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**Physical proximity and occupational  
employment change by gender during the  
COVID-19 pandemic**

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**Abstract:** Previous economic downturns such as the 2008–09 Global Financial Crisis disproportionately affected male employment due to greater contractions in industries typically filled by men (e.g., manufacturing). However, after the imposition of the ‘hard’ COVID-19 lockdown between 2020 quarter 1 and 2 in South Africa, both men and women lost about a million jobs. We show a higher ratio of female-to-male job loss in the 2020 recession compared to 2008–09 is partly explained by South African women’s clustering in occupations high in physical proximity (e.g., services). South African labour market data are combined with occupational work context data from O\*NET to show that employment change between 2020 quarter 1 and 2 (but not 2008 and 2009) is well explained by factors specific to COVID-19 social distancing protocols. Occupations higher in physical proximity, difficult to perform from home, or deemed non-essential by government were most likely to shed jobs.

**Key words:** pandemic, COVID-19, occupational sorting, O\*NET, physical proximity, work from home, gender

**JEL classification:** I10, J01, J16, J24

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# 1 Introduction

## 1.1 Background

In the past, depressions and recessions have unintentionally reduced gender inequality in the labour market due to a larger negative effect on male employment (Blau and Kahn 2017). In South Africa, men lost about two times the number of jobs lost by women during the 2008–09 Global Financial Crisis (GFC), reducing the gender gap in probability of employment<sup>1</sup> by about 2 percentage points. The sensitivity of male employment to previous recessions has been partly attributed to gendered sectoral and occupational sorting (Albanesi and Sahin 2018). Male employment is clustered in production sectors such as construction and manufacturing, which are typically sensitive to business cycles, while female employment is clustered in service sectors, which tend to be less cyclical (Albanesi and Sahin 2018; Albanesi and Kim 2021). However, the health nature of the COVID-19 recession and measures taken to curb the pandemic spread have been particularly adverse for service occupations (Mosomi et al. 2020; Lewandowski et al. 2021). This led many researchers to predict a reversal of the gains in gender equality in the labour market (Alon et al. 2020; Beland et al. 2020; Casale and Shepherd 2020; Mosomi et al. 2020; Lewandowski et al. 2021). More than 2 years into living with COVID-19 lockdown policies, these predictions have proven true to some extent. In the US, UK, and Germany, women have lost more jobs than men or they have lost more jobs than might have been expected had the recession been only financial in nature (i.e. without a health risk and social distancing aspect) (Adams-Prassl et al. 2020; Albanesi and Kim 2021). The latter was the case in South Africa, according to national labour market data.

Table 1 compares employment change at the two-digit occupation code level between 2020 Q1 and Q2 and between 2008 and 2009. South Africa went into complete lockdown<sup>2</sup> on 26 March 2020, meaning the break between 2020 Q1 (January–March) and 2020 Q2 (April–June) closely corresponds with a before and after period. The first thing to note about 2020 compared to the GFC is that the scale of job loss was greater. A total of 2.3 million jobs, or 14 per cent of Q1 total employment, was lost. However, job loss was distributed much more evenly across men and women. Men lost 1.2 million jobs between 2020 Q1 and Q2, a 13.3 per cent drop; while women lost 1.1 million jobs, a 14.8 per cent drop. In other words, women lost almost as many jobs as men, with the ratio of the number of women’s jobs lost to men’s being 88 per cent. In contrast, during the GFC, men lost 285,000 jobs between 2008 and 2009, a 3.4 per cent reduction, while women lost 116,000 jobs, a 1.8 per cent reduction. The ratio of women’s to men’s jobs lost was 41 per cent (being 116,000 divided by 285,000). Based only on the precedent of the GFC, the higher ratio of female-to-male job loss in 2020 is unexpected. Not only were more jobs lost in 2020, but some of the occupations experiencing the most job losses were those that were previously protected during typical economic downturns. For example, science technicians expanded over the GFC but contracted in 2020, as did life science and health technicians and, to a lesser extent, personal and protective services. On the other hand, other professionals grew in 2020 but contracted in 2009 (see Section 1.2 for a more in-depth discussion of trends in occupational change).

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<sup>1</sup> In the second quarter of 2008, the gender gap in the employment rate was about 14.5 per cent, and this reduced to about 12.5 per cent in the third quarter of 2009 (own calculations using PALMS v3.3).

<sup>2</sup> This was a ‘hard’ lockdown in the sense that only people working in sectors of the economy deemed essential by the government could leave their homes to work; the rest of the population could work from home if they could.

Table 1: Change in employment at the two-digit occupational level in 2020 and 2008–09 (thousands)

2020	MEN				WOMEN			
	Q1	Q2	Diff.	%	Q1	Q2	Diff.	%
11. Leg. + sen. officials	40.7	39.2	- 1.5	- 3.6	20.9	19.2	- 1.6	- 7.8
12. Corp. man.	627.6	612.1	- 15.5	- 2.5	334.0	341.5	7.5	2.2
13. Man. small enterp.	358.7	268.2	- 90.4	- 25.2	108.0	52.7	- 55.3	- 51.2
21. Science prof.	117.9	156.5	38.5	32.7	29.5	32.2	2.8	9.4
22. Life sci. + health prof.	52.3	49.1	- 3.2	- 6.1	59.9	64.3	4.4	7.3
23. Teaching prof.	114.9	106.3	- 8.6	- 7.5	256.2	257.3	1.1	0.4
24. Other prof.	161.0	206.1	45.1	28.0	170.2	213.9	43.8	25.7
31. Science technic.	237.6	221.8	- 15.8	- 6.6	92.1	67.5	- 24.6	- 26.7
32. Life sci. + health technic.	66.2	53.3	- 13.0	- 19.6	197.6	180.7	- 16.9	- 8.6
33. Teaching assoc. prof.	90.7	86.1	- 4.5	- 5.0	198.8	164.4	- 34.4	- 17.3
34. Other technic.	243.9	214.4	- 29.5	- 12.1	250.0	254.5	4.5	1.8
41. Office clerks	348.9	295.6	- 53.3	- 15.3	753.9	674.1	- 79.8	- 10.6
42. Customer services clerk	129.4	107.0	- 22.4	- 17.3	455.6	403.8	- 51.8	- 11.4
51. Pers. + protec. serv.	1,028.2	918.5	- 109.7	- 10.7	993.5	784.5	- 209.0	- 21.0
52. Salespersons	411.7	364.4	- 47.3	- 11.5	338.9	245.0	- 93.9	- 27.7
61. Skilled agri	40.1	52.4	12.3	30.6	14.5	11.3	- 3.2	- 22.1
62. Subsistence agri	18.5	9.9	- 8.6	- 46.3	5.2	3.5	- 1.7	- 32.9
71. Building trades	865.2	689.4	- 175.7	- 20.3	45.1	24.0	- 21.1	- 46.8
72. Metal, mach. + trades	679.5	534.2	- 145.3	- 21.4	26.0	30.4	4.3	16.7
73. Precision, handcraft, printing trades	56.8	47.7	- 9.2	- 16.1	14.5	3.9	- 10.6	- 73.2
74. Other craft trades	115.5	78.5	- 37.0	- 32.0	155.2	131.3	- 23.9	- 15.4
81. Stationary plant ops	130.7	96.9	- 33.8	- 25.9	21.6	15.9	- 5.7	- 26.5
82. Machine ops + assemblers	194.1	168.3	- 25.8	- 13.3	119.8	99.3	- 20.6	- 17.2
83. Drivers + mobile plant ops	901.3	814.9	- 86.4	- 9.6	32.5	30.9	- 1.7	- 5.2
91. Elementary sales + serv.	743.5	601.0	- 142.6	- 19.2	2,019.2	1,585.6	- 433.6	- 21.5
92. Agricultural labourers	785.8	671.5	- 114.3	- 14.5	270.3	246.6	- 23.8	- 8.8
93. Mining, construc, manu labourers	709.7	573.9	- 135.8	- 19.1	341.1	298.6	- 42.5	- 12.5
<b>TOTAL</b>	<b>9,270.6</b>	<b>8,037.4</b>	<b>- 1,233.2</b>	<b>- 13.3</b>	<b>7,324.0</b>	<b>6,236.8</b>	<b>- 1,087.1</b>	<b>- 14.8</b>
<b>MEN + WOMEN</b>	<b>16,594.6</b>	<b>14,274.3</b>	<b>- 2,320.3</b>	<b>- 14.0</b>				

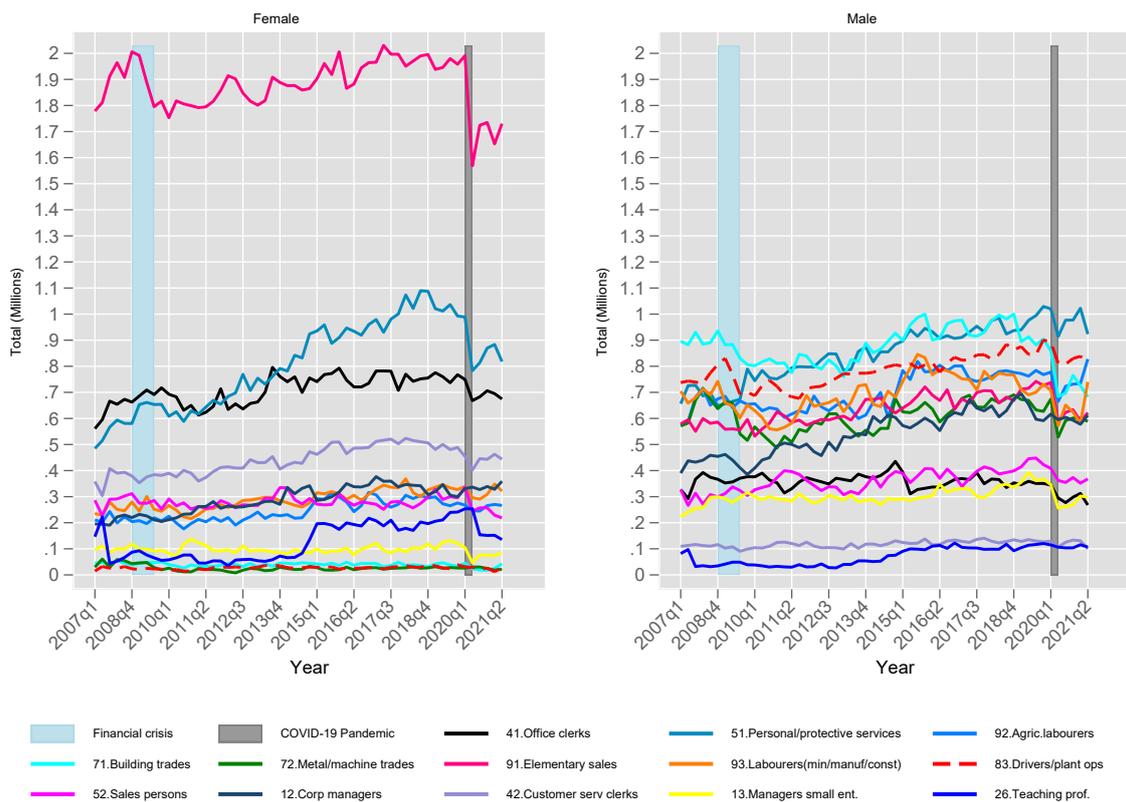
2008–09	2008	2009	Diff.	%	2008	2009	Diff.	%
11. Leg. + sen. officials	46.0	47.7	1.7	3.7	21.1	20.8	- 0.3	- 1.2
12. Corp. man.	452.2	432.2	- 20.1	- 4.4	216.1	221.4	5.3	2.5
13. Man. small enterp.	288.1	306.7	18.6	6.4	104.1	99.1	- 5.0	- 4.8
21. Science prof.	157.9	134.7	- 23.2	- 14.7	35.1	39.7	4.6	13.0
22. Life sci. + health prof.	47.0	39.5	- 7.5	- 15.9	93.8	78.4	- 15.4	- 16.4
23. Teaching prof.	34.2	45.5	11.4	33.2	63.0	73.1	10.1	16.0
24. Other prof.	208.0	195.9	- 12.0	- 5.8	183.2	165.6	- 17.6	- 9.6
31. Science technic.	217.7	252.1	34.4	15.8	53.1	60.9	7.7	14.5
32. Life sci. + health technic.	59.7	62.7	3.1	5.1	175.2	188.1	12.9	7.4
33. Teaching assoc. prof.	154.7	157.7	3.0	1.9	392.5	382.3	- 10.2	- 2.6
34. Other technic.	287.6	290.2	2.5	0.9	269.3	259.3	- 9.9	- 3.7
41. Office clerks	378.2	366.4	- 11.8	- 3.1	667.8	705.4	37.6	5.6
42. Customer services clerk	114.9	101.0	- 13.9	- 12.1	394.0	375.3	- 18.7	- 4.7
51. Pers. + protec. serv.	693.9	700.7	6.7	1.0	585.1	659.9	74.8	12.8
52. Salespersons	301.0	321.8	20.8	6.9	300.3	273.5	- 26.8	- 8.9
61. Skilled agri	77.9	68.4	- 9.5	- 12.2	24.4	15.8	- 8.6	- 35.4
62. Subsistence agri	8.1	7.7	- 0.4	- 5.4	5.7	5.7	0.0	0.2
71. Building trades	917.2	854.6	- 62.6	- 6.8	44.7	47.5	2.7	6.1
72. Metal, mach. + trades	677.5	597.7	- 79.9	- 11.8	46.5	35.3	- 11.1	- 24.0
73. Precision, handcraft, printing trades	67.0	61.3	- 5.7	- 8.5	30.5	19.2	- 11.2	- 36.8
74. Other craft trades	117.9	100.9	- 17.0	- 14.4	182.3	136.4	- 45.9	- 25.2
81. Stationary plant ops	94.2	111.7	17.5	18.5	10.7	11.0	0.4	3.3
82. Machine ops + assemblers	242.9	217.6	- 25.3	- 10.4	145.8	151.0	5.2	3.6
83. Drivers + mobile plant ops	769.0	752.1	- 16.9	- 2.2	26.5	22.7	- 3.8	- 14.3
91. Elementary sales + serv.	585.0	574.7	- 10.2	- 1.8	1,964.1	1,886.2	- 77.9	- 4.0
92. Agricultural labourers	688.9	669.1	- 19.7	- 2.9	218.5	207.9	- 10.6	- 4.9
93. Mining, construc, manu labourers	710.0	641.3	- 68.7	- 9.7	264.7	260.4	- 4.3	- 1.6
<b>TOTAL</b>	<b>8,396.6</b>	<b>8,111.8</b>	<b>- 284.9</b>	<b>- 3.4</b>	<b>6,518.1</b>	<b>6,402.0</b>	<b>- 116.2</b>	<b>- 1.8</b>
<b>MEN + WOMEN</b>	<b>14,914.8</b>	<b>14,513.7</b>	<b>- 401.0</b>	<b>- 2.7</b>				

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data. Adjusted using sampling weights.

## 1.2 Gendered occupational sorting in South Africa

Occupational segregation by gender has been one of the most enduring characteristics of labour markets globally and is cited as an important explanatory variable for the gender wage gap (Bergman 1974; Levanon et al. 2009; Anker 1997; Blau and Kahn 2017; Goldin 2014). In fact, some researchers posit that women are not paid lower wages relative to men for doing the same job, but rather, jobs where women are over-represented tend to be characterized by low wages (England et al. 2002; Budlender 2019). These jobs tend to be mostly in the service sectors and are highly interpersonal in nature. South Africa is no exception, and gender inequality is a structural feature of the South African labour market. In addition, occupational segregation in South Africa is along racial lines (Rospabé 2001; Casale et al. 2021). During the apartheid regime, under the job reservation laws, Black South Africans had restricted access to skilled occupations. Alongside the racial discrimination laws, South Africa is also historically a patriarchal society. Thus, while White women were somewhat advantaged due to apartheid laws, the notion that the place of a woman was in the home meant that White women were encouraged to pursue careers that reflected their role in the home such as nursing and teaching. As shown in Figure A1 in the Appendix, over 80 per cent of employed women in South Africa are employed in four major sectors, namely domestic services, community services, trade, and financial services. What jobs in these sectors have in common is that they are highly interpersonal and require workers to be in close physical proximity with either co-workers or clients.

Figure 1: Trends in total employment by occupation and gender



Source: authors' calculations using PALMS and the QLFSs.

Figure 1 describes the trends in employment of the most significant occupations for male and female employment at the two-digit code level in the South African labour market between 2007 and 2020. The most notable change since 2007 is that employment in personal and protective services has grown for both men and women, although men and women sort further within this occupational code. Women are mainly employed in personal care (e.g., mostly cooks, then childcare workers), whereas about half of

men in this occupation are in protective services not elsewhere classified (e.g., private security guards), followed by police and traffic officers. For men, there has been an expansion in elementary sales and services, while for women, this occupation was just getting back to pre-financial crisis figures before the COVID-19 pandemic hit.

The figure illustrates well how gendered occupational sorting undermined women's employment outcomes in 2020. Women are clustered in four main occupations: elementary sales and services (over 2 million women employed in this occupation in 2020 Q1), personal and protective services (just under a million women employed here in 2020 Q1), and office and customer services clerks. Together, these occupations account for more than 57.6 per cent of female employment (see Table A1 in the Appendix). Domestic workers fall into the elementary sales and services occupations, with half of the women in this occupation code being domestic workers. These occupations all suffered severe job loss between 2020 Q1 and Q2. More importantly for this study, these also happen to be the occupations that cushioned women against job loss in previous recessions. For example, whereas in 2008–09, personal and protective services and office clerks expanded in number, this was not the case in 2020. Also, personal and protective services has become an even more important employer of women, growing by about half a million jobs between 2008 and 2020 and increasing the share of female employment from 9 per cent to 13 per cent (see Table A1 in the Appendix).

In contrast, men are more evenly distributed across different occupations compared to women. For example, men were most highly concentrated in personal and protective services, and this made up 11 per cent of male employment in 2020 Q1 (see Table A1 in the Appendix). Men are also concentrated in building trades, drivers and mobile plant operators, elementary sales and services, agricultural labourers, and mining, construction, and manufacturing labourers. For comparison to the female case, the four largest occupations for men make up only 38.54 per cent of male employment (see Table A1 in the Appendix). Figure 1 shows that the broad-based nature of the 2020 recession meant that men lost jobs in most occupations, most severely in building trades; elementary sales and services; mining, construction, and manufacturing labourers; agricultural labourers; personal and protective services; and drivers and mobile plant operators. Men lost the most jobs in building trades at 175,000; followed by metal, machinery, and trade workers at 145,000; and then elementary sales and services at 142,000. In comparison, women lost 433,000 jobs in elementary sales and services alone, most of them domestic work jobs, and 208,000 jobs in personal and protective services. Women were clustered in a smaller number of sectors that were devastated by lockdown, but men lost smaller, but still considerable, numbers across more occupations. In this paper, we are interested in why women lost relatively more jobs than men in 2020 compared to 2008–09. In particular, we are interested in whether gendered occupational sorting—women clustering in service occupations—set women up to lose more jobs in 2020 compared to the GFC.

### 1.3 The current study

In this study we use South African labour market data to construct three measures to try to explain the different job loss pattern between 2008–09 and 2020 based on how the restrictions of lockdown and social distancing protocols mediated the chance of job loss. We expect jobs that require more physical proximity will be more vulnerable. And, we expect jobs that were classified as essential services or that were possible to carry out remotely from home will be most protected from job loss. Our measure of physical proximity is constructed using O\*NET and merged into South African labour market data, along with classification of essential services from Kerr and Thornton (2020) and self-reported ability to work from home. In this way, we can study how social distancing protocols structured employment change over 2020.

We find that the ability to work from home emerges as the most important protective factor in 2020. However, only a small portion of workers (less than 10 per cent pre-lockdown) are able to work remotely

in South Africa, and this group tends to already be socio-economically advantaged. Work that is more physically proximate or non-essential is found to be more vulnerable to job loss, and the vast majority of women who cannot work from home are significantly more likely than men to be in work that requires more physical proximity or which is deemed non-essential. Women's clustering in high-proximity service occupations like personal and protective services; domestic work; and customer service clerking is then an important explanation for relatively worse female labour market outcomes in 2020 compared to the GFC. These types of occupations together make up almost 60 per cent of female employment, whereas men are much more evenly distributed across different types of occupations.

Our work contributes to several strands of literature. First, rich literature exists on gender inequality and its link to gendered occupational sorting in South Africa (Rospabé 2001; Mosomi 2019; Budlender 2019; Gradín 2021; Casale et al. 2021). Occupation is therefore a critical lens with which to understand gender inequality—and inequality more broadly. There is well-established literature in labour economics using differences in occupations to explain trends in inequality, particularly wage polarization in industrialized countries (Acemoglu and Autor 2011; D. H. Autor and Dorn 2009; Firpo et al. 2011; D. Autor 2014). A key tool in this literature has been to utilize data on occupational tasks or work context, such as the O\*NET data from the U.S. Bureau of Labour Statistics. The expectation that COVID-19 lockdowns and social distancing protocols would have differential impacts on risk of job loss depending on occupation has led to an offshoot of this literature adapting these tools to understand 2020 employment change (Albanesi and Kim 2021; Lewandowski et al. 2021; Mongey et al. 2021). An early example is the study by Dingel and Neiman (2020) who used O\*NET to estimate how many workers could work from home, or telework, in the United States. Kerr and Thornton (2020) adapted this for the South African case before the release of the 2020 labour market data, and we use this measure as an alternative measure of working from home in this paper. Dingel and Neiman (2020) estimated that about 37 per cent of the US workforce could telework, compared to an estimate of 14 per cent for the South African case from Kerr and Thornton (2020).

More recently, Mongey et al. (2021) showed that an O\*NET measure of physical proximity and remote work was correlated with employment change over lockdown in the United States. Mongey et al. (2021) use these measures to identify groups vulnerable to job loss over lockdown, being less educated, lower-earning workers. Women in the United States were found to be concentrated in high physical proximity work, while men were more concentrated in low work-from-home jobs. Interestingly, women are often more likely to be able to work from home in the developing world (although the share of workers who can work from home is much smaller, in general) (Gottlieb et al. 2021). Mongey et al. (2021) also make a comparison to the GFC and similarly conclude that although many COVID-19-impacted workers are usually more economically vulnerable, the COVID-19 pandemic has produced a unique pattern of job loss.

Research in this strand of the literature is expanding quickly, although few studies to our knowledge test these occupational work measures in a developing country setting. Wide variation in the structure of labour markets, as well as the set-up, enforcement, and timeline to COVID-19 vaccine access, mean it is far from obvious that economies in the developing world would react uniformly with the developed. South Africa is classified as an upper-middle-income country by the World Bank and is amongst the most income-unequal countries in the world. Of the 153 countries for which the World Bank has data over the decade 2010–20, South Africa logged the highest Gini coefficient of 63 (World Bank 2022). This intense level of income concentration is primarily owed to a highly exclusive and unequal labour market (Leibbrandt et al. 2012), home to both high levels of unemployment and wage inequality. In the fourth quarter of 2019, the narrow unemployment rate stood at 29.1 per cent (StatsSA 2020), and the wage Gini coefficient has increased since the end of apartheid hovering around 55 by the end of 2010 (Wittenberg 2017).

There are therefore several contributions of our work. First and most substantively, we provide an analysis of how occupational characteristics can help us understand how COVID-19 lockdowns might impact the evolution of gender inequality in the South African labour market based on existing knowledge about occupational sorting. By doing so, we, second, contribute a developing country perspective to the growing literature utilizing occupational measures constructed using O\*NET data to analyse employment change in 2020 from a uniquely unequal setting. Third, we provide an account of the pattern of job loss by occupation and gender for South Africa over the 2020 ‘hard’ lockdown using South Africa’s official labour market data. Heretofore, much labour market research in South Africa has relied on a much smaller telephone survey conducted by a private consortium of researchers called the National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM) (Spaull et al. 2021). The speedier release of NIDS-CRAM meant it provided some of the first vital information about the fall-out of the lockdown to the South African public, available from around June 2020 [see Spaull et al. (2020) for an overview], whilst the official Q2 data from Statistics South Africa (StatsSA) was only released in October 2020. As a result, the lion’s share of South African research about the socio-economic impact of COVID-19 has used NIDS-CRAM, and fewer researchers have engaged with the official data. NIDS-CRAM and the official data have different strengths and weaknesses, and both sources provide important information to learn about what happened in the labour market in 2020 (Daniels et al. 2021). Notably, the level of detailed occupation data required for the analysis in this paper is only available in the national labour market data.

We introduce the South African labour market data in Section 2. Still in Section 2, we discuss how we construct measures of occupational job-loss risk using O\*NET and the South African labour market data. In Section 3 we discuss our analytical strategy, and in Section 4 we answer the question of what employment change might have been in 2020 had the recession been only financial in nature using a simple decomposition. Using the data introduced in Section 2, we first describe the initial distribution of our measures of job loss risk in the labour market prior to lockdown in Section 5.1. Next, we set out to describe what makes 2020 job loss unique. In Sections 5.2 and 6 we show that these measures are able to predict changes in employment in 2020 by presenting plots and running a series of regression models, respectively. We show in Section 6 that these measures distinguish 2020 job loss from GFC job loss: factors specific to lockdown explain 2020 job loss patterns and are not correlated with GFC job loss patterns. Even if some groups of workers who have lost jobs in 2020 are vulnerable anyway, lockdown-specific factors made them more so. We discuss some implications of our findings and conclude in Section 7.

## 2 Data

### 2.1 South African labour market data

We use the five quarters between 2020 Q1 and 2021 Q1 from the Quarterly Labour Force Surveys (QLFS) collected by Statistics South Africa (StatsSA) (StatsSA 2020-1). The QLFS is South Africa’s main source of labour market data. It is a cross-sectional household survey of approximately 30,000 dwelling units based on about 3,000 Primary Sampling Units from the most recent census and uses a two-stage cluster sampling design to be nationally representative. The surveys cover the spectrum from basic demographic to detailed labour market information. Importantly for our purposes, the data include the 2003 South African System of Occupational Classification (SASCO) codes for employed workers at a detailed four-digit level.

Important to know is that the onset of lockdown in South Africa on 26 March 2020 forced changes to the collection of the QLFS. The QLFS changed from what had previously been a survey collected using face-to-face interviews to one using Computer Assisted Telephone Interviewing (CATI). As such, the

sampling design was forced to change from a cross-sectional design with a quarter of the sample being a rotating panel up until 2020 Q1 to a panel of the 2020 Q1 sample that was contactable by telephone from 2020 Q2 onwards. The implications of this structural break in the sampling method is still being investigated.<sup>3</sup> However, the documentation released with the data subsequent to 2020 Q1 describes how StatsSA have adjusted the survey weights to account for this change.

To compare 2020 to the GFC, we utilize a subset of the Post-Apartheid Labour Market Series (PALMS) (Kerr et al. 2019). PALMS v3.3 is a harmonized series of South African labour market surveys for the years 1993–2019 curated by DataFirst at the University of Cape Town. For this analysis we use data for the period 2008–09. Unlike lockdown in 2020, it is much harder to identify the date around which to delineate the before and after period for the GFC. We use 2008 as the before period and 2009 as the after period because 2009 is the first year in which total employment fell. Some analysts also include 2010 in the after period because employment continued to fall [e.g., Verick (2012)]. The original data for these years come from the QLFS. However, the PALMS series offers some advantages over using the QLFS, mainly a survey weight underpinned by a more consistent population model, which is useful for time trend analysis.

## 2.2 Measuring COVID-19 job-loss risk

### *Physical proximity*

The first measure we construct to measure job-loss risk during lockdown is one of occupational physical proximity. We construct this measure using work context data from the Occupation Information Network (O\*NET) Survey conducted by the US Department of Labour. The O\*NET uses standardized surveys of a representative sample of job incumbents drawn from the US Bureau of Labour Statistics (Handel 2016). The O\*NET data collect a wide range of detailed occupational information on topics such as skills, tasks, and work context. The data are collected by surveying job incumbents in different occupations who fill in questionnaires on their level of education and training, knowledge, work activities, work context, and work styles, while a small number of job analysts fill in the questionnaires on skills and abilities according to job descriptions (Handel 2016). Within occupation responses are averaged across respondents (Handel 2016), resulting in a continuous measure between 1 and 5. We use the following question from the O\*NET survey to measure COVID-19 risk:

- To what extent does this job require the worker to perform job tasks in close physical proximity to other people?
  1. I do not work near other people (beyond 100 ft).
  2. I work with others but not closely (e.g., private office).
  3. Slightly close (e.g., shared office).
  4. Moderately close (at arm's length).

---

<sup>3</sup> The QLFS asks a detailed set of questions based on the International Labour Organisation's (ILO) best practise to determine employment status, and people who were on furlough should have been captured as employed according to the questionnaire. More specifically, people who had carried out zero hours of work for pay in the reference period were asked if they had a paid job or business to which they could definitely return. We calculate that about 2 million employed people in the 2020 Q2 QLFS fall into this category. The remainder of the employed answered 'yes' to working at least one hour in the reference period for pay. It is possible respondents answered 'yes' to this question because they were being paid even if it was impossible for them to work. However, it is unclear how furlough or a hiatus in work might have been interpreted by people working in the informal sector, home to the vast majority of the country's domestic workers. Verbal and informal contracts mean that such individuals may have been rightly skeptical of whether the break in work triggered by lockdown necessarily implied a job to return to with the same employer after what at that point was some unspecified amount of time.

## 5. Very close (near touching).

Scores for physical proximity are merged into the QLFS and PALMS data using crosswalks between the US occupational classification system and the International Standard for the Classification of Occupations from 1988 (ISCO-88) on which SASCO is based. We achieve a 94 per cent match between the ISCO data and SASCO. For the remaining 6 per cent we identify what we judge to be appropriate adjacent occupations and allocate the proximity score from adjacent occupations to unmerged occupations. For example, mini-bus taxi drivers are not in the ISCO classification, and we allocate them the same score as bus and tram drivers who are in ISCO. We only make one direct adjustment to the O\*NET scores to account for the South African context—for domestic workers, a very important category of employment in South Africa’s labour market. We allocate domestic workers (ISCO-88 code 9131) a score that is the average of the O\*NET score for domestic workers and childcare workers (ISCO-88 code 5131) in the United States. In South Africa, domestic workers often undertake childcare as part of their duties in addition to cleaning services.

### *Essential worker status*

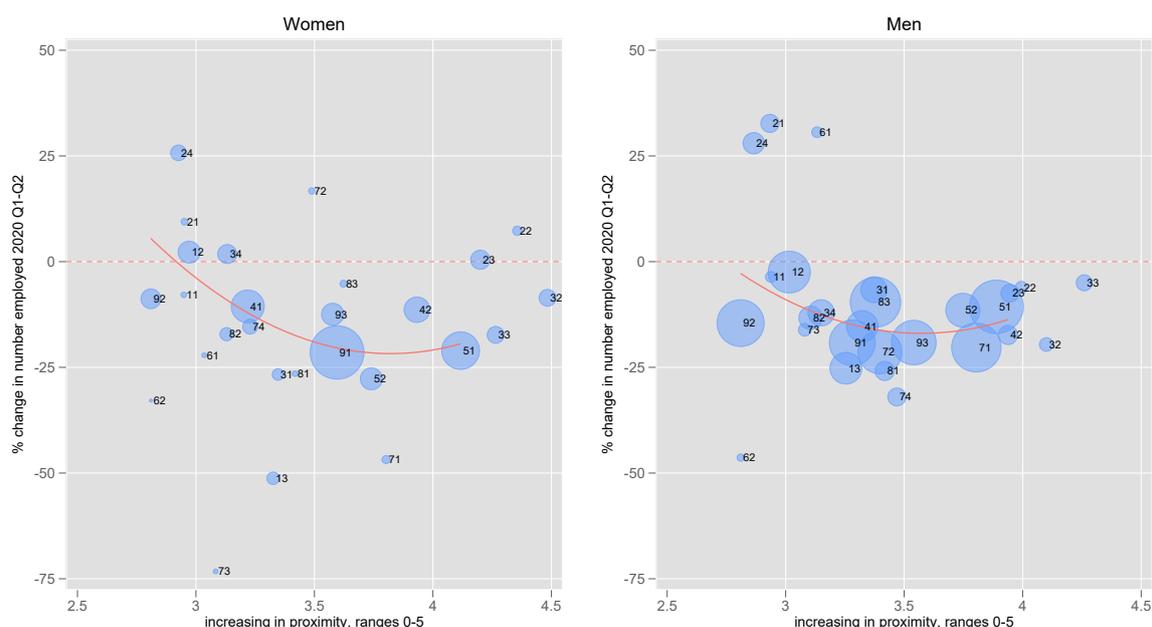
We use an indicator variable for whether a job was classified as an essential service according to Government Gazette Numbers 11062 and 11089 (the update on 16 April 2020) from Kerr and Thornton (2020). The Government Gazettes indicated which sectors of the economy were deemed essential and should continue to operate during the hard lockdown. Kerr and Thornton (2020) use this information to classify the three-digit industry codes in the PALMS data as essential or not. We apply this classification to the QLFS data. Note that this classification applies most readily to the lockdown imposed on 26 March. The South African government created a system of lockdown levels ranging from Level 5 (strictest) to Level 1 (most flexible). The state has adjusted the lockdown level according to the evolution of the COVID-19 viral load in the country. The share of workers who are allowed to go to work varies by lockdown level, with the fewest and only most essential for the operation of the economy allowed in Level 5 and incrementally more until Level 1.

When the pandemic first hit South Africa, the country went into a Level 5 lockdown on 26 March 2020 until 30 April 2020. The lockdown level then incrementally eased up to a Level 4 lockdown (until 31 May 2020), Level 3 lockdown (until 17 August 2020), Level 2 lockdown (until 20 September 2020), and Level 1 lockdown (until 28 December 2020). Owing to a second wave of the virus during the festive season, the country was shifted back into an Adjusted Lockdown Level 3 (until 28 February 2021) and then reverted to an Adjusted Lockdown Level 1 from March 2021. Adjusted lockdown levels are a slightly updated version of the same incremental population lockdown system.

### *Working from home (WFH)*

Our final measure is the share per occupation who can work from home. In 2020 Q2 and Q3 of the QLFS, employed respondents were asked whether they were expected to work during the lockdown and whether they were working from home. This provided some self-reported information about which occupations could be carried out from home in South Africa. However, this is a select sample because the question was only asked of employed people and only after the effect of the hard lockdown had taken place. To parse out the effect of occupational change on this variable, we use the Q2 and Q3 data to measure which occupations at the four-digit level answer that they can work from home. Like with the O\*NET data, we then have an occupational measure of WFH that we merge back into the QLFS Q1 and PALMS data.

Figure 2: Change in occupational employment at the two-digit level between 2020 Q1 and Q2



Note: bubbles weighted by 2020 Q1 employment and numbered with two-digit occupation codes as labelled in Table 1.  
 Source: authors' calculations using QLFS from StatsSA.

The WFH variable in the four-digit level occupational data set is continuous and not a dummy. Multiple people per occupation provide a yes/no answer to whether they are working from home, resulting in an occupational mean. This could be interpreted as a weight or a score of how easily this occupation can be performed remotely. When we aggregate our WFH measure to the two-digit occupational level for our analysis later on, this is the share per occupation who can work from home *weighted* by how many people in that occupation agree they can work from home. As a validation exercise, we plot our WFH variable against our physical proximity variable for 2020 Q1 in Figure 2. As expected, occupations that are high in physical proximity are low in WFH. As a robustness check, we also use a WFH measure created for South Africa using O\*NET by Kerr and Thornton (2020).

### 3 Method

We first run a simple counterfactual exercise to show that different patterns of job loss by occupation contributed to a higher female-to-male job-loss ratio in 2020 compared to the GFC. Having established that this different job-loss pattern is important, we go on to use regression analysis to demonstrate that our measures of job-loss risk are relevant to explaining 2020 job loss but not GFC job loss.

#### 3.1 Simple counterfactual

Since the ratio of female-to-male job loss is so much higher in 2020 compared to the GFC, a question we are interested in is: what might job loss by gender have looked like if the 2020 recession was purely financial in nature? Or, would the distribution of job loss by gender have looked very different if social distancing was not a consideration? To get an initial answer to this question, we treat the GFC as a proxy for job loss during a 'financial-only' recession and apply GFC occupational job-loss rates to the 2020 Q1 labour market. This provides us with simple counterfactual job loss for men and women, from which we can calculate the ratio of female-to-male job loss. Let  $Y_{gt}$  be the total job loss per gender,  $g = men, women$ , in time period,  $t = 2009, 2020$ . Our goal is to calculate  $Y_{women,t}/Y_{men,t}$ , the gender ratio

of job loss.  $Y_{gt}$  can be written as the sum of the job loss per occupation,  $i$ ,  $y_{igt}$ . Occupational job loss is the rate of job loss,  $r_{igt}$ , for that occupation multiplied by the number of jobs in that occupation in the respective before period for each recession,  $n_{igt}$ . Our counterfactual for 2020 job loss,  $Y_{g,2020}^*$ , is then calculated by applying job-loss rates from 2009,  $r_{ig,2009}$ , to the 2020 Q1 labour market structure,  $n_{ig,2020}$ , and can be written as follows:

$$Y_{g,2020}^* = \sum^{ig,2020} y_{ig,2020}^* = \sum^{ig,2020} n_{ig,2020} * r_{ig,2009}$$

### 3.2 Regression

We are interested in how well our measures of job-loss risk explain patterns of job loss over 2020 and 2008–09. To investigate this, we run the following set of models for the 2020 sample and GFC sample separately. Our outcome,  $Y_i$ , is the percentage change in occupational employment at the two-digit occupation code level,  $i$ , between either 2020 Q1 and Q2 or 2008 and 2009. We regress this on a gender dummy,  $f$ , and the baseline (Q1 for 2020; 2008 for the GFC) levels of each job-loss measure: proximity ( $P_i$ ), essential ( $E_i$ ), and WFH ( $WFH_i$ ). In a final specification, we combine all measures at the same time. For each two-digit occupation,  $i$ , we run:

$$Y_i = \beta_0 + f + P_i + i \quad (1)$$

$$Y_i = \beta_0 + f + E_i + i \quad (2)$$

$$Y_i = \beta_0 + f + WFH_i + i \quad (3)$$

$$Y_i = \beta_0 + f + P_i + E_i + WFH_i + i \quad (4)$$

Models 1–4 test the association between our job-loss risk measures in 2020 and 2008–09 separately. In order to assess more carefully the extent to which our job-loss measures predict 2020 job loss, but not GFC job loss, we pool the 2020 and GFC data to compare them directly in a second set of models. For each occupation  $i$  in  $t = 2008/09, 2020$  we run:

$$Y_{it} = \beta_0 + f + T_t + P_i + T_t * P_i + it \quad (5)$$

$$Y_{it} = \beta_0 + f + T_t + E_i + T_t * E_i + it \quad (6)$$

$$Y_{it} = \beta_0 + f + T_t + WFH_i + T_t * WFH_i + it \quad (7)$$

$$Y_{it} = \beta_0 + f + T_t + P_i + T_t * P_i + E_i + T_t * E_i + WFH_i + T_t * WFH_i + it \quad (8)$$

where  $T_t$  is a dummy for the year being 2020.

A final set of regressions explore the explanatory power of the measures over the course of 2020 and the first quarter of 2021. We have five quarters in our data between 2020 Q1 and 2021 Q1. We refer to these as Q1–Q5, for convenience, where Q5 is 2021 Q1. In this specification, we create an outcome variable that is employment change in each quarter relative to 2020 Q1. We have  $q = 2 - 5$ . These outcomes are regressed on the Q1 levels of each job-loss risk measure in the same sequence as models 1–4. For each occupation  $i$  in quarter  $q$ :

$$Y_{iq} = \beta_0 + f + P_{iq} + iq \quad (9)$$

$$Y_{iq} = \beta_0 + f + E_{iq} + iq \quad (10)$$

$$Y_{iq} = \beta_0 + f + WFH_{iq} + iq \quad (11)$$

$$Y_{iq} = \beta_0 + f + P_{iq} + E_{iq} + WFH_{iq} + iq \quad (12)$$

## 4 Employment change during the GFC and COVID-19 recession

A question we are interested in is: what might the ratio of female-to-male job loss have looked like if the 2020 recession was only financial in nature? We report the results for our simple counterfactual exercise in Table 2 with the detailed breakdown by occupation in Appendix Table A5. The main result is in line (a): if South Africans had lost jobs in 2020 according to the same pattern as the 2008 GFC, men would have lost about 229,000 jobs, but women would have approximately broken even with a marginal net job growth of about 1,000 jobs. The main reason for this positive result is personal and protective services (see Appendix Table A5). Because this occupation grew during the GFC *and* the number of women employed in this occupation about doubled between 2008 and 2020, personal and protective services grew by 126,000 female jobs in the counterfactual 2020. The result is that the ratio of female-to-male job loss would have been negative, with men almost exclusively experiencing net job loss. If we omit the out-sized effect of personal and protective services in line (b), men would have lost slightly more jobs at 239,000 jobs and women 125,000. In other words, men would still have done substantially worse with a gender job-loss ratio of 52 per cent—much lower than the observed 2020 result of 88 per cent.

Table 2: Counterfactual 2020 job loss based on GFC pattern of job loss

	Female job loss (thousands)	Male job loss (thousands)	Female-to-male job loss*100
2008–09 observed	- 116.2	- 284.9	40.8
2020 observed	- 1,087.1	- 1,233.2	88.2
(a) 2020 counterfactual	1.1	- 229.9	- 0.5
(b) 2020 counterfactual minus pers. + protec. services	- 125.9	- 239.8	52.5

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data.

This exercise shows that if South Africans had lost jobs in 2020 according to the pattern of the GFC, the distribution of job loss by gender would have looked very different to what it has in reality. Although this is a simple exercise, it provides suggestive evidence that the occupational pattern of job loss in 2020 contributed towards relatively more adverse outcomes for women in 2020 compared to the GFC. This provides motivation to use our measures of occupational job-loss risk to unpack what makes 2020 job-loss patterns unique.

## 5 Physical proximity, WFH, and essential work in the South African labour market

### 5.1 Distribution of job-loss risk in the South African labour market prior to lockdown

Table 3 describes the distribution of our three measures of job-loss risk by two-digit occupation, as well as our robustness measure for WFH (WFH-ONET). The proximity measure is a score increasing in intensity and ranging from 1 to 5. The WFH, WFH-ONET, and essential measures are shares per occupation. Occupations with the highest levels of physical proximity are teachers and life science and health workers. Occupations with the lowest levels are agricultural labourers and other professionals. This corresponds with the WFH measure: occupations with the highest share of WFH are science professionals, other professionals, and legislators and senior officials.<sup>4</sup> The WFH-ONET measure, which was constructed prior to the 2020 QLFS being released, partly agrees with the self-reported WFH. WFH-ONET overestimates the shares of workers in occupations below and including main occupation (one digit)

<sup>4</sup> Subsistence agriculture actually has the highest share of WFH, but this is probably by definition, making it hard to think about subsistence farmers as WFH by our idea of remote work.

code 4 who can work from home and underestimates the shares above and including main occupation code 5.

Large shares of life science and health professionals counted as essential workers, although this was gendered to some extent. For example, many more men in protective sales and services counted as essential compared to women, owing to police being classified as essential service.

Table 4 describes the characteristics of people who can WFH or who work in high-proximity or essential occupations before lockdown. The vast majority of South Africans work in occupations that cannot be performed from home. Only 9.5 per cent of women and 8.3 per cent of men could WFH in 2020 Q1. Within the much larger group in low WFH occupations, women are more likely than men to do jobs that require physical proximity and are less likely to be classified as essential. Of the minority who can WFH, Table 4 shows that there is a severe race dimension. White people are much more likely than other groups to be able to WFH and least likely to work in high proximity jobs if WFH is difficult. Less than 10 per cent of Black African and Coloured workers could WFH, instead being much more likely to work in high-proximity occupations. This bodes poorly for the existing levels of racial inequality in the South African labour market.

WFH has a positive gradient with age and skill—older and more educated people are more likely to be able to WFH. Younger people are more likely to work in high-proximity occupations if they cannot WFH. Similar shares of men and women can WFH. However, women who WFH are more likely to live with young children than men who WFH. Using the self-reported WFH data from 2020 Q2 and Q3, the share of women who WFH who co-resided with young children increased from 31 per cent in Q2 to 35 per cent in Q3. The same figures for men are 29 per cent in Q2 up to 30 per cent in Q3. This means it is not immediately clear that just because a similar share of men and women could WFH in 2020 Q1 that WFH will have an equally protective effect on women's work. Even if women are able to keep their jobs, this scenario could simply mean an increase in women's double burden of work and childcare.

Table 3: Means of occupational measures of job-risk loss in 2020 Q1

Two-digit occupation code	MEN				WOMEN			
	Proximity	WFH	Essential	WFH-ONET	Proximity	WFH	Essential	WFH-ONET
11. Leg. + sen. officials	2.94	34.35	16.57	45.08	2.95	41.58	14.91	68.05
12. Corp. man.	3.02	25.97	22.64	71.18	2.97	26.07	26.70	77.35
13. Man. small enterp.	3.25	15.48	15.58	58.78	3.33	16.56	7.39	60.23
21. Science prof.	2.93	41.18	17.86	89.51	2.95	32.48	41.42	75.38
22. Life sci. + health prof.	3.99	7.48	80.90	2.76	4.36	3.10	83.43	3.04
23. Teaching prof.	3.95	15.45	0.00	27.08	4.20	12.84	0.32	12.21
24. Other prof.	2.87	36.52	19.89	91.93	2.93	35.47	22.45	81.01
31. Science technic.	3.37	9.75	26.56	20.37	3.35	9.58	38.08	13.14
32. Life sci. + health technic.	4.10	20.27	80.98	0.00	4.48	6.85	87.06	2.50
33. Teaching assoc. prof.	4.26	6.74	0.56	0.00	4.26	6.69	0.58	0.00
34. Other technic.	3.15	23.75	28.57	85.06	3.13	24.00	29.63	86.14
41. Office clerks	3.32	10.49	25.02	15.51	3.22	15.55	25.04	29.21
42. Customer services clerk	3.94	7.97	32.68	5.83	3.93	6.83	25.53	5.59
51. Pers. + protec. serv.	3.89	3.62	62.58	0.00	4.12	6.26	28.20	0.00
52. Salespersons	3.75	4.46	41.65	0.00	3.74	4.66	25.77	0.00
61. Skilled agri	3.13	9.76	81.96	0.00	3.03	14.60	79.41	0.00
62. Subsistence agri	2.81	41.87	100.00	0.00	2.81	41.87	100.00	0.00
71. Building trades	3.80	2.27	4.80	0.00	3.80	2.47	17.97	0.00
72. Metal, mach. + trades	3.40	10.57	7.29	0.00	3.49	9.29	27.44	0.00
73. Precision, handicraft, printing trades	3.08	5.07	2.00	0.00	3.08	3.27	39.10	0.00
74. Other craft trades	3.47	9.19	33.79	0.00	3.23	17.36	33.59	0.00
81. Stationary plant ops	3.42	0.47	30.74	0.00	3.42	0.00	47.24	0.00
82. Machine ops + assemblers	3.11	1.44	10.32	0.00	3.13	3.62	11.87	0.00
83. Drivers + mobile plant ops	3.38	0.79	18.33	0.00	3.62	0.73	15.46	0.00
91. Elementary sales + serv.	3.28	8.72	7.54	0.00	3.60	5.40	2.78	0.00
92. Agricultural labourers	2.81	0.57	51.78	0.00	2.81	0.57	81.66	0.00
93. Mining, construc, manu labourers	3.54	0.67	16.20	0.00	3.58	1.00	31.11	0.00
				0.00				0.00
<b>Total</b>	<b>3.42</b>	<b>8.26</b>	<b>26.18</b>	<b>13.80</b>	<b>3.61</b>	<b>9.48</b>	<b>23.13</b>	<b>13.77</b>

Source: authors' calculations using QLFS data. Adjusted using sampling weights.

Table 4: Characteristics of workers by job-loss risk measure in 2020 Q1

	2020 Q1 per cent who can WFH	2020 Q1 per cent who are high prox, low WFH†	2020 Q1 per cent who are essential, low WFH
<b>Female</b>	9.5	45.6	23.2
<b>Male</b>	8.3	40.7	28.9
<b>African</b>	7.2	46.3	18.4
<b>Coloured</b>	7.8	39.3	24.8
<b>Indian</b>	15.9	30.5	10.8
<b>White</b>	17.8	27.3	10.1
<b>15–34 years</b>	7.8	44.0	18.6
<b>35–49 years</b>	8.9	43.6	18.9
<b>50+ years</b>	10.4	39.3	14.2
<b>No schooling</b>	5.6	39.7	22.9
<b>Less than primary</b>	6.1	37.7	18.2
<b>Primary</b>	5.1	39.5	19.8
<b>Less than secondary</b>	5.2	45.0	19.1
<b>Secondary</b>	8.3	45.1	18.1
<b>Tertiary</b>	16.7	38.1	14.9

	For low WFH	
	Men	Women
<b>Mean proximity score</b>	3.50	3.74***

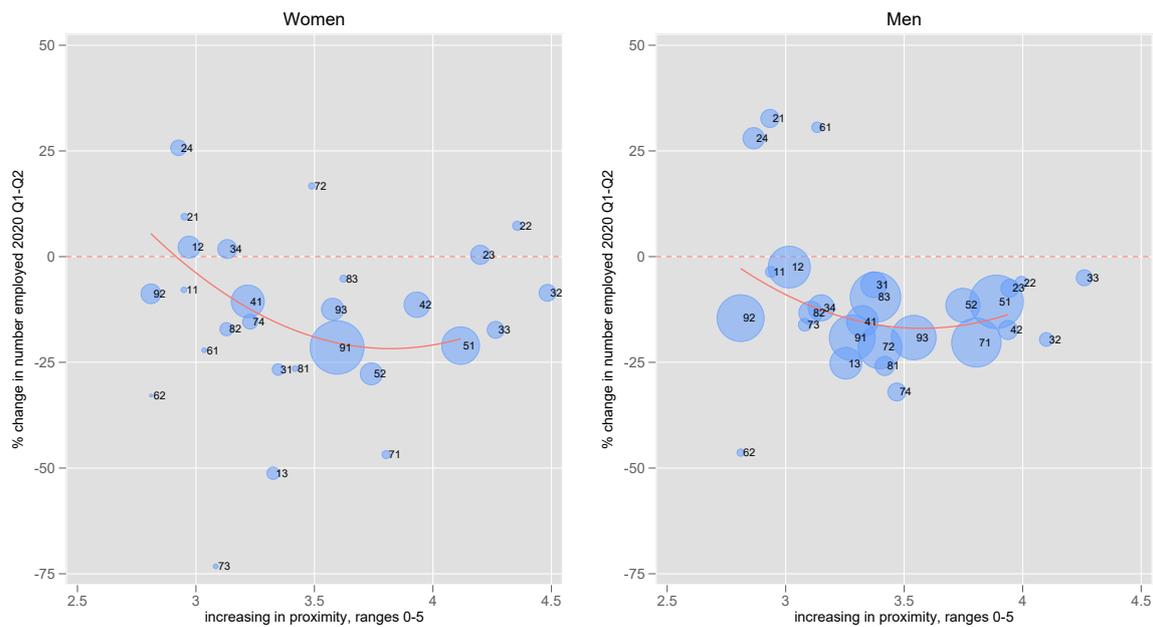
Note: † high proximity is defined as a score of 3.5 or higher (the median of the proximity variable distribution), and low WFH is defined as less than 10% of that occupation say they can WFH. \*\*\*  $p < 0.001$  in a two-sided t-test.

Source: authors' calculations using QLFS 2020 Q1 data and adjusted using sampling weights.

## 5.2 Using job-loss risk measures to describe real lockdown job loss

Figures 3–5 plot our occupational job-loss risk measures against rates of job loss between Q1 and Q2 in 2020, with an employment-weighted regression line overlaid. We find a negative, somewhat quadratic relationship between occupational physical proximity and job loss in Figure 3. More proximate occupations, like personal and protective services (code 51) and domestic workers in elementary sales and services (code 91), lost a greater share of jobs than less proximate occupations, like corporate managers and other professionals (codes 12 and 24, respectively). The relationship is stronger for women than for men. Teaching and life science and health occupations (codes 22, 23, 32, and 33) stand out as outliers in this figure because both occupations are very high in physical proximity and likely to keep their jobs but for different reasons. Life science and health occupations were likely to keep their jobs because there were very high shares of essential workers in these occupations. Teachers were not classified as essential, but many are employed by the public sector, and it was anticipated that children would be returning to school in the short- to medium-term future. Teachers and life science and health occupations are omitted from the estimation of the regression line.

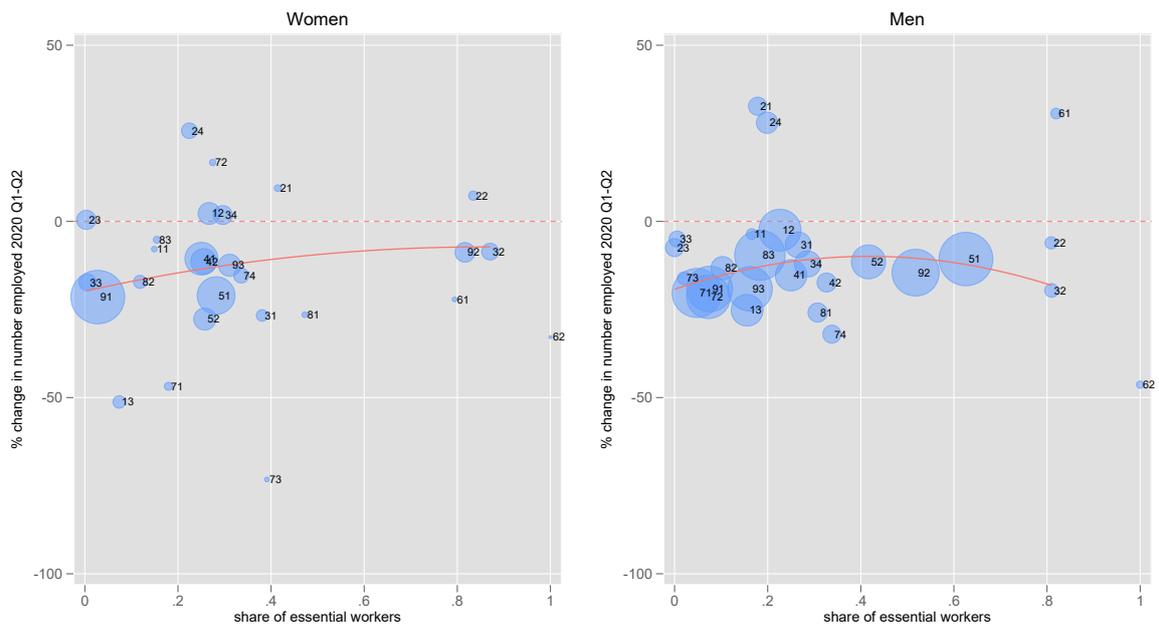
Figure 3: Correlation between employment change and occupational physical proximity between 2020 Q1 and Q2



Note: bubbles weighted by 2020 Q1 employment and numbered with two-digit occupation codes as labelled in Table 1.  
 Source: authors' calculations using QLFS from StatsSA.

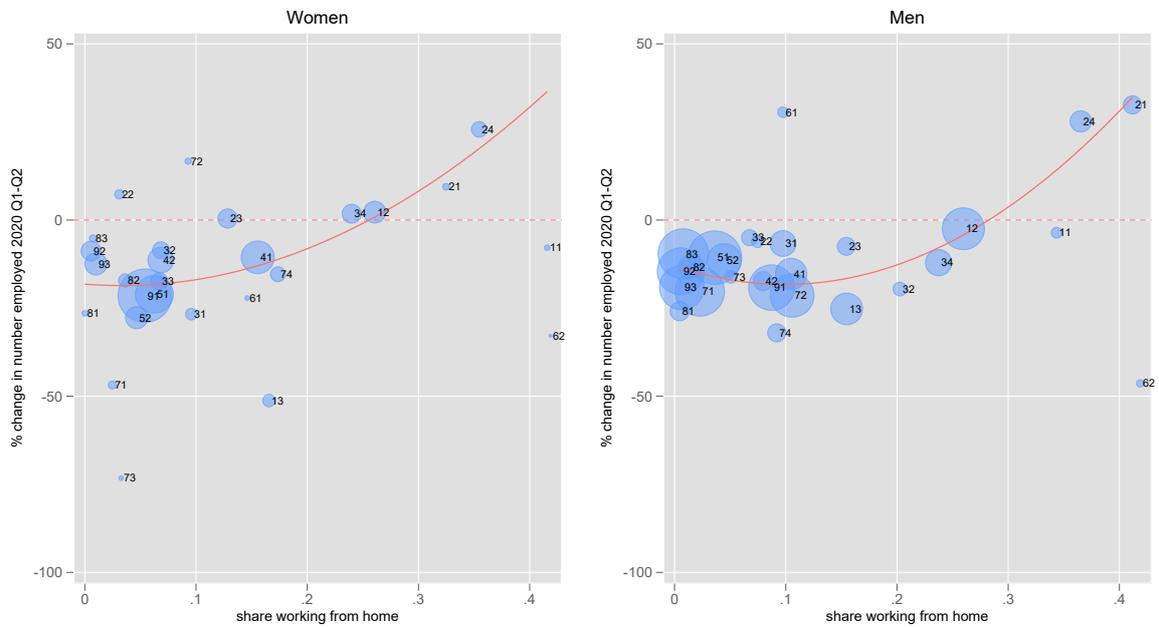
There is a positive relationship between the occupational share of essential workers and job loss for women in Figure 4. Male occupations follow a more quadratic pattern owing to male life science and health technicians (code 32) suffering substantial job loss despite a high share of essential workers in this occupation. Within life science and health technicians, about one-third of men are nurses and another third are traditional medical practitioners, the latter of whom would have struggled to work during the hard lockdown. By contrast, two-thirds of women in this occupational category are nurses who were classified as essential. The regression for essential worker status and occupational job loss omits skilled agricultural and subsistence farmers because the distinction between home and workplace is blurred for these occupations. We also make this omission when assessing the relationship between WFH ability and job loss in Figure 5. In this case, there is a very strong positive relationship between these variables for both men and women. Occupations that are impossible (e.g., mining, construction, and manufacturing labourers) or very difficult (e.g., personal and protective services) to do from home lost more jobs than those with WFH ability, like science and other professionals.

Figure 4: Correlation between employment change and occupational share of essential workers between 2020 Q1 and Q2



Note: bubbles weighted by 2020 Q1 employment and numbered with two-digit occupation codes as labelled in Table 1.  
 Source: authors' calculations using QLFS from StatsSA.

Figure 5: Correlation between employment change and occupational share who can work from home between 2020 Q1 and Q2



Note: bubbles weighted by 2020 Q1 employment and numbered with two-digit occupation codes as labelled in Table 1.  
 Source: authors' calculations using QLFS from StatsSA.

## 6 Regression model of lockdown job loss

### 6.1 Regression results

Table 5 presents the results of specifications 1–4 for 2020 and the GFC separately. WFH emerges as the most important covariate of job loss in 2020. A percentage point increase in the share of an occupation who can WFH increases employment by almost 70 percentage points. This result holds when controlling for other explanations of job loss in specification 5. Using our alternative O\*NET measure of WFH yields a similarly strong result in Appendix Table A2. Physical proximity also emerges as an important explanation for the pattern of job loss in 2020. A one-unit increase in an occupation’s physical proximity score is associated with a 12.62 percentage point contraction in employment in 2020; however, physical proximity loses significance when included in the full specification 4, likely because it is closely correlated with WFH. Interestingly, essential worker status is not significant on its own in specification 3 but becomes significant at the 5 per cent level in specification 4. A percentage point increase in the share of essential workers in an occupation increases employment change by 14 percentage points.

Table 5 also shows that none of these explanatory variables have any statistical significance for explaining employment change between 2008 and 2009. The pooled regression results in Table 6 more precisely compare patterns of job change in 2020 and the GFC and echo the results from Table 5. These results confirm that lockdown-specific factors are only relevant in 2020. The variables that emerge as important in Table 6 are the same as in Table 5: WFH is most preeminent, followed by proximity. However, when included in the full specification in model 8, physical proximity again loses significance likely because of its correlation with WFH. The strength of the WFH result is again resilient to a robustness check using the O\*NET measure in Appendix Table A3.

Table 5: Regression output for the correlation between lockdown job-loss risk measures and employment change in 2020 and 2008–09

Spec.:	2020 Q1 vs Q2				2008 vs 2009			
	1	2	3	4	1	2	3	4
<b>Female</b>	-0.59 (3.22)	-1.02 (3.14)	-2.33 (2.58)	-1.81 (2.64)	1.31 (2.42)	1.68 (2.24)	1.60 (2.32)	0.98 (2.33)
<b>Proximity</b>	-12.62** (4.44)			-0.73 (3.56)	2.78 (3.32)			3.25 (3.16)
<b>Essential</b>		11.66 (7.62)		13.87* (6.04)		6.87 (5.82)		5.54 (5.64)
<b>WFH</b>			74.71*** (14.64)	72.40*** (15.73)			-0.75 (11.71)	4.54 (13.56)
<b>_Cons</b>	29.39 (15.20)	-16.42*** (2.86)	-19.54*** (2.09)	-20.39 (13.04)	-13.00 (11.29)	-4.85* (2.04)	-3.13 (1.77)	-16.16 (11.53)
<b>N</b>	<b>46.00</b>	<b>50.00</b>	<b>50.00</b>	<b>54.00</b>	<b>46.00</b>	<b>50.00</b>	<b>50.00</b>	<b>54.00</b>

Note: standard errors in parentheses. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Regressions are weighted by employment in the before period (2008 for the GFC and Q1 for 2020). Specifications 1 and 2 omit life science and health occupations (codes 22 and 32) and teaching occupations (codes 23 and 33). Specifications 3 and 4 omit skilled agriculture and subsistence agriculture (codes 61 and 62).

Source: authors’ calculations using a combination of QLFS and PALMS v3.3 data.

Table 6: Regression output for pooled regression model of job-loss risk during the GFC and 2020

Model	5	6	7	8
<b>Female</b>	0.89 (1.84)	1.09 (1.73)	0.33 (1.70)	0.23 (1.70)
<b>Year == 2020</b>	43.31* (20.76)	-12.88*** (3.24)	-17.62*** (2.82)	-0.28 (19.65)
<b>Proximity</b>	2.90 (2.85)			3.82 (2.53)
<b>Proximity x 2020</b>	-15.90** (5.99)			-5.32 (5.25)
<b>Essential</b>		6.81 (5.10)		5.47 (4.64)
<b>Essential x 2020</b>		5.25 (10.35)		8.71 (9.42)
<b>WFH</b>			0.57 (9.67)	8.70 (11.20)
<b>WFH x 2020</b>			63.92** (20.90)	61.59* (23.77)
<b>_Cons</b>	-13.24 (9.74)	-4.57** (1.74)	-2.70 (1.43)	-18.19 (9.29)
<b>N</b>	92.00	100.00	100.00	108.00

Note: standard errors in parentheses. \* p<0.05, \*\* p<0.01, \*\*\* p<0.001. Regressions are weighted by employment in the before period (2008 for the GFC and Q1 for 2020). Specifications 1 and 2 omit life science and health occupations (codes 22 and 32) and teaching occupations (codes 23 and 33). Specifications 3 and 4 omit skilled agriculture and subsistence agriculture (codes 61 and 62).

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data.

Finally, Table 7 compares the explanatory power of our job-loss risk measures across the duration of the lockdown until 2020 Q1 (which we term Q5 here for convenience). The strictness of lockdown levels fluctuated over the period of study. Lockdown levels sometimes changed partway through a quarter but always in the same direction of easing up until Q5. Lockdown was strictest in Q2 (Level 5 and then down to Level 4) and then eased down over the course of Q3 (Level 3 and then down to Level 2 and briefly Level 1) and Q4 (Level 1). Quarter 5 was ramped up to Adjusted Lockdown Level 3 from the beginning of 2021 until 28 February 2021 and then eased down to Adjusted Level 1 for the remaining month of that quarter. Many of the coefficients in Table 6 reflect this downward trajectory across Q2–Q4 and then the uptick in Q5.

The protective power of WFH wanes only slightly over the period, from a coefficient size of 74.71 in Q2 to 52.17 in Q5 (2021 Q1). The importance of the coefficient dips the most in Q4, when the lockdown level was at its laxest. This result is confirmed again using the O\*NET measure in Appendix Table A4. Essential work is protective in Q2 and Q5 in specification 12 but is not significant in between. In specification 9, the vulnerability associated with more physically proximate work is most severe in Q2 but weakens over time. By Q4 and Q5, it is no longer an important explanatory factor. As was the case with the previous regression output, physical proximity is outweighed by WFH and essential work in the full specification 12.

Table 7: Regression output comparing lockdown job-loss risk measures across the duration of the lockdown in 2020 and into 2021

Spec:	Dep var:	% jobs lost between			
		Q2 vs Q1	Q3 vs Q1	Q4 vs Q1	Q5 vs Q1
9	<b>Female</b>	-0.59 (3.22)	-0.51 (3.39)	0.31 (2.89)	0.73 (3.40)
	<b>Proximity</b>	-12.62** (4.44)	-9.92* (4.68)	-7.53 (3.98)	-8.97 (4.68)
	<b>_Cons</b>	29.39 (15.20)	23.71 (16.02)	16.87 (13.66)	21.26 (16.04)
	<b>N</b>	<b>46.00</b>	<b>46.00</b>	<b>46.00</b>	<b>46.00</b>
10	<b>Female</b>	-1.02 (3.14)	-1.70 (3.69)	-0.29 (3.29)	0.44 (3.80)
	<b>Essential</b>	11.66 (7.62)	9.12 (8.98)	9.52 (7.99)	17.47 (9.22)
	<b>_Cons</b>	-16.42*** (2.86)	-11.86*** (3.36)	-10.98*** (2.99)	-13.25*** (3.46)
	<b>N</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>
11	<b>Female</b>	-2.33 (2.58)	-2.73 (3.42)	-1.10 (3.17)	-0.78 (3.70)
	<b>WFH</b>	74.71*** (14.64)	58.57** (19.42)	40.27* (18.02)	52.17* (21.04)
	<b>_Cons</b>	-19.54*** (2.09)	-14.31*** (2.77)	-11.83*** (2.57)	-13.03*** (3.00)
	<b>N</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>
12	<b>Female</b>	-1.18 (2.67)	-1.64 (3.52)	-0.29 (3.34)	-0.15 (3.60)
	<b>Proximity</b>	0.45 (3.79)	0.06 (5.00)	-0.07 (4.75)	2.74 (5.11)
	<b>WFH</b>	23.48*** (5.46)	17.14* (7.19)	12.13 (6.83)	19.81** (7.36)
	<b>Essential</b>	12.88* (6.14)	8.99 (8.10)	10.95 (7.68)	17.43* (8.28)
	<b>_Cons</b>	-21.45 (13.59)	-14.49 (17.92)	-12.67 (17.00)	-25.35 (18.33)
	<b>N</b>	<b>54.00</b>	<b>54.00</b>	<b>54.00</b>	<b>54.00</b>

Note: standard errors in parentheses. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Regressions are weighted by employment in the before period. Specifications 1 and 2 omit life science and health occupations (codes 22 and 32) and teaching occupations (codes 23 and 33). Specifications 3 and 4 omit skilled agriculture and subsistence agriculture (codes 61 and 62).

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data.

## 7 Conclusion

Previous economic downturns have tended to hurt male employment more than female partly because industries that employ relatively more men, like manufacturing, contract more. For example, the 2008–09 GFC hit the manufacturing sector hard and women only lost 40 per cent of the jobs that men lost. The 2020 recession triggered by the COVID-19 pandemic and associated population lockdowns presented differently. Services was one of the sectors most hard hit, and women lost 88 per cent of the jobs that men lost, meaning men and women lost almost the same number of jobs. We show that, had job-loss patterns in 2020 been what they were in the 2008 GFC, female net job change would have roughly broken even while men would still have suffered considerable job loss. Factors specific to the 2020 recession then explain this relatively worse performance by women. Our analysis shows that occupational measures of the ability to work from home, and to a lesser extent the degree of physical proximity required by one's job, and essential worker status explain patterns of 2020 job loss. The same factors were not relevant for explaining job loss during the GFC.

When these explanations are compared to the distribution of men and women across occupations in the economy, we arrive at an understanding of why women have done relatively worse in 2020 than they might have under a purely financial recession, like the GFC. Although working from home was the most protective job trait, only a small share (about 8 per cent) of the employed in 2020 Q1 could work from home. For the vast majority of workers facing the imposition of national lockdown on 26 March 2020, women were significantly more likely to be working in jobs that required more physical proximity. Women are also clustered in few occupations, whereas men are more evenly distributed across different types of occupations. And, the occupations women are mainly clustered in are those that require high levels of physical proximity. These job traits made their jobs relatively more vulnerable given the imposition of social distancing protocols. Women who could not work from home were also less likely to be classified as essential workers.

Similar shares of men and women represent the small group of workers who could work from home. However, we caution that other research has shown that working women, more than working men, have upped their hours of childcare in the wake of school and ECD closures. Even if women are hanging onto their jobs by working from home, they may be working fewer hours of labour in total when household production is considered.

## References

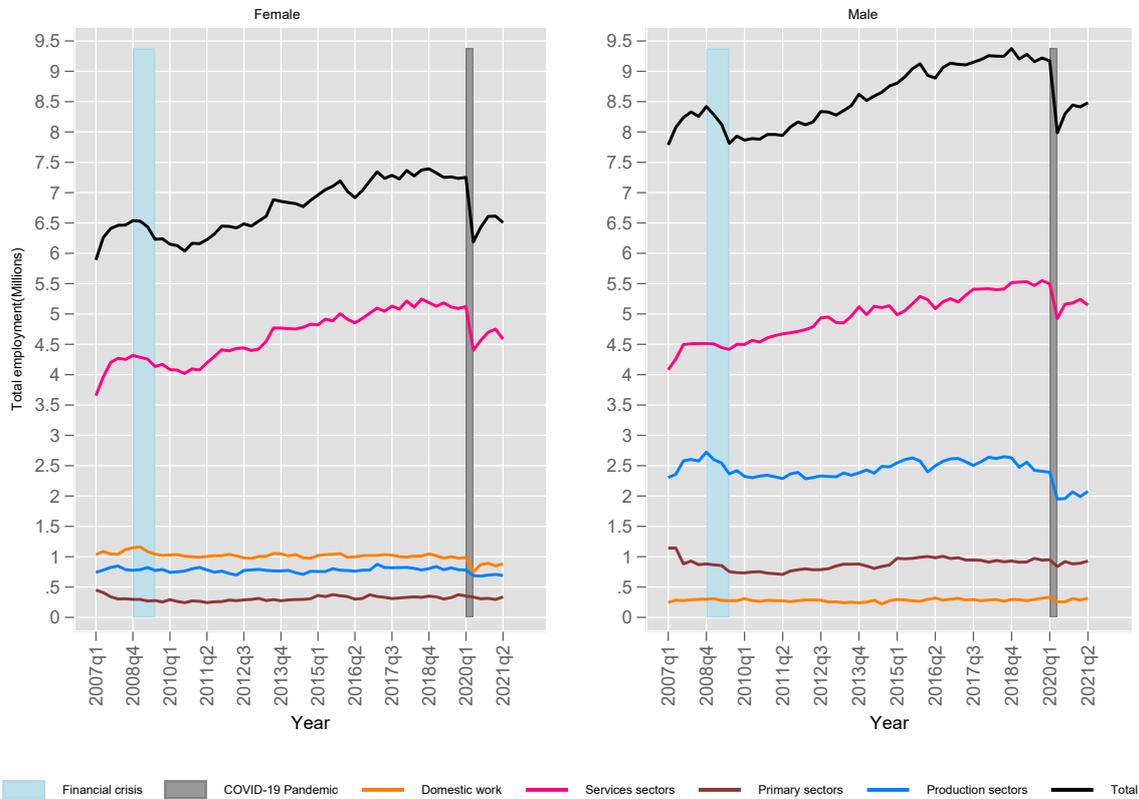
- Acemoglu, D., and Autor, D. (2011). 'Skills, Tasks and Technologies: Implications for Employment and Earnings'. In *Handbook of Labor Economics* (Vol. 4, pp. 1043–171). Amsterdam: Elsevier. <https://doi.org/10.3386/w16082>
- Adams-Prassl, A., Boneva, T., Golin, M., and Rauh, C. (2020). 'Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys'. *Journal of Public Economics*, 189(-): 104245.
- Albanesi, S., and Kim, J. (2021). 'Effects of the COVID-19 Recession on the US Labor Market: Occupation, Family, and Gender'. *Journal of Economic Perspectives*, 35(3): 3–24. <https://doi.org/10.3386/w28505>
- Albanesi, S., and Sahin, A. (2018). 'The Gender Unemployment Gap'. *Review of Economic Dynamics*, 30(-): 47–67. <https://doi.org/10.1016/j.red.2017.12.005>
- Alon, T. M., Doepke, M., Olmstead-Rumsey, J., and Tertilt, M. (2020). 'The Impact of COVID-19 on Gender Equality'. Tech. Rep.. Cambridge, MA: National Bureau of Economic Research. <https://doi.org/10.3386/w26947>
- Anker, R. (1997). 'Theories of Occupational Segregation by Sex: An Overview'. *International Labour Review*, 136(-): 315.
- Autor, D. (2014). 'Polanyi's Paradox and the Shape of Employment Growth'. 20485. Cambridge, MA: National Bureau of Economic Research. <https://doi.org/10.3386/w20485>

- Autor, D. H., and Dorn, D. (2009). 'Inequality and Specialization: the Growth of Low-Skill Service Jobs in the United States'. NBER Working Paper 15150. Cambridge, MA: NBER. <https://doi.org/10.2139/ssrn.1434624>
- Beland, L.-P., Brodeur, A., and Wright, T. (2020). 'COVID-19, Stay-at-Home Orders and Employment: Evidence from CPS Data'. Tech. Rep.. IZA Discussion Paper. <https://doi.org/10.2139/ssrn.3608531>
- Bergman, B. (1974). 'Occupational Segregation, Wages and Profits When Employers Discriminate by Race and Sex'. *Eastern Economic Journal*, 1(1–2): 103–10.
- Blau, F. D., and Kahn, L. M. (2017). 'The Gender Wage Gap: Extent, Trends, and Explanations'. *Journal of Economic Literature*, 55(3): 789–865. <https://doi.org/10.3386/w21913>
- Budlender, D. (2019). 'Unresolved Issues: Equal Pay for Work of Equal Value'. *Agenda*, 33(4): 62–6. <https://doi.org/10.1080/10130950.2019.1676164>
- Casale, D., Posel, D., and Mosomi, J. (2021). 'Gender and Work in South Africa'. In A. Oqubay, F. Tregenna, and I. Valodia (eds), *The Oxford Handbook of the South African Economy*. Oxford: Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780192894199.013.32>
- Casale, D., and Shepherd, D. (2020). 'The Gendered Effects of the Ongoing Lockdown and School Closures in South Africa: Evidence from NIDS-CRAM Waves 1 and 2'. Tech. Rep.. NIDS-CRAM Policy Paper.
- Daniels, R. C., Ingle, K., and Brophy, T. (2021). 'Employment Uncertainty in the Era of COVID-19: Evidence from NIDS-CRAM and the QLFS'. Southern African Labour and Development Research Unit (SALDRU) Working Paper No. 282. Cape Town: University of Cape Town. <https://doi.org/10.1080/0376835X.2022.2089635>
- Dingel, J. I., and Neiman, B. (2020). 'How Many Jobs Can be Done at Home?' *Journal of Public Economics*, 189(-): 104235. <https://doi.org/10.1016/j.jpubeco.2020.104235>
- England, P., Budig, M., and Folbre, N. (2002). 'Wages of Virtue: The Relative Pay of Care Work'. *Social Problems*, 49(4): 455–73. <https://doi.org/10.1525/sp.2002.49.4.455>
- Firpo, S., Fortin, N. M., and Lemieux, T. (2011). 'Occupational Tasks and Changes in the Wage Structure'. Tech. Rep.. <https://doi.org/10.2139/ssrn.1778886>
- Goldin, C. (2014). 'A Grand Gender Convergence: Its Last Chapter'. *American Economic Review*, 104(4): 1091–119. <https://doi.org/10.1257/aer.104.4.1091>
- Gottlieb, C., Grobovšek, J., Poschke, M., and Saltiel, F. (2021). 'Working from Home in Developing Countries'. *European Economic Review*, 133(-): 103679. <https://doi.org/10.2139/ssrn.3699854>
- Gradiń, C. (2021). 'Occupational Gender Segregation in Post-Apartheid South Africa'. *Feminist Economics*, 27(3): 102–33.
- Handel, M. J. (2016). 'The O\* NET Content Model: Strengths and Limitations'. *Journal for Labour Market Research*, 49(2): 157–76. <https://doi.org/10.1007/s12651-016-0199-8>
- Kerr, A., Lam, D., and Wittenberg, M. (2019). *Post-Apartheid Labour Market Series: 1993–2019 [Dataset]*. University of Cape Town: DataFirst [producer and distributor]. (Version 3.3)
- Kerr, A., and Thornton, A. (2020). 'Essential Workers, Working from Home and Job Loss Vulnerability in South Africa'. Technical Paper No. 41. Cape Town: DataFirst.
- Leibbrandt, M., Finn, A., and Woolard, I. (2012). 'Describing and Decomposing Post-Apartheid Income Inequality in South Africa'. *Development Southern Africa*, 29(1): 19–34. <https://doi.org/10.1080/0376835X.2012.645639>
- Levanon, A., England, P., and Allison, P. (2009). 'Occupational Feminization and Pay: Assessing Causal Dynamics Using 1950–2000 US Census Data'. *Social Forces*, 88(2): 865–91.
- Lewandowski, P., Lipowska, K., and Magda, I. (2021). 'The Gender Dimension of Occupational Exposure to Contagion in Europe'. *Feminist Economics*, 27(1–2): 48–65. <https://doi.org/10.2139/ssrn.3627036>
- Mongey, S., Pilossoph, L., and Weinberg, A. (2021). 'Which Workers Bear the Burden of Social Distancing?' *The Journal of Economic Inequality*, 19(3): 509–26. <https://doi.org/10.3386/w27085>
- Mosomi, J. (2019). 'An Empirical Analysis of Trends in Female Labour Force Participation and the Gender Wage Gap in South Africa'. *Agenda*, 33(4): 29–43. <https://doi.org/10.1080/10130950.2019.1656090>
- Mosomi, J., Thornton, A., and Branson, N. (2020). 'Unpacking the Potential Implications of COVID-19 for Gender Inequality in the SA Labour Market'. Working Paper No. 269. University of Cape Town: Southern African Labour and Development Research Unit.
- Rospabé, S. (2001). 'An Empirical Evaluation of Gender Discrimination in Employment, Occupation Attainment and Wage in South Africa in the Late 1990s'.
- Spaull, N., Ardington, C., Bassier, I., Bhorat, H., Bridgman, G., Brophy, T., Budlender, J., Burger, R., Burger, R., Carel, D., et al. (2020). 'NIDS-CRAM Wave 1 Synthesis Report: Overview and Findings'. NIDS-CRAM Working Paper No. 1. NIDS-CRAM.

- Spaull et al. (2021). *National Income Dynamics Study - Coronavirus Rapid Mobile Survey (NIDS-CRAM) 2020, Wave 1 [dataset]*. Cape Town: Allan Gray Orbis Foundation [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer]. (Version 3.0.0.) <https://doi.org/10.25828/7tn9-1998>
- StatsSA. (2020). 'Statistical Release P0211: Quarterly Labour Force Survey Quarter 4: 2019 '. Tech. Rep.. Pretoria, South Africa: Statistics South Africa.
- StatsSA. (2020-1). *Quarterly Labour Force Survey: 2020Q1 - 2021Q1 [datasets]*. Pretoria: Statistics South Africa (StatsSA) [producer]. University of Cape Town: DataFirst [distributor]. (Version 1.0 [2020Q1, 2021Q1]; Version 2.0 [2020Q2, 2020Q3])
- Verick, S. (2012). 'Giving Up Job Search During a Recession: The Impact of the Global Financial Crisis on the South African Labour Market'. *Journal of African Economies*, 21(3): 373–408. <https://doi.org/10.2139/ssrn.1965133>
- Wittenberg, M. (2017). 'Wages and wage inequality in south africa 1994–2011: Part 1–wage measurement and trends'. *South African Journal of Economics*, 85(2): 279–97. <https://doi.org/10.1111/saje.12148>
- World Bank. (2022). *Gini Index (World Bank Estimate)*. Available at: <https://data.worldbank.org/indicator/SI.POV.GINI> (World Bank DataBank Development Indicators)

# A1 Appendix

Figure A1: Trends in employment by gender in South Africa (2007–21)



Note: The service sectors include transport, trade, finance, and community services; the production sectors include manufacturing, utilities, and construction; the primary sectors include agriculture and mining.  
 Source: authors' calculations using PALMS and the QLFs.

Table A1: Occupational make-up of men's and women's employment in 2008 and 2020 Q1

Two-digit occupation code	2008			2020 Q1		
	Female emp.	Male emp.	Per cent female	Female emp.	Male emp.	Per cent female
11. Leg. + sen. officials	0.32	0.55	31.56	0.28	0.44	33.90
12. Corp. man.	3.32	5.40	32.37	4.56	6.77	34.74
13. Man. small enterp.	1.59	3.33	27.11	1.47	3.87	23.14
21. Science prof.	0.53	1.89	18.04	0.40	1.27	19.98
22. Life sci. + health prof.	1.44	0.56	66.71	0.82	0.56	53.39
23. Teaching prof.	0.96	0.41	64.63	3.50	1.24	69.03
24. Other prof.	2.82	2.49	46.86	2.32	1.74	51.38
31. Science technic.	0.82	2.61	19.63	1.26	2.56	27.93
32. Life sci. + health technic.	2.69	0.71	74.75	2.70	0.71	74.89
33. Teaching assoc. prof.	6.04	1.86	71.73	2.71	0.98	68.68
34. Other technic.	4.14	3.45	48.35	3.41	2.63	50.62
41. Office clerks	10.26	4.54	63.83	10.29	3.76	68.36
42. Customer services clerk	6.05	1.38	77.40	6.22	1.40	77.88
51. Pers. + protec. serv.	9.00	8.32	45.75	13.57	11.09	49.14
52. Salespersons	4.62	3.60	49.99	4.63	4.44	45.15
61. Skilled agri	0.28	0.56	27.97	0.20	0.43	26.49
62. Subsistence agri	0.04	0.06	36.91	0.07	0.20	21.84
71. Building trades	0.69	11.00	4.65	0.62	9.33	4.95
72. Metal, mach. + trades	0.71	8.13	6.42	0.36	7.33	3.69
73. Precision, handicraft, printing trades	0.47	0.80	31.32	0.20	0.61	20.31
74. Other craft trades	2.79	1.41	60.64	2.12	1.25	57.34
81. Stationary plant ops	0.16	1.13	10.19	0.30	1.41	14.20
82. Machine ops + assemblers	2.24	2.91	37.51	1.64	2.09	38.17
83. Drivers + mobile plant ops	0.41	9.22	3.33	0.44	9.72	3.49
91. Elementary sales + serv.	30.19	6.99	77.12	27.57	8.02	73.09
92. Agricultural labourers	3.33	8.18	24.11	3.69	8.48	25.59
93. Mining, construc, manu labourers	4.07	8.51	27.17	4.66	7.65	32.46
	<b>100.00</b>	<b>100.00</b>		<b>100.00</b>	<b>100.00</b>	

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data. Adjusted using sampling weights.

Table A2: Robustness regression output for the correlation between lockdown job-loss risk measures and employment change in 2020 and 2008–09: alternative measure of WFH

Spec:	2020 Q1–Q2		2008–09	
	4	5	4	5
<b>Female</b>	-1.37 (2.64)	-1.64 (2.76)	1.63 (2.25)	0.34 (2.37)
<b>Proximity</b>		-1.06 (4.36)		3.91 (3.96)
<b>Exposure</b>		1.82 (2.54)		1.05 (2.27)
<b>Essential</b>		12.43 (6.20)		4.70 (5.76)
<b>WFH_O*NET</b>	22.92*** (4.86)	23.80*** (5.50)	2.10 (4.01)	5.84 (4.62)
<b>_Cons</b>	-16.61*** (1.88)	-19.28 (13.99)	-3.60* (1.59)	-20.35 (12.38)
<b>N</b>	<b>50.00</b>	<b>54.00</b>	<b>50.00</b>	<b>54.00</b>

Note: standard errors in parentheses. \* p<0.05, \*\* p<0.01, \*\*\* p<0.001. Regressions are weighted by employment in the before period (2008 for the GFC and Q1 for 2020). Specification 4 omits skilled agriculture and subsistence agriculture (codes 61 and 62).

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data.

Table A3: Robustness regression output for a difference-in-differences model of job-loss risk during the GFC and 2020: alternative WFH measure

<b>Model:</b>	<b>4</b>	<b>5</b>
<b>Female</b>	0.98 (1.65)	-0.11 (1.74)
<b>Year = 2020</b>	-14.34*** (2.23)	2.21 (21.14)
<b>Proximity</b>		4.00 (3.28)
<b>Proximity x 2020</b>		-5.33 (6.63)
<b>Exposure</b>		1.15 (1.88)
<b>Exposure x 2020</b>		0.34 (3.76)
<b>Essential</b>		4.60 (4.78)
<b>Essential x 2020</b>		8.16 (9.50)
<b>WFH_O*NET</b>	2.12 (3.33)	5.99 (3.82)
<b>WFH_O*NET x 2020</b>	20.81** (7.31)	17.38* (8.17)
<b>_Cons</b>	-3.31* (1.26)	-20.63* (10.26)
<b>N</b>	<b>100.00</b>	<b>108.00</b>

Note: standard errors in parentheses. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Regressions are weighted by employment in the before period (2008 for the GFC and Q1 for 2020). Specification 4 omits skilled agriculture and subsistence agriculture (codes 61 and 62).

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data.

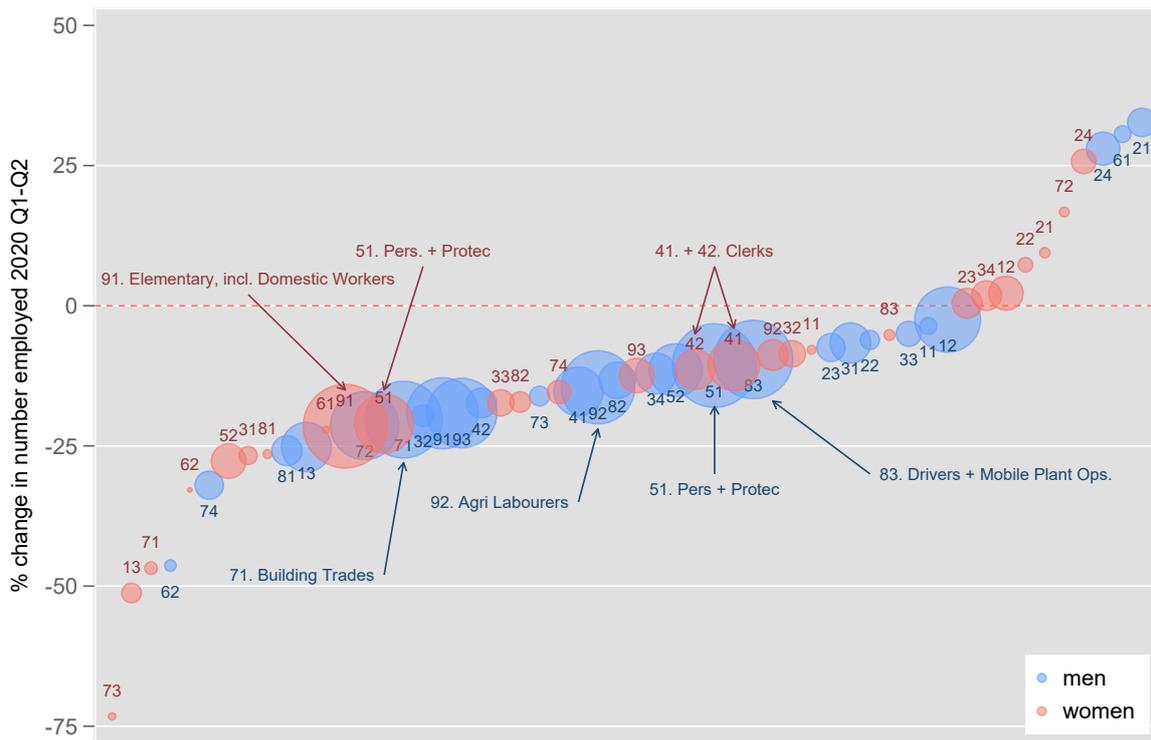
Table A4: Robustness regression output comparing lockdown job-loss risk measures across the duration of lockdown in 2020 and into 2021: alternative WFH measure

Spec:	Dep var:	% jobs lost between			
		Q2 vs Q1	Q3 vs Q1	Q4 vs Q1	Q5 vs Q1
9	<b>Female</b>	-0.59 (3.22)	-0.51 (3.39)	0.31 (2.89)	0.73 (3.40)
	<b>Proximity</b>	-12.62** (4.44)	-9.92* (4.68)	-7.53 (3.98)	-8.97 (4.68)
	<b>_Cons</b>	29.39 (15.20)	23.71 (16.02)	16.87 (13.66)	21.26 (16.04)
	<b>N</b>	<b>46.00</b>	<b>46.00</b>	<b>46.00</b>	<b>46.00</b>
10	<b>Female</b>	-1.02 (3.14)	-1.70 (3.69)	-0.29 (3.29)	0.44 (3.80)
	<b>Essential</b>	11.66 (7.62)	9.12 (8.98)	9.52 (7.99)	17.47 (9.22)
	<b>_Cons</b>	-16.42*** (2.86)	-11.86*** (3.36)	-10.98*** (2.99)	-13.25*** (3.46)
	<b>N</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>
11	<b>Female</b>	-2.33 (2.58)	-2.73 (3.42)	-1.10 (3.17)	-0.78 (3.70)
	<b>WFH</b>	74.71*** (14.64)	58.57** (19.42)	40.27* (18.02)	52.17* (21.04)
	<b>_Cons</b>	-19.54*** (2.09)	-14.31*** (2.77)	-11.83*** (2.57)	-13.03*** (3.00)
	<b>N</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>	<b>50.00</b>
12	<b>Female</b>	-1.18 (2.67)	-1.64 (3.52)	-0.29 (3.34)	-0.15 (3.60)
	<b>Proximity</b>	0.45 (3.79)	0.06 (5.00)	-0.07 (4.75)	2.74 (5.11)
	<b>WFH</b>	23.48*** (5.46)	17.14* (7.19)	12.13 (6.83)	19.81** (7.36)
	<b>Essential</b>	12.88* (6.14)	8.99 (8.10)	10.95 (7.68)	17.43* (8.28)
	<b>_Cons</b>	-21.45 (13.59)	-14.49 (17.92)	-12.67 (17.00)	-25.35 (18.33)
	<b>N</b>	<b>54.00</b>	<b>54.00</b>	<b>54.00</b>	<b>54.00</b>

Note: standard errors in parentheses. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Regressions are weighted by employment in the before period (2008 for the GFC and Q1 for 2020). Specification 4 omits skilled agriculture and subsistence agriculture (codes 61 and 62).

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data.

Figure A2: Change in occupational employment at the two-digit level between 2020 Q1 and Q2



Note: bubbles weighted by 2020 Q1 employment and numbered with two-digit occupation codes as labelled in Table 1.  
 Source: authors' calculations using QLFS from StatsSA.

Table A5: Naive counterfactual 2020 job-loss method (a): GFC job-loss rates applied to the 2020 Q1 occupational distribution

	Men				Women			
	Q1 employed	GFC job- loss rate	CF Q2 employed	CF job loss	Q1 employed	GFC job- loss rate	CF Q2 employed	CF job loss
11. Leg. + sen. officials	40,691.4	0.04	42,177	1,485.97	20,864.6	- 0.01	20,612.3	- 252.3
12. Corp. man.	627,602.9	- 0.04	599,771	-27,831.97	334,038.3	0.02	342,261.1	8,222.8
13. Man. small enterp.	358,676.4	0.06	381,784	23,108.02	107,976.3	- 0.05	102,803.3	- 5,173.0
21. Science prof.	117,941.6	- 0.15	100,601	-17,340.23	29,453.8	0.13	33,297.4	3,843.7
22. Life sci. + health prof.	52,311.0	- 0.16	43,983	- 8,328.10	59,931.5	- 0.16	50,077.4	- 9,854.0
23. Teaching prof.	114,896.9	0.33	153,084	38,187.52	256,152.7	0.16	297,202.6	41,049.9
24. Other prof.	161,044.8	- 0.06	151,728	- 9,316.80	170,164.0	- 0.10	153,826.7	- 16,337.3
31. Science technic.	237,612.0	0.16	275,155	37,543.15	92,093.4	0.15	105,450.4	13,357.0
32. Life sci. + health technic.	66,238.9	0.05	69,645	3,406.49	197,607.1	0.07	212,165.0	14,557.9
33. Teaching assoc. prof.	90,660.5	0.02	92,427	1,766.70	198,805.9	- 0.03	193,642.6	- 5,163.3
34. Other technic.	243,921.6	0.01	246,064	2,141.92	250,010.5	- 0.04	240,777.2	- 9,233.3
41. Office clerks	348,949.0	- 0.03	338,066	-10,883.36	753,895.1	0.06	796,344.6	42,449.5
42. Customer services clerk	129,407.5	- 0.12	113,708	-15,699.39	455,582.1	- 0.05	433,963.7	- 21,618.4
51. Pers. + protec. serv.	1,028,172.0	0.01	1,038,140	9,967.75	993,524.9	0.13	1,120,480.9	126,956.0
52. Salespersons	411,699.4	0.07	440,085	28,385.46	338,851.3	- 0.09	308,608.5	- 30,242.8
61. Skilled agri	40,128.1	- 0.12	35,245	- 4,883.34	14,459.2	- 0.35	9,347.7	- 5,111.4
62. Subsistence agri.	18,525.5	- 0.05	17,531	- 994.68	5,176.4	0.00	5,184.5	8.1
71. Building trades	865,158.1	- 0.07	806,105	-59,053.49	45,068.7	0.06	47,837.4	2,768.7
72. Metal, mach. + trades	679,529.9	- 0.12	599,415	-80,114.47	26,013.5	- 0.24	19,776.3	- 6,237.1
73. Precision, handicraft, printing trades	56,849.1	- 0.08	52,035	- 4,814.05	14,489.2	- 0.37	9,153.8	- 5,335.4
74. Other craft trades	115,500.7	- 0.14	98,850	-16,650.80	155,222.7	- 0.25	116,113.6	- 39,109.1
81. Stationary plant ops	130,658.8	0.19	154,884	24,225.23	21,624.6	0.03	22,335.0	710.4
82. Machine ops + assemblers	194,064.1	- 0.10	173,854	-20,209.91	119,826.6	0.04	124,131.9	4,305.3
83. Drivers + mobile plant ops	901,320.5	- 0.02	881,500	-19,820.95	32,546.0	- 0.14	27,901.8	- 4,644.2
91. Elementary sales + serv.	743,549.1	- 0.02	730,522	-13,026.77	2,019,161.0	- 0.04	1,939,060.4	- 80,100.6
92. Agricultural labourers	785,805.9	- 0.03	763,310	-22,495.85	270,300.4	- 0.05	257,169.9	- 13,130.5
93. Mining, construc, manu labourers	709,702.2	- 0.10	641,076	-68,625.86	341,123.9	- 0.02	335,519.1	- 5,604.8
<b>TOTAL</b>	<b>9,270,617.9</b>		<b>9,040,746</b>	<b>-229,871.8</b>	<b>7,323,963.5</b>		<b>7,325,045.0</b>	<b>1,081.4</b>

Note: CF = counterfactual. GFC = Global Financial Crisis 2008–09.

Source: authors' calculations using a combination of QLFS and PALMS v3.3 data.