UNIVERSITY OF JOHANNESBURG

ECONOMIC DEVELOPMENT AND WELL-BEING RESEARCH GROUP

EDWRG Working Paper Series
February 2023

The role of personal characteristics in shaping gender-biased job losses during the COVID-19 pandemic: The case of South Africa

Working Paper Number 08-23

Lumengo Bonga-Bonga, Thabiso Molemohi and Frederich Kirsten

Cite this paper: Bonga-Bonga, L., Molemohi. T., & Kirsten, F. (2023). The role of personal characteristics in shaping gender-biased job losses during the COVID-19 pandemic: The case of South Africa. EDWRG Working Paper Number 08-23.

The role of personal characteristics in shaping gender-biased job losses during the COVID-19 pandemic: The case of South Africa

LUMENGO BONGA-BONGA
School of Economics and Econometrics, University of Johannesburg.
Email: lbonga@uj.ac.za

THABISO MOLEMOHI
School of Economics and Econometrics, University of Johannesburg.
Email: sirmolemohi@gmail.com

FREDERICH KIRSTEN*
School of Economics and Econometrics, University of Johannesburg.
Email: fkirsten@uj.ac.za

Abstract

The Coronavirus pandemic has caused major economic restrictions and job losses that have disproportionately affected the most vulnerable in society. Studies report that in South Africa females have suffered greater job losses compared to males during the pandemic and while extensive research has been conducted on the gender-biased impact of national restrictions, little is known about how personal characteristics could have further exacerbated gender inequalities. By using the NIDS-CRAM waves and the NIDS Wave 5 dataset this paper estimated the impact personal characteristics like the level of education, age and number of children have had on dissimilar job losses for males and females in South Africa before and during the COVID-19 pandemic. The results confirm the importance of personal characteristics reducing job losses for both males and females in the pre-pandemic and pandemic period. However, the results also confirm that these personal characteristics do have gender-biased impact on job losses during the pre-pandemic and pandemic period. For example, tertiary education was a stronger protector against job losses for females before the covid 19 pandemic. However, during the pandemic education reduces significantly as protector against job losses for females and becomes more relevant for males keeping their jobs. Age remained a strong positive protector against job loss for females compared to males in both periods, while the number of children increased the chances of females losing their job more so than males during the pandemic period. These results provide vital insight into the role of personal characteristics in shaping gender-biased job losses during the pre-pandemic and pandemic periods in South Africa.

Keywords: *COVID-19, Gender inequality, job losses, South Africa, National Income Dynamics Study-Coronavirus Rapid Mobile Survey*

*Corresponding author. School of Economics, University of Johannesburg.
Address: 8 Hercules close,1724, South Africa. Email: fkirsten@uj.ac.za

1. Introduction

With the advent of COVID-19, the global economy was thrown into chaos. In the United States alone, it was estimated that between March 2020 and April 2020, there were 30.3 million initial unemployment claims filed, with the unemployment rate reaching a staggering 16% in May, up from 4.4% in March (Sahin et al., 2020).

Globally, the number of jobs lost because of COVID-19 exceeded those lost during the 2007-2008 recession (Coibion et al., 2020; Nguyen et al., 2021). The most affected segments of the economy were businesses and the labour market, with specific industries, such as Airlines, being more affected than others (Mack et al., 2021). As a result of the pandemic's massive economic and social effects, studies are beginning to unravel the impact of the pandemic to determine its true impact globally. To this effect, a few studies have assessed the unemployment impact of the pandemic on different social groups, like race (Witteveen (2020), different skill levels (Fairlie et al., 2020; The Lancet, 2020) and gender (Montenovo et al., 2022; Albanesi and Kim, 2021).

Concerning gender, Studies show that women were more affected than their male counterparts during the pandemic, as they constitute the majority of the unskilled labour category (see Chitiga et al., 2022). In addition, Adams-Prassl et al. (2020) found that women had a higher probability than men of being jobless or working fewer hours during the early onset of the pandemic in the US, Germany, and the United Kingdom. Gezici and Ozay (2020) employed data from the Current Population Survey (CPS) to estimate the likelihood of joblessness during COVID-19. The authors find that race and gender play a pivotal role in the prospect of being jobless, even when considering the ability to work from home. Specifically, people of colour and women had a higher likelihood of being unemployed, which indicates that discrimination may be responsible for elevated levels of unemployment in these demographic groups.

While these studies emphasise women's awkward position during crisis periods, especially during COVID-19, no study has ever assessed which attributes or personal characteristics of women contributed to the likelihood of unemployment during COVID-19 and whether the contribution of these personal characteristics to the probability of being unemployed varies from normal to crisis periods.

Extant literature focuses on the drivers of women's unemployment in general (see Gobebo et al., 2017; Lazaro et al., 2000). These studies underline the importance of personal characteristics (such as education and age), family background, socio-economic variables (the number of household earners and household income) and the effect of unemployment benefits in driving women's unemployment. On the other hand, studies have assessed the determinants of women's unemployment during crisis periods, such as the COVID-19 crisis. For example, Gezici and Ozay (2020) use the April 2020 Current Population Survey (CPS) micro dataset to assess the racialised and gendered effects of the COVID-19 pandemic on the probability of being unemployed in the US. Reichelt et al. (2021) analyse a representative sample of respondents in the U.S., Germany, and Singapore during COVID-19 to assess whether the pandemic has had an impact beyond the immediate restructuring of employment and shifts in gender-role attitudes within households. The authors show that transitions to unemployment, reductions in working hours and transitions to working from home have been more frequent for women than for men – although not to the same extent across the three countries.

It is worth noting that not only that many studies about the effects of COVID-19 on unemployment have mainly been undertaken in developed economies, but also these studies fail to uncover to what extent women personal characteristics has contributed to the likelihood of unemployment during the pandemic in countries with high socio-economic inequalities, such as South Africa. Thus, this paper contributes to the literature by firstly assessing how women' personal characteristics have contributed to unemployment in a country with large inequality, such as South Africa, during the COVID-19 pandemic. Secondly, the paper will assess whether these personal characteristics of women have contributed differently to unemployment during the different levels of restrictions, namely lockdown restrictions. Thirdly, the paper will evaluate whether the contribution of these personal characteristics to the probability of being unemployed varies from normal to crisis periods.

The findings of this paper will provide insights to policymakers on how to monitor some socio-economic and personal characteristics of women to mitigate their vulnerability to unemployment during normal and crisis periods. This is relevant in a country with high socio-economic inequality and gender-based injustice.

The rest of the paper is divided as follows. Section 2 reviews relevant literatures. Section 3 discusses the methodology used. Section 4 present data and estimate the model and discuss the findings of the paper. Section5 concludes the paper.

2. Methodology

This study employs data from the NIDS-CRAM and NIDS Wave 5 dataset, which uses a panel structure and tracks various responses from the same individuals and households over successive periods. The NID-CRAM data is ideal for measuring the effect of COVID-19 on unemployment since it covers a question that asks whether respondents whether incapable of working due to the pandemic. Some studies that have utilized this dataset to evaluate labour market outcomes include Ranchhod and Daniels (2021) and Bassier et al. (2021). Both the NIDS and NIDS-CRAM datasets include individuals characteristics like gender, age, education, race, household size and the number of children, variables that have been observed to be vital in disseminating employment effects related to COVID-19 (Beland et al., 2020; Borjas and Cassidy, 2020; Fairlie et al., 2020; Montenovo et al., 2022).

The NIDS-CRAM is a nationally representative survey that successfully interviewed around 7000 of the adult NIDS Wave 5 sample. Wave 1 of NIDS-CRAM was conducted with 7073 adults 18 years of age and older selected from the NIDS Wave 5 sampling frame (Kerr et al., 2020). The sample was weighted to guarantee the statistical representation of the model to the population (Kerr et al., 2020). Wave 1 was carried out between May 2020 and June 2020 during level 5 of lockdown restrictions. Wave 2 included 5 676 participants interviewed between 13 July 2020 and 13 August 2020, and this coincided with level 3 lockdown restrictions, which are considered less restrictive. Wave 3 was undertaken between 2 November 2020 and 13 December 2020; South Africa was in level 1 lockdown restrictions, regarded as the least restrictive of all the lockdown levels. In this wave, 5 046 persons were re-interviewed; however, 1 084 people were added because of attrition, topping the initial sample to 6 130. In wave 4, data was recorded between February 2021 and March 2021, with 5 629 individuals interviewed. During that time, the country was in adjusted level 3 lockdown. Lastly for wave 5 data was recorded between April and May 2021 during which South Africa was on an adjusted level 1 lockdown.

3. Descriptive statistics

This section employs three econometric techniques namely: kernel density, Ordinary Least Squares (OLS) and the Blinder-Oaxaca decomposition method. As a first step in understanding our sample, we provide a set of descriptive statistics. In Table 1, we report the descriptive statistics for each wave of the NIDS CRAM and NIDS Wave 5. We report on the percentages of the respondents across gender, race, educational attainment while also reporting the mean age and number of children. The descriptive statistics shows that there might be some discrepancy among the number of females, our variable of interest, in each one of the wave samples. However, these differences are mainly small and due to the non-response of individuals across waves. Interestingly observing the percentage unemployed across waves shows that unemployment has increased significantly from NIDS Wave 5 (24.5%) through to pandemic period. Where the strict lockdowns in the beginning of the pandemic have had the largest impact on unemployment with unemployment rates during NIDS-CRAM Wave 1 and 2 being 48.05% and 46.88% respectively.

TABLE 1: DESCRIPTIVE STATISTICS (MEAN AND PERCENTAGE)

Variables	NIDS W5	NIDS-CRAM W1	NIDS-CRAM W2	NIDS-CRAM W3	NIDS-CRAM W4	NIDS-CRAM W5
Gender						
Female (%)	61.11	61.02	61.24	61.08	61.7	61.65
Male (%)	38.89	38.98	38.76	38.92	38.3	38.35
Employment status						
Employed (%)	75.5	51.95	53.13	59.03	57.99	62.27
Unemployed (%)	24.5	48.05	46.88	40.97	42.01	37.73
Education						
Tertiary education completed (%)	23.54	33.8	33.46	33.09	34.45	35.06
No tertiary education completed (%)	76.46	66.2	66.54	66.91	65.55	64.94
Age (mean)	37.55	40.58	40.85	40.81	41.09	41.28
Number of children (mean)	1.94	2.22	2.27	0.99	0.91	0.9
Race						
African (%)	85.51	85.49	86.06	87.26	86.98	86.52
Coloured (%)	8.81	8.84	8.49	7.67	7.82	8.36
Indian/Asian (%)	1.13	1.09	0.88	0.78	0.76	0.78
White (%)	4.55	4.58	4.56	4.29	4.44	4.33

Notes: Number of children is measured differently in NIDS and NIDS-CRAM surveys. In NIDS the question is used about the number of biological children living with the adult. While for the NIDS-CRAM the question about the number of residents who are under 18 years of age are used for the first two waves of the NIDS-CRAM and the number of residents who are under 7 years of age used for waves three to five. Alternatively, we would like to have had the number of children variable consistent throughout the surveys however this is not the case, and the assessment has been conducted with these heterogenous measures.

To fully understand the difference between job loss before and during the pandemic, a detailed assessment is needed about the unemployment ratios among males and females during these varying time periods. Table 2 below shows the percentage of males and females unemployed in the NIDS Wave 5 sample and the corresponding NIDS-CRAM Waves. The results show a few interesting n patterns. Firstly, the across all the waves the number of females unemployed are high relatively to male unemployment, a statistical finding consistent with literature that focusses on the pandemic period (Casale and Posel, 2021; Ranchhod and Daniels, 2021). Secondly, observing female unemployment over time reports that before the pandemic female unemployment was around 30%, while during the pandemic it averaged around 47% with wave 1 and 2 reporting the highest level of female unemployment. This assessment points to the possibility that job losses were highest among females at the early stages of the pandemic while decreasing as the pandemic went on. Thirdly during the pandemic female unemployment was higher compared to their male counterparts and this holds true for both the pre-pandemic and pandemic stages. However, upon close observation we also estimated a gender unemployment gap, which is simply the difference between female and male unemployment ratios and find that the gap between females and male unemployment has increased during the covid 19 pandemic and confirms that females suffered from greater job losses during the pandemic relative to before the pandemic, compared to males. A pattern consistently found in other studies (Bassier et al. 2021; Casale and Posel, 2021; Ranchhod and Daniels, 2021).

TABLE 2: PERCENTAGE OF UNEMPLOYED FEMALES AND MALES (PRE-PANDEMIC AND PANDEMIC LEVEL)

	NIDS W5	NIDS CRAM W1	NIDS CRAM W2	NIDS CRAM W3	NIDS CRAM W4	NIDS CRAM W5
male	20.01	40.81	40.46	33.37	34.01	31.08
female	30.55	53.25	51.4	46.2	47.48	42.33
gender unemployment gap	10.54	12.44	10.94	12.83	13.47	11.25

The results presented in table 2 prompted a further discussion of the various factors behind the high job loss rate among females before and during a pandemic-level event. As reported in literature personal characteristics like education, age, race and number of children in the household tend to disproportionately influence female unemployment compared to male unemployment. The next section aims to empirically assess the statistical significance of these personal characteristics and determine the level of influence they have on the job loss possibility of females before and during a pandemic-level event, controlled for by race.

4. Empirical results

This paper investigates the impact of affirmative action policies on the gender wage gap in South Africa by making use of the PALMS dataset for the years 1997 and 2015. To evaluate the impact of personal characteristics in driving gender biased job losses during different stages of crisis periods the table below (table 3) reports multivariate logit panel regressions before the Covid 19 pandemic (NIDS wave 5) and during the Covid 19 pandemic (NIDS-CRAM Wave 1 to 5). The results show that for both pre-pandemic and pandemic waves, having tertiary education is a negative regressor for job losses among females. Meaning females who have completed some level of tertiary education had a better chance of keeping their jobs compared to those who have not completed any tertiary education. While the results also show that age is statistically significant negative contributor towards female unemployment. Meaning younger females are more vulnerable towards job losses in both the before and during pandemic stages. Lastly the number of children in a household does not significantly influence job losses before the pandemic, however during the pandemic the number of children significantly and negatively influences job losses for females. At first glance the non-significance before the pandemic might seem peculiar, but caution should be taken to compare the pre-pandemic and pandemic results for number of children, since the variables is measured differently. However, the results still show that during the pandemic the number of children did negatively lead to job losses for females in particular.

To further compare the impact personal characteristic, have on job losses for females, the results need to be compared to males. Using similar logit regression for all the waves the regressions for males and the full sample are included (results in the appendix). These results should provide better insight into the predictive role of personal characteristics furthering the job loss gap between males and females before and during pandemic-level events. The results show that education, age, race and the number of children have similar impacts on the unemployment of both females and males before and during the covid 19 pandemic. However, it does not report on the degree to which personal characteristics have an impact on job losses for males and females. In order to assess the possible varying impact of personal characteristics on gender unemployment the odds ratios are reported in table 4 and 5.

TABLE 3: LOGIT REGRESSIONS PREDICTING THE DETERMINANTS BEHIND JOB LOSSES AMONG FEMALES BEFORE AND DURING THE PANDEMIC

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	NIDS W5	NIDS-CRAM W1	NIDS-CRAM W2	NIDS-CRAM W3	NIDS-CRAM W4	NIDS-CRAM W5
Tertiary education	-0.609***	-0.562***	-0.644***	-0.495***	-0.658***	-0.644***
	(0.131)	(0.0897)	(0.101)	(0.0912)	(0.0985)	(0.0975)
Age	-0.0811***	-0.0431***	-0.0508***	-0.0447***	-0.0414***	-0.0466***
	(0.00755)	(0.00447)	(0.00519)	(0.00451)	(0.00496)	(0.00505)
Number of children	0.0646	0.0620***	0.0833***	0.0693*	0.0722*	0.0898**
	(0.0602)	(0.0224)	(0.0258)	(0.0365)	(0.0413)	(0.0418)
Coloured	-0.554***	-0.863***	-0.825***	-0.682***	-0.746***	-0.676***
	(0.207)	(0.155)	(0.180)	(0.173)	(0.192)	(0.195)
Indian/Asian	-0.305	0.350	-0.541	-0.137	-0.167	-0.455
	(0.669)	(0.417)	(0.563)	(0.474)	(0.550)	(0.613)
White	-1.157*	-0.755***	-0.655**	-0.823***	-1.072***	-0.616*
	(0.619)	(0.247)	(0.293)	(0.316)	(0.348)	(0.318)
Constant	2.161***	1.850***	2.018***	1.602***	1.587***	1.548***
	(0.272)	(0.182)	(0.210)	(0.179)	(0.196)	(0.199)
Observations	1,603	2,417	1,948	2,366	2,011	2,077

Table 4 and 5 presents the odds ratio, which indicates how a change in the unit of one explanatory variable is linked with changes in the likelihood of losing employment during and before the pandemic in relation to the odds of finding employment. The results in table 4, which reports the pre-pandemic results (NIDS Wave 5), shows that personal characteristics like having completed tertiary education and being older have a significantly stronger influence on reducing the chances of females being unemployed compared to males during pre-pandemic. While race is also a stronger predictor of male unemployment compared to females.

Observing the odds ratios during the pandemic using the NID-CRAM Wave 1, table 5 reports that tertiary education is reduced as a protector for females against unemployment. Were the pre-pandemic odds ratio of education was 0.0811, but during the pandemic the odds ratio was 0.0431. Furthermore, having tertiary education protects males more than females from job losses during the pandemic. Observing the impact of age shows that similarly to pre-pandemic levels, age is a greater protector for females against job loss compared to males. While the number of children enhances the probability of females losing their jobs during the pandemic period, more so than males.

Overall, the results confirm the importance of personal characteristics as reducing job losses for both males and females during the pre-pandemic and pandemic period. However, the results also confirm that these personal characteristics do have a gender-biased impact on job losses during the pre-pandemic and pandemic period. Mainly tertiary education was a stronger protector against job loss for females before the covid 19 pandemic. However, during the pandemic education reduces significantly as protector against job losses for females and becomes more relevant for males. Age however remains a strong protector against job loss for females compared to males in both periods and the number of children increases the chances of females losing their job more so than males during the pandemic period.

TABLE 4: ODD RATIOS (NIDS WAVE 5)

	NIDS Wave 5	
VARIABLES	Females	Males
Tertiary education	-0.609***	-0.425***
	(0.131)	(0.146)
Age	-0.0811***	-0.0533***
	(0.00755)	(0.00698)
Number of children	0.0646	
	(0.0602)	
Coloured	-0.554***	-0.585**
	(0.207)	(0.241)
Indian/Asian	-0.305	-0.768
	(0.669)	(0.751)
White	-1.157*	-1.182**
	(0.619)	(0.525)
Constant	2.161***	0.594**
	(0.272)	(0.237)
Observations	1,603	1,754

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 5: ODD RATIOS (NIDS-CRAM WAVE 1)

	(1)	(2)
VARIABLES	Females	Males
Tertiary education	-0.562***	-0.574***
	(0.0897)	(0.116)
Age	-0.0431***	-0.0359***
	(0.00447)	(0.00556)
Number of children	0.0620***	0.0546**
	(0.0224)	(0.0276)
Coloured	-0.863***	-0.640***
	(0.155)	(0.193)
Indian/Asian	0.350	0.160
	(0.417)	(0.503)
White	-0.755***	-1.003***
	(0.247)	(0.329)
Constant	1.850***	1.070***
	(0.182)	(0.204)
Observations	2,417	1,630

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

Understanding the impact of personal characteristics on gender-biased job losses during the Covid-19 pandemic is important for future policies aimed at further reducing gender inequalities in South Africa. Since women were already in a more vulnerable socio-economic position compared to men, before the pandemic; the Covid-19 pandemic has further exacerbated gender inequalities. However, little is still known about the role personal characteristics like education, age and number of children has played in driving gender-biased job losses before and during the pandemic. This study reports that not having tertiary education, being younger and those with more children increases the chances of females losing their jobs, more than males, during the pandemic. Comparing these results with the pre-pandemic levels confirms that education and age have remained vital for female employability even before the pandemic. We suggest policies should take note of these results for future policies and counter pandemic level events that disproportionately cause job losses for females without tertiary education, the youth and those with more children, with measures that protect these vulnerable individuals from economic harm of pandemic level events.

References

Adams-Prassl, A., Boneva, T., Golin, M. & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics,* 189: 104245. https://doi.org/10.1016/j.jpubeco.2020.104245.

Albanesi, S., & Kim, J. (2021). Effects of the COVID-19 Recession on the US Labor Market: Occupation, Family, and Gender. *The Journal of Economic Perspectives*, *35*(3): 3–24. https://www.jstor.org/stable/27041212

Bassier, I., Budlender, J., Zizzamia, R., Leibbrandt, M. & Ranchhod, V. (2021). Locked down and locked out: Repurposing social assistance as emergency relief to informal workers, *World Development*, 139(C): 105271, https://doi.org/10.1016/j.worlddev.2020.105271.

Beland, L. P., Brodeur, A. & Wright, T. (2020). COVID-19, Stay-At-Home Orders, and Employment: Evidence from CPS Data, IZA Discussion Paper, No. 13282.

Borjas, G. J. & Cassidy, H. (2020). The Adverse Effect of the COVID-19 Labor Market Shock on Immigrant Employment. NBER Working Papers 27243, National Bureau of Economic Research, Inc.

Casale, D. & Posel, D. (2021). Gender inequality and the COVID-19 crisis: Evidence from a large national survey during South Africa's lockdown, *Research in Social Stratification and Mobility*, 71: 1000559. https://doi.org/10.1016/j.rssm.2020.100569**.**

Chitiga, M., Henseler, M., Mabugu, R. E. & Maisonnave, H. (2022). How COVID-19 Pandemic Worsens the Economic Situation of Women in South Africa. *The European Journal of Development Research*. 34: 1627–1644. https://doi.org/10.1057/s41287-021-00441-w

Coibion, O & Gorodnichenko, Y. & Weber, M. (2020). Labour Markets During the COVID-19 Crisis: A Preliminary View, NBER Working Papers 27017, National Bureau of Economic Research, Inc.

Fairlie, R. W. Couch, K. & Xu, H. (2020). The Impacts of COVID-19 on Minority Unemployment: First Evidence from April 2020 CPS Microdata. NBER Working Papers 27246, National Bureau of Economic Research, Inc.

Gezici, A. & Ozay, O. (2020). An Intersectional Analysis of COVID-19 Unemployment. *Journal of Economics, Race, and Policy*. **3**: 270–281. https://doi.org/10.1007/s41996-020-00075-w

Gobebo, G., Mulugeta, W. & Yaekob, T. (2017). Determinants of women unemployment: evidence from Ethiopia (case of Halabatown, SNNPR). International Journal of Development Research, 7(11): 16630-16639.

Kerr, A., Ardington, C., Burger, R. (2020). Sample design and weighting in the NIDS-CRAM survey. Cape Town: SALDRU, UCT. (SALDRU Working Paper No. 267).

Lazaro, N., Molto, M. & Sanchez, R. (2000). Unemployment and consumption patterns. *Applied Economics*, 32(3): 367-379, DOI: 10.1080/000368400322796

Mack, E. A., Agrawal, S. & Wang, S. (2021). The impacts of the COVID-19 pandemic on transportation employment: A comparative analysis. *Transportation Research Interdisciplinary Perspectives*, 12, p.100470. doi: 10.1016/j.trip.2021.100470.

Montenovo L, Jiang X, Lozano-Rojas F, Schmutte I, Simon K, Weinberg B. A, & Wing C. (2022). Determinants of Disparities in Early COVID-19 Job Losses. *Demography*, 59(3):827-855. doi: 10.1215/00703370-9961471. PMID: 35583671; PMCID: PMC9177772.

Nguyen, T.D, , Gupta, S., Andersen, M. S., Bento, A. I., Simon, K. I. & Wing, C. (2021). Impacts of state COVID-19 reopening policy on human mobility and mixing behavior. *Southern Economic Journal*. 88(2): 458-486. doi:10.1002/soej.12538.

Ranchhod V. & Daniels, A. R. C. (2021). Labour Market Dynamics in South Africa at the Onset of the Covid-19 Pandemic. *South African Journal of Economics*, 89(1): 44-62. https://doi.org/10.1111/saje.12283

Reichelt, M., Makovi, K. & Sargsyan, A. (2021). The impact of COVID-19 on gender inequality in the labor market and gender-role attitudes. *European Societies*, 23(1): S228-S245. DOI: 10.1080/14616696.2020.1823010
Sahin, A. & Tasci, M. (2020). The Unemployment Cost of COVID-19: How High and How Long?, Economic Commentary, Federal Reserve Bank of Cleveland, vol. 2020(09), May.
The Lancet. (2020). The plight of essential workers during the COVID-19 pandemic. Lancet. 395(10237): 1587. doi: 10.1016/S0140-6736(20)31200-9.
Witteveen, D. (2020). Sociodemographic inequality in exposure to COVID-19-induced economic hardship in the United Kingdom. *Research in Social Stratification and Mobility*. 69:100551. doi: 10.1016/j.rssm.2020.100551.

Appendix A

TABLE A.1: LOGIT REGRESSION PREDICTING UNEMPLOYMENT DETERMINANTS (NIDS WAVE 5)

	(1)	(2)	(3)
VARIABLES	Full sample	Females	Males
Tertiary education	-0.487***	-0.609***	-0.425***
	(0.0868)	(0.131)	(0.146)
Age	-0.0635***	-0.0811***	-0.0533***
	(0.00438)	(0.00755)	(0.00698)
Number of children		0.0646	
		(0.0602)	
Coloured	-0.568***	-0.554***	-0.585**
	(0.145)	(0.207)	(0.241)
Indian/Asian	-0.515	-0.305	-0.768
	(0.423)	(0.669)	(0.751)
White	-1.573***	-1.157*	-1.182**
	(0.372)	(0.619)	(0.525)
Constant	1.331***	2.161***	0.594**
	(0.154)	(0.272)	(0.237)
Observations	3,955	1,603	1,754

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

TABLE A.2: LOGIT REGRESSION PREDICTING UNEMPLOYMENT DETERMINANTS (NIDS CRAM WAVE 1)

	(1)	(2)	(3)
VARIABLES	Full sample	Females	Males
Tertiary education	-0.534***	-0.562***	-0.574***
	(0.0700)	(0.0897)	(0.116)
Age	-0.0376***	-0.0431***	-0.0359***
	(0.00342)	(0.00447)	(0.00556)
Number of children	0.0727***	0.0620***	0.0546**
	(0.0173)	(0.0224)	(0.0276)
Coloured	-0.765***	-0.863***	-0.640***
	(0.120)	(0.155)	(0.193)
Indian/Asian	0.263	0.350	0.160
	(0.316)	(0.417)	(0.503)
White	-0.863***	-0.755***	-1.003***
	(0.194)	(0.247)	(0.329)
Constant	1.403***	1.850***	1.070***
	(0.133)	(0.182)	(0.204)

Observations	4,047	2,417	1,630

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

TABLE A.3: LOGIT REGRESSION PREDICTING UNEMPLOYMENT DETERMINANTS (NIDS CRAM WAVE 2)

	(1)	(2)	(3)
VARIABLES	Full sample	Females	Males
Tertiary education	-0.581***	-0.644***	-0.554***
	(0.0798)	(0.101)	(0.134)
Age	-0.0443***	-0.0508***	-0.0385***
	(0.00400)	(0.00519)	(0.00657)
Number of children	0.0784***	0.0833***	0.0373
	(0.0199)	(0.0258)	(0.0324)
Coloured	-0.808***	-0.825***	-0.848***
	(0.143)	(0.180)	(0.244)
Indian/Asian	-0.765*	-0.541	-0.963
	(0.423)	(0.563)	(0.658)
White	-1.055***	-0.655**	-2.137***
	(0.248)	(0.293)	(0.606)
Constant	1.604***	2.018***	1.208***
	(0.155)	(0.210)	(0.239)
Observations	3,180	1,948	1,232

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

TABLE A.4: LOGIT REGRESSION PREDICTING UNEMPLOYMENT DETERMINANTS (NIDS CRAM WAVE 3)

	(1)	(2)	(3)
VARIABLES	Full sample	Females	Males
Tertiary education	-0.443***	-0.495***	-0.476***
	(0.0719)	(0.0912)	(0.122)
Age	-0.0382***	-0.0447***	-0.0382***
	(0.00346)	(0.00451)	(0.00583)
Number of children	0.111***	0.0693*	0.0845*
	(0.0276)	(0.0365)	(0.0440)
Coloured	-0.658***	-0.682***	-0.725***
	(0.139)	(0.173)	(0.247)

Indian/Asian	-0.241	-0.137	-0.632
	(0.389)	(0.474)	(0.783)
White	-1.189***	-0.823***	-2.243***
	(0.276)	(0.316)	(0.727)
Constant	1.048***	1.602***	0.696***
	(0.130)	(0.179)	(0.202)
Observations	4,040	2,366	1,674

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

TABLE A.5: LOGIT REGRESSION PREDICTING UNEMPLOYMENT DETERMINANTS (NIDS CRAM WAVE 4)

	(1)	(2)	(3)
VARIABLES	Full sample	Females	Males
Tertiary education	-0.538***	-0.658***	-0.477***
	(0.0779)	(0.0985)	(0.133)
Age	-0.0363***	-0.0414***	-0.0381***
	(0.00381)	(0.00496)	(0.00640)
Number of children	0.111***	0.0722*	0.0736
	(0.0324)	(0.0413)	(0.0551)
Coloured	-0.676***	-0.746***	-0.645**
	(0.153)	(0.192)	(0.263)
Indian/Asian	-0.209	-0.167	-0.266
	(0.416)	(0.550)	(0.676)
White	-1.186***	-1.072***	-1.394***
	(0.285)	(0.348)	(0.532)
Constant	1.051***	1.587***	0.715***
	(0.143)	(0.196)	(0.224)
Observations	3,409	2,011	1,398

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

TABLE A.6: LOGIT REGRESSION PREDICTING UNEMPLOYMENT DETERMINANTS (NIDS CRAM WAVE 5)

	(1)	*(2)*	*(3)*
VARIABLES	*Full sample*	*Female*	*Male*
Tertiary education	*-0.556****	*-0.644****	*-0.564****
	(0.0771)	*(0.0975)*	*(0.132)*

Age	*-0.0369****	*-0.0466****	*-0.0328****
	(0.00388)	*(0.00505)*	*(0.00650)*
Number of children	*0.145****	*0.0898***	*0.139***
	(0.0327)	*(0.0418)*	*(0.0550)*
Coloured	*-0.729****	*-0.676****	*-0.839****
	(0.153)	*(0.195)*	*(0.261)*
White	*-0.0225*	*-0.455*	*0.503*
	(0.412)	*(0.613)*	*(0.564)*
Indian/Asian	*-0.802****	*-0.616**	*-1.240***
	(0.265)	*(0.318)*	*(0.532)*
Constant	*0.873****	*1.548****	*0.373**
	(0.144)	*(0.199)*	*(0.225)*
Observations	*3,562*	*2,077*	*1,485*

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*