.016	0.131***	0.114***	0.045*	−0.012	0.111***	0.106***	0.056***
	(0.003)	(0.018)	(0.019)	(0.023)	(0.023)	(0.054)	(0.032)	(0.015)	(0.015)
Gender*Lockdown	0.010**	0.067	−0.007	−0.063**	−0.054	0.097	−0.048	0.021	0.107**
	(0.004)	(0.043)	(0.029)	(0.031)	(0.054)	(0.099)	(0.054)	(0.042)	(0.049)
N	273 024	2263	4188	3184	1175	637	1814	4824	2647

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
1 = White; 2 = Mixed/Multiple ethnic groups; 3 = Indian; 4 = Pakistani; 5 = Bangladeshi; 6 = Chinese; 7 = Any other Asian background; 8 = Blacks; 9 = Other ethnic group. The model controls for education, religion, marital status, lone parent, household with dependent children, over 65, AGE, AGE2, region, month-year, quarter and survey type, and interaction of region#month-year.

the multifaceted factors at play.

CRediT authorship contribution statement

Joan Madia: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Francesco Moscone:** Conceptualization, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Catia Nicodemo:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

I have no conflicts of interest to disclose.

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Appendix. Additional material

Description of essential jobs in UKLFS and additional regression models with interaction between month-year and geographical area

See Tables A.2a–A.2m.

Data availability

The data that has been used is confidential.

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