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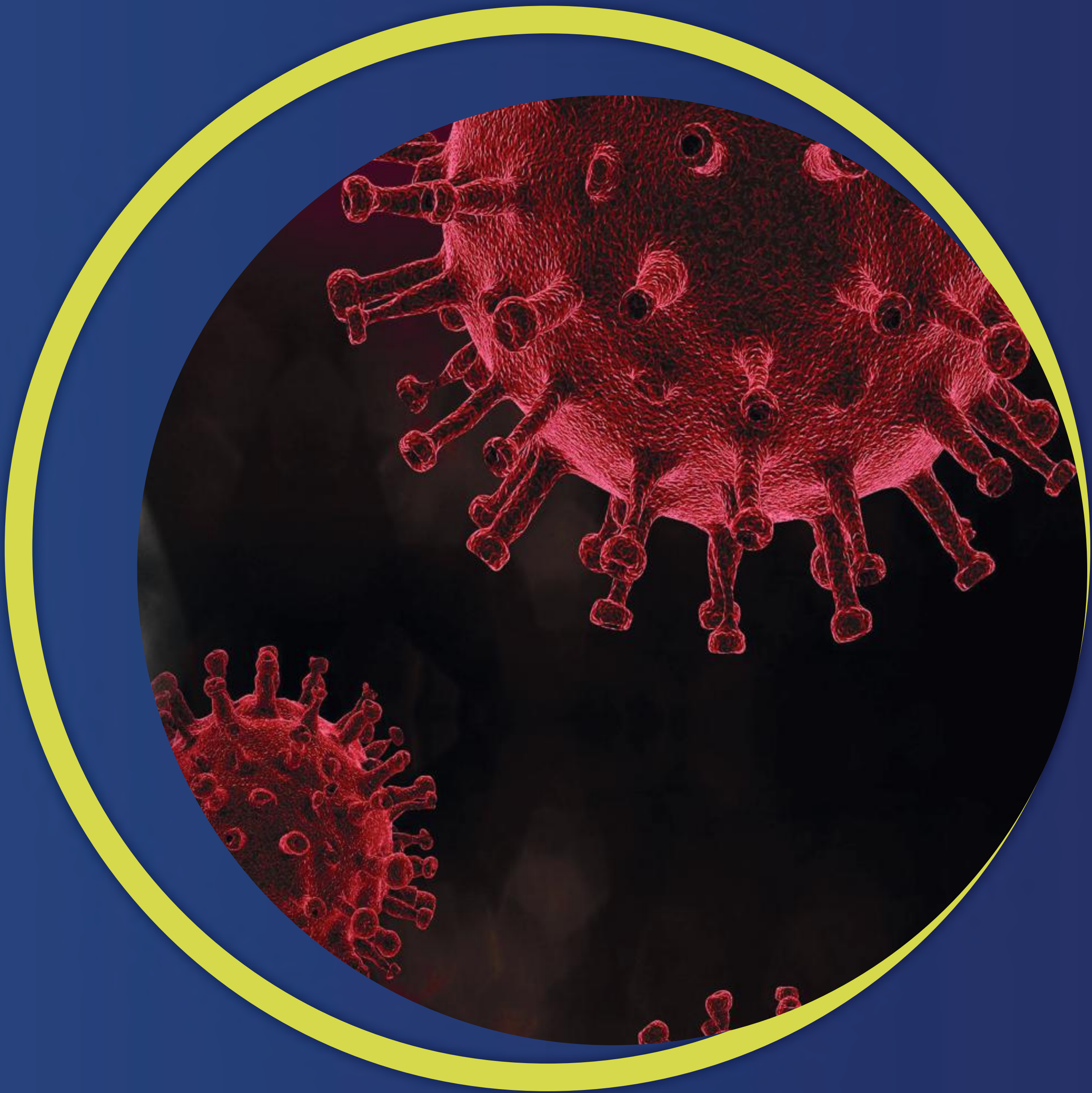

COVID-19 and the labour market: Estimating the effects of South Africa’s national lockdown)

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(February 2021)[1]

1. Introduction

South Africa has been one of the countries affected most adversely by the COVID-19 pandemic in Africa. By the end of November 2020, South Africa accounted for the highest number of confirmed cases per capita – with approximately 800 000 cumulative cases, representing over a third (36%) of total cases on the continent. In response, like most governments around the world, South Africa implemented a national lockdown to prepare the necessary health infrastructure as well as to delay and minimise the spread of the virus. This initial lockdown, which began on 26 March 2020 and lasted for five weeks, was relatively stringent by international standards (Bhorat et al. 2020; Gustafsson 2020), making no allowance for any non-essential activities outside the home. Following this, a phased easing of restrictions was introduced in five levels, with the initial lockdown period classified as level 5. Regulation under levels 4 (1 to 31 May) and 3 (1 June to 17 August) gradually permitted specific categories of 'non-essential' work to resume. Estimates using pre-crisis data suggest that just 40% of the employed were permitted to work under level 5, rising to 71% under level 3 (Francis, Ramburuth-Hurt, and Valodia 2020).[2]

Although the pandemic continues to pose important risks to public health, South Africa's lockdown was always expected to lead to substantial short- and long-term economic costs. Official labour force data shows that there were approximately 2.2 million fewer people employed in the second quarter of 2020 relative to the first[3] *– essentially erasing the last 10 years of job growth in the economy. Only a partial recovery can be observed in data from the third and fourth quarters of the year, with net employment still down 1.4 million relative to pre-pandemic levels. Research conducted during the lockdown suggests that job losses have been concentrated among a range of already vulnerable groups, particularly individuals in the poorest households (Köhler and Bhorat 2020), less-skilled and low-wage workers (Jain et al. 2020; Ranchhod and Daniels 2020), informal workers (Benhura and Magejo 2020), those with transient employment or persistent non-employment histories (Espi, Leibbrandt, and Ranchhod 2020), those living in poor urban communities (Visagie and Turok 2020), and women – particularly the poorest (Hill and Köhler 2020; Casale and Posel 2020; Casale and Shepherd 2020). Many of these findings are consistent with those observed in labour markets across the world (International Labour Organization (ILO) 2020).*

Despite the large amount of important work that has already been done to measure the various socio-economic impacts of South Africa's lockdown, many of these studies are largely descriptive

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[2] The assumptions to arrive at these estimates are discussed in detail in Francis et al. (2020).
[3] A similar change in employment is observed if one alternatively uses year-on-year changes.

in nature. In this paper, we use representative labour force data – the Quarterly Labour Force Survey (QLFS) – to provide both a detailed descriptive and econometric account of the effects of the COVID-19 pandemic on employment. In terms of the econometric approach, we rely on a quasi-experimental estimation technique by exploiting the variation in South Africa's lockdown policy to estimate the causal effect of the lockdown on the probability of employment for those not permitted to work. We do so by making use of the coincidental timing of the national lockdown and the data collection dates of the QLFS. Specifically, we employ a propensity score-matched (PSM) difference-in-differences (DiD) approach to measure employment effects across observationally comparable affected and unaffected workers. Simply put, we examine the effect of the lockdown on the probability of employment amongst workers who were not permitted to work, relative to those who were.

Several findings from our analysis stand out. In our descriptive analysis, we show that employment loss was concentrated amongst the youth, those with lower levels of formal education, those living in urban areas, the private sector, non-union members, the secondary sector (particularly manufacturing and construction), and low- and semi-skilled workers. Notably, the lockdown disproportionately affected informal-sector workers, who accounted for one in every two net jobs lost, despite representing just 25% of pre-pandemic employment. This latter finding is consistent with our quasi-experimental findings. We find that the national lockdown decreased the probability of employment for those not permitted to work, by eight percentage points relative to the control group – a finding that holds across several robustness tests. We find larger effects for more stringent lockdown levels and distinct sub-groups – specifically own-account workers (most of whom are in the informal sector) – who experienced a nearly three times larger negative employment effect than the overall average treatment effect. This latter finding is indicative that working in the informal sector seems to be a key determinant of not being employed during the lockdown period.

The rest of the paper is structured as follows. We begin by describing our data and identification strategy in Section 2. In Section 3, we present descriptive statistics on labour market outcomes prior to and during the first three months of South Africa's national lockdown, including a disaggregated assessment of differences between and within various groups of workers. In Section 4, we present and discuss the main findings of our PSM-DiD models. Section 5 reflects on our results and concludes.

2. Data and identification strategy

2.1. The Quarterly Labour Force Survey

The analysis in this paper uses individual-level survey data from Statistics South Africa's (StatsSA) Quarterly Labour Force Survey (QLFS). The QLFS is a cross-sectional, nationally representative household survey, conducted every quarter since 2008, that contains detailed information on a wide array of demographic and socioeconomic characteristics and labour market activities for *individuals aged 15 years and older. Although it is a cross-sectional dataset, the QLFS does have a panel component, where 75% of the household sample is resurveyed in each quarter. This makes it possible to follow the same dwelling unit for four consecutive quarters. However, there are a number of important differences in the 2020 QLFS data that are worth noting in some detail here.*

Prior to the COVID-19 pandemic in South Africa, the QLFS sample consisted of nearly 70 000 individuals, living in approximately 30 000 dwelling units, with data being collected via face-to-face interviews. However, towards the end of March 2020, StatsSA suspended face-to-face data collection as a result of COVID-19. Because of this, 621 sampled dwelling units (or 2% of the sample) were not interviewed in the quarter 1 dataset. To adjust for this, StatsSA used the panel component of the survey and made imputations where possible, using data from the previous quarter.

To continue providing labour market statistics for the second quarter of the year during the national lockdown, StatsSA changed its data collection model from face-to-face interviews to computer-assisted telephone interviewing (CATI). To facilitate this, and unlike in previous quarters, the sample that was surveyed in 2020Q1 and for which StatsSA had contact numbers was surveyed again in 2020Q2. The result was that the 2020Q2 data included about 71% of the 2020Q1 sample because not all dwelling units had contact numbers.[4] The obvious concern here is that this will produce 2020Q2 estimates that suffer from selection bias; that is, it is likely that the underlying characteristics of 'telephone' and 'non-telephone' households are different. For example, we know from the 2020Q1 data that individuals in 'non-telephone households' were significantly more likely to be unemployed relative to those in 'telephone households'. To address this source of bias, StatsSA took a number of steps to adjust the calibrated survey weights, using the 2020Q1 data and several bias-adjustment factors, which we do not discuss here in detail (StatsSA, 2020a).

Table 1 below presents an overview of the sample sizes and weighted estimates of the South African labour market for 2020Q1 and 2020Q2. We use the relevant bias-adjusted sampling weights provided by StatsSA unless otherwise indicated, and restrict the sample to the working-age population (those aged 15 to 64 years). Looking at the aggregated data, the bias-adjusted 2020Q2 weights appear to be appropriately computed. From an unweighted sample of 66 657 individuals, the weighted estimate of the South African population in 2020Q1 is 57.8 million. The relevant 2020Q2 estimate is just under 58 million, despite the 2020Q2 sample consisting of nearly 20 000 fewer individuals. This is similar for the working-age population. In contrast, the weighted estimates of specific labour market groups (such as the labour force and number of employed) are statistically significantly different in size between quarters, which is what we would expect to see as a result of the pandemic and associated government responses. However, it should be noted that the sampling bias adjustments by StatsSA relied on observable characteristics, such as age, gender, and race; however, respondents may still be unobservably different from non-respondents, and hence possibly from the broader population. At the time of writing, an explicit external review of the construction of these weights has yet to be conducted, and would require more information

[4]Additionally, amongst those who did have contact numbers, some contact numbers were found to be invalid or were not answered during data collection, and some households indicated that they were no longer residing at the dwelling units they had occupied during 2020Q1. All of these were regarded as non-contact and were adjusted for during the weighting processes.

than is available in the public QLFS documentation.

Table 1: Sample sizes and weighted population estimates, by quarter

	2020Q1		2020Q2	
	Unweighted	Weighted	Unweighted	Weighted
Total	66 657	57 792 395	47 103	57 973 917
Working-age population	41 827	38 873 945	29 495	39 021 017
Labour force	24 549	23 452 204	13 023	18 443 066 *
Employed	17 044	16 382 555	10 001	14 148 215 *
Unemployed	7 505	7 069 649	3 022	4 294 851 *
Discouraged	3 149	2 918 028	1 865	2 470 782 *
Not economically active	14 129	12 503 712	14 607	18 107 168 *

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
*Notes: [1] Relevant estimates weighted using sampling weights. [2] Labour market groups restricted to the working age (15 to 64 years). [3] Official (narrow) definitions of unemployment used. [4] * denotes statistical significance of a different 2020Q2 estimate relative to the relevant 2020Q1 estimate at the 95% confidence level.*

2.2. Identification strategy: Propensity Score-Matched Difference-in-Differences

Our aim in this paper is to estimate the causal effect of South Africa's national lockdown on employment probability, for which we require a suitable identification strategy. Using vocabulary from the randomised evaluation literature, the ideal way to estimate a causal effect entails randomised assignment of treatment (in this case, a national lockdown). Such randomisation would, subject to several conditions, allow us to directly measure the effect of the policy in isolation. In the context of South Africa's national lockdown, however, treatment was not assigned randomly. Every worker in the country was legally obligated to adhere to the lockdown regulations as they were specified and adjusted over time. However, being permitted and able to continue working was dependent on job type, which does provide a neat division of 'treated' and 'untreated' individuals over time. As such, we estimate the causal effect of the lockdown by exploiting variation across industries that were and were not permitted to work, as per the relevant Government Gazettes. We cross-examine these lockdown regulations with the three-digit industry codes in the QLFS data to identify individuals who were and were not permitted to work. To address selection bias and ensure that employment probabilities are driven only by differences in treatment, we then employ a propensity score matching (PSM) reweighting technique that seeks to provide a comparable set of individuals across our treatment and control groups. We then use the timing of the national lockdown, and the timing of the QLFS data collection interviews, to estimate difference-in-differences (DiD) models on a matched panel sample. This approach is outlined in more detail below.

2.2.1. Difference-in-Differences

The DiD approach is a popular quasi-experimental technique for evaluating the effects of policies or interventions that are implemented at a particular point in time. In this case, it exploits across-group (treatment and control) and across-time (before and during the national lockdown) variation. We use the 2020Q1 QLFS (January to March 2020) as our pre-treatment period and the 2020Q2 QLFS (April to June 2020) as our post-treatment period.[5] This is motivated by the observation that the lockdown was implemented from the end of March 2020, coinciding with the change in QLFS quarters. We thus can compare employment outcomes effectively for those not permitted to work versus those permitted to work over the period. Specifically, our treatment group consists of all the individuals in our sample who, as per legislation, were not permitted to work during the national lockdown. We identify these individuals by cross-analysing over 150 three-digit industry codes in the QLFS with the relevant Government Gazettes. Our control group thus consists of those who were legally permitted to work. We additionally include in the control group anyone who was able to work due to specific characteristics of their occupation and sector. This sub-category of workers would be anyone working in the public sector and those, amongst the employed, who report working from home.[6,7] In our analysis to follow, we estimate several specifications using alternative control group definitions (that is, 'pure legal' as well as 'pure legal plus ability to work' definitions) to examine the sensitivity of our results.

Importantly, South Africa's lockdown rules were not time-invariant. As noted above, from April 2020 the country adopted a five-stage risk-adjusted lockdown strategy, which outlined who was permitted to work at each lockdown level. To account for this, we make use of QLFS 2020Q2 'interview date' data provided by StatsSA, which indicates whether an individual was surveyed in April, May or June 2020. These periods fortunately coincide with changes in the national lockdown levels, with Level 5 in place from 1 to 30 April, Level 4 from 1 to 31 May, and Level 3 from 1 to 30 June in the 2020Q2 data.[8] For example, individuals were included in the treatment group if they were not permitted to work under Level 5 regulations and they were interviewed in April during Level 5, and similarly for Levels 4 and 3. Regardless of permission to work as per legislation or lockdown level, all individuals working in the public sector or working from home were assigned to our main control group. In some instances, firms in a given industry were permitted to operate, but only at partial capacity. However, we cannot identify which workers were permitted to work in these 'limited capacity industry' situations. To address this, we assign relevant individuals to the control group (i.e. 'permitted to work') if they were permitted to work in a 'limited capacity industry', in which the legislated capacity was equal to or exceeded 50%. In our analysis, we use alternative thresholds to examine the sensitivity of our results to this assumption.

To give an indication of the groups we identified in the data, Table 2 presents the sample sizes and weighted population estimates of the treatment and control groups by quarter. The table is arranged

[5]It should be noted that our identification strategy cannot account for seasonality, which may be important to note considering that the South African economy went into recession prior to the pandemic in 2020Q1.
[6]The relevant work-from-home variable was included as an additional variable in the 2020Q2 QLFS as part of a special COVID-19 module and was only asked of the employed. We exploit the panel nature of the 2020Q1 and 2020Q2 QLFS datasets to impute responses in 2020Q1 based on individuals' 2020Q2 responses to this question.
[7]We include the unemployed who have worked before in the sample and use the relevant three-digit previous industry variable to assign them to treatment and control groups.
[8]We cannot account for any changes in legislature within lockdown levels, given that the frequency of the interview date data is monthly.

according to our alternative treatment and control group definitions. As discussed above, our treatment group consistently consists of individuals who were legally not permitted to work during a given lockdown level when they were interviewed. Our main control group (Group 3) consists of those who were permitted to work during a given lockdown level when they were interviewed, as well as anyone able to work (those working in the public sector or from home). The first alternative control group consists solely of those who were legally permitted to work (Group 1), whereas the second consists of those who were legally permitted to work or work in the public sector (Group 2).

Within each period it is clear that more individuals are assigned to the control group as the criteria expand. For instance, when legislated permission to work is the only treatment criterion, our control group in 2020Q1 consisted of about 10 000 individuals. Including those in the public sector in the control group increases this sample to over 11 000. Following the inclusion of those who report working from home, this sample further increases to just under 12 000. The size of the 2020Q2 samples are expectedly smaller than the 2020Q1 samples due to the changes in the QLFS sample discussed above, where employment decreased dramatically.

Table 2: Sample sizes and weighted population estimates of treatment groups, by period

	2020Q1		2020Q2	
	Unweighted	Weighted	Unweighted	Weighted
(1) Control group: permitted to work				
Treatment	12 392	11 809 151	5 193	7 262 499
Control	9 863	9 271 421	9 486	13 236 518
(2) Control group: permitted to work or public sector				
Treatment	11 059	10 610 351	4 485	6 405 255
Control	11 196	10 470 221	10 194	14 093 762
(3) Control group: permitted to work or public sector or working from home				
Treatment	10 355	9 933 383	3 995	5 741 106
Control	11 999	11 236 771	10 684	14 757 911

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Relevant estimates weighted using sampling weights.

Based on the PSM reweighting approach discussed below, our DiD model is estimated according to the following specification using ordinary least squares (OLS):

$$y_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 Treatment_i \times Post_t + \beta_4 \boldsymbol{X}_{it} + \gamma_i + \varepsilon_{it},$$

where y_{it} is the outcome of interest for individual i in time period t (in this case, a binary employment variable), $Treatment_i$ is a binary treatment variable, $Post_t$ is a binary variable equal to one for the post-treatment period (2020Q2) and zero otherwise (2020Q1), and ε_{it} is the regression error term. Furthermore, even though PSM accounts for pre-existing observational differences between individuals in the treatment and control groups, and the matched DiD approach controls for pre-existing unobservable differences (under the parallel trend assumption) and time-variant observational differences, we further control for a vector of pre-existing individual-level characteristics, $\boldsymbol{X}_{it}$ (including a categorical national lockdown level variable), to improve (i) the plausibility of the DiD identifying assumption and (ii) the efficiency of our estimates. Finally, we exploit the panel nature of the data to control for individual fixed effects (FE), represented by γ_i. β_3 is the main coefficient of interest, as it measures the causal effect of the onset of lockdown policy, i.e. the average difference in outcomes between the treatment and control groups in the post-treatment period relative to the pre-treatment period.

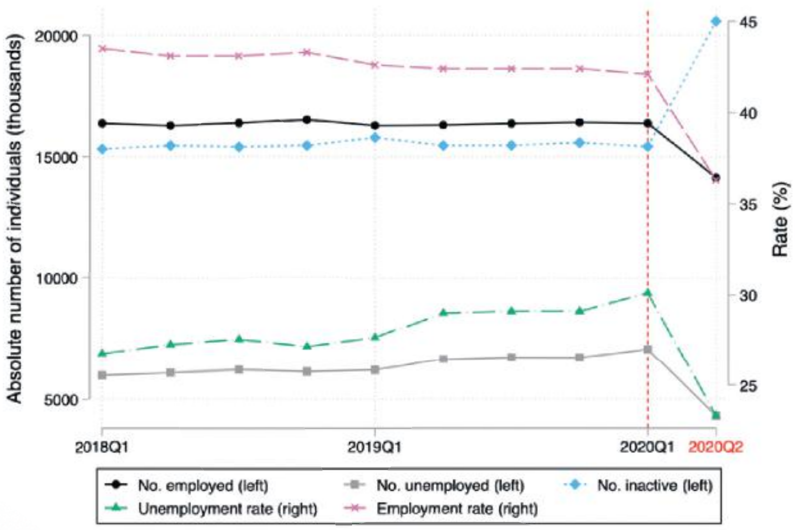
2.2.2. Propensity Score Matching

Out approach above measures differences in labour market outcomes between individuals who were and were not permitted to work, but these may not necessarily be explained by the treatment alone. Individuals in these two groups may differ by other characteristics, which may affect the employment outcomes we are trying to identify. To address such selection bias we use PSM, which seeks to identify similar individuals across treatment and control groups. Put differently, PSM is a method to ensure balance in a set of common observable characteristics across treatment and control groups in the pre-treatment period. The idea is to compare individuals who, conditional on a set of observables, have very similar probabilities of being categorised in the treatment group (i.e. propensity scores), even though those individuals differ with regard to actual treatment status. If two individuals have the same propensity scores conditional on a vector of observable covariates, but one is in the treatment group and one is not, then the two individuals are observationally exchangeable and differences in their observed outcomes of interest are attributable to differences in treatment.[9] Additional technical details regarding our use of PSM are in the Appendix.

3. Descriptive analysis

3.1. Aggregate shifts in key labour market indicators

In Figure 1 we present the aggregate trends in key labour market indicators in South Africa for recent years, supplemented by Table 3, which estimates even more recent annual and quarterly changes. Expectedly, the effects of the pandemic have led to a substantial reduction in the number of people who are employed in the country. Perhaps less expectedly, this was coupled with a decrease in the number of official (searching) unemployed individuals, and an even larger increase in the number of economically inactive individuals. These shifts can to a large extent be explained by the nature of lockdown policy, which restricted the ability of people to work and to search for work. Relative to 2020Q1, there were more than 2.2 million less employed people in the labour market in 2020Q2 – a 14% decrease, which is equivalent to employment levels between 2008 and 2012. The drop in the employment rate can be summarised as follows: for every 100 people in the working-age population, 42.1 were employed in 2020Q1, in contrast to 36.3 in 2020Q2.



[9]Assuming the conditional independence assumption (CIA) holds; that is, treatment (legislature not permitting work) conditional on the propensity score is independent of potential outcomes, or is "as good as random".

Figure 1: Trends in key labour market indicators in South Africa, 2018Q1 to 2020Q2

Source: QLFS 2018Q1 to 2020Q2 (StatsSA 2018, 2019, 2020a, 2020b). Authors' own calculations.
Notes: [1] All estimates weighted using relevant sampling weights. [2] Official (narrow) definition of unemployment used throughout.

Importantly, this substantial decrease in employment was coupled with more than 5 million more economically inactive people – an increase of more than 33%. This latter group are not classified amongst the discouraged unemployed because, when asked why they were not looking for work, individuals in this group responded with reasons 'Other' than discouragement. This reason can be attributed to the national lockdown policy, which restricted any activity deemed 'non-essential' outside the home. Indeed, this explains the changes in unemployment and, if observed alone, the misleading decrease in the official unemployment rate – a simple definitional consequence of so many people becoming economically inactive. Because individuals were not permitted to search for work, the number of official (searching) unemployed individuals dropped by nearly 40%, from 7 million to 4.3 million. Coupled with the reduction in the labour force from reduced total employment and searching unemployed, the official unemployment rate decreased from 30.1% to 23.3% – the lowest recorded since the start of the QLFS in 2008. These unusual changes in unemployment and inactivity have been observed in labour markets across the world (ILO 2020), but must be accepted as nothing more than a statistical anomaly brought about by the inability of the unemployed to search for jobs.

Table 3: Changes in key labour market indicators in South Africa

	2019Q2	2020Q1	2020Q2	Y-o-Y change		Q-o-Q change	
				Absolute	%	Absolute	%
Sub-populations (thousands)							
Working-age population	38 433	38 874	39 021	588	1.5	147	0.4
Labour force (narrow)	22 968	23 452	18 443	-4 525	-19.7	-5 009	-21.4
Employment	16 313	16 383	14 148	-2 164	-13.3	-2 234	-13.6
Unemployment	6 655	7 070	4 295	-2 360	-35.5	-2 775	-39.2
Not economically active	15 465	15 422	20 578	5 113	33.1	5 156	33.4
Discouraged	2 749	2 918	2 471	-278	-10.1	-447	-15.3
Other	12 716	12 504	18 107	5 391	42.4	5 603	44.8
Rates (%)							
Unemployment rate (narrow)	29.0	30.1	23.3	-5.7	-19.7	-6.8	-22.6
Labour force participation rate	59.8	60.3	47.3	-12.5	-20.9	-13.0	-21.6

Source: QLFS 2019Q2, 2020Q1, and 2020Q2 (StatsSA 2019, 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant sampling weights.

In addition to these cross-sectional trends, we can use the panel nature of the QLFS 2020Q1 and 2020Q2 data to measure transitions between different labour market states for a more accurate sense of the quarter-on-quarter shifts taking place. Table 4, below, shows that nearly one in every four (22.05%) of those who were employed in 2020Q1 were no longer employed in the following quarter, with most (16.14%) becoming economically inactive. Importantly, just under 6% of the previously employed reported looking for work in the next quarter. Also, more than half (55%) of the searching unemployed in 2020Q1 became inactive the next quarter, whereas only a third (34%) continued searching for work. The vast majority (80%) of those who were economically inactive in 2020Q1 remained inactive in 2020Q2. Again, the substantial increase in the number of individuals who became inactive for reasons categorised as 'Other' is evident here. This is a notable characteristic of the lockdown: the policy induced an inability to engage in the labour market, either due to job loss or to the implicit prohibition of job search for both first-time entrants and long-term job-seekers.

Table 4: Transition matrix of conventional labour market statuses, 2020Q1 to 2020Q2

			2020Q2 (%)				
					NEA		
			Employed	Unemployed	Discouraged	Other	Total
2020Q1 (%)	Employed		77.95	5.91	2.04	14.10	100.00
	Unemployed		10.55	34.06	10.38	45.01	100.00
	NEA	Discouraged	7.68	12.51	33.86	45.95	100.00
		Other	3.15	3.22	2.59	91.04	100.00
	Total		34.95	9.96	5.68	49.41	100.00

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] Estimates weighted using 2020Q2 bias-adjusted sampling weights.

Our descriptive analysis here focuses largely on the extensive margin. However, in addition to changes in employment status, the pandemic has resulted in significant changes in labour market outcomes, even amongst those who managed to retain their employment; that is, changes in the intensive margin. In particular, we observe a sharp reduction in working hours. Figure 2 presents the distribution of weekly working hours by quarter. The shapes of the distributions are clearly dissimilar, with a distributional shift downward and to the left, with the most notable changes at the bottom and in the middle of the distribution.

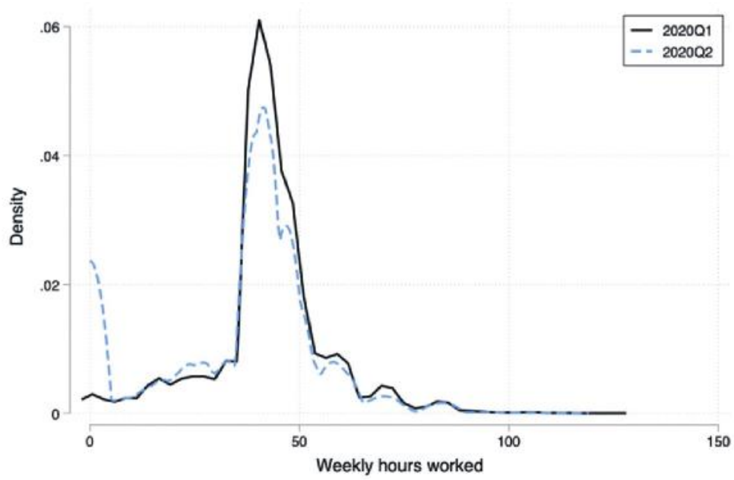


Figure 2: Distribution of weekly working hours, by quarter

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant sampling weights. [3] Epanechnikov kernels estimated using a bandwidth of 2. [4] Weekly working hours computed as the sum of actual daily working hours for Monday to Sunday in the reference week.

Only 1.5% of workers reported working zero hours per week in 2020Q1, but this jumps to 16% in the next quarter after the lockdown was introduced. This represents an increase from 250 000 workers to 2.2 million workers. Importantly, the data suggests that this increase was driven mostly by reductions amongst those who previously worked 40 and 45 hours per week. Overall, through examining changes in the aggregation of working hours amongst the employed, the South African labour market lost approximately 200 million working hours from 2020Q1 to 2020Q2, equivalent to over 4.4 million weekly working hour jobs. Another notable change in labour market outcomes on the intensive margin relates to changes in the wages of those who remained employed. Unfortunately, due to data unavailability we are unable to conduct such an analysis here.

3.2. Variation in labour market outcomes within and between groups

The observed changes in aggregate labour market outcomes above are important to note, but they also hide substantial underlying variation, both between and within various groups of individuals. Figure 3 presents trends in employment and inactivity between individuals grouped by sex and race. Clearly every group experienced a substantially lower level of employment, and A higher level of inactivity, in 2020Q2 relative to all previous years. The extent of these changes, however, vary considerably. In relative terms, self-reported Coloured men experienced the largest reduction in employment rates (20%), followed by African/Black women (16%) and African/Black men (15%). In absolute terms, nearly 80% of employment loss in 2020Q2 was accounted for by African/Black individuals – this is discussed in more detail later. Interestingly, with the exception of Coloured men, the ordinal rankings of these employment rates prior to 2020Q2 remained unchanged in 2020Q2. Amongst the working-age population (WAP), White men (African/Black women) were consistently more (less) likely to be employed relative to every other group.

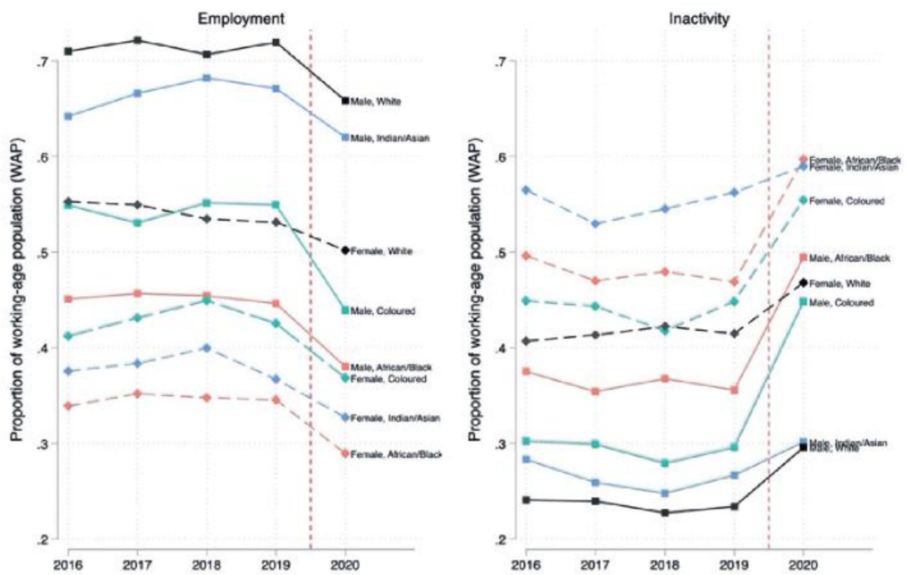


Figure 3: Trends in employment and inactivity, by sex and race, 2016Q2 to 2020Q2

Source: QLFS 2016Q2, 2017Q2, 2018Q2, 2019Q2, and 2020Q2 (StatsSA 2016, 2017, 2018, 2019, 2020a, 2020b). Authors' own calculations.

Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] Quarter 2 of each year used to control for seasonality.

Considering inactivity, every group exhibited higher levels in 2020Q2 relative to previous years. Again, Coloured men experienced the largest increase, from 29.5% of the group's WAP to 44.8% (representing a 52% increase). This increase in inactivity is followed by the 39% increase among African/Black men, whereas Indian/Asian and White women experienced the smallest increases, of 5% and 13%, respectively. The ordinal rankings of inactivity amongst these groups also remained largely unchanged.

Table 5 presents year-on-year changes in employment for a variety of demographic characteristics, and includes employment shares and the shares of change in each case. This helps us to determine (i) how the composition of the labour market has changed and (ii) which groups were disproportionately affected. Of the 2.2 million fewer people employed in 2020Q2, African/Black individuals accounted for nearly 78%, or 1.7 million people – a slightly disproportionate burden of employment loss given that this group accounted for 75% of the employed prior to the lockdown. On the other hand, just 150 000 fewer White individuals were employed in 2020Q2 relative to before the pandemic, representing just 7% of employment loss despite accounting for 11.3% of the pre-pandemic employed. Considering gender, men accounted for a slightly higher share of employment loss (55.5%), with 1.2 million less employed. However, women were disproportionately affected, given that they accounted for a smaller share of pre-pandemic employment (43.7%), although this is small differentially. Perhaps most significantly, youth accounted for about half (50.6%, or 1.1 million) of employment loss, despite representing only over a third (36.6%) of pre-pandemic employment.

Table 5: Changes in employment by select demographic and labour market groups, 2019Q2 to 2020Q2

	2019Q2	2020Q2	Change Absolute	Change %	Employment shares (%) 2019Q2	Employment shares (%) 2020Q2	Share of change (%)
Total	**16 312 706**	**14 148 215**	**-2 164 491**	**-13.3**	**100.0**	**100.0**	**100.0**
Race							
African/Black	12 250 320	10 554 996	-1 695 324	-13.8	75.1	74.6	78.3
Coloured	1 686 611	1 412 289	-274 322	-16.3	10.3	10.0	12.7
Indian/Asian	530 391	488 224	-42 167	-8.0	3.3	3.5	1.9
White	1 845 384	1 692 706	-152 678	-8.3	11.3	12.0	7.1
Sex							
Male	9 179 612	7 977 963	-1 201 649	-13.1	56.3	56.4	55.5
Female	7 133 094	6 170 252	-962 842	-13.5	43.7	43.6	44.5
Age group							
15-34	5 964 514	4 869 685	-1 094 829	-18.4	36.6	34.4	50.6
35-54	8 749 069	7 866 851	-882 219	-10.1	53.6	55.6	40.8
55-64	1 599 122	1 411 680	-187 442	-11.7	9.8	10.0	8.7
Education							
Primary or less	1 879 845	1 329 658	-550 188	-29.3	11.7	9.5	26.33
Secondary incomplete	5 360 983	4 443 230	-917 753	-17.1	33.3	31.7	43.91
Secondary complete (matric)	5 346 917	4 846 446	-500 471	-9.4	33.2	34.6	23.95
Post-secondary	3 511 214	3 389 699	-121 516	-3.5	21.8	24.2	5.81
Geography							
Urban	12 475 465	10 762 283	-1 713 182	-13.7	77.5	76.8	79.1
Rural or traditional area	3 837 240	3 385 932	-451 308	-11.8	23.8	24.2	20.9
Formality							
Formal	12 012 387	10 881 660	-1 130 727	-9.4	73.6	76.9	52.2
Informal	3 249 666	2 435 950	-813 716	-25.0	19.9	17.2	37.6
Private households	1 273 358	1 019 109	-254 249	-20.0	7.8	7.2	11.7
Sector							
Private	13 629 880	11 599 189	-2 030 691	-14.9	83.6	82.0	93.8
Public	2 843 080	2 698 836	-144 244	-5.1	17.4	19.1	6.7
Unionisation							
Member	3 948 660	4 203 095	254 436	6.4	24.2	29.7	-11.8
Non-member	9 339 867	7 280 290	-2 059 577	-22.1	57.3	51.5	95.2
Do not know	475 084	320 010	-155 074	-32.6	2.9	2.3	7.2

Source: QLFS 2019Q2 and 2020Q2 (StatsSA 2019, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant sampling weights.

Employment loss was disproportionately concentrated amongst individuals with relatively low levels of formal education, those living in urban areas, those working in the informal sector or private households, the private sector, and the non-unionised. Individuals whose highest level of education is less than Grade 12 (matric) or equivalent accounted for more than 70% of employment loss (or 1.5 million people), despite representing only 45% of pre-pandemic employment. Job losses were also concentrated in urban areas – as rural areas accounted for only 21% of the total employment loss. Notably, although employment loss in the informal sector and private households together represent about half of total employment loss, these sectors accounted for just under 28% of pre-pandemic employment, showing that they were affected disproportionately. Most pre-pandemic employment (73.6%) in South Africa is in the formal sector, although just 52.2% of employment loss was located in this sector. Remarkably, almost all (93.8%) jobs lost were in the private sector, despite the public sector accounting for nearly one in every five (17.4%) of the employed prior to the pandemic. Similarly, nearly all those who lost jobs (95.2%) were non-union members. In fact, union membership numbers grew slightly over the period, from 3.95 million to 4.2 million individuals.

Significant regional variation in employment changes is also evident. Figure 4 presents a map of absolute and relative changes in employment levels, by province. Gauteng, KwaZulu-Natal, and the Western Cape experienced the largest absolute reductions in employment, with approximately 670 000, 380 000, and 320 000 fewer people employed, respectively. Gauteng alone accounts for nearly 30% of total jobs lost. However, these estimates do not account for differences in the number of people employed in the provinces prior to the pandemic. In relative terms then, the right panel of Figure 4 shows that the Northern Cape, Free State, and Limpopo were hardest hit, with 23%, 17%, and 17% fewer people employed, respectively.

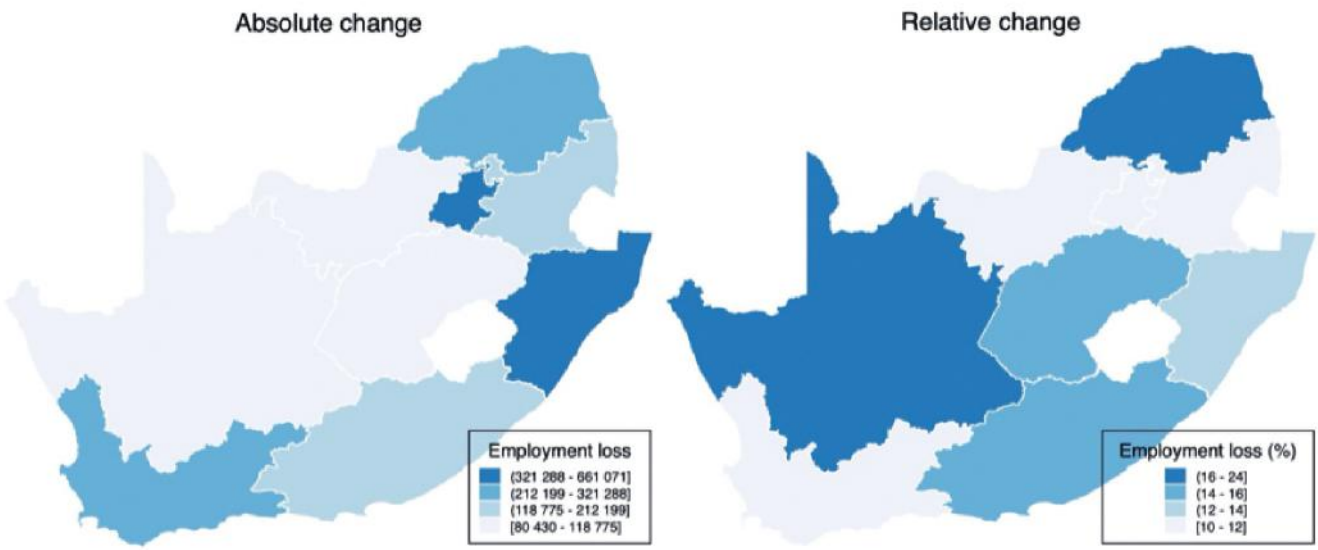


Figure 4: Changes in employment by province, 2020Q1 to 2020Q2

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant sampling weights.

We now turn to examine changes in employment by industry and occupation, as presented in Table 6. By sector, whilst the tertiary sector accounted for most of the total employment decrease (67.1%), this was not unexpected, given that most jobs can be found in this sector (72.2% prior to the pandemic). On the other hand, nearly a third (30.6%) of all jobs lost were in the secondary sectors, which exceed its share of total employment. These job losses were mostly in manufacturing (334 000 jobs lost) and construction (297 000 jobs lost). The primary sectors appear to have been relatively well insulated from the negative employment effects, but still shed over 50 000 jobs.

By occupational category, we observe that low- and semi-skilled workers account for almost all jobs lost, with employment levels amongst high-skilled workers remaining statistically unchanged. Amongst the semi-skilled, shares of total job loss by occupation largely followed pre-pandemic *employment shares. The notable exception is craft workers, who alone accounted for 20% of total employment loss (or 436 000 less people employed), despite representing just 12% of the employed prior to the pandemic. Examples of these jobs include individuals working as bricklayers and stonemasons, motor vehicle mechanics, and building electricians.*

Table 6: Changes in employment by main industry and occupation, 2019Q2 to 2020Q2

	2019Q2	2020Q2	Change		Employment shares (%)		Share of change (%)
			Absolute	%	2019Q2	2020Q2	
Industry							
Primary	**1 223 144**	**1 172 236**	**-50 908**	**-4.2**	**7.5**	**8.3**	**2.3**
Agriculture, etc.	842 062	799 033	-43 029	-5.1	5.2	5.7	2.0
Mining and quarrying	381 082	373 203	-7 879	-2.1	2.3	2.6	0.4
Secondary	**3 303 486**	**2 634 571**	**-668 915**	**-20.2**	**20.3**	**18.7**	**30.6**
Manufacturing	1 789 388	1 455 825	-333 564	-18.6	11.0	10.3	15.3
Utilities	151 339	112 926	-38 412	-25.4	0.9	0.8	1.8
Construction	1 362 759	1 065 820	-296 939	-21.8	8.4	7.5	13.6
Tertiary	**11 780 270**	**10 314 562**	**-1 465 709**	**-12.4**	**72.2**	**73.0**	**67.1**
Trade	3 428 621	2 946 463	-482 158	-14.1	21.0	20.9	22.1
TSC	982 502	884 683	-97 819	-10.0	6.0	6.3	4.5
Finance	2 495 239	2 234 281	-260 958	-10.5	15.3	15.8	11.9
CSP	3 622 492	3 243 976	-378 517	-10.4	22.2	23.0	17.3
Private households	1 251 416	1 005 159	-246 256	-19.7	7.7	7.1	11.3
Total	**16 306 900**	**14 121 369**	**-2 185 531**	**-13.4**	**100.0**	**100.0**	**100.0**
Occupation							
High-skilled	**2 367 575**	**2 360 096**	**-7 479**	**-0.3**	**14.5**	**16.8**	**0.3**
Legislators	1 527 944	1 287 769	-240 175	-15.7	9.4	9.1	10.8
Professionals	839 631	1 072 327	232 696	27.7	5.1	7.6	-10.5
Semi-skilled	**9 228 963**	**7 790 407**	**-1 438 556**	**-15.6**	**56.6**	**55.3**	**64.6**
Technical professionals	1 436 393	1 213 133	-223 259	-15.5	8.8	8.6	10.0
Clerks	1 708 008	1 470 386	-237 622	-13.9	10.5	10.4	10.7
Service workers	2 687 359	2 301 782	-385 577	-14.3	16.5	16.3	17.3
Skilled agriculture	53 782	67 454	13 671	25.4	0.3	0.5	-0.6
Craft	1 957 006	1 520 915	-436 091	-22.3	12.0	10.8	19.6
Plant and machine operators	1 386 415	1 216 737	-169 678	-12.2	8.5	8.6	7.6
Low-skilled	**4 715 050**	**3 935 253**	**-779 797**	**-16.5**	**28.9**	**27.9**	**35.0**
Elementary occupations	3 720 516	3 190 566	-529 950	-14.2	22.8	22.7	23.8
Domestic workers	994 535	744 687	-249 847	-25.1	6.1	5.3	11.2
Total	**16 311 588**	**14 085 756**	**-2 225 832**	**-13.6**	**100.0**	**100.0**	**100.0**

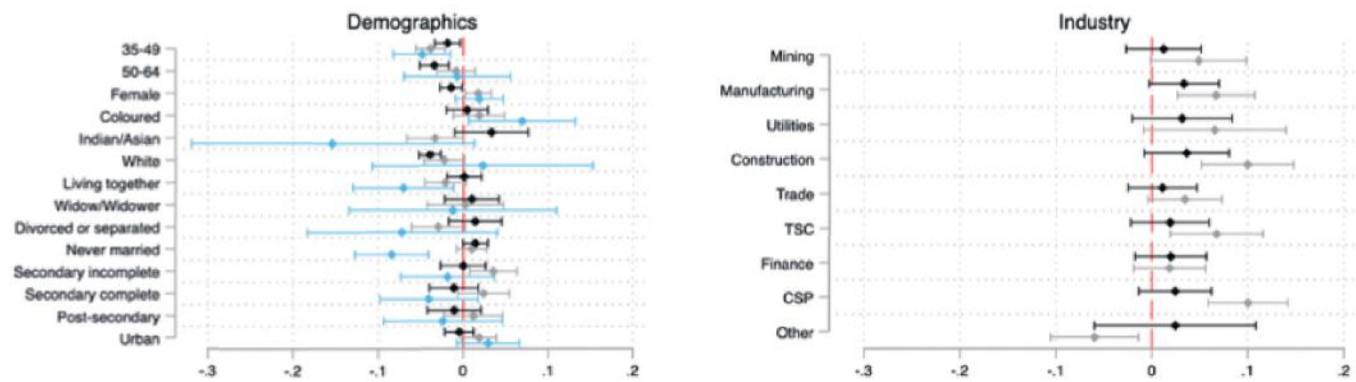
Source: QLFS 2019Q2 and 2020Q2 (StatsSA 2019, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant sampling weights. [3] Industry and occupation totals do not sum because sample here excludes workers in 'Other' industries and occupations.

Amongst low-skilled occupations, one in every four (or 250 000) domestic workers lost their jobs, accounting for 11.2% of total employment loss despite representing just 6% of the pre-pandemic employed. More than half a million (530 000) other less-skilled workers lost their jobs, including farm labourers, manufacturing labourers, helpers and cleaners in offices and hotels, and street food vendors.

Overall, our descriptive analysis thus far has shown that, of the 2.2 million fewer individuals employed in the first few months of the lockdown, employment loss was concentrated amongst the youth, those with lower levels of formal education, and those living in urban areas. Almost all employment loss was observed in the private sector. We also observe some evidence of job protection amongst union members, with non-union members accounting for nearly 100% of employment loss. Additionally, low- and semi-skilled workers accounted for almost all jobs lost. Although the tertiary sector accounted for the greatest absolute number of jobs lost, the secondary sector was disproportionately affected – specifically within the manufacturing and construction sectors. One key question going forward is whether these job losses in these industries are temporary or permanent. Geographically, after accounting for national employment shares, we observe that the Northern Cape, Free State, and Limpopo suffered the largest relative employment losses. Considering outcomes other than employment, we document notable changes in the distribution of working hours, with 2.2 million workers working zero hours in the second quarter. Finally, we show that the lockdown disproportionately affected workers in the informal and domestic services sector, with about 50% of total job loss attributable to the sector, despite it accounting for just under 28% of pre-pandemic employment.[10] It should be noted that these sectors are characterised by low costs of entry, lending some hope for a potentially strong recovery.

3.3. Multivariate analysis: Estimating probabilities of employment transition

Before running our main PSM-DiD model, we exploit the panel nature of the QLFS data to examine variation in the probability of transitioning into different labour market statuses during the lockdown. That is, we ask: who was more or less likely to become (i) unemployed after being employed, (ii) economically inactive after being employed, and (iii) economically inactive after being unemployed?[11] To do so, we generate the three relevant dependent variables and then use ordinary least squares (OLS) to estimate multivariate linear probability models (LPMs) by regressing these dependent variables on a vector of covariates. These covariates include a wide array of demographic and labour market variables.[12] We present the results of these models visually in several coefficient plots in Figure 5, while the complete results are presented in Table A2 in the Appendix.



[10] The informal sector here is inclusive of workers in private households.
[11] We use the official (searching) definition of unemployment here.
[12] In the models where we estimate the probability of transitioning from unemployment to inactivity, we do not include covariates relating to the labour market, given that these questions were not asked of the unemployed in the questionnaire.

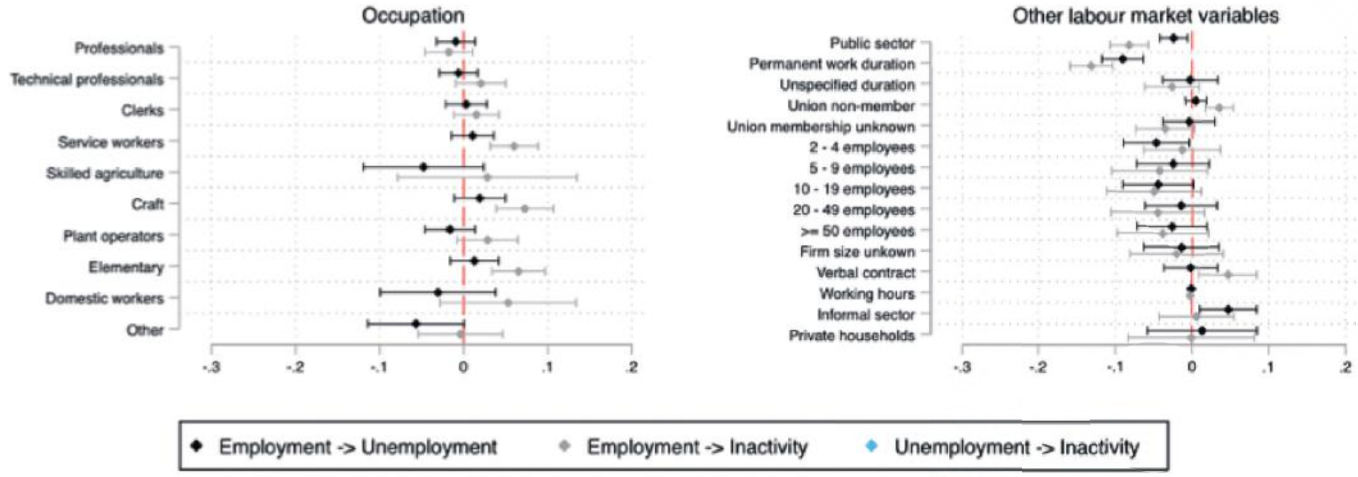


Figure 5: Coefficient plots of conditional probabilities of transitioning between employment statuses between 2020Q1 and 2020Q2

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.

Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant bias-adjusted weights for 2020Q2. [3] Estimates obtained by regressing select labour market status transitions from 2020Q1 to 2020Q2 on a vector of observable covariates in 2020Q1. Estimates as per models (2), (4), and (5), with full results presented in Table A1. [4] 90% confidence intervals presented as capped spikes. [5] Reference groups = 15–34, African/Black, Married, Primary education or less, Western Cape, Limited job duration, Union member, Firm size = 1 employee, Formal sector, Agriculture, Legislators.

Several results stand out. Individuals employed in the informal sector were significantly more likely to become unemployed, whereas those less likely to experience such a transition include women, older individuals, White relative to African/Black individuals, those living in KwaZulu-Natal and Mpumalanga relative to the Western Cape, and those whose contract is of a permanent nature. We observe no significant variation in the probability of transitioning from employment to unemployment by industry or occupation. Notably, those working in the public sector were significantly less likely to transition from employment to either unemployment or inactivity. Considering the latter transition, women were more likely to become inactive after being employed (as opposed to becoming unemployed, as observed above), in addition to those with less than a complete secondary education, those living in Limpopo relative to the Western Cape, union ¬non¬-members, and those with verbal employment contracts. Youth were also more likely to experience an employment-inactivity transition relative to older individuals. Moreover, our estimates suggest substantial heterogeneity in this transition by industry and occupation. Lastly, relative to the Western Cape, individuals living in any province other than Gauteng and the Eastern Cape were more likely to become inactive after being unemployed. Again, the youth were also more likely to experience this transition.

The results from these employment transition regressions confirm much of our prior descriptive analysis. Specifically, it seems more apparent that the pandemic disproportionately affected workers in the informal sector, the youth, and those with lower levels of formal education. Again, union members and those working in the public sector exhibit a notable extent of job protection.

Although we observe no significant differences in the probability of transitioning from employment to unemployment by industry or occupation, we do find that workers in construction, TSC, and CSP services (by industry), as well as service workers, craft workers, and elementary workers (by occupation), were significantly more likely to experience an employment-inactivity transition. Notably, we estimate that women were no more likely than men to transition from employment to unemployment; however, they were more likely to become inactive, all else being equal.

4. Model results

4.1. Main results

We now turn to our PSM-DiD analysis, where we estimate the causal effect of South Africa's national lockdown policy on the probability of employment for those not allowed to work. A key identifying assumption of the DiD approach is the parallel trends assumption. We want to be sure that the control group (those permitted to work, those who can work from home, or those who work in the public sector) provides an appropriate counterfactual of the trend that the treatment group (those not permitted to work) would have followed in the absence of treatment (the onset of the national lockdown). We therefore first investigate whether this assumption holds visually in Figure 6, which presents the trends in our dependent variable of interest – the probability of employment – by treatment and control group over a five-year period, prior to accounting for any confounding variables through our PSM reweighting technique.

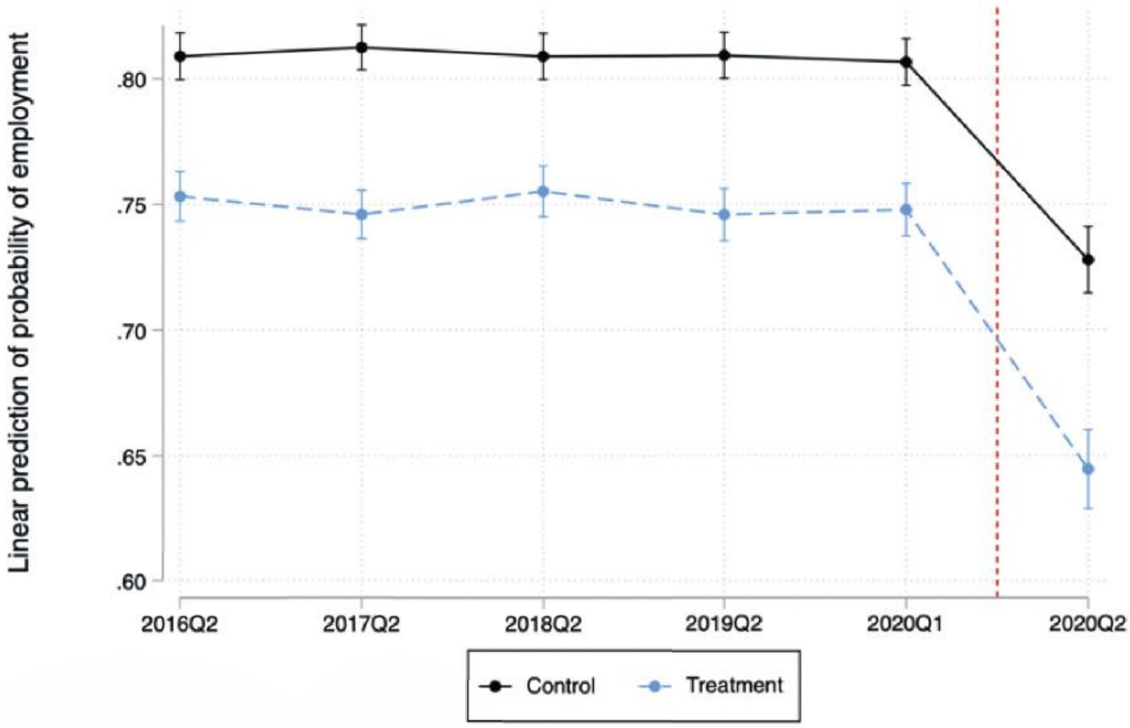


Figure 6: Trends in the probability of employment, by treatment group

Source: QLFS 2016Q2, 2017Q2, 2018Q2, 2019Q2, 2020Q1, and 2020Q2 (StatsSA 2016, 2017, 2018, 2019, 2020a, 2020b). Authors' own calculations.

Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted *using relevant sampling weights. [3] Standard errors clustered at the PSU level. [4] Capped spikes represent 95% confidence intervals. [5] Treatment group here excludes those who can work from home due to data limitations in pre-treatment years.*

It is clear that both groups followed a relatively constant trend prior to the lockdown, which informally satisfies the parallel trends assumption. Interestingly, individuals in the control group were consistently more likely to be employed by about six percentage points relative to the treatment group. This difference in levels is not a concern for our DiD analysis, given that this can be considered as a group 'fixed effect', which is controlled for in the model. Once the lockdown commenced, both groups experienced a substantial reduction in employment probability. The treatment group experienced a larger reduction in employment probability, of about 14%, whereas the control group experienced a reduction of 9.77%. This is indicative of the treatment effect we intend to measure; however, this informal comparison is conducted on the unmatched sample and may be subject to bias due to differences in characteristics between treatment groups. Our matched sample and econometric results are presented next.

Table 7 presents our PSM-DiD results for the estimated effect of South Africa's national lockdown on the probability of employment, where the coefficient of interest represents the difference between those permitted and not permitted to work during the national lockdown period.[15] We present four sets of results: first for the full 2020Q2 period, and then separately for the three lockdown stages within this period. Noting, as per Figure 6, that employment probability was decreasing for both the treatment and the control group, our overall estimates in model (1) suggest that the lockdown decreased the probability of employment for those not permitted to work by eight percentage points relative to the control group. When we disaggregate treatment by lockdown level,[14] we find (as expected) that the estimated effect is larger for more stringent lockdown levels: those not permitted to work in level 5 were 9.3 percentage points less likely to be employed during the lockdown relative to the control group, while for level 4 this decreases to 7.8 percentage points. We find no significant effect on differential employment probabilities during level 3. This latter null result may be driven by the fact that most individuals in our sample were permitted to work in level 3; however, it may also be affected by the small sample size.

[13]The complete model results are presented in Table A3 in the Appendix, which presents our estimates before and after matching and controlling for a vector of observable covariates and individual fixed effects.
[14]We do so by only including individuals in the treatment group for a given lockdown level if they were not permitted to work in the lockdown level and they were interviewed during the lockdown level.

Table 7: Propensity score-matched difference-in-difference estimates on the probability of employment, by lockdown level

Sample:	Matched sample			
Lockdown level:	Overall (1)	Level 5 (2)	Level 4 (3)	Level 3 (4)
Treatment	0.064*** (0.015)	0.012 (0.038)	0.208* (0.116)	0.197 (0.221)
Post	-0.073*** (0.014)	-0.058*** (0.016)	-0.046 (0.029)	-0.176* (0.092)
Treatment x Post	-0.080*** (0.012)	-0.093*** (0.022)	-0.078** (0.032)	-0.021 (0.123)
Constant	-0.159 (0.326)	0.637 (0.496)	0.369 (1.011)	-4.826 (5.346)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	15 576	10 752	7 328	642
Adjusted R^2	0.097	0.125	0.110	0.390

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant inverse probability weights. [3] Standard errors clustered at the individual level.

4.2. Variation by group: Triple difference-in-differences estimates

The above estimated effect ought to be interpreted as an average treatment effect on the treated (ATT); however, it is plausible that this effect varies between different groups. To investigate possible heterogeneity, we re-estimate our above PSM-DiD model by interacting the DiD term with binary variables for specific sub-groups, using triple difference-in-difference models.[15] The results of these models for select sub-groups of individuals are presented in Table 8.

[15]Also referred to as difference-in-difference-in-difference (DiDiD) models.

Table 8: Propensity score-matched triple difference-in-difference estimates

Group:	Male	Urban	Youth	Completed secondary or more	Own account worker	Low-skill worker
Treatment	0.064**	0.074*	0.069***	0.056***	0.060***	0.082***
	(0.031)	(0.042)	(0.018)	(0.020)	(0.020)	(0.023)
Post	-0.105***	-0.074***	-0.065***	-0.069***	-0.074***	-0.063***
	(0.023)	(0.024)	(0.014)	(0.016)	(0.014)	(0.015)
Treatment x Post	-0.049**	-0.033	-0.076***	-0.099***	-0.053***	-0.084***
	(0.024)	(0.027)	(0.017)	(0.020)	(0.015)	(0.018)
Group	0.002	n. e.	-0.015	-0.023	0.128***	0.034
	(0.060)		(0.050)	(0.033)	(0.048)	(0.028)
Treatment x Group	0.000	-0.012	-0.010	0.025	0.049	-0.051*
	(0.035)	(0.043)	(0.035)	(0.030)	(0.057)	(0.030)
Post x Group	0.046**	0.000	-0.025	-0.007	-0.009	-0.037
	(0.021)	(0.026)	(0.024)	(0.021)	(0.038)	(0.023)
Treatment x Post x Group	-0.036	-0.053*	0.010	0.042	-0.224***	0.038
	(0.030)	(0.032)	(0.033)	(0.030)	(0.075)	(0.035)
Constant	-0.168	-0.169	0.726***	-0.202	-0.144	-0.181
	(0.354)	(0.350)	(0.084)	(0.348)	(0.345)	(0.343)
Controls	Y	Y	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y	Y	Y
Observations	15 576	15 576	15 576	15 576	15 576	15 576
Adjusted R^2	0.096	0.095	0.092	0.095	0.098	0.094

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant inverse probability weights. [3] Standard errors clustered at the individual level. [4] n.e. = not estimated.

We find statistically significant, negative effects for two distinct groups: individuals living in urban areas versus those in rural areas, and own-account workers versus employees. We estimate a particularly large effect for the latter group. We do not find any evidence of variation in effects by sex, age, education, or skill level. Specifically, our estimates suggest that the national lockdown decreased the probability of employment for those who live in urban areas and were not permitted to work by 5.3 percentage points relative to the control group. Amongst own-account workers, the relative effect was a reduction in the probability of employment by 22.4 percentage points – an effect nearly three times larger compared to the ATT of eight percentage points observed above.[16] Importantly, given that the vast majority of own-account workers work in the informal sector (86.4% of own-account workers, or 1.4 million workers as of 2020Q1), this result is arguably indicative of the disproportionate effect of the lockdown on informal sector workers – in line with our descriptive analysis in Section 3.[17] What this suggests is that, while the ostensible disproportionate effects amongst other vulnerable groups (the youth, less-educated, and less-skilled) seem to be muted in these conditional estimates, working in the informal sector seems to be a key determinant of not being employed during the lockdown period.

[16] Importantly, these effects by group (i.e. for urban individuals and own-account workers) do not imply that only these groups were affected by the lockdown, but rather that the effects relevant to them are statistically significantly different relative to their counterparts (i.e. non-urban individuals and non-own-account workers).
[17] The informal sector here includes workers in private households. As opposed to own-account workers, we are unable to estimate a triple DiD effect for an explicit informal sector group of workers, given that only the employed were asked the relevant question in the QLFS.

4.3. Robustness tests

In this section, we conduct two sample-specific robustness tests to examine the sensitivity of our results to alternative (i) control group definitions and (ii) 'limited capacity industry' assumptions. In our main results, although our treatment group consistently consists of individuals legally not permitted to work during a given lockdown level at the time they were interviewed, the control group consists of individuals who were legally permitted to work, as well as anyone able to work during the lockdown (measured by working in the public sector or from home). Here we re-estimate our PSM-DiD models to examine the implications of including the latter two groups of workers in the control group. Specifically, we estimate models for the distinct control group definitions, similar to those in Table 2. The results of these models are presented in Table 9.

Regardless of control group definition, we continue to find statistically significant and negative effects on the probability of employment that vary between four and eight percentage points. The estimated effect is smallest (50% of the estimate of our preferred control group) when the control group either includes only those legally not permitted to work, or additionally those who work in the public sector – the effects based on these two definitions are not statistically different from one another. Lastly, when the control group consists of those who were permitted to work or could work from home, the estimate increases by 85% to -0.074, which is not statistically different from the estimate for our preferred control group: -0.080. This suggests that our main result is slightly sensitive to control group criteria. Irrespective of this, however, the estimated effect is consistently negative and statistically significant – in line with our overall finding.

Table 9: Propensity score-matched difference-in-difference estimates, by varying control group definition

Control group definition:	Legally permitted to work	Legally permitted to work, public sector	Legally permitted to work, work-from-home	Legally permitted to work, public sector, work-from-home **(main group)**
Treatment	0.028	0.039**	0.056***	0.064***
	(0.017)	(0.020)	(0.016)	(0.015)
Post	-0.098***	-0.094***	-0.079***	-0.073***
	(0.017)	(0.015)	(0.016)	(0.014)
Treatment x Post	-0.039**	-0.040**	-0.074***	-0.080***
	(0.017)	(0.016)	(0.016)	(0.012)
Constant	-0.179	-0.184	-0.178	-0.159
	(0.347)	(0.347)	(0.348)	(0.326)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	15 576	15 576	15 576	15 576
Adjusted R^2	0.090	0.091	0.094	0.097

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant inverse probability weights. [3] Standard errors clustered at the individual level.

In our main results, we assume that individuals were permitted to work if their industry's legislated capacity was equal to, or exceeded, 50%, and not otherwise. This is an arbitrary threshold and has implications for who is included in our control group, thus influencing our results. Our second robustness check entails re-estimating our PSM-DiD models using several alternative threshold assumptions to assign relevant individuals to the control group. Table 10 presents the four alternative assumptions we make, and their implications for our treatment-group samples. Under a 'very progressive' assumption, we assign individuals to the control group if any proportion of their industry was permitted to work. As expected, this results in the relatively largest control group of 31 500 observations. Under the 'very conservative' assumption, we assign individuals to the control group only if 100% of their industry was permitted to work. This results in a much larger treatment group and smaller control group. Intuitively, moving from 'very progressive' to 'very conservative' increases (decreases) the size of our treatment (control) group. Our main results – which use the '50%' assumption – can be regarded as moderate in this regard.

Table 10: Treatment group sample sizes by varied 'limited capacity industry' assumptions

Group	Description	Treatment	Control	Total
Very progressive	Permitted to work if **any** capacity of firm is permitted	5 534	31 497	37 031
Progressive	Permitted to work if **at least 25%** of firm is permitted	12 611	24 420	37 031
Main results	Permitted to work if **at least 50%** of firm is permitted	14 348	22 683	37 031
Conservative	Permitted to work if **at least 75%** of firm is permitted	19 384	17 647	37 031
Very conservative	Permitted to work **only if 100%** of firm is permitted	20 616	16 415	37 031

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years).

The results of our re-estimated models under these varying assumptions are presented in Table 11.[18] Regardless of assumption, we continue to find statistically significant and negative effects on the probability of employment, which varies between eight and 14.9 percentage points.

[18] It should be noted that it is expected that the number of observations in our regression models in Table 11 are expected to vary, and in particular increase from 'very progressive' to 'very conservative'. This is because the size of the treatment group grows in this direction, and the propensity score-matching technique attempts to match appropriate control observations to the number of treatment observations.

Table 11: Propensity score-matched difference-in-difference estimates, by 'limited industry capacity' assumption

Assumption:	Very progressive	Progressive	Main results	Conservative	Very conservative
Treatment	0.059*	0.058***	0.064***	0.046***	0.058***
	(0.031)	(0.016)	(0.015)	(0.016)	(0.018)
Post	-0.047	-0.084***	-0.073***	-0.089***	-0.063***
	(0.032)	(0.016)	(0.014)	(0.014)	(0.015)
Treatment x Post	-0.149***	-0.081***	-0.080***	-0.081***	-0.080***
	(0.040)	(0.019)	(0.012)	(0.015)	(0.014)
Constant	0.179	0.302	-0.159	0.021	0.123
	(0.533)	(0.364)	(0.326)	(0.330)	(0.328)
Controls	Y	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y	Y
Observations	7 504	15 094	15 576	19 039	19 039
Adjusted R^2	0.188	0.098	0.097	0.088	0.098

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant inverse probability weights. [3] Standard errors clustered at the individual level.

Although the estimate under the 'very progressive' assumption is nearly two times larger in magnitude compared to our main estimate of -0.080, we note that in three of the four assumptions we find very similar results to those of our main estimate. Arguably, the 'very progressive' assumption – that is, individuals are permitted to work if any capacity of their firm in their industry was permitted to work – is not a plausible assumption. We therefore take the remaining estimates as evidence that our main result under the moderate '50%' is fairly robust to alternative assumptions.

5. Conclusion

South Africa imposed a relatively stringent national lockdown in response to the COVID-19 pandemic to prepare the necessary health infrastructure, as well as to delay and minimise the spread of the virus. Although the pandemic continues to pose important risks to public health, the lockdown was always expected to result in substantial short- and long-term economic costs. Several studies using data collected during South Africa's lockdown show that these costs have been disproportionately borne by several vulnerable groups, such as less-skilled, low-wage, informal, and female workers.[19] These studies, however, are largely descriptive in nature. In this paper, in addition to providing a detailed descriptive account of the effects of the COVID-19 pandemic on the South African labour market outcomes, we exploit quasi-experimental variation in the country's national lockdown policy to estimate the causal effect of the lockdown on the probability of employment for those not permitted to work. By cross-examining the relevant legislature with three-digit industry codes in representative labour force data, we do so by exploiting the coincidental timing of the lockdown

[19] See Benhura and Magejo (2020), Casale and Posel (2020), Casale and Shepherd (2020), Hill and Köhler (2020), Jain et al. (2020), and Ranchhod and Daniels (2020).

and survey data collection dates through the use of a propensity score-matched (PSM) difference-in-differences (DiD) approach.

Our descriptive analysis shows that, of the 2.2 million fewer individuals employed in the first few months of the lockdown, employment loss was concentrated amongst the youth, those with lower levels of formal education, and those living in urban areas. Considering labour market characteristics, almost all employment loss was observed in the private sector, with the lockdown disproportionately affecting individuals working in the informal sector. Specifically, about 50% of total employment loss is attributable to the informal and domestic services sector, despite these workers accounting for just under 25% of pre-pandemic employment. We also observe some evidence of job protection amongst union members, with non-union members accounting for nearly 100% of employment loss. Although the tertiary sector accounted for two-thirds of employment loss, the secondary sector – particularly manufacturing and construction – was affected disproportionately. Low- and semi-skilled workers accounted for almost all jobs lost. Geographically, after accounting for national employment shares, we observe that the Northern Cape, Free State, and Limpopo suffered the largest relative employment losses. Considering outcomes other than employment, we document the notable changes in the distribution of working hours, and the substantial increase in inactivity. This latter observation is characteristic of national lockdown policy, which induced an inability for both job-losers and job-seekers to engage in the labour market.

Finally, our preferred estimate of the quasi-experimental results suggests that, relative to the control group, the national lockdown decreased the probability of employment for those not permitted to work by eight percentage points. This significant and negative effect holds when subjected to sample-specific robustness tests relating to control group definitions and assumptions regarding industries in which individuals were permitted to work, but at limited capacity. We observe significant heterogeneity by lockdown level, with an estimated effect of nearly 10 percentage points for the most stringent level. Our triple difference-in-differences analysis suggests that two distinct sub-groups were affected significantly: individuals living in urban areas (versus those in rural areas), and own-account workers (versus employees). The estimated effect for the latter group was nearly three times larger than the overall average treatment effect, indicative that working in the informal sector seems to be a key determinant of not being employed during the lockdown period.

Although it is clear that the COVID-19 pandemic and subsequent national lockdown has had a substantially adverse effect on the South African labour market, it is important to note that our analysis presented here serves as a set of initial estimates. Subsequent analysis may entail the use of occupation data to further fine-tune control group criteria and, as more data is released, we can investigate effects on alternative labour market outcomes other than employment, such as working hours and wages. Availability of this latter data will also permit us to examine heterogeneity in effects across the wage distribution. Importantly, more data will give us new information on the nature and extent of recovery in the labour market and, unfortunately, the scale of permanent job destruction across the South African economy.

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5. Conclusion

Technical Note on Propensity Score Matching

Prior to our difference-in-differences (DiD) estimation, we first estimate propensity scores, and thereafter use these probabilities to construct inverse probability weights (IPW). To estimate these scores, we use a logit model to estimate the probability of being in the treatment group based on a vector of observable covariates.[20] These include age, age squared, sex, race, marital status, highest level of education, province, household geographic area, lockdown level, and type of employment. Our inclusion of specific covariates in the propensity score model is guided by the aim of credibly satisfying the conditional independence assumption (CIA): conditional on the propensity score, the outcome of interest is independent of treatment. This entails including variables that are thought to be related to both the treatment and the outcome of interest, but are unaffected by the treatment itself. We adopt a parsimonious model and avoid including too many variables, given that doing so may exacerbate the common support problem.[21] Using nearest-neighbour matching, we match exclusively on pre-treatment data, given that post-treatment characteristics may be endogenous (i.e. affected by treatment), as follows:

$$Pr(z_i) \stackrel{\text{def}}{=} Pr(Treatment_i = 1 \mid \boldsymbol{X}_i),$$

where $Treatment_i$ is a binary variable equal to one if an individual is included in the treatment group and zero if included in the control group, and $\boldsymbol{X}_i$ is the vector of observable covariates discussed above. The propensity scores are estimated using caliper matching, using a relatively small caliper of 0.02. That is, we only consider a pair of observations a match if the absolute difference in the propensity score is less than 0.02. We then generate IPWs using these scores to reweight observations, as follows:

$$w_i = \delta_i \left\{ \frac{Treatment_i}{z_i} - \frac{1-Treatment_i}{1-z_i} \right\},$$

where w_i is the final inverse probability weight of individual i, which is equal to the QLFS sampling weight (δ_i) multiplied by a function of the dichotomous treatment variable and the estimated propensity score z_i.[22] This function is equivalent to $\frac{1}{z_i}$ for treated observations and $\frac{1}{1-z_i}$ for control observations, and is based on inverse-probability regression (Brunell and DiNardo 2004). That is, it weighs up treated observations with lower propensity scores and control observations with higher propensity scores. The weights obtained from this method are then used to control for conditional selection into treatment and minimise bias in the DiD regressions.

It is then important to examine whether or not our PSM approach achieves balance in observable covariates. Table A1 presents diagnostic statistics to examine covariate balance between treatment groups in the raw and matched samples. Our PSM approach appears to have worked well: the matched sample results show that matching on the estimated propensity score balanced the covariates. For every covariate in the matched sample, the standardised differences are all close to zero, and the variance ratios are all close to one.[23] This is reflected by the propensity score

[20] The choice of using a logit as opposed to a probit model for the binary treatment case is not critical, because these models usually yield similar estimates; however, the former is used because the logistic distribution has higher density mass in the bounds (Caliendo and Kopeinig, 2008).
[21] When there is an insufficient overlap in observables of individuals in the treatment and control groups to find appropriate matches (Bryson et al., 2002).
[22] This latter function is normalised using min-max normalisation prior to being included in this formula.
[23] Despite these results suggesting success in achieving balance of observables, inference here is regarded as informal because we do not have standard errors for these statistics.

distributions by treatment group and sample in Figure A1. The left panel shows that the distributions for the matched sample are nearly indistinguishable, implying that matching on the estimated propensity score balanced the covariates. The histogram in the right panel highlights the sufficient overlap in the distribution of propensity scores across treatment groups.

Table A1: Propensity score matching balance summary diagnostics of pre-treatment covariates

Variable	Standardised differences		Variance ratio	
	Raw	Matched	Raw	Matched
Sex				
Male	0.211	0.026	0.982	0.993
Female	-0.252	-0.020	0.923	0.991
Race				
Black/African	0.090	-0.021	0.880	1.035
Coloured	-0.040	0.007	0.904	1.019
Indian/Asian	0.006	0.011	1.037	1.072
White	-0.093	0.019	0.747	1.070
Education				
Primary education or less	0.086	0.053	1.214	1.122
Secondary incomplete	0.216	-0.013	1.114	0.997
Secondary complete	0.042	-0.012	1.033	0.992
Tertiary	-0.411	-0.020	0.469	0.948
Age and geographic area				
Age	-0.115	0.058	1.003	1.042
Urban	0.064	-0.007	0.935	1.008
Traditional areas	0.005	-0.002	1.007	0.997
Farms	-0.152	0.025	0.488	1.161

Source: QLFS 2020Q1 (StatsSA 2020a). Authors' own calculations.
Notes: [1] Labour market groups restricted to the working-age population (15 to 64 years). [2] Propensity scores estimated for the panel through logit regression on a pre-treatment vector of covariates using a caliper of 0.02 and independent and identically distributed (i.i.d.) standard errors.

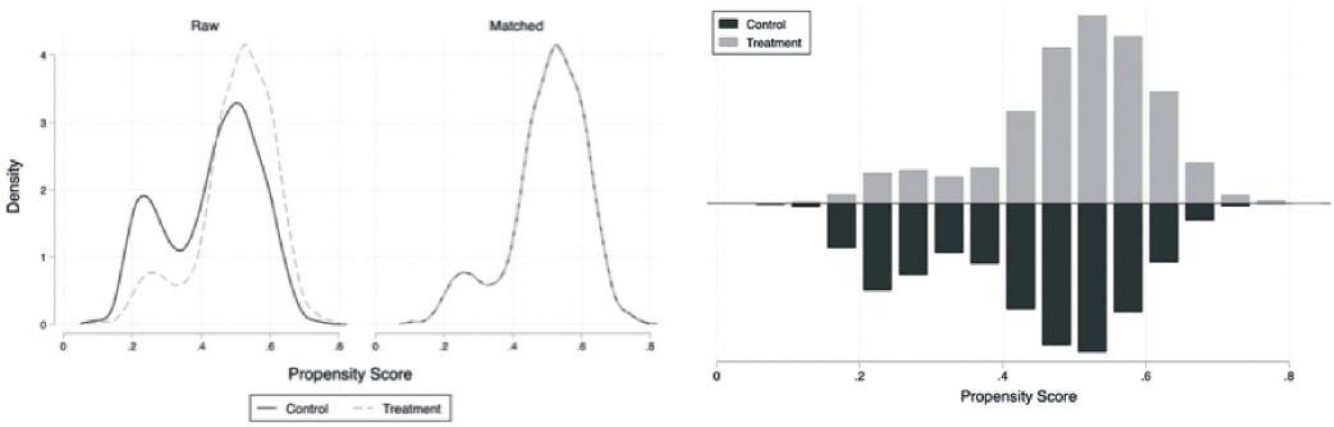

Figure A1: Kernel density plots and histogram of propensity scores, by treatment group and sample
Source: QLFS 2020Q1 (StatsSA 2020a). Authors' own calculations.
Notes: [1] Labour market groups restricted to the working-age population (15to 64 years). [2] Propensity scores estimated for the panel through logit regression on a pre-treatment vector of covariates using a caliper of 0.02 and independent and identically distributed (i.i.d.) standard errors.

Table A2: Linear probability model estimates of employment transition probabilities from 2020Q1 to 2020Q2

	(1)	(2)	(3)	(4)	(5)
	Employment --> Unemployment		Employment --> Inactivity		Unemployment--> Inactivity
35–49	-0.027***	-0.018**	-0.054***	-0.038***	-0.048**
	(0.009)	(0.009)	(0.010)	(0.010)	(0.020)
50–64	-0.046***	-0.034***	-0.018	-0.008	-0.006
	(0.010)	(0.010)	(0.013)	(0.014)	(0.038)
Female	-0.012*	-0.013*	0.043***	0.019**	0.019
	(0.007)	(0.008)	(0.008)	(0.009)	(0.017)
Coloured	0.006	0.005	-0.004	0.021	0.069*
	(0.015)	(0.015)	(0.018)	(0.018)	(0.038)
Indian/Asian	0.007	0.034	-0.050**	-0.033*	-0.153
	(0.022)	(0.026)	(0.021)	(0.020)	(0.101)
White	-0.033***	-0.039***	-0.014	-0.023	0.023
	(0.008)	(0.008)	(0.014)	(0.014)	(0.078)
Living together	0.012	0.001	-0.002	-0.021	-0.068*
	(0.012)	(0.012)	(0.014)	(0.015)	(0.036)
Widow/Widower	0.023	0.008	0.017	-0.003	-0.012
	(0.017)	(0.019)	(0.025)	(0.027)	(0.074)
Divorced or separated	0.019	0.014	-0.029	-0.026	-0.072
	(0.018)	(0.019)	(0.019)	(0.019)	(0.068)
Never married	0.028***	0.014	0.032***	0.010	-0.083***
	(0.008)	(0.009)	(0.010)	(0.011)	(0.026)
Secondary incomplete	-0.000	0.000	0.007	0.037**	-0.018
	(0.014)	(0.016)	(0.015)	(0.017)	(0.033)
Secondary complete (matric)	-0.029**	-0.011	-0.049***	0.025	-0.040
	(0.014)	(0.017)	(0.016)	(0.018)	(0.035)
Post-secondary	-0.051***	-0.010	-0.118***	0.013	-0.021
	(0.014)	(0.019)	(0.016)	(0.021)	(0.042)
Urban	-0.009	-0.006	0.008	0.016	0.029
	(0.009)	(0.010)	(0.011)	(0.012)	(0.022)
Eastern Cape	0.027*	0.025	0.021	0.026	0.060
	(0.016)	(0.017)	(0.020)	(0.020)	(0.043)
Northern Cape	-0.005	-0.019	0.031	0.019	0.213***
	(0.019)	(0.017)	(0.026)	(0.025)	(0.054)
Free State	0.002	-0.002	0.031	0.032	0.164***
	(0.016)	(0.017)	(0.022)	(0.022)	(0.044)
KwaZulu-Natal	-0.032**	-0.047***	0.009	0.003	0.211***
	(0.013)	(0.013)	(0.017)	(0.017)	(0.041)
North West	0.000	-0.001	0.008	0.027	0.178***
	(0.018)	(0.018)	(0.024)	(0.024)	(0.053)
Gauteng	0.025**	0.020	0.012	0.016	0.037
	(0.012)	(0.012)	(0.016)	(0.016)	(0.037)
Mpumalanga	-0.035**	-0.045***	-0.013	-0.010	0.335***
	(0.014)	(0.014)	(0.019)	(0.019)	(0.042)
Limpopo	-0.002	-0.009	0.075***	0.057***	0.165***
	(0.016)	(0.017)	(0.021)	(0.021)	(0.050)
Public sector		-0.023**		-0.081***	
		(0.011)		(0.015)	
Permanent nature		-0.092***		-0.133***	
		(0.016)		(0.017)	
Unspecified duration		-0.004		-0.028	
		(0.022)		(0.022)	
Union non-member		0.005		0.035***	
		(0.008)		(0.011)	
Union membership unknown		-0.004		-0.034	

		(0.021)		(0.023)	
Between 2 and 4 employees		-0.045*		-0.012	
		(0.026)		(0.030)	
Between 5 and 9 employees		-0.021		-0.041	
		(0.029)		(0.038)	
Between 10 and 19 employees		-0.041		-0.050	
		(0.028)		(0.037)	
Between 20 and 49 employees		-0.010		-0.044	
		(0.029)		(0.037)	
50 or more employees		-0.022		-0.038	
		(0.028)		(0.036)	
Do not know firm size		-0.010		-0.022	
		(0.030)		(0.037)	
Do not have written contract		-0.001		0.050**	
		(0.021)		(0.023)	
Weekly working hours		-0.001		-0.002***	
		(0.000)		(0.000)	
Informal sector		0.049**		0.005	
		(0.023)		(0.029)	
Private households		0.017		-0.004	
		(0.043)		(0.049)	
Mining and quarrying		0.012		0.046	
		(0.024)		(0.030)	
Manufacturing		0.035		0.066***	
		(0.022)		(0.024)	
Utilities		0.031		0.062	
		(0.032)		(0.045)	
Construction		0.038		0.099***	
		(0.027)		(0.029)	
Wholesale and retail trade		0.012		0.034	
		(0.022)		(0.023)	
TSC		0.019		0.068**	
		(0.025)		(0.029)	
Finance		0.020		0.018	
		(0.022)		(0.023)	
CSP		0.026		0.099***	
		(0.023)		(0.025)	
Other		0.025		-0.059**	
		(0.051)		(0.028)	
Professionals		-0.008		-0.014	
		(0.014)		(0.017)	
Technical professionals		-0.006		0.021	
		(0.014)		(0.018)	
Clerks		0.004		0.016	
		(0.015)		(0.016)	
Service and shop workers		0.010		0.062***	
		(0.015)		(0.018)	
Skilled agricultural		-0.050		0.018	
		(0.042)		(0.062)	
Craft and related trades		0.020		0.074***	
		(0.018)		(0.021)	
Plant and machine operators		-0.016		0.029	
		(0.018)		(0.022)	
Elementary occupation		0.014		0.066***	
		(0.017)		(0.019)	
Domestic workers		-0.028		0.057	
		(0.041)		(0.048)	
Other		-0.057		0.001	
		(0.035)		(0.031)	
Constant	0.113***	0.180***	0.186***	0.231***	0.576***
	(0.023)	(0.052)	(0.024)	(0.058)	(0.056)
Observations	8 934	7 586	10 108	8 449	4 109
Adjusted R^2	0.024	0.062	0.031	0.097	0.037

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant sampling-adjusted weights for 2020Q2. [3] Reference groups = 15-34, African/Black, Married, Primary education or less, Western Cape, Limited job duration, Union member, Firm size = 1 employee, Formal sector, Agriculture, Legislators. [4] Standard errors clustered at the individual level.

Table A3: Propensity score-matched difference-in-difference estimates of the probability of employment, by sample

	Probability of employment					
Sample:	Unmatched			Matched		
Treatment	-0.075***	-0.048***	0.061***	-0.064***	-0.057***	0.064***
	(0.007)	(0.008)	(0.013)	(0.009)	(0.010)	(0.015)
Post	-0.084***	-0.079***	-0.065***	-0.089***	-0.092***	-0.073***
	(0.006)	(0.009)	(0.008)	(0.010)	(0.015)	(0.014)
Treatment x Post	-0.049***	-0.055***	-0.085***	-0.023	-0.025	-0.080***
	(0.012)	(0.012)	(0.010)	(0.017)	(0.017)	(0.012)
Constant	0.809***	0.135***	0.170	0.959***	0.056	-0.159
	(0.005)	(0.050)	(0.299)	(0.021)	(0.104)	(0.326)
Controls	N	Y	Y	N	Y	Y
Fixed effects	N	N	Y	N	N	Y
Observations	37 033	36 583	27 303	22 328	22 278	15 576
Adjusted R^2	0.020	0.104	0.081	0.020	0.100	0.097

Source: QLFS 2020Q1 and 2020Q2 (StatsSA 2020a, 2020b). Authors' own calculations.
Notes: [1] Sample restricted to working-age population (15 to 64 years). [2] All estimates weighted using relevant inverse probability weights. [3] Standard errors clustered at the individual level.

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