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The motherhood penalty in employment: Evidence from UK Asian mothers during the pandemic

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ABSTRACT

This study explores the impact of the COVID-19 pandemic on the labour market outcomes of mothers with school-aged children in the UK, with a focus on gender and ethnicity. We find that Asian mothers face a more pronounced motherhood penalty in terms of unemployment compared to both their White counterparts and Asian fathers. This penalty is particularly strong and statistically significant in contact-intensive industries. Our findings are in line with the view that cultural and social norms associated with ethnicity play a key role in shaping Asian mothers' responsibilities, both within the home and in the labour market. During school closures, Asian mothers are more likely to assume primary caregiving duties, which increases their risk of unemployment. Further analysis reveals that Asian mothers experience greater mental health challenges during the pandemic. Our findings underscore the need for policies that promote a more equitable distribution of childcare responsibilities, especially within Asian communities. Lessons from this study may also be applicable to Asian countries.

1. Introduction

Motherhood penalty refers to the negative impact of having children on women's earnings, employment opportunities, and career progression compared to men or childless women. Economists have long argued that childcare decision within a family have a direct impact on women's labour force participation and earnings. Greater caregiving responsibilities, perceived as significant time and mental costs, often lead to fewer working hours and complete withdrawal from employment.

The COVID-19 pandemic exacerbated motherhood penalty for two reasons. First, the pandemic has led to severe job losses in service-oriented contact intensive sectors such as retail, hospitality, and education where women are overrepresented. Second, as school closures disproportionately have increased caregiving responsibilities for working mothers. Using data from the Understanding Society and its COVID-19 Study, this paper examines whether the motherhood penalty exists on the UK labour market outcomes during the initial stage of the pandemic. We compare unemployment among Asian women with school-aged children to their White women counterparts and investigate whether Asian mothers are more likely to be negatively affected by the pandemic shocks. Furthermore, we explore the other factors such as mental health and whether the workplace is contact-intensive that may contribute to the motherhood penalty for Asian mothers.

Our research contributes to the existing literature by exploring how ethnicity intersects with gender and caregiving responsibility. While previous studies have documented broad gendered effects of the pandemic on employment, less attention has been paid to how

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ethnicity interacts with gender roles and caregiving duties. The COVID-19 crisis, with its sudden school closures and increased caregiving demands, offers a quasi-experimental opportunity to investigate how childcare responsibility may differ across ethnic groups in terms of female unemployment during a period of unexpected disruptions.

This study highlights how cultural and social norms tied to ethnicity may act as a powerful mechanism in shaping women's roles, both within the home and in the labour market. Asian mothers may face distinct challenges due to the strong cultural and social norms that place women in the role of primary caregivers in the household. These norms often conflict with more egalitarian views of shared parenthood prevalent in the UK. These conflicting norms exacerbate the challenges Asian mothers face in balancing work and family responsibilities when childcare services are not available, thereby increasing their vulnerability to unemployment or reduced employment opportunities.

Although our research is focused on the UK, the experiences of ethnic minority Asian women provide valuable insights for Asian countries, where similar expectations around gender roles and caregiving persist. Our findings suggest that traditional Asian cultural norms may act as a barrier to women's workforce participation, reinforcing gender inequality in both the domestic and labour market spheres.

The rest of this paper is structured as follows. Section 2 reviews the existing literature on gendered labour market disparities and the factors influencing them. Section 3 describes the data, samples, variables, and empirical models. Section 4 presents and discusses the baseline findings on the motherhood penalty. Section 5 examines the motherhood penalty among Asian mothers, particularly those working in contact-intensive industries. Section 6 discusses possible explanations for the motherhood penalty and provides empirical evidence related to mental health. Section 7 concludes.

2. Literature review

2.1. Gender inequality in employment: impact of COVID-19

The COVID-19 pandemic has exacerbated pre-existing gender disparities in employment across the globe, with women disproportionately affected compared to men (Wenham et al., 2020). Unlike previous economic recessions, which predominantly impacted male-dominated industries such as manufacturing and construction, the pandemic led to severe job losses in service-oriented sectors such as retail, hospitality, and education where women are overrepresented (Alon et al., 2020; Hupkau & Petrongolo, 2020). Research from various countries highlights this trend. Alon et al. (2020) found that in the US women, particularly mothers, experienced steeper declines in employment rates during the pandemic due to increased childcare responsibilities and the closure of schools and daycare centres. Similar patterns emerged in the UK, where women with dependent children were significantly more likely than men to reduce working hours or leave employment altogether due to school closures (see Sevilla & Smith, 2020). In China, Zhang, Liu, et al. (2024) documented a widening gender gap in employment due to increased childcare responsibilities during the pandemic. These studies collectively underscore the pandemic's role in amplifying gender-based employment disparities, with childcare responsibilities emerging as a critical factor.

2.2. Childcare responsibilities and labour market outcomes

Economic theories concerning labour supply and household decision-making provide useful insights into how childcare responsibilities influence employment outcomes, particularly for women. Becker (1981) model of household specialization posits that in two-parent households, partners often divide labour based on comparative advantage, with one partner (typically the woman) specializing in unpaid care work and the other in market work. This model helps explain why mothers, particularly those with young children, are more likely to exit the labour force when external childcare options become unavailable (Lundberg & Pollak, 1996).

Becker (1981) and Heckman (1974) elaborate on how women's employment decisions are influenced by the opportunity cost of time, particularly in relation to unpaid caregiving responsibilities. When the cost of childcare outweighs potential earnings, women are more likely to withdraw from the labour market. Del Boca et al. (2020) provide empirical evidence supporting this theory, demonstrating that access to affordable childcare significantly influences maternal employment rates, with inadequate childcare services acting as a substantial barrier to workforce participation.

Goldin's (2024) work expands on these theoretical perspectives by demonstrating how childcare responsibilities contribute to persistent gender disparities in employment and wages. She argues that childcare decisions within a family have a direct impact on women's labour force participation and earnings, with increased caregiving demands often leading to reduced working hours or complete withdrawal from employment. This effect is particularly pronounced in households where women are perceived as the primary caregivers. Goldin's framework underscores the intersection of cultural norms, family expectations, and individual preferences in shaping the division of childcare responsibilities and, consequently, women's employment outcomes.

Additionally, Cultural and social norm is not the only reason for persistent gender disparities in employment outcomes. Employment discrimination against mothers has been well explored and documented in reinforcing the motherhood penalty (see e.g., Andresen & Nix, 2022; Budig & England, 2001).

2.3. Influence of cultural expectations on female employment: the case of asian women

In the UK, mainstream societal norms increasingly promote shared childcare responsibilities between both parents (NatCen Social Research, 2023; UK Government, 2023). However, cultural expectations, family dynamics, and individual preferences still

significantly influence caregiving roles (Friedemann & Buckwalter, 2014; Sharma et al., 2016), often disproportionately burdening women. This imbalance affects their employment opportunities, career progression, and long-term economic stability.

In many Asian societies, cultural and social norms dictate that women should prioritize family and childcare responsibilities over career advancement, reinforcing a gendered division of labour (Nazroo & Kapadia, 2013). The widely practiced Confucian values, which emphasize women's roles as caregivers, further constrain their labour market participation (Brinton, 2001). Research by Chung and van der Horst (2020) in East Asia revealed that the pandemic exacerbated the "double burden" on working mothers, as cultural norms discouraged men from sharing caregiving responsibilities equally. This cultural dimension adds another layer of complexity to the gendered employment disparities observed during the pandemic, highlighting the interplay between societal expectations and labour market outcomes. In India and Pakistan, both societies are predominantly patriarchal, where men are viewed as authority figures and women are often relegated to domestic roles. Islamic traditions in Pakistan and Hindu customs in India have also reinforces the notion that caregiving and household responsibilities are primarily women's duties.

The contrast between cultural and social norms in the UK and Asia also contributes to the greater gender gap in unpaid care work in Asian countries. For example, women in Asia and the Pacific perform four times more unpaid care work than men (International Labour Organization, 2024), whereas in the UK, women do 60 % more unpaid work than men (UK Office for National Statistics, 2022). Although this gender inequality in unpaid care work is a result of a combination of cultural, social, economic factors and public policy on childcare support. But little has been done empirically to identify the impact of culture and social norms in shaping women's decision in employment.

The pandemic provides a unique opportunity to examine whether cultural, social and family values from migrants' countries of origin continue to influence family decisions. Since all families faced the same lockdown restrictions and lack of childcare services during the initial stages of the pandemic, it is likely that the factors related to the pre-existing cultural beliefs and social norms on gendered caregiving responsibilities may play a role in motherhood penalty among Asian mothers. We intend to provide some empirical evidence,

3. Data and methodology

3.1. Data and sample

To investigate labour market outcomes during the early stages of the pandemic, this study employs data from the April and May waves of the Understanding Society (USoc) COVID-19 Study in 2020.[1] Some contextual information is obtained from the Wave 9 of the main USoc dataset in 2019.[2] This timeframe captures the initial impacts of the pandemic in the UK, marked by stringent lockdown measures, including mandatory closures of non-essential businesses, social distancing protocols, and stay-at-home orders. Although the pandemic began in March 2020, the earliest data available starts in April 2020, providing the first full month of observations under these restrictions. The data from April and May 2020 offer a focused snapshot of labour market conditions during the most acute phase of the pandemic, prior to significant policy adjustments or economic recovery efforts. This early period is critical for isolating the immediate effects of the pandemic on labour market outcomes, particularly for vulnerable groups such as women and ethnic minorities, while avoiding confounding factors from later recovery phases.

The USoc dataset was chosen for our research over other UK surveys for several reasons. First, the USoc dataset provides comparable reliable population inferences both before and during the COVID-19 pandemic, allowing for a controlled comparison of employment outcomes. The dataset includes detailed information on family, sociodemographic groups, occupation, and industry, allowing for controls of these confounding factors. Second, the USoc dataset incorporates gender-related information about employment outcomes adhering to an established definition in line with legislation, which ensures a consistent and reliable basis for our analysis. Third, the dataset provides a sufficiently large sample size, which allows for robustness checks and enhances the validity of our findings. This dataset has been used for investigating pandemic impacts in many studies, see e.g., Benzeval et al., 2020; Crossley et al., 2021; Perelli-Harris & Walzenbach, 2020).

Our sample for empirical study was constructed as follows. We first included individuals who had taken part in at least one of the COVID-19 waves and had previously participated in USoc Wave 9. Next, we kept observations aged 16–64—the commonly recognized working-age population according to the UK Office for National Statistics—and reported being employed during pre-pandemic period as of January-February 2020. In total, 1493 observations were dropped due to missing data on key variables including gender, ethnicity, caregiving responsibility, employment status during the pandemic, and pre-pandemic employment status. It is important to note that these exclusions were not due to selection bias but were the result of incomplete data in the survey and no available information can be retrieved from previous waves of the USoc dataset. Among the 1493 dropped cases, over 86.7 % did not report to have school-aged children. This means that the exclusion of these cases is unlikely to introduce meaningful bias into our analysis of how school-aged children affect employment outcomes. Therefore, the remaining sample can still be considered both representative and reliable for our analysis (Diatta & Berchtold, 2023). Finally, to focus on comparing labour market disparities between Asian and White

[1] Web-based or telephone-based self-completed questionnaires were conducted to track the experiences and behaviours of participants from Wave 9 of the Understanding Society (USoc) surveys. The first web survey was fielded on April 24th and the second on May 27th.

[2] Understanding Society, conducted by the University of Essex's Institute for Social and Economic Research, is the UK's primary and comprehensive longitudinal household survey. It interviews all adults in sample households annually, employing a mixed-mode design that involves face-to-face interviews and web-based questionnaires.

populations, individuals from ethnic groups outside these categories, such as Black, Arab, and mixed ethnicities other than White-Asian, were excluded. This additional exclusion removed 1518 cases, allowing us to examine differences between Asian and White populations. Descriptive statistics by gender in each employment status for our sample are reported in Table 1.

3.2. Variables

Table 2 reports the summary statistics of these variables, with detailed information on variable constructions and definition in Appendix Table A1.

3.2.1. Dependent variable-employment status

A categorical dependent variable is used to capture four types of employment statuses during the early stage of the pandemic period (see Kautonen et al., 2017). It includes paid employment, self-employment, both paid employment and self-employment, and un-employment. Among these four categories, paid employment is selected as the group of our focus. This is because paid employment, as shown in Table 1, is the major form of employment status both in the female and male samples before the pandemic and during the pandemic in 2020.

3.2.2. Independent variables

Gender and the presence of school-aged children are included as the main independent variables. We also use the interaction term of these two variables to investigate the persistence of the motherhood penalty during the initial stage of the pandemic.

3.2.3. Control variables

The lagged dependent variable is used as one of the control variables reflecting the employment status prior to the pandemic. Other variables may influence employment outcomes (see e.g., Collins et al., 2021; Goldin, 2022; Reichelt et al., 2021). To be specific, sociodemographic features (such as age, age squared, education level, and urban residency), employment-related features (such as remote working and occupational class), and household income level are included as control variables.

Additionally, factors potentially influencing employment outcomes, such as ethnicity (White or Asian), cohabitation (living with a partner or not), physical health (clinically at risk for COVID-19 or not), mental health and industry type (contact-intensive or non-contact-intensive industries) are also included as control variables. Adding these control variables is important to identify and assess whether our test on the motherhood penalty is a robust factor influencing employment status during the pandemic. We discuss these important factors as follows.

Ethnicity indicates either Whites or Asians. Previous studies have documented that systemic inequities, language barriers, cultural expectations, and limited access to professional networks as key factors driving persistent employment and wage gaps across ethnic groups (Dustmann & Theodoropoulos, 2010; Longhi & Brynin, 2017; Nandi & Platt, 2023). Heath and Di Stasio (2019) find that ethnic minorities, including Asians, face disadvantages in recruitment processes, while Nazroo and Kapadia (2013) highlight that Asian women are disproportionately concentrated in low-paying sectors with fewer opportunities for career progression due to structural biases.

Cohabitation status accounts for differences in household structures that influence employment resilience during the pandemic. Historically, economic downturns have triggered an “added worker effect”, where women increase their labour supply to compensate for a partner’s job loss, serving as a form of within-household income insurance (Pruitt & Turner, 2020). However, the COVID-19 pandemic presents unique constraints due to widespread childcare disruptions, which makes it difficult for families to compensate for employment losses by increasing work hours (Alon et al., 2020). The effect of cohabitation is expected to differ across family structures. Among partnered mothers, access to spousal support may have buffered employment losses, particularly for those in jobs with remote work flexibility (Carlson & Petts, 2022; Sevilla & Smith, 2020). However, single mothers, who lack a co-parent to share

Table 1
Descriptive statistics by gender of the analytical sample.

	Employment status (pre-pandemic – Jan-Feb of 2020)			Employment status (during the pandemic – April and May 2020)		
		Observation	Percent		Observation	Percent
Male	Paid employment	4017	81.84	Paid employment	3882	79.07
	Self-employment	724	14.74	Self-employment	683	13.92
	Paid employment and self-employment	168	3.42	Paid employment and self-employment	166	3.39
	Unemployment	0	0	Unemployment	178	3.62
	Sum (male)	4909	100.00	Sum (male)	4909	100.00
Female	Paid employment	5981	87.82	Paid employment	5679	83.42
	Self-employment	605	8.89	Self-employment	545	8.00
	Paid employment and self-employment	223	3.28	Paid employment and self-employment	195	2.86
	Unemployment	0	0	Unemployment	390	5.73
	Total (female)	6809	100.00	Total (female)	6809	100.00
Entire sample	Total	11,718	100.00	Total	11,718	100.00

Note: The sample includes 8438 unique individuals. Some individuals contribute multiple observations due to repeated measures across waves. Of these individuals, 4903 are female and 3535 are male.

Table 2
Summary statistics of independent categorical variables.

Variables	Obs	Categories	Percentage
Gender	11,718	Male	41.91 %
		Female	58.09 %
Education	11,718	Bachelor's degree and above	12.36 %
		Below bachelor's degree and no qualification	87.64 %
School-aged children	11,718	No	66.71 %
		Yes	33.29 %
Asian	11,718	No (White)	92.03 %
		Yes (Asian)	7.97 %
Occupational class	11,718	Managerial, administrative, and technical	46.32 %
		Others	53.68 %
Urban	11,718	Urban	75.72 %
		Rural	24.28 %
Work at home	11,718	Never	66.75 %
		Ever	33.25 %
Household income (qnt)	11,718	Relatively low	39.54 %
		Relatively high	60.46 %
Cohabitation	10,912	No	23.70 %
		Yes	76.30 %
Industry	10,273	Contact-intensive	32.75 %
		Non-contact-intensive	67.25 %
Physical health	11,586	Clinically vulnerable to Coronavirus	76.30 %
		Not clinically vulnerable to Coronavirus	23.70 %
Mental health (depression)	11,586	Not depressed	73.15 %
		Depressed	26.85 %
Baseline employment status (pre-pandemic)	11,718	Paid employment	85.21 %
		Self-employment	11.41 %
		Both paid employment and self-employment	3.38 %
Employment status during the pandemic	11,718	Paid employment	81.59 %
		Self-employment	10.48 %
		Both paid employment and self-employment	3.08 %
		Unemployment	4.85 %

childcare burdens, are more vulnerable to employment disruptions (Alon et al., 2020).

Physical health may also affect employment decisions. Women, particularly those with pre-existing physical health conditions like diabetes and cardiovascular diseases, faced heightened job loss risks due to greater susceptibility to severe COVID-19 outcomes (Joyce & Xu, 2020; Sevilla & Smith, 2020). In the UK, disabled and chronically ill women were disproportionately furloughed or forced into unemployment, as shielding requirements and health risks limited their ability to work (Blundell et al., 2022; Office for National Statistics, 2020).

Mental health conditions, such as anxiety, depression, and stress-related disorders, have been shown to affect individuals' ability to secure and maintain employment, as well as their overall productivity and workplace engagement (OECD, 2021). During the pandemic, the prevalence of mental health issues surged due to factors such as social isolation, economic uncertainty, and the psychological toll of the health crisis (Pierce et al., 2020; Xiong et al., 2020). Women are more likely to experience deteriorating mental health due to increased caregiving responsibilities, job insecurity, and the disproportionate burden of pandemic-related stressors (Alon et al., 2020; Sevilla & Smith, 2020; Zhang, Sun, et al., 2024). By incorporating mental health as a variable, we intend to examine whether mental health status may serve as a contributing factor in explaining the employment disparities observed among Asian mothers.

Finally, industry type (contact-intensive vs. non-contact-intensive) is included to capture sector-specific vulnerabilities. Unlike previous recessions, which primarily affected male-dominated industries, the pandemic disproportionately has impacted service-oriented sectors such as retail, hospitality, and healthcare, where women are overrepresented (Cajner et al., 2020; Montenovo et al., 2020). These industries, reliant on face-to-face interactions, experienced severe job losses, while sectors accommodating remote work provided greater employment stability (Adams-Prassl et al., 2020; Dingel & Neiman, 2020; Papanikolaou & Schmidt, 2020).

3.3. *Model specification*

We use a dynamic multinomial logistic model (DMNL model) to investigate how the pandemic has affected individual labour market outcomes during the early stages of the outbreaks. A DMNL model is selected for the following main reasons. First, the DMNL model is widely used to model categorical outcome variables that lack a natural ordering of categories (Hartzel et al., 2001), which in our analysis is the employment status of individuals during the global pandemic.[3] Secondly, the DMNL model allows us to account for state dependence by capturing an individual's pre-pandemic employment status, for instance (Cowling & Wooden, 2021), which in our

[3] A Brant test indicates that the multinomial logistic regression is considered as the more appropriate choice over the ordinal logistic regression.

analysis is the influence of the initial employment status in January-February 2020 on employment status during the pandemic. This is achieved by including lagged dependent variables ($y_{i,t-1}$) in the model. Finally, the DMNL model accommodates heterogeneity in individuals' choice patterns over time (Cowling & Wooden, 2021).

The DMNL model is specified as follows:

$$\text{Prob}\left(y_{it} = \text{j} \mid x_{it}, y_{i,t-1}, \alpha_{ij}\right) = \frac{\exp\left(\beta_j' x_{it} + \gamma_j' y_{i,t-1} + \alpha_{ij}\right)}{\sum_{k=1}^{4} \exp\left(\beta_k' x_{it} + \gamma_k' y_{i,t-1} + \alpha_{ik}\right)}$$

where y_{it} represents the individual's employment status j at time t during the Covid period, $y_{i,t-1}$ captures one's pre-pandemic employment status in Jan-Feb 2020, accounting for state dependence. x_{it} is a vector of observed individual characteristics (as discussed in 3.2 on control variables). α_{ij} and α_{ik} are error terms that capture unobserved heterogeneity across individuals.

Following Hupkau and Petrongolo (2020), we cluster standard errors at the individual level to account for potential serial correlation in the error terms within individuals over time. We prefer standard errors clustered at the individual level rather than the household level because our analysis focuses on individual-level employment outcomes. While households may share common characteristics or shocks, the primary source of correlation in the error terms is likely to be within individuals over time (serial correlation), rather than across individuals within the same household. Clustering at the individual level ensures that our inference is robust to within-individual dependence, which is particularly relevant given some repeated individual observations in our data.

The examination of the motherhood penalty is conducted with additional analyses to ensure the robustness and the consistency of the results. We also conduct further investigations using gender-specific samples. This allows us to identify whether the motherhood penalty is primarily driven by Asian mothers. We report the results in Sections 4 and 5.

4. Empirical results on motherhood penalty

4.1. Baseline regressions

Our baseline regression model results that include the interaction between gender and the presence of school-aged children are reported in Table 3. In Columns (1) and (2), the interaction between gender and the presence of school-aged children is positive but statistically insignificant for both self-employment and combined employment categories. This suggests that school-aged children may not significantly lead women toward entrepreneurial work. It is possible that self-employment often requires upfront financial resources and professional networks, which may have been harder to access for women with school-aged children during the pandemic. Additionally, the economic uncertainty and instability likely made self-employment a less viable option for mothers already facing caregiving demands.

In contrast, Column (3) presents strong evidence that the presence of school-aged children is associated with significant increase in the likelihood of unemployment for women, as indicated by the positive coefficient of the interaction term significant at 1 %. Though female is found to be significantly associated with lower probability of being unemployment, the gender barriers in remaining employed during the pandemic are the result of having school-aged children for females. This finding suggests childcare demands may negatively affect employment vulnerabilities for women, leading to a "motherhood penalty" in the labour market. As revealed in the existing literature, with schools and childcare facilities closed for extended periods, many mothers find it increasingly challenging to balance work and caregiving. Unlike in previous economic downturns, when women often increased their labour supply to offset household income losses (Pruitt & Turner, 2020). The nature of the COVID-19 crisis left many with little choice but to exit the workforce (Alon et al., 2020). The increased burden of unpaid childcare means that continuing employment is not a viable option for some working mothers, particularly those in jobs with rigid schedules or limited remote work opportunities.

The results in Table 3 show that the interaction term is statistically significant only for the unemployment outcome, while no significant effects are found for self-employment or combined employment. These results suggest that the primary impact of caregiving is job loss rather than shifts to alternative employment. We will focus our further analysis on the unemployment outcome as follows. This is because unemployment is the only outcome which increases significantly in number of observations during the pandemic, and it is an important sign of economic vulnerabilities of working mothers.

As for the control variables in Table 3 Column (3), we report the following findings. Having a bachelor's degree is statistically insignificant on the probability of job loss. Being born outside the UK significantly increases one's job loss risk at 1 %. Age exhibits a nonlinear effect on employment transitions. The coefficient on age is negative for unemployment, while the squared term is positive and significant at 5 %. Lower household income is associated with a significantly higher probability of unemployment. Individuals in lower occupational classes, compared to those in managerial, administrative, and technical occupations, are significantly more likely to transition into unemployment. Finally, the positive and significant coefficients of being self-employed and in combined employment categories before the pandemic suggest that employment status before the pandemic had a strong path-dependent effect leading to unemployment.

In Table 4, we focus on the unemployment outcome by extending the baseline model and adding controls for ethnicity, cohabitation, physical health, and employment industry. The interaction term between gender and the presence of school-aged children remains significant and varies between 0.64 and 1.401 according to Columns (1) to (4) of Table 4. These results confirm our initial finding of motherhood penalty.

Table 3
Different employment status and motherhood penalty (entire sample).

Variables	(1) Self-employment	(2) Both paid employment and self-employment	(3) Unemployment
Gender (ref.=male)	−0.896*	−0.367	−0.863*
	(0.507)	(0.458)	(0.484)
Children (ref.=no)	−0.625	0.00802	0.125
	(0.451)	(0.405)	(0.401)
Gender#Children	0.300	0.0859	1.458***
	(0.599)	(0.532)	(0.540)
Education (ref.=Bachelor's degree and above)	−0.144	−0.482	0.196
	(0.421)	(0.667)	(0.540)
Whether born in the UK (ref.=yes)	−0.202	−0.238	1.246***
	(0.558)	(0.770)	(0.417)
Age	−2.432***	0.0511	−1.263**
	(0.821)	(0.910)	(0.643)
Age_squared	0.301***	0.0393	0.171**
	(0.0968)	(0.104)	(0.0746)
Urban	0.217	0.168	−0.220
	(0.284)	(0.284)	(0.237)
Work at home (ref.=never)	−0.477	−0.318	−0.593
	(0.381)	(0.385)	(0.388)
Household income (ref.=low)	−0.503*	−0.187	−0.355*
	(0.270)	(0.283)	(0.210)
Occupational class (ref.=managerial, administrative, and technical)	0.202	−0.0914	0.732***
	(0.307)	(0.271)	(0.280)
Baseline employment status (ref.=paid employment)			
Self-employment	9.469***	4.866***	3.556***
	(0.509)	(0.414)	(0.359)
Both paid and self-employment	5.096***	6.692***	1.515***
	(0.528)	(0.302)	(0.466)
Observations	11,718	11,718	11,718

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

Among the additional controls, we find in Columns (1) to (4) of Table 4 that being Asian is significantly associate with an increase in the probability of job loss. We will investigate this important issue on Asian ethnicity later. It is surprising that cohabitation shows no significant effect on reducing unemployment risk across all regressions. This suggests that living with a partner did not mitigate job loss during the pandemic. Also, physical health is not significantly associated with the probability of transitioning to unemployment. Finally, in Column (4), the coefficient of industry is negative and insignificant, indicating that working in a non-contact-intensive sector did not significantly reduce the likelihood of job loss. This suggests that sectoral differences alone may not explain the employment impact of the pandemic.

The positive and significant gender and children interaction effects in Table 4 Columns (1)-(4) confirms the motherhood penalty, irrespective of ethnicity, cohabitation status, physical health conditions, or industry type. While these factors contributed to broader patterns of job loss, they are not significant factors in explaining the heightened unemployment risk among mothers. However, we notice that the magnitude of the gender-child interaction term has dropped when controlling for the contact-intensive industry factor. We will explore the role of industry type and motherhood penalty in the next section.

Panel A of Fig. 1 plots predicted probabilities of unemployment across four groups based on regression in Column (4): males without school-aged children, males with school-aged children, females without school-aged children, and females with school-aged children. For males, the presence of school-aged children is associated with an insignificant increase in unemployment risk, evidenced by overlapping confidence intervals. In contrast, for females, having school-aged children significantly increases the likelihood of transitioning from paid employment to unemployment by approximately 4.5 %. These results indicate the persistent caregiving burden faced by women during the pandemic, even after adjusting for ethnicity, family composition, physical health conditions, and industry type (Correll et al., 2007; Kelley et al., 2020).

To ensure the robustness of our findings, the same regressions are conducted for the April and May 2020 samples, with results presented in Columns (5) to (8) and (9) to (12) of Table 4, respectively. We find these results are consistent with the empirical results we obtained using the full sample. Importantly, the interaction between gender and the presence of school-aged children remains statistically significant in both waves, underscoring the persistence of the motherhood penalty. Mothers with school-aged children are more likely to transition to unemployment than men and women without school-aged children. This suggests that caregiving responsibilities may be a key driver of gendered employment disparities. As visualized in Panels B and C of Fig. 1, the unemployment probabilities for mothers with school-aged children exceed those mothers without school-aged children by approximately 4.2 % and 4.6 % in the April and May samples, respectively. Among men, having school-aged children has no significant effect on unemployment risk.

Table 4
Unemployment and motherhood penalty with additional controls (entire sample, the April sample, the May sample, and the rebalanced samples).

	Entire sample				April sample				May sample				Rebalanced 1	Rebalanced 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Variables														
Gender (ref.=male)	−1.005**	−1.026**	−1.019**	−0.442**	−1.192***	−1.215***	−1.212***	−0.398**	−0.889*	−0.929*	−0.926*	−0.459*	0.613**	0.595*
	(0.425)	(0.427)	(0.421)	(0.224)	(0.433)	(0.437)	(0.438)	(0.202)	(0.503)	(0.504)	(0.505)	(0.255)	(0.307)	(0.331)
Children (ref.=no)	0.187	0.171	0.180	0.641	0.109	0.120	0.125	0.606	0.225	0.200	0.209	0.703	−0.298	−0.127
	(0.383)	(0.383)	(0.391)	(0.539)	(0.386)	(0.381)	(0.381)	(0.540)	(0.416)	(0.414)	(0.415)	(0.561)	(0.195)	(0.590)
Gender#Children	1.361***	1.400***	1.401***	0.640**	1.457***	1.478***	1.476***	0.547**	1.408**	1.424**	1.417**	0.633**	0.796*	0.636*
	(0.478)	(0.480)	(0.480)	(0.326)	(0.490)	(0.492)	(0.493)	(0.260)	(0.561)	(0.565)	(0.566)	(0.316)	(0.435)	(0.327)
Asian (ref.=White)	1.611***	1.629***	1.624***	2.208***	1.577***	1.584***	1.575***	2.227***	1.661***	1.653***	1.648***	2.321***	1.828***	1.835***
	(0.276)	(0.276)	(0.277)	(0.337)	(0.284)	(0.285)	(0.288)	(0.334)	(0.310)	(0.311)	(0.312)	(0.346)	(0.495)	(0.527)
Cohabitation (ref.=no)		−0.349	−0.226	−0.317		−0.369	−0.419	−0.345		−0.470	−0.515	−0.175	−0.383	−0.487
		(0.243)	(0.359)	(0.289)		(0.252)	(0.282)	(0.307)		(0.328)	(0.355)	(0.297)	(0.334)	(0.398)
Physical health (ref.=poor)			−0.353	−0.284			−0.438	−0.253			−0.322	−0.328	−0.182	−0.174
			(0.383)	(0.467)			(0.389)	(0.484)			(0.416)	(0.516)	(0.293)	(0.249)
Industry (ref.=contact-intensive)				−0.0912				−0.137				−0.501	−0.149	−0.168
				(0.217)				(0.225)				(0.339)	(0.241)	(0.277)
Education (ref.=Bachelor's degree and above)	0.925*	0.986*	0.993*	1.431*	0.895*	0.865*	0.870*	1.463*	0.774*	0.784*	0.788*	1.143*	1.039	0.980
	(0.504)	(0.548)	(0.548)	(0.822)	(0.503)	(0.503)	(0.517)	(0.838)	(0.422)	(0.458)	(0.469)	(0.602)	(0.841)	(1.240)
Whether born in the UK (ref.=yes)	0.260	0.0405	0.0560	0.0690	0.260	0.117	0.139	−0.00785	0.328	0.0294	0.0458	0.107	0.201	0.265
	(0.445)	(0.513)	(0.515)	(0.781)	(0.445)	(0.534)	(0.538)	(0.805)	(0.536)	(0.649)	(0.653)	(0.896)	(0.344)	(0.383)
Age	−1.613**	−1.509**	−1.498**	−3.946***	−1.613**	−1.421*	−1.425*	−4.068***	−1.519**	−1.559**	−1.548**	−3.297***	−2.030***	−2.589***
	(0.672)	(0.761)	(0.761)	(0.775)	(0.672)	(0.819)	(0.817)	(0.794)	(0.661)	(0.683)	(0.684)	(0.817)	(0.923)	(1.025)
Age_squared	0.201**	0.188**	0.187**	0.458***	0.201**	0.178*	0.179*	0.470***	0.197**	0.199**	0.198**	0.386***	0.474***	0.439***
	(0.0792)	(0.0890)	(0.0888)	(0.0867)	(0.0792)	(0.0956)	(0.0952)	(0.0893)	(0.0767)	(0.0798)	(0.0799)	(0.0937)	(0.108)	(0.116)
Urban	−0.225	−0.282	−0.284	−0.289	−0.225	−0.331	−0.333	−0.0544	−0.227	−0.229	−0.229	0.0997	−0.185	−0.197
	(0.221)	(0.233)	(0.233)	(0.286)	(0.221)	(0.246)	(0.247)	(0.296)	(0.245)	(0.256)	(0.256)	(0.308)	(0.350)	(0.255)
Work at home (ref.=never)	−0.413	−0.275	−0.279	−0.801	−0.413	−0.319	−0.325	−0.869*	−0.529	−0.428	−0.433	−1.229***	−0.641	−0.771
	(0.367)	(0.423)	(0.422)	(0.590)	(0.367)	(0.434)	(0.433)	(0.493)	(0.424)	(0.481)	(0.480)	(0.467)	(0.493)	(0.558)
Household income (ref.=low)	−0.597**	−0.526**	−0.535**	−0.652**	−0.597**	−0.579**	−0.591**	−0.663**	−0.478*	−0.496*	−0.465*	−0.666**	−0.501***	−0.497**
	(0.240)	(0.249)	(0.250)	(0.263)	(0.240)	(0.261)	(0.261)	(0.275)	(0.259)	(0.272)	(0.271)	(0.301)	(0.193)	(0.251)
Occupational class (ref.=managerial, administrative, and technical)	0.741***	0.755***	0.760***	0.725***	0.741***	0.648**	0.652**	−0.724**	0.667**	0.696**	0.698**	0.666*	0.617*	0.661**
	(0.278)	(0.284)	(0.284)	(0.250)	(0.278)	(0.305)	(0.304)	(0.344)	(0.296)	(0.307)	(0.306)	(0.394)	(0.356)	(0.327)
Baseline employment status (ref.=paid employment)														
Self-employment	3.282***	3.342***	3.340***	3.556***	3.282***	3.483***	3.484***	3.620***	3.434***	3.543***	3.543***	3.655***	6.481***	1.765***
	(0.364)	(0.370)	(0.369)	(0.502)	(0.364)	(0.394)	(0.393)	(0.538)	(0.385)	(0.398)	(0.398)	(0.578)	(0.340)	(0.323)
Both paid and self-employment	1.472***	1.613***	1.612***	1.648***	1.472***	1.580***	1.572***	1.545***	1.240***	1.424***	1.419***	1.533***	3.164**	2.033**
	(0.405)	(0.400)	(0.400)	(0.492)	(0.405)	(0.420)	(0.423)	(0.538)	(0.441)	(0.440)	(0.443)	(0.585)	(1.532)	(0.994)
Observations	11,633	10,681	10,681	9828	6197	5245	5245	5234	5436	5436	5436	4594	5680	5040

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

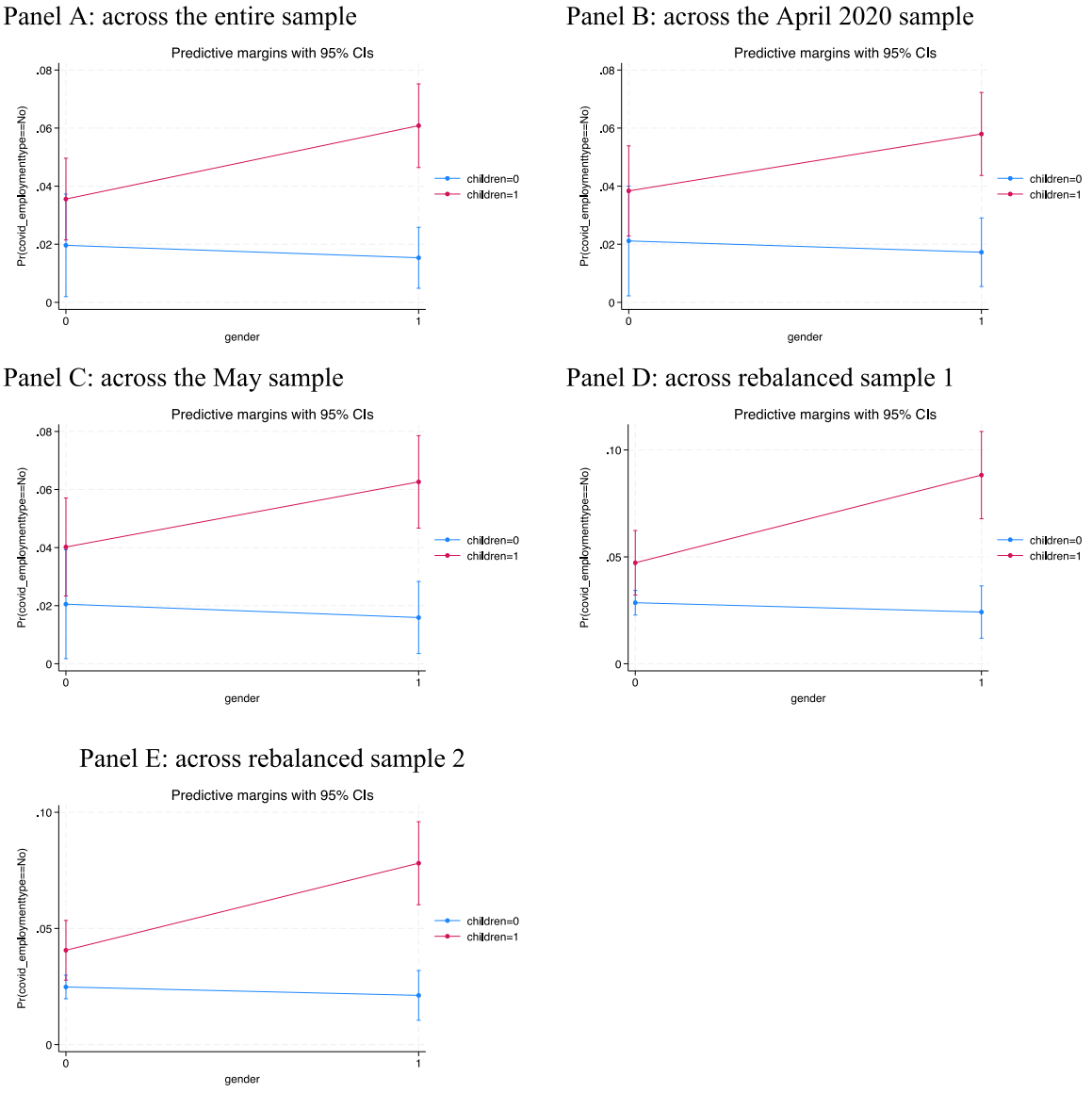


Fig. 1. The relationship between gender and probability of transitioning to unemployment with full controls.

4.2. Robustness checks

We use a binary logit model to re-estimate the regressions from Table 4, with results presented in Appendix Table A2. These results continue to show a positive and significant interaction between gender and having school-aged children. This pattern is confirmed by the margins plot in Appendix Figure B1 which shows higher predicted job loss probabilities for mothers with school-aged children and their sizes are similar to the ones we found in Fig. 1 based on the DMNL model. These findings provide robust support for our main results regarding the motherhood penalty during the early pandemic. This exercise justifies that we continue to use the DMNL model.

To address concerns regarding the relatively small proportion of Asian respondents in our original sample and to strengthen the empirical validity of our findings, we conduct additional robustness checks using rebalanced samples we reconstructed. Rebalanced sample 1 combines all available Asian observations from both the April and May 2020 waves with a subsample of White observations drawn from the April 2020 wave. Rebalanced sample 2 similarly includes all Asian observations from both waves alongside a subsample of White observations from the May 2020 wave. These samples are specifically constructed to increase the representation of Asian individuals from around 8 % to more than 15 %.

The results for rebalanced sample 1 and 2 are reported in Columns (13) and (14) of Table 4, respectively. In both cases, our main findings are consistently confirmed, with the gender-children interactions remaining positive and significant. As visualized in Panels D and E of Fig. 1, females with school-aged children on average face an approximately 6.4 percentage points and 5.8 percentage points

higher probability of unemployment than women without school-aged children in these two rebalanced samples, respectively. This demonstrates that the motherhood penalty effect remains robust, with a slight increase in the magnitude with altered sample compositions. These results from the two rebalanced samples highlight the motherhood penalty during the early pandemic against different comparison groups. In the subsequent sections we continue to use the two rebalanced samples to conduct robustness checks.

5. Driving force of motherhood penalty: Asian females

5.1. Motherhood penalty in non-Asian samples

To assess whether Asian females are the primary contributors to the observed employment disparities, we re-estimate the regression model after excluding Asian females and then both Asian females and males from the sample. As shown in Column (1) of Table 5, the interaction between gender and the presence of school-aged children becomes negative and loses its statistical significance. This indicates that parenthood penalty is not evident among White females, White males, or Asian males. To ensure the robustness of this result, we re-estimate the same regression separately for the April and May samples, as reported in Columns (2) and (3). The insignificant interaction term in these two cases suggest that the previously observed association between school-aged child and unemployment risk is primarily driven by Asian females.

We further restricted the regression by excluding Asian males as well, as reported in Column (4). The interaction between gender and having school-aged children remains negative and insignificant. This result supports the view that parenthood unemployment penalty is specific to Asian females. This pattern holds when conducting the same regression separately for the April and May waves, as shown in Columns (5) and (6), where the interaction remains insignificant. These findings provide consistent evidence that Asian women are the primary contributors to the observed motherhood penalty in employment during the pandemic.

Table 5
Unemployment status, gender and the presence of school-aged children (sample excluding Asian females and Asian males).

	Excluding Asian females			Excluding both Asian females and males		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	All	April	May	All	April	May
Gender (ref.=male)	−0.0195	−0.249	−0.274	0.0247	−0.103	−0.0825
	(0.582)	(0.529)	(0.623)	(0.579)	(0.635)	(0.661)
Children (ref.=no)	0.340	0.273	0.309	0.298	0.404	0.384
	(0.831)	(0.714)	(0.662)	(0.517)	(0.529)	(0.644)
Gender#Children	−0.201	−0.193	−0.184	−0.197	−0.156	−0.185
	(0.527)	(0.571)	(0.593)	(0.469)	(0.428)	(0.509)
Asian (ref.=White)	−0.207	−0.194	−0.181			
	(0.391)	(0.385)	(0.299)			
Cohabitation (ref.=no)	−0.204	−0.233	−0.253	−0.386	−0.354	−0.295
	(0.427)	(0.401)	(0.438)	(0.403)	(0.339)	(0.357)
Physical health (ref.=poor)	−0.349	−0.409	−0.472	−0.474	−0.551	−0.536
	(0.478)	(0.414)	(0.413)	(0.601)	(0.614)	(0.589)
Industry (ref.=contact-intensive)	−0.0395	−0.0673	0.0765	−0.285	−0.278	−0.0235
	(0.249)	(0.277)	(0.262)	(0.379)	(0.265)	(0.258)
Education (ref.=Bachelor's degree and above)	0.798	0.754	0.794	0.845	0.893	0.909
	(0.976)	(0.891)	(0.902)	(1.098)	(1.002)	(1.105)
Whether born in the UK (ref.=yes)	1.835**	1.868**	1.844**	1.698**	1.676**	1.702**
	(0.865)	(0.893)	(0.936)	(0.795)	(0.842)	(0.851)
Age	−5.013***	−4.965***	−5.021***	−4.907***	−4.854***	−4.325***
	(0.671)	(0.754)	(0.878)	(0.946)	(0.905)	(0.887)
Age_squared	0.614***	0.663***	0.579***	0.576***	0.537***	0.526***
	(0.168)	(0.189)	(0.147)	(0.105)	(0.112)	(0.136)
Urban	0.139	0.127	0.203	0.218	0.203	0.296
	(0.256)	(0.235)	(0.214)	(0.232)	(0.294)	(0.303)
Work at home (ref.=never)	−0.483	−0.504	−0.582	−0.547	−0.582	−0.539
	(0.749)	(0.792)	(0.736)	(0.680)	(0.672)	(0.683)
Household income (ref.=low)	−0.478**	−0.507**	−0.566**	−0.623**	−0.656**	−0.675*
	(0.203)	(0.239)	(0.283)	(0.272)	(0.274)	(0.338)
Occupational class (ref.=managerial, administrative, and technical)	−0.0738	−0.0984	0.0842	−0.0478	−0.109	−0.0793
	(0.247)	(0.319)	(0.287)	(0.172)	(0.136)	(0.184)
Baseline employment status (ref.=paid employment)						
Self-employment	4.842***	3.940***	4.782***	3.893***	3.924***	3.769***
	(0.486)	(0.471)	(0.582)	(0.598)	(0.484)	(0.580)
Both paid and self-employment	2.350**	2.054**	2.439*	1.437	1.034	1.183
	(1.138)	(0.937)	(1.132)	(1.843)	(0.934)	(0.876)
Observations	9185	4839	4346	8697	4703	4059

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

5.2. Analysis based on female and male samples

To better understand the motherhood penalty and ethnicity during the pandemic, we conduct separate analyses for female and male samples, including an interaction term between ethnicity (Asian) and the presence of school-aged children.

Column (1) of Table 6 reports the results across the female sample. The positive and significant coefficient of the interaction between being an Asian and having school-aged children suggests an increased likelihood of job loss during the pandemic. In contrast, for men, the interaction between ethnicity and caregiving responsibilities is not statistically significant in Column (2). This suggests that caregiving responsibilities do not intersect with Asian background in a way that significantly affects men's employment outcomes. This finding is consistent with Stefanova et al. (2023), who found that caregiving had little impact on men's career trajectories during the pandemic.

Panels A and B of Fig. 2 visualize the interaction between ethnicity (Asian) and caregiving responsibilities (children) on the of job loss risk for female and male samples, respectively, at 95 % confidence intervals. The probability of unemployment is approximately 7.5 % higher for Asian mothers with school-aged children compared to their White counterparts. This result indicates a strong ethnic disparity in job loss risks among women. In contrast, among the male sample, being Asian does not significantly affect the likelihood of unemployment, regardless of the presence of school-aged children (caregiving responsibilities).

Using the two rebalanced samples, we conducted the same regressions for both females and males. We report the regression results in Columns (3)–(6) of Table 6, with the marginal effects plotted in Panels C-F of Fig. 2. In Panels C and E, the patterns are very similar to those obtained earlier, confirming the probability of unemployment is significantly higher for Asian mothers with school-aged children compared to their White counterparts. This penalty does not exist among Asian fathers with school-aged children. Despite the significant children-Asian interaction among males, Panels D and F show no clear difference in unemployment risk between Asian and White fathers, as their confidence intervals overlap.

Table 6
Unemployment status and Asian with Children (female and male samples).

VARIABLES	(1) Female	(2) Male	(3) Rebalanced 1 Female	(4) Rebalanced 1 Male	(5) Rebalanced 2 Female	(6) Rebalanced 2 Male
Children (ref.=no)	−0.174	0.563	0.416	1.615***	0.158	1.898***
	(0.754)	(0.465)	(0.649)	(0.281)	(0.670)	(0.435)
Asian (ref.=White)	0.273	0.287	0.420	0.537	0.180	0.896
	(0.381)	(0.596)	(0.571)	(0.450)	(0.572)	(0.581)
Children#Asian	1.903**	−0.667	1.069**	−0.921**	1.564**	−1.473***
	(0.801)	(0.727)	(0.504)	(0.423)	(0.738)	(0.676)
Cohabitation (ref.=no)	−0.122	0.0503	−0.292*	−0.336	−0.139	−0.496***
	(0.205)	(0.461)	(0.158)	(0.219)	(0.165)	(0.191)
Physical health (ref.=poor)	0.238	−0.265	−0.185	−0.356	−0.208	−0.478
	(0.263)	(0.374)	(0.231)	(0.250)	(0.235)	(0.376)
Industry (ref.=contact-intensive)	−0.529	−0.0988	0.601**	−0.406	0.719***	−0.124
	(0.497)	(0.345)	(0.268)	(0.405)	(0.263)	(0.395)
Education (ref.=Bachelor's degree and above)	0.618	2.183**	0.476	0.572**	0.388	0.353
	(0.448)	(1.098)	(0.400)	(0.250)	(0.402)	(0.413)
Whether born in the UK (ref.=yes)	2.593***	1.114**	2.448***	1.793***	2.551***	1.884***
	(0.298)	(0.519)	(0.240)	(0.248)	(0.253)	(0.335)
Age	−2.067***	−0.625	−2.819***	−0.853	−1.859***	−0.275
	(0.591)	(1.341)	(1.039)	(0.600)	(0.581)	(0.502)
Age_squared	0.253***	0.0886	0.351***	0.105*	0.224***	0.0360
	(0.0686)	(0.152)	(0.125)	(0.0606)	(0.0696)	(0.0610)
Urban	−0.627**	0.0384	−0.205	−0.447*	−0.489**	−0.652***
	(0.269)	(0.419)	(0.357)	(0.268)	(0.222)	(0.239)
Work at home (ref.=never)	−0.183	−0.444	−0.399	−0.430	−0.513	−0.525
	(0.475)	(0.704)	(0.534)	(0.644)	(0.555)	(0.459)
Household income (ref.=low)	−0.664***	−0.257	−0.705***	−0.633***	−0.561***	−0.622*
	(0.256)	(0.437)	(0.201)	(0.228)	(0.213)	(0.377)
Occupational class (ref.=managerial, administrative, and technical)	0.648**	0.752	0.906***	0.842***	0.711***	1.555***
	(0.263)	(0.497)	(0.263)	(0.225)	(0.261)	(0.520)
Baseline employment status (ref.=paid employment)						
Self-employment	3.564***	3.390***	3.623***	3.957***	3.789***	4.080***
	(0.526)	(0.546)	(0.488)	(0.441)	(0.501)	(0.486)
Both paid and self-employment	1.554***	1.510**	1.740***	2.266***	1.783***	2.555***
	(0.264)	(0.687)	(0.456)	(0.262)	(0.476)	(0.280)
Observations	4570	3769	3051	2322	2669	2117

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

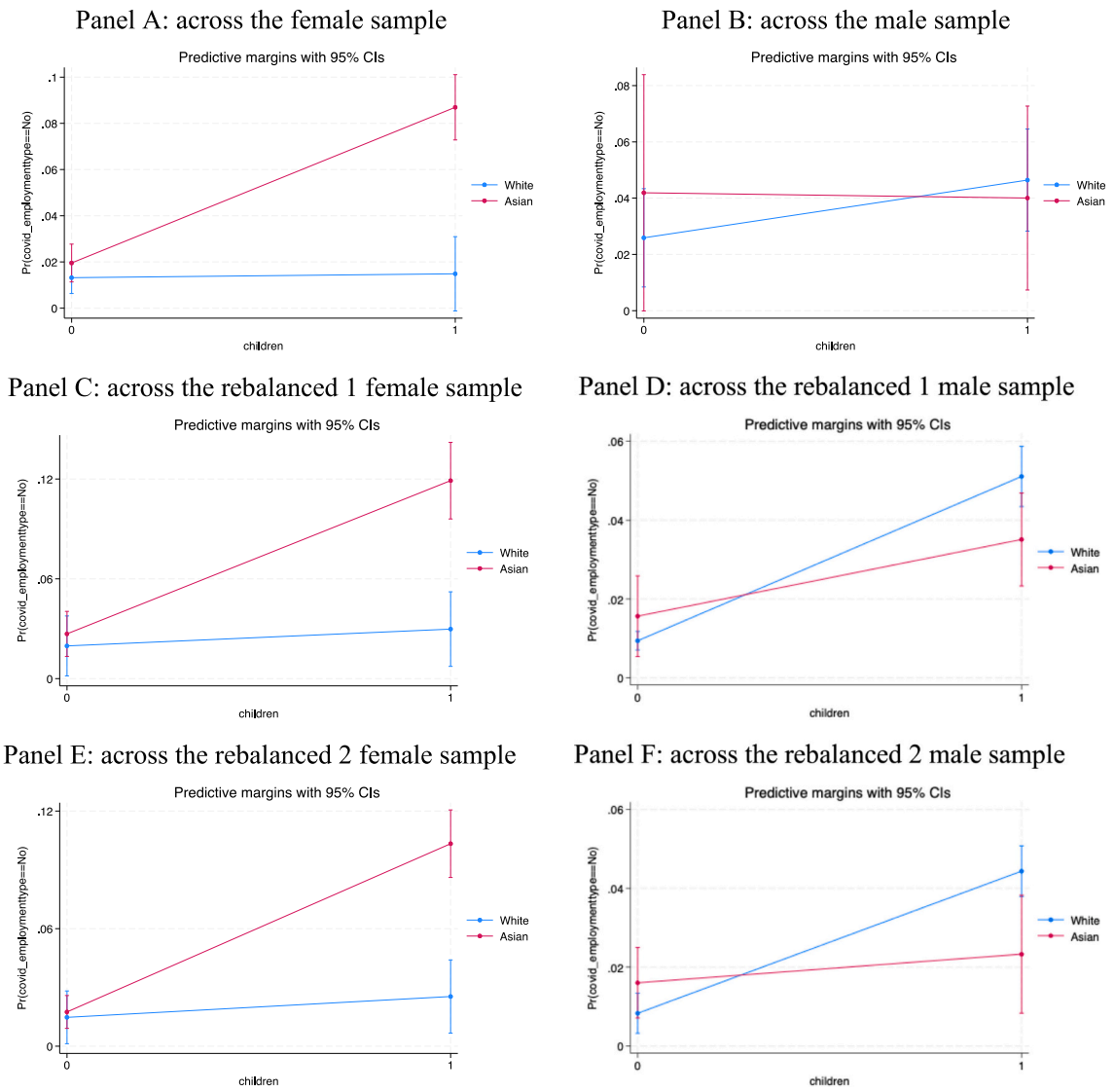


Fig. 2. Probability of unemployment conditional on ethnicity and presence of school-aged children.

5.3. Unemployment risk among females in contact-intensive industries

Contact-intensive industries, such as health and social care, retail, hospitality, and education, were disproportionately impacted during the pandemic due to health risks and social distancing measures. These industries, characterized by high levels of physical presence and face-to-face interactions with customers and clients, pose significant challenges for individuals with caregiving responsibilities due to factors such as increased exposure to Coronavirus and unpredictable schedules during lockdown. Women are overrepresented in these industries with high contact intensity, making them more vulnerable to job losses during the period of economic disruption (Public Health Wales World Health Organization Collaborating Centre on Investment for Health & Well-being, 2023). To investigate whether the intersectionality of ethnicity and caregiving responsibilities is specific to contact-intensive industries, we focus on the sample of females working in contact-intensive and non-contact-intensive industries with results reported in Column (1) and (2) of Table 7, respectively.

For females working in contact-intensive industries, the positive and significant coefficient of the interaction between being Asian and having school-aged children suggests that Asian mothers with school-aged children are disproportionately more likely to transition to unemployment compared to their White counterparts in these sectors. Panel A of Fig. 3 further illustrated this disparity by demonstrating the probability of unemployment for Asian mothers is approximately 5.1 percentage points higher than that for White mothers in the same group. In contrast, the interaction term was not statistically significant for females in non-contact-intensive industries.

Table 7
Unemployment status in contact-intensive and non-contact-intensive industries (female sample).

	Original sample		Rebalanced sample 1		Rebalanced sample 2	
	(1) Contact-intensive industries	(2) Non-contact-intensive industries	(3) Contact-intensive industries	(4) Non-contact-intensive industries	(5) Contact-intensive industries	(6) Non-contact-intensive industries
Children (ref.=no)	0.00792	0.865	0.273	1.154	0.607	2.336***
	(0.993)	(0.754)	(0.647)	(0.851)	(0.520)	(0.680)
Asian (ref.=White)	0.273	0.183	0.324	0.253	0.214	1.403**
	(0.861)	(0.709)	(0.437)	(0.784)	(0.459)	(0.644)
Children#Asian	1.147**	0.839	1.801**	0.746	1.213**	0.698
	(0.578)	(0.798)	(0.742)	(0.888)	(0.589)	(0.721)
Cohabitation (ref.=no)	−0.385	−0.332*	−0.178	−0.267	−0.123	−0.182
	(0.297)	(0.191)	(0.208)	(0.181)	(0.209)	(0.196)
Physical health (ref.=poor)	−0.132	−0.154	−0.195	−0.403	−0.205	−0.128
	(0.289)	(0.440)	(0.211)	(0.261)	(0.234)	(0.425)
Education (ref.=Bachelor's degree and above)	0.165	−0.459	0.527	−0.481	0.751*	−0.388
	(0.337)	(0.668)	(0.446)	(0.668)	(0.447)	(0.675)
Whether born in the UK (ref.=yes)	−0.972	3.012***	−0.776*	2.979***	−0.539*	2.911***
	(0.838)	(0.349)	(0.412)	(0.360)	(0.295)	(0.351)
Age	−3.934***	−1.818***	−2.191***	−1.933***	−2.209***	−2.169***
	(0.914)	(0.575)	(0.529)	(0.586)	(0.598)	(0.647)
Age_squared	0.457***	0.243***	0.268***	0.256***	0.262***	0.282***
	(0.103)	(0.0667)	(0.0628)	(0.0703)	(0.0694)	(0.0745)
Urban	−0.765**	−0.842***	−0.661**	−0.795***	−0.669**	−0.824***
	(0.336)	(0.209)	(0.284)	(0.205)	(0.282)	(0.209)
Work at home (ref.=never)	−1.251***	1.349	−0.227	1.369	−0.193	1.400
	(0.413)	(0.997)	(0.475)	(1.073)	(0.460)	(1.035)
Household income (ref.=low)	−0.402	−0.816	−0.747***	−0.748	−0.796***	−0.936*
	(0.296)	(0.529)	(0.268)	(0.539)	(0.246)	(0.502)
Occupational class (ref.=managerial, administrative, and technical)	0.581	0.790	0.627**	0.744	0.642***	0.656
	(0.397)	(0.641)	(0.274)	(0.607)	(0.245)	(0.584)
Baseline employment status (ref.=paid employment)						
Self-employment	4.129***	4.865***	3.739***	4.816***	3.760***	5.111***
	(0.633)	(0.634)	(0.557)	(0.433)	(0.552)	(0.614)
Both paid and self-employment	2.046***	0.789**	1.840***	0.853**	1.514***	0.877**
	(0.477)	(0.374)	(0.432)	(0.371)	(0.253)	(0.387)
Observations	1322	2730	1474	3131	1315	3068

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

In the robustness checks with rebalanced samples, the children-Asian interactions remain positive and significant among females in contact-intensive industries, as reported in Columns (3) and (5) of Table 7. In contrast, the interaction remains insignificant among females in non-contact-intensive industries, as reported in Columns (4) and (6). Consistent with Panel A of Fig. 3, the predicted probabilities plotted in Panels B and C show that Asian mothers are approximately 5.3 percentage points (rebalanced sample 1) and 6.5 percentage points (rebalanced sample 2) more likely to experience unemployment than their White counterparts within the same sector.

6. Further discussions

6.1. *Assessing the role of discrimination in Asian mothers' unemployment risk*

There is an ongoing argument that motherhood penalty may be due to discriminatory practices in employment. Proponents of this view suggest that employers might consciously or unconsciously discriminate against mothers, perceiving them as less committed or capable due to caregiving responsibilities (Andresen & Nix, 2022). If this is a primary driver of motherhood penalty, we would expect to observe disproportionate unemployment risk prior to the Covid-19 Pandemic when childcare is generally available to mothers in the UK. We test this discrimination hypothesis directly by running the same regressions based on unemployment information obtained prior to the Pandemic (see Wave 9 of the main USoc dataset).

We show the results in Table 8. Our interested variables include gender, children, Asian ethnicity and their related interactions. In Column (1), the statistically insignificant three-way interaction term indicates that, prior to the pandemic, Asian women with school-

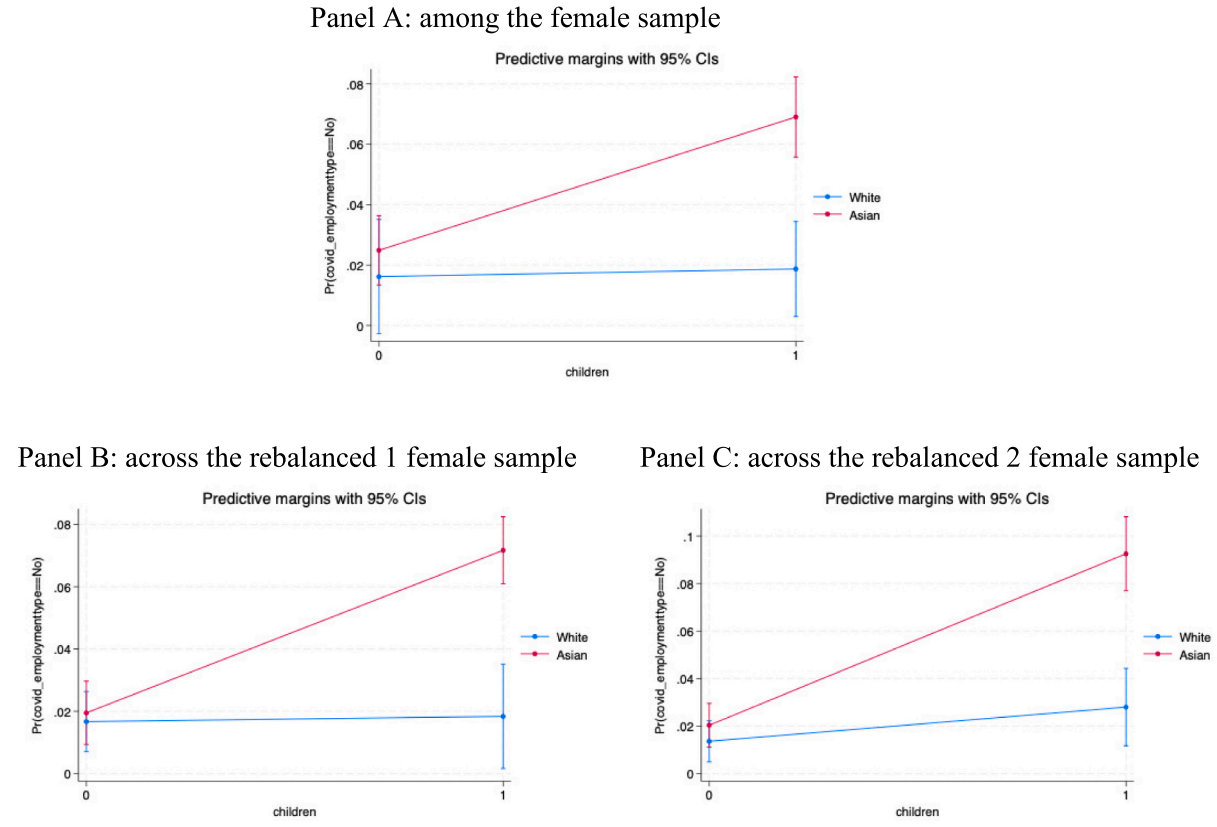


Fig. 3. The relationship between the presence of school-aged children and probability of transitioning to unemployment conditional on ethnicity among females working in contact-intensive industries.

aged children in the UK labour market are not inherently more susceptible to unemployment due to discriminatory practices targeting this intersectional group. As demonstrated in Appendix Figure B2, having children on unemployment is not significantly associated with higher unemployment risk for Asian mothers compared to White mothers. This points to discrimination not being a primary factor in explaining employment status[4] discrepancies in the UK labour market.

We also extend our examination to consider the influence of the interaction between parenthood and Asian ethnicity on female unemployment across all, contact-intensive, and non-contact-intensive sectors, reported in Columns (2), (3), and (4) of Table 8. In Column (2), the insignificant coefficient of the interaction suggests that there is no additional motherhood penalty in general for Asian women. For Columns (3) and (4), this insignificant effect also holds for women in contact-intensive or non-contact-intensive industries. Altogether, these findings tend to support our view that we should be cautious in relying on discrimination to explain the motherhood penalty during the Pandemic. While our data do not allow us to directly observe employer behaviour, the lack of significant ethnic differences in these stratified models suggests that discrimination is unlikely to be the primary driver of the observed motherhood penalty during the pandemic.

6.2. Motherhood and caregiving–influences of social and cultural norms

Another explanation for the motherhood penalty found for Asian mothers is related to the influences of social and cultural norms that reinforce Asian mothers' role as caretaker for children. In many Asian communities, women are often expected to take on the majority of childcare and household responsibilities (Nazroo & Kapadia, 2013; UNESCAP, 2021). For instance, women in Asia and the Pacific perform four times more unpaid care work than men (International Labour Organization, 2024). These uneven distributions of care work likely placed additional pressure on Asian mothers during the pandemic, especially with the closure of schools and childcare services. With limited alternatives, many Asian women may have had little choice but to prioritize caregiving over paid employment, which increased their likelihood of exiting the workforce at a disproportionate rate (Nugraheni & Hastings, 2021; World Bank, n.d.).

What we have found in Section 5 may reflect broader societal norms and traditional gender roles, where men are less likely to take on primary caregiving responsibilities and, as a result, face fewer employment disruptions related to child caregiving burdens. The

[4] Discrimination may still play a greater role in explaining wage gap or career development.

Table 8
Pre-Pandemic unemployment and motherhood penalty.

VARIABLES	(1) All	(2) All	(3) Contact-intensive	(4) Non-contact-intensive
Gender (ref.=male)	0.176			
	(0.413)	0.0773	0.398	0.138
Children (ref.=no)	0.525	(0.607)	(0.754)	(0.672)
	(0.626)			
Gender#Children	−0.206			
	(0.768)			
Asian (ref.=white)	0.471	0.734	1.311	0.831
	(0.785)	(0.646)	(0.831)	(0.691)
Gender#Asian	0.589			
	(0.934)			
Children#Asian	0.192	0.140	0.754	0.203
	(1.167)	(1.024)	(1.328)	(0.829)
Gender#Children#Asian	−0.192			
	(1.516)			
Education (ref.=Bachelor's degree and above)	0.273	0.420	0.687	1.115
	(0.332)	(0.452)	(0.550)	(1.902)
Whether born in the UK (ref.=yes)	0.674	0.301	0.696	0.307
	(0.465)	(0.595)	(0.809)	(0.279)
Age	−1.390*	−0.432	−0.464	−1.866**
	(0.781)	(1.259)	(1.575)	(0.895)
Age_squared	0.184**	0.0405	0.0807	0.524**
	(0.092)	(0.157)	(0.198)	(0.256)
Urban	−0.305	0.276	0.412	0.329
	(0.372)	(0.496)	(0.527)	(0.460)
Work at home (ref.=never)	−0.164	−0.235	−0.463	−0.538
	(1.019)	(0.638)	(0.687)	(0.434)
Household income (ref.=low)	−0.433	−0.762	−0.406	−0.577**
	(0.352)	(0.495)	(0.635)	(0.302)
Occupational class (ref.=managerial, administrative, and technical)	0.332**	0.357	1.531	0.863
	(0.167)	(0.519)	(1.118)	(0.667)
Baseline employment status				
Self-employment	0.389	0.284	0.273	0.302
	(0.247)	(0.373)	(0.294)	(0.377)
Both paid and self-employment	0.246	0.468	0.352	0.432
	(0.482)	(0.391)	(0.344)	(0.361)
Observations	16,709	9067	2767	5486

Notes: (1) ref. = Reference category; (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (3) Standard errors in parentheses.

absence of a significant effect for men highlights the gendered nature of employment vulnerabilities, with Asian women bearing the brunt of caregiving responsibilities. These disparities may be exacerbated by social norms and cultural expectations that often place the burden of childcare disproportionately on women, intensifying their challenges in balancing paid work and family production.

The observed differences in unemployment risks between mothers in contact-intensive and non-contact-intensive industries can be attributed to the challenges associated with caregiving during the pandemic, particularly concerns about of virus exposure and transmission. Contact-intensive industries, such as healthcare, retail, and hospitality, require physical presence and frequent interaction, which increases the risk of contracting the Coronavirus. For mothers, especially those with school-aged children, this heightened exposure risk may have raised fears of transmitting the virus to their children. Consequently, some mothers may have left their jobs voluntarily or faced unemployment due to unsafe working conditions or insufficient accommodations to reduce exposure risks. Additionally, the lack of childcare options during school closures may have exacerbated these challenges, forcing mothers to prioritize caregiving responsibilities over employment. Our results suggest that Asian mothers working in the contact intensive industries are much more sensitive to the negative impact of virus exposure and transmission than their White counterparts. This ultimately leads to Asian mothers' higher unemployment.

In contrast, mothers in non-contact-intensive industries, where remote work is more accessible, are less exposed to such risks. The option to work from home likely alleviated concerns about virus transmission and help mothers manage caregiving responsibilities while maintaining employment. This workplace flexibility explains why the interaction between caregiving responsibilities and ethnicity is not statistically significant in non-contact-intensive industries, highlighting its "protective" role in reducing unemployment risks.

Our empirical findings are consistent with this hypothesis. In the following section, we provide some indirect evidence on mental health.

6.3. Mental health of Asian mothers

The COVID-19 pandemic brought about profound disruptions to daily life, including school closures, increased caregiving

responsibilities, and economic uncertainty, all of which may negatively impact mental health. While a body of literature examines mental health deterioration as a consequence of unemployment, and other studies explore the impact of motherhood on health outcomes more broadly (see e.g. Dehos et al., 2024 and Sun et al., 2024). It has been also shown that women are more likely than men to experience mental health challenges, often due to societal caregiving expectations (World Health Organization, 2020). Mothers taking greater childcare responsibilities are more likely to face mental health problems (see e.g. Ahammer et al., 2024; Zhang, Sun, et al., 2024). These pressures may have been particularly acute for Asian mothers, who face the dual burden of intensified caregiving at home and employment choice during the pandemic. The greater deterioration in mental health among Asian females, coincided with their heightened caregiving responsibilities, likely contributed to their increased risk of unemployment during the pandemic (see for example, Fukai et al., 2023; Liu et al., 2022; Martucci, 2023; Zhang, Sun, et al., 2024).

We hypothesize that the intensified caregiving burdens and related stressors directly contributed to worsening mental health, which, in turn, compromised mothers' ability to maintain or seek employment. To test this hypothesis, we employ mental health (i.e., self-reported binary variable "depression and unhappiness") and examine: (1) mental health is associated with Asian mothers; (2) unemployment is linked to deterioration in mental health.

The result, presented in Column (1) of Table 9, indicates that the interaction between being Asian and having school-aged children is positive and significant, suggesting a strong association between these factors and worsening mental health in the female sample. As visualized in Panel A of Fig. 4, Asian mothers with school-aged children are 17.5 % more likely to experience worse mental health than White mothers with school-aged children. This highlights the compounded challenges faced by this group during the pandemic, including heightened caregiving demands, which likely elevated stress levels and deteriorated mental health.

Further analysis in Column (2) includes mental health as a covariate. The coefficient of mental health is positive and significant, indicating that worsening mental health may partially explain the relationship between being an Asian mother with children and the probability of job loss. Specifically, the interaction effect between Asian and caregiving responsibilities on unemployment decreases from 1.903 in column (1) of Table 6 to 0.609 in column (2) of Table 9, and its significance falls from the 5 % to the 10 % level. This suggests that intensified caregiving responsibilities, if leading to elevated stress levels and depressive symptoms, may reduce Asian mothers' labour market participation. After including mental health, the probability of job loss between Asian and White mothers with children narrows from 7.5 percentage points, as in Panel A of Fig. 2, to approximately 2.5 percentage points in Panel B of Fig. 4.

To explore whether this relationship also holds for Asian males, we conduct similar regression with mental health on the male sample. However, as reported in Column (4), the interaction between being Asian and having school-aged children was not significantly associated with mental health outcomes for males. This finding suggests that school-aged children do not appear to influence Asian fathers' mental health, which is likely due to their limited involvement in childcare. This underscores the stark gender differences among Asians and highlights the unique vulnerabilities faced by Asian mothers in navigating pandemic-induced economic and social challenges.

We also examined whether physical health may be correlated to the disproportionate unemployment risk among Asian mothers. The coefficient of the interaction between being Asian and having school-aged children is not significant in predicting physical health, as shown in Column (3) of Table 9. This suggests that mental rather than physical health is the more relevant factor influencing the unemployment risk for Asian mothers during the pandemic.

Robustness checks using rebalanced sample 1 and 2 also confirm our findings. As in Column (5) and (9) of Table 9, the positive and significant interaction between being Asian and having school-aged children remains consistent in the female sample. Panels C and D of Fig. 4 show that Asian mothers with school-aged children are 21.5 % and 17.3 % more likely than their White counterparts to experience worse mental health, in rebalanced samples 1 and 2, respectively. After accounting for mental health, the unemployment probability falls from approximately 9 percentage points (Panel C of Fig. 2) to around 3.6 percentage points (Panel E of Fig. 4) in rebalanced sample 1, and from 7.8 percentage points (Panel E of Figs. 2) to 4 percentage points (Panel F of Fig. 4) in rebalanced sample 2. These results further confirm that mental health associated with school-aged children may play a consistent role in explaining the heightened unemployment risk faced by Asian mothers during the early pandemic.

7. Conclusions

Using data from the UK Understanding Society, we find significant gender disparities in the labour market outcome, measured by unemployment, for females with school-aged children at home during the initial stage of the pandemic. This result of motherhood penalty is primarily concentrated among Asian mothers, while their White counterparts appear unaffected. We also find that Asian mothers in contact-intensive industries, such as healthcare, retail, and hospitality, are more likely to experience job loss compared to those in non-contact-intensive industries which are more flexible with work from home at flexible working hours.

We discuss two possible explanations behind our empirical findings. We find no support for the role of discrimination in explaining unemployment risk for Asian mothers, as there is no evidence of pre-pandemic disproportionate unemployment risk for Asian mothers.

Our empirical findings are in line with the explanation that cultural and social norms tied to ethnicity may act as a powerful mechanism in shaping women's roles, both within the home and in the labour market. During the pandemic school closure periods, it is likely that Asian mothers took primary caregiving responsibilities for school-aged children while White mothers experienced a more equal caregiving responsibilities shared within their family. These greater caregiving burdens may have made Asian mothers more likely to be unemployed despite having been employed before the pandemic.

We find some indirect evidence supporting the hypothesis that cultural and social norms may influence employment outcomes. For example, Asian mothers with school-aged children are more likely to report mental health problems suggesting that mental costs related to childcare responsibilities are likely to increase unemployment risks for these women. Our empirical work only focuses on

Table 9
Unemployment, mental health and physical health (female and male samples).

	Female			Male	Female (rebalanced 1)			Male (rebalanced 1)	Female (rebalanced 1)			Male (rebalanced 1)
Variables	(1) Mental health	(2) Unemployment	(3) Physical health	(4) Mental health	(5) Mental health	(6) Unemployment	(7) Physical health	(8) Mental health	(9) Mental health	(10) Unemployment	(11) Physical health	(12) Mental health
Children (ref.=no)	−0.400**	0.546***	0.0605	−0.385*	−0.205	1.218*	0.114	−0.0906	−0.260**	0.642*	0.137	−0.0714
	(0.179)	(0.202)	(0.0940)	(0.211)	(0.190)	(0.633)	(0.668)	(0.508)	(0.128)	(0.287)	(0.510)	(0.356)
Asian (ref.=White)	0.375**	0.249	0.340*	0.556	0.600***	0.515	0.330	0.680	0.455***	0.326	0.308	0.467
	(0.169)	(0.281)	(0.197)	(0.470)	(0.180)	(0.673)	(0.583)	(0.512)	(0.124)	(0.523)	(0.449)	(0.351)
Children#Asian	0.478**	0.609*	0.346	−0.859	0.299**	0.320*	0.460	−1.159	0.303**	0.326*	0.496	−0.544
	(0.211)	(0.346)	(0.437)	(0.627)	(0.150)	(0.169)	(0.723)	(0.708)	(0.153)	(0.186)	(0.614)	(0.469)
Mental (ref.=no worsening)		0.387**				0.448*				0.376*		
		(0.184)				(0.260)				(0.207)		
Cohabitation (ref.=no)	−0.235*	0.377*	0.0978	−0.168	−0.298	0.353	0.194	−0.236	−0.296***	0.429*	0.146	−0.553*
	(0.126)	(0.218)	(0.0986)	(0.270)	(0.286)	(0.273)	(0.441)	(0.502)	(0.104)	(0.245)	(0.319)	(0.315)
Physical health (ref.=poor)	0.207*	−0.372		0.258	0.263**	−0.311		0.484	0.225**	−0.140		0.205
	(0.116)	(0.364)		(0.202)	(0.133)	(0.465)		(0.380)	(0.0948)	(0.417)		(0.270)
Industry (ref.=essential)	−0.201**	−0.0253	0.0989	−0.388**	−0.269**	−0.0737	0.224		−0.0921	0.00960	0.180	
	(0.0997)	(0.170)	(0.208)	(0.167)	(0.105)	(0.225)	(0.393)		(0.0841)	(0.197)	(0.286)	
Education (ref.=Bachelor's degree and above)	0.225	1.366	−0.305	−0.285	0.0199	1.316	−0.433	−0.355	0.0356	0.786	−0.0658	−0.316
	(0.314)	(0.970)	(0.237)	(0.545)	(0.342)	(0.987)	(1.115)	(0.432)	(0.278)	(0.763)	(1.039)	(0.941)
Whether born in the UK (ref.=yes)	0.0776	1.141***	−0.0227	−0.0555	0.0547	1.337**	−1.390	−0.646*	0.112	0.444	−1.447	−0.101
	(0.171)	(0.268)	(0.176)	(0.334)	(0.197)	(0.586)	(1.072)	(0.377)	(0.141)	(0.363)	(1.019)	(0.253)
Age	−0.723*	−3.302***	0.0518	−0.879	−0.644*	−3.656***	0.583	−0.397	−0.266	−3.029***	0.267	−0.475
	(0.386)	(0.602)	(0.359)	(0.690)	(0.346)	(0.783)	(0.393)	(1.556)	(0.353)	(0.704)	(0.405)	(0.847)
Age_squared	0.0635	0.385***	0.00828	0.0766	0.0476	0.431***	0.0755***	0.0903	0.0101	0.353***	−0.0279*	0.0716
	(0.0435)	(0.0663)	(0.0412)	(0.0776)	(0.0396)	(0.0878)	(0.0221)	(0.195)	(0.0396)	(0.0785)	(0.0153)	(0.102)
Urban	−0.137	−0.0829	0.0889	−0.227	−0.134	−0.168	0.273	−0.218	−0.0604	−0.267	0.136	−0.406
	(0.110)	(0.212)	(0.0917)	(0.190)	(0.121)	(0.283)	(0.465)	(0.981)	(0.0968)	(0.238)	(0.335)	(0.666)

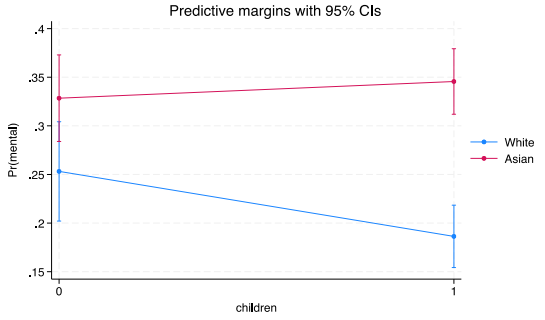
(*continued on next page*)

Table 9 (*continued*)

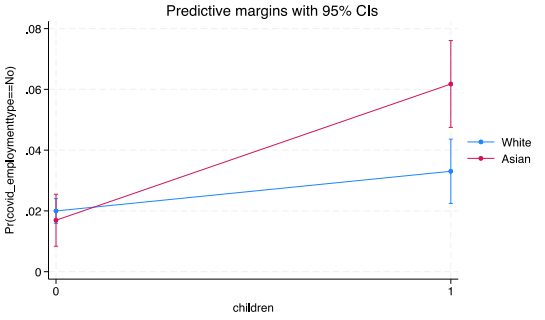
	Female			Male	Female (rebalanced 1)			Male (rebalanced 1)	Female (rebalanced 1)			Male (rebalanced 1)
Variables	(1) Mental health	(2) Unemployment	(3) Physical health	(4) Mental health	(5) Mental health	(6) Unemployment	(7) Physical health	(8) Mental health	(9) Mental health	(10) Unemployment	(11) Physical health	(12) Mental health
Work at home (ref.= never)	0.275	−0.807***	0.00776	0.975**	0.241	−0.524	0.399	0.501	0.268	−0.575*	0.171	0.322
	(0.186)	(0.269)	(0.176)	(0.426)	(0.202)	(0.421)	(0.706)	(0.522)	(0.171)	(0.301)	(0.621)	(0.400)
Household income (ref.=low)	−0.163	−0.501***	0.497***	−0.0164	−0.0655	−0.533**	0.786*	−0.190	−0.157*	−0.932***	0.124	−0.0579
	(0.109)	(0.193)	(0.0811)	(0.228)	(0.114)	(0.245)	(0.467)	(0.153)	(0.0926)	(0.327)	(0.325)	(0.268)
Occupational class (ref.=managerial, administrative, and technical)	−0.286	0.194	−0.270*	−0.232	−0.0298	0.0437	−0.475	−0.291	−0.192	0.0931	−0.204	−0.399
	(0.182)	(0.351)	(0.146)	(0.291)	(0.203)	(0.433)	(0.582)	(0.382)	(0.145)	(0.338)	(0.509)	(0.276)
Baseline employment status (ref.=paid employment)												
Self-employment	0.246	3.693***	−0.743***	0.386	0.145	3.699***	−0.523	0.593	0.140	3.304***	−0.240	0.212
	(0.183)	(0.430)	(0.172)	(0.294)	(0.203)	(0.504)	(0.601)	(0.435)	(0.149)	(0.442)	(0.538)	(0.311)
Both paid and self-employment	0.0127	1.790***	−0.494***	0.171	0.0151	2.070***	−1.128	0.579	0.0196	1.950***	−0.507	0.399
	(0.242)	(0.411)	(0.161)	(0.394)	(0.278)	(0.525)	(0.977)	(0.768)	(0.198)	(0.400)	(0.772)	(0.518)
Observations	4096	4096	4155	3513	2928	2928	3011	2206	2589	2589	2614	2028

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

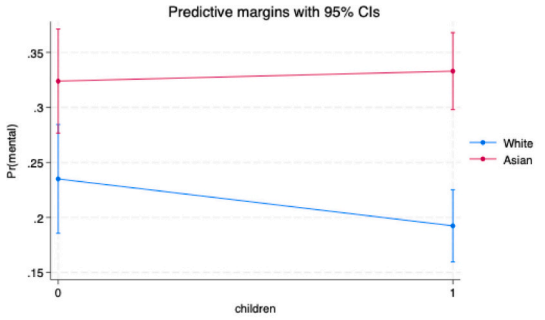
Panel A: mental health



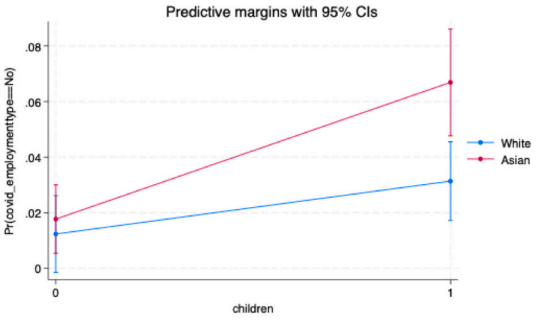
Panel B: Unemployment (after controlling for mental health)



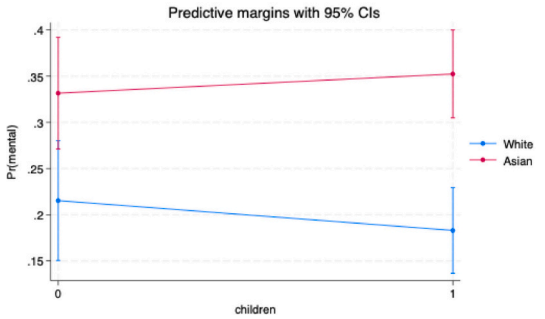
Panel C: mental health across rebalanced sample 1



Panel D: Unemployment (after controlling for mental heath) rebalanced sample 1



Panel E: mental health across rebalanced sample 2



Panel F: Unemployment (after controlling for mental health) rebalanced sample 2

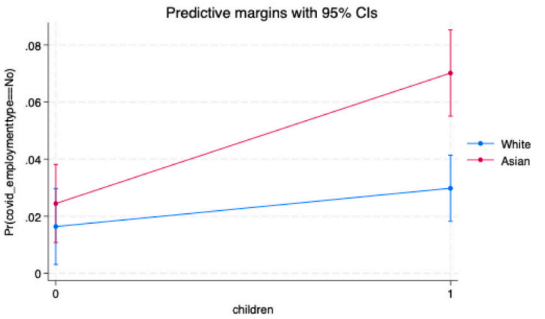


Fig. 4. Interaction effects between Asian ethnicity and school-aged children on mental health status and unemployment risk.

correlation which may reflect causality effect that we do not aim to identify in this paper due to data limitation. We recognise the limitation of our findings and believe that more empirical research is needed to investigate on Asian mothers, specifically on their view concerning the role of mother's caregiving responsibilities shared within their partners and on their actual responsibilities and time spent during the Covid-19 pandemic when childcare services are not available.

Our findings highlight the need for UK policies that address both cultural and social norms, promoting more equal sharing of childcare responsibilities, particularly in Asian communities. While our primary focus has been on the distinct experiences of Asian mothers, we acknowledge the broader diversity within the UK's non-White communities.[5]

[5] In Appendix Table A3 and Figure B2, we show that motherhood penalty exists in other ethnic groups, though this is less pronounced compared to Asian mothers. Future research should investigate the varied experiences of these other ethnic minority groups in more detail to develop more nuanced and comprehensive policy interventions that address the full spectrum of pandemic-related labour market vulnerabilities.

Our results also carry implications for policy development in Asian countries, where traditional cultural norms continue to strongly influence women's caregiving roles. In addition to advocating for better maternity leave, improved childcare services, and greater workplace flexibility, it is crucial to shift cultural and social attitudes to promote a more equal sharing of childcare responsibilities between parents. As our research demonstrates, cultural values play a critical role in shaping the caregiving burden, with Asian mothers bearing the brunt of childcare responsibilities when public services are unavailable, such as during the pandemic.

We also believe, addressing these cultural and social barriers can help mitigate the long-term consequences of gender inequality, such as low female labour force participation or even declining fertility rates, which are observed in many advanced economies and emerging markets (Goldin, 2024).

CRediT authorship contribution statement

Yuemei Ji: Writing – original draft, Investigation, Formal analysis, Conceptualization. **Weiwen Qi:** Writing – original draft, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Variable description

Dependent variable	Description
Employment status during the COVID-19 lockdown	Four categories: "employed," "self-employed," "both employed and self-employed," and "not employed."
Independent variables	
Gender	0 denoting male and 1 denoting female.
Presence of school-aged children	0 denoting not having school-aged children and 1 denoting having school-aged children.
Age	self-reported age
Age_squared	The quadratic term of age
Baseline employment status (ref.=paid employment)	Information about baseline employment status of respondents in January-February in 2020 "paid employment", "self-employment", and "both paid employment and self-employment"
Education (ref. = bachelor's degree)	0 denoting a bachelor's degree or above and 1 denoting below a bachelor's degree or no qualifications.
Cohabitation (ref.=no)	1 denoting living with a couple and otherwise 0.
Ethnicity (ref.=White)	0 denotes White (the reference group) and value 1 denotes Asian. Ethnicity is categorized according to the USoc official data collection framework. The "Asian" category includes individuals who self-identify as Indian, Pakistani, Bangladeshi, Chinese, or belonging to any other Asian background. This group reflects a diverse population with ancestral roots primarily in South Asia and East Asia, acknowledging both British-born individuals and those who migrated to the UK. The "White" category encompasses those who identify as British, English, Scottish, Welsh, or Northern Irish (White), Irish (White), Gypsy or Irish Traveller, or belonging to any other White background. These definitions are consistent with the standard ethnic group categorization to ensure consistency and comparability to other similar research on ethnicity issues. Ethnic groups outside of these categories, such as Black, Arab, or other mixed ethnicities, are excluded from the analysis and this allows us to focus specifically on the comparative outcomes of Asian and White populations.
Physical health (ref.=poor)	0 denoting poor health conditions that are in high risk (clinically extreme vulnerable to Coronavirus) and moderate risk (clinically vulnerable) and 1 denoting good health conditions that are in no risk (not clinically vulnerable).
Household income (ref.=low)	With 0 denoting household income below or equal to the median and 1 denoting household income above the median.
Industry classification (ref.=contact-intensive)	Contact-intensive and non-contact industries, represented by values 0 and 1, respectively. Contact-intensive industries include Restaurants, Health Service, Education/Sport, Communication/Entertainment, Retail, Service Industry, Construction, Wholesale, Food Industry, Transportation - Train System, Trash Removal, and Other Transportation. Non-contact-intensive industries include Agriculture/Forestry, Fisheries, Energy/Water, Mining, Chemicals, Synthetics, Earth/Clay/Stone, Iron/Steel, Mechanical Engineering, Electrical Engineering, Wood/Paper/Printing, Clothing/Textiles, Construction Related, Trading Agents, Financial Institutions, Insurance, Legal Services, Other Services, Voluntary/Church, Private Household, Public Administration, and Social Security.
Mental health (ref.=no worsening)	psychiatric conditions: with 0 denoting no worsening of mental health (not at all or no more than usual), indicating stable mental well-being, and 1 denoting worsening of mental health (rather more than usual or much more than usual), indicating increased symptoms of depression or unhappiness.
Occupational class (ref.=managerial, administrative, and technical)	With 1 denoting non-managerial and other occupations and 0 denoting managerial and professional occupations

(*continued on next page*)

Table A1 (*continued*)

Dependent variable	Description
Employment status during the COVID-19 lockdown	Four categories: "employed," "self-employed," "both employed and self-employed," and "not employed."
Independent variables	
Work at home (ref.=never)	With 0 denoting no frequency of working at home (never) and 1 denoting some frequency of working at home (always, often, or sometimes).
Urban residency (ref. = rural)	with 0 denoting rural and 1 denoting urban.

Table A2
Binary logit regression results: Employment status and motherhood penalty

	The entire sample				The April sample				The May sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES												
Gender (ref.=male)	−0.761*	−0.781**	−0.783**	−0.552*	−0.869**	−0.889**	−0.891**	−0.517*	−0.583*	−0.622*	−0.623*	−0.451*
	(0.399)	(0.398)	(0.398)	(0.308)	(0.408)	(0.408)	(0.408)	(0.312)	(0.349)	(0.367)	(0.362)	(0.272)
Children (ref.=no)	0.372	0.283	0.285	0.655	0.307	0.255	0.257	0.674	0.449	0.345	0.347	0.750
	(0.377)	(0.375)	(0.375)	(0.549)	(0.384)	(0.377)	(0.377)	(0.557)	(0.424)	(0.414)	(0.414)	(0.586)
Gender#Children	1.261***	1.350***	1.353***	1.782***	1.322***	1.381***	1.384***	1.622***	1.245**	1.306**	1.307**	1.677***
	(0.442)	(0.442)	(0.443)	(0.394)	(0.453)	(0.451)	(0.451)	(0.315)	(0.514)	(0.510)	(0.510)	(0.401)
Asian (ref.=White)	1.748***	1.788***	1.785***	2.204***	1.764***	1.768***	1.762***	2.230***	1.811***	1.800***	1.799***	2.286***
	(0.233)	(0.237)	(0.237)	(0.320)	(0.239)	(0.246)	(0.247)	(0.324)	(0.260)	(0.268)	(0.268)	(0.337)
Cohabitation (ref.=no)		−0.0957	−0.102	−0.315		−0.0926	−0.0975	−0.362		−0.0950	−0.0975	−0.223
		(0.233)	(0.234)	(0.277)		(0.243)	(0.243)	(0.293)		(0.228)	(0.229)	(0.284)
Physical health (ref.= poor)			−0.285	−0.304			−0.322	−0.274			−0.157	−0.302
			(0.362)	(0.455)			(0.364)	(0.468)			(0.384)	(0.506)
Industry (ref.=contact-intensive)				−0.0670				−0.111				−0.0199
				(0.207)				(0.215)				(0.229)
Education (ref.= Bachelor's degree and above)	0.675	1.030*	1.033*	1.469*	0.479	0.838	0.839*	1.480*	0.277	0.688	0.685	1.228
	(0.492)	(0.533)	(0.534)	(0.884)	(0.489)	(0.531)	(0.467)	(0.876)	(0.512)	(0.566)	(0.566)	(1.015)
Whether born in the UK (ref.=yes)	0.136	−0.190	−0.178	−0.320	0.0978	−0.159	−0.143	−0.295	0.158	−0.208	−0.202	−0.223
	(0.395)	(0.453)	(0.455)	(0.737)	(0.415)	(0.470)	(0.472)	(0.773)	(0.460)	(0.554)	(0.555)	(0.846)
Age	−1.114*	−1.152*	−1.138*	−3.271***	−1.091*	−1.065*	−1.058*	−3.458***	−0.955	−1.125*	−1.116*	−2.782***
	(0.615)	(0.697)	(0.685)	(0.733)	(0.652)	(0.641)	(0.622)	(0.732)	(0.627)	(0.649)	(0.650)	(0.734)
Age_squared	0.136*	0.140*	0.139*	0.376***	0.135*	0.131*	0.130*	0.396***	0.123*	0.141*	0.140*	0.320***
	(0.0724)	(0.0815)	(0.0816)	(0.0824)	(0.0767)	(0.0771)	(0.0769)	(0.0826)	(0.0731)	(0.0763)	(0.0764)	(0.0842)
Urban	−0.270	−0.274	−0.276	−0.0797	−0.301	−0.314	−0.315	−0.0610	−0.254	−0.211	−0.211	0.0682
	(0.202)	(0.209)	(0.209)	(0.261)	(0.214)	(0.220)	(0.220)	(0.271)	(0.226)	(0.231)	(0.231)	(0.283)
Work at home (ref.= never)	−0.143	−0.162	−0.164	−0.243	−0.114	−0.118	−0.120	−0.320	−0.0890	−0.179	−0.179	−0.493
	(0.325)	(0.333)	(0.333)	(0.477)	(0.340)	(0.338)	(0.338)	(0.478)	(0.377)	(0.385)	(0.385)	(0.500)
Household income (ref.= low)	−0.514**	−0.426*	−0.435*	−0.608**	−0.532**	−0.450*	−0.461*	−0.597**	−0.414	−0.314	−0.320	−0.571*
	(0.234)	(0.243)	(0.243)	(0.258)	(0.245)	(0.254)	(0.255)	(0.270)	(0.254)	(0.264)	(0.264)	(0.298)
Occupational class (ref.= managerial, administrative, and technical)	0.744***	0.707***	0.710***	0.789**	0.650**	0.622**	0.624**	0.0191	0.665**	0.645**	0.646**	0.0624
	(0.262)	(0.274)	(0.273)	(0.390)	(0.280)	(0.290)	(0.289)	(0.386)	(0.277)	(0.290)	(0.290)	(0.414)
Baseline employment status (ref.=paid employment)												
Self-employment	−0.197	−0.162	−0.164	−0.365	−0.164	−0.122	−0.124	−0.376	−0.00119	0.0246	0.0227	−0.332
	(0.292)	(0.309)	(0.309)	(0.416)	(0.309)	(0.323)	(0.323)	(0.438)	(0.310)	(0.325)	(0.325)	(0.493)
Both paid and self-employment	−0.232	−0.0155	−0.0142	0.0158	−0.241	−0.0114	−0.0166	−0.114	−0.473	−0.209	−0.211	−0.132
	(0.368)	(0.358)	(0.358)	(0.430)	(0.394)	(0.379)	(0.381)	(0.476)	(0.397)	(0.378)	(0.380)	(0.516)
Observations	11,633	10,681	10,681	9828	6197	5245	5245	5234	5436	5436	5436	4594

Notes: (1) ref. = Reference category; (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (3) Standard errors in parentheses.

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Table A3
Regression results on employment status: Analysis including black and mixed ethnicities (other ethnicities)

VARIABLES	(1) Sample (Whites, Black and mixed ethnicities)	(2) Female sample	(3) Male sample
Gender (ref.=male)	−0.842		
	(0.804)		
Children (ref.=no)	−1.337	0.261	−0.0549
	(0.986)	(0.481)	(0.445)
Gender#Children	2.784**		
	(1.301)		
Other ethnic group (ref.=White)	1.004	0.254	−0.506
	(0.752)	(0.384)	(0.330)
Children#Other ethnic group		1.135**	0.671
		(0.552)	(0.474)
Cohabitation (ref.=no)	−0.692	−0.166	−0.0204
	(0.523)	(0.159)	(0.155)
Physical health (ref.=poor)	0.255	0.150	0.313*
	(0.521)	(0.226)	(0.172)
Industry (ref.=contact-intensive)	0.738	0.988*	0.824*
	(0.612)	(0.541)	(0.483)
Education (ref.=Bachelor's degree and above)	0.933	0.488	0.780**
	(0.580)	(0.409)	(0.387)
Whether born in the UK (ref.=yes)	1.221*	2.529***	1.565***
	(0.718)	(0.254)	(0.222)
Age	0.106	0.840	0.701
	(1.812)	(1.546)	(1.484)
Age_squared	−0.0384	−0.0224	−0.0235
	(0.218)	(0.652)	(0.565)
Urban	−1.303*	−0.468**	−0.281
	(0.705)	(0.220)	(0.228)
Work at home (ref.=never)	−1.084	−0.564	−0.677*
	(0.848)	(0.545)	(0.374)
Household income (ref.=low)	0.151	−0.308	−0.0827
	(0.827)	(0.257)	(0.165)
Occupational class (ref.=managerial, administrative, and technical)	1.676**	0.807***	0.762***
	(0.822)	(0.276)	(0.264)
Baseline employment status (ref.=paid employment)			
Self-employment	2.839***	3.860***	3.794***
	(0.740)	(0.475)	(0.320)

(*continued on next page*)

Table A3 (*continued*)

VARIABLES	(1) Sample (Whites, Black and mixed ethnicities)	(2) Female sample	(3) Male sample
Both paid and self-employment	0.125	1.883***	2.056***
	(1.205)	(0.439)	(0.261)
Observations	9720	4842	4106

Notes: (1) Base category of the dependent variable is paid employment; (2) ref. = Reference category; (3) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; (4) Standard errors in parentheses.

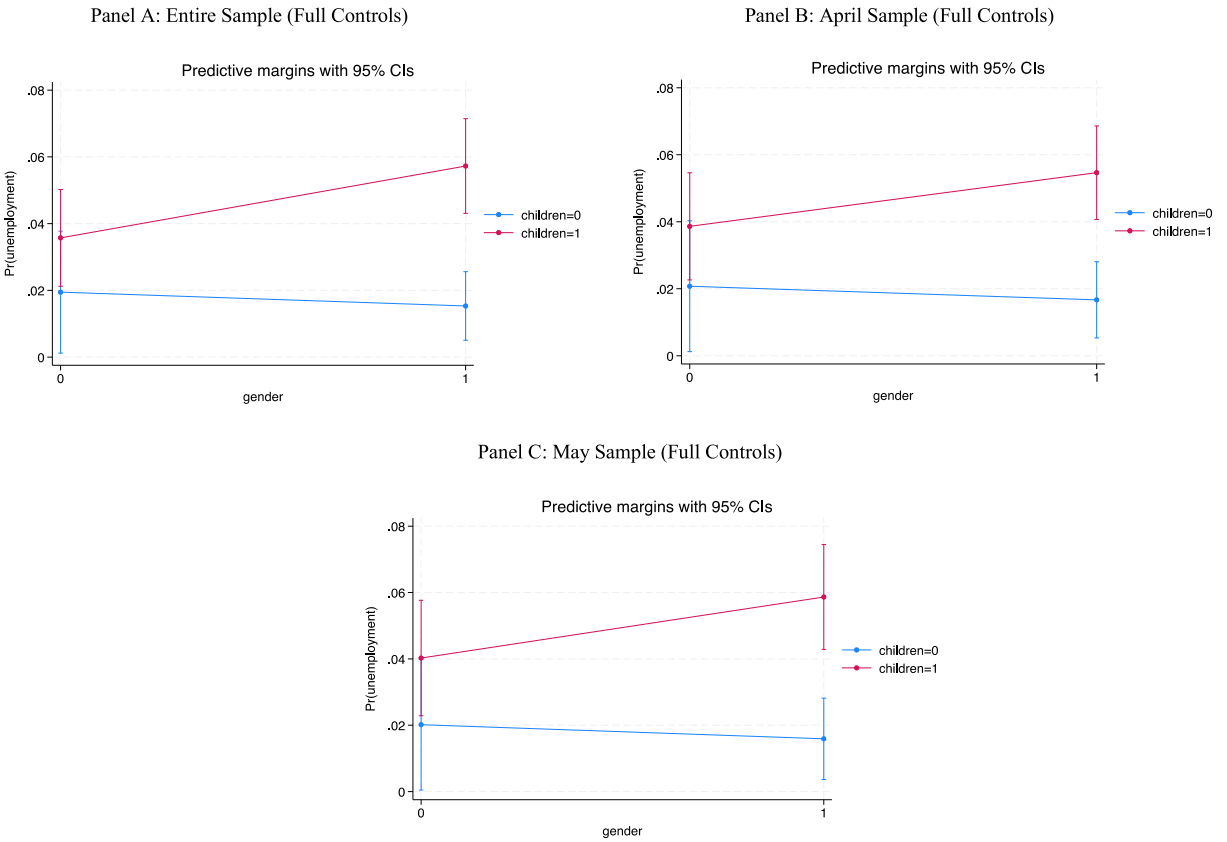

Fig. B1. The relationship between gender and probability of transitioning to unemployment conditional on the presence of school-aged children using binary logit models

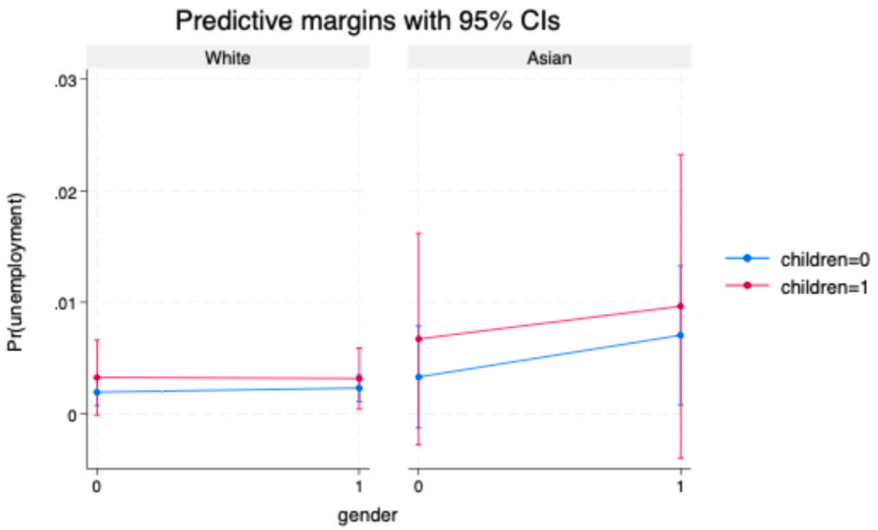

Fig. B2. Testing the discrimination hypothesis

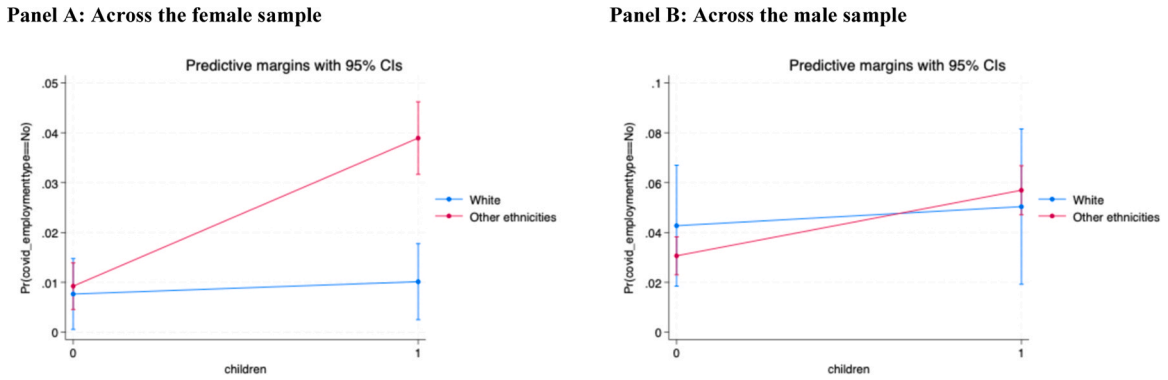

Fig. B3. Predicted probability of employment transition across White and other ethnicities sample

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