The labour market and poverty impacts of Covid-19 in South Africa

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Abstract

We use a newly-released South African panel dataset to present some of the first estimates of COVID-19-related employment and poverty impacts in a developing country. We observe a 40% net decline in active employment compared to pre-lockdown. Approximately half of this decline is comprised of job terminations as opposed to temporary lay-offs or paid leave, suggesting that labour market impacts are likely to be persistent. Women, manual workers and those at the bottom half of the income distribution have suffered disproportionately higher rates of job loss. In the absence of data on pre-lockdown income, we cannot directly observe poverty changes over the lockdown period; instead we compare lockdown incomes of job-losers and job-retainers after DiNardo-Fortin-Lemieux re-weighting. We estimate that 15 - 30% of job losers fall into poverty, which corresponds to approximately 1 million individuals. Social protection efforts have provided inadequate coverage to substantially mitigate this poverty impact, with only one in five temporarily unemployed workers receiving the relief designed for them, while other job-losers must rely on the existing social grant system. About one in three job losers had no social protection at all.

Keywords— Labor market; poverty; recessions; unemployment; coronavirus; social protection; social policy.

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Executive Summary

We estimate that the number of actively employed adults in South Africa decreased by approximately 40% between February and April 2020. This net loss can be accounted for by shifts into three distinct categories in April: “paid leave” (those with positive wages but no working hours), “temporary lay-offs” (those attached to an employer but without wages or working hours), and terminated employment relationships. Of the 40% net loss in employment, almost half is accounted for by terminated employment relationships, indicating a dramatic change in labour market structure and suggesting large longer term effects on unemployment.

Importantly, we find that the labour market shock has exacerbated existing inequalities. Women, those with lower levels of education, those in manual occupations, informal workers, and the poor in general face the greatest net employment losses, with these employment losses being disproportionately made-up of terminated employment relationships. This indicates an enduring worsening of inequality.

While the data does not allow direct calculation of poverty changes over the lockdown, we match job-losers with observably similar job-retainers in order to estimate an approximate poverty impact of the COVID-19 labour market shock. Our estimates suggest that approximately one million job-losers have fallen into poverty as a direct result of the COVID shock. Indirectly, accounting for the dependents of these workers, we tentatively estimate that this job loss has increased poverty by about 3 million people. We stress that these estimates are not direct poverty calculations, and are highly approximate.

Part of the explanation for these large poverty impacts is the relatively low rate of social insurance coverage: For those workers remaining in an employment relationship but reporting zero days of active work in April, only 20% received TERS. While social assistance measures (especially the Child Support Grant) progressively provide broader coverage, 30% of those whose February employment relationships were terminated report no household-level grant protection at all. We estimate that the poverty impact in April would have been much smaller had the additional grant rollout occurred sooner.

Our results ought to be interpreted with several important caveats in mind. First, NIDS-CRAM data cannot be considered representative of the South African population in 2020. It is best understood as being representative -- when appropriately weighted -- of the 2017 NIDS sample from which it was drawn. Second, key welfare and labour market variables in NIDS-CRAM data are only approximately comparable across February and April and in general are not comparable to 2017 NIDS or other South African household surveys. Finally, while our empirical strategy for identifying the poverty impact of a job loss over February and April 2020 conditions on a rich set of observable individual characteristics from the 2017 NIDS survey, there are numerous factors which may bias our estimates, with the direction of overall direction of bias being indeterminate. Estimated poverty impacts therefore ought to be interpreted as tentative until subsequent waves of NIDS-CRAM allow us to better track changes in poverty over time.
1. Introduction

Little is known about the labour market impacts of the COVID-19 pandemic in developing countries and yet less is known about the welfare consequences of this shock in these less-protected labour markets. Using new broadly representative South African survey data, we estimate that after one month of intensive lockdown active employment had decreased by 40%. In nearly half of these cases workers did not expect to return to their jobs, suggesting scarring effects which may have long-run consequences. The pattern of job-loss severely exacerbated existing inequalities, and we estimate a substantial increase in poverty for job losers.

As evidence becomes available from across the world, expectations that the economic disruption caused by COVID-19 would lead to widespread job-losses have been confirmed. The first countries in which detailed labour market data has become available – primarily in Western Europe and North America – have recorded historic labour market contractions. However, these have also been the countries which introduced the most comprehensive set of social protection relief measures.

It is widely expected that the poverty impact of the COVID-19 pandemic will be most severe in emerging market economies. In response, even developing countries with underdeveloped social protection infrastructures have responded rapidly and creatively in delivering forms of emergency relief. However, without real-time data, it has been impossible to evaluate the labour market impact of COVID-19 in developing countries or how effective the newly introduced social protection response measures have been in offsetting the welfare consequences of this labour market shock.

In this paper we use a newly-released developing country dataset – the National Income Dynamics Study: Coronavirus Rapid Mobile Survey (NIDS-CRAM) – to present some of the first estimates on the impact of COVID-19 on employment and welfare outcomes in South Africa. The NIDS-CRAM sample is approximately 30% of the adult sub-sample drawn from the 2017 wave of the National Income Dynamics Study (NIDS), a nationally representative longitudinal household survey.

In this paper, we investigate two key empirical questions: (1) What are the labour market effects of COVID-19 in South Africa and (2) How has this labour market shock affected individual welfare?

In order to investigate the labour market impacts of COVID-19 in South Africa, we introduce a new employment status typology that modifies the standard categorisation of “not economically active”, “discouraged unemployed”, “searching unemployed” and “employed”. Instead, we adopt a definition of employment status that distinguishes between the “not employed”, the “temporarily laid-off”, those on “paid leave”, and the “actively employed”. The context of the COVID-19 crisis calls for a more nuanced definition of the “employed” category, within which key cleavages exist between those able to continue working, those who cease working but whose earnings are not compromised, and those who are temporarily laid off without pay. Having proposed this re-categorisation of employment status, we measure the effects of COVID-19 on employment by comparing net changes in employment status from February (prior to the COVID-19 shock) to April 2020 (following the imposition of a stringent lockdown).

Of the 40% net decline that we find in active employment, almost half is accounted for by increases in nonemployment as opposed to temporary layoffs or paid leave. Women, those with lower levels of education, those in manual occupations, informal workers, and the poor in general face the greatest net employment losses, with these employment losses being disproportionately made-up of shifts into non-employment.

Identifying the effect that job losses had on poverty over February 2020 to April 2020 is less straightforward than identifying the labour market effects of COVID-19. This poverty impact analysis presents two key challenges. First, we observe household income for April 2020 (post-shock) but not February 2020 (pre-shock), preventing us from directly observing the change in this key variable. Secondly, household income in the NIDS-CRAM data is not directly comparable to income reported in earlier waves of the dataset the sample is drawn from, or other South African pre-COVID-19 household surveys, preventing us from making between-waves and crosssurvey comparisons.
Instead, we estimate poverty impacts by comparing April incomes of those who lose jobs between February and April to those who retain their employment. In order to overcome selection effects, we DFL re-weight the household income distribution of job-retainers, after using a logit LASSO regression to predict job-loss from a rich set of 2017 individual-level characteristics.

A number of diagnostic and robustness tests suggest that our re-weighting procedure works well, and per our preferred specification we estimate that between 15% to 30% of job losers – approximately 1 million individuals – fall into poverty as a result of COVID-19-related job loss. Using a rough estimate of the dependency ratio of job-losers, we speculate that this job-loss is associated with an increase in overall poverty of just over 3 million people including dependents. This number closely matches the COVID-19 poverty prediction of Bassier et al., 2020, of 2.5 to 3 million more individuals falling into poverty as a result of the lockdown labour market shock.

Part of the explanation for these large poverty impacts is the relatively low rate of social protection coverage in April. For those workers who lost jobs and move into temporary unemployment, only 20% received the emergency social insurance scheme designed to support them – the Temporary Employee/Employer Relief Scheme (TERS). While social assistance measures (especially the Child Support Grant) progressively provide broader coverage, 30% of those who lost jobs into non-employment reported no household-level grant protection at all, and the monetary value of these grants is in any case small relative to the scale of the labour market shock. Based on a hypothetical counterfactual, we tentatively estimate that the April poverty increase associated with job-loss would have been mitigated by between roughly 20 and 40% if social grant top-ups had been implemented from April rather than May.

Our results ought to be interpreted with several important caveats in mind. First, NIDS-CRAM data cannot be considered representative of the South African population in 2020. It is best understood as being representative – when appropriately weighted – of the 2017 NIDS sample from which it was drawn, which is itself roughly representative of the South African population. Second, key welfare and labour market variables in NIDS-CRAM data are only approximately comparable across February and April and in general are not comparable to 2017 NIDS or other South African household surveys. Finally, while our empirical strategy for identifying the poverty impact of a job loss over February and April 2020 conditions on a rich set of observable individual characteristics from the 2017 NIDS survey, there are factors which may make our poverty impact estimate an over- or underestimate of the actual impact. These estimates are therefore tentative best estimates until subsequent waves of NIDS-CRAM allow us to better track changes in poverty over time.

Even with these caveats, we believe that this work provides valuable initial evidence on the labour market and welfare impacts of the COVID-19 pandemic in South Africa. An important advantage of the longitudinal survey design is that NIDS-CRAM respondents can be linked back to their records in earlier NIDS waves. In addition to exploiting this in our estimation strategy, unlike many other recent rapid mobile surveys conducted to measure the impact of COVID-19, this allows us to assess the likely direction of over- or under-reporting of key variables in our sample, compared to an in-person survey.

Our paper contributes to the emerging cross-country literature on the economic impact of COVID-19, as well as a more established literature on the impact of economic downturns on labour markets and poverty in developing countries. We provide one of the first assessments of the economic impacts of COVID-19 in a developing-country context. We introduce a new employment typology appropriate for analysing the COVID-19 labour market impact in South Africa, and use this typology to examine both overall effects as well as heterogeneity by important social cleavages. Lastly, we employ a new methodology to estimate poverty effects when changes in income are not directly observed over time, and present the first COVID-19 poverty estimates for South Africa based on contemporaneous data.

This paper is structured as follows. Section 2 reviews relevant literature and discusses the South African institutional context. Section 3 describes our sample. Section 4 presents results on the labour market impact of the COVID-19 shock, including on heterogeneity of impact across key
groups. Section 5 provides evidence on social protection coverage. Section 6 presents our estimates of the COVID-19 poverty impact and outlines our empirical methodology for this result. Section 7 discusses the implications of our poverty results for population-level poverty impacts, and considers a counterfactual policy response. Section 8 concludes.

2. Literature and context

2.1. Broader Literature

Research on the impact of the COVID-19 crisis on firms and workers is emerging in real time. Most of this research has focused on countries in Western Europe and the United States (Adams-Prassl et al., 2020; Alon et al., 2020; Bartik et al., 2020; Hassan et al., 2020). There have been significant decreases in employment (Coibion, Gorodnichenko, and Weber, 2020), especially for those working in small and medium enterprises (Bartik et al., 2020) and for younger workers, low income workers, the self-employed, and those working variable hours (Adams-Prassl et al., 2020). In addition, women have also faced higher rates of job loss than men (Adams-Prassl et al., 2020; Alon et al., 2020).

While evidence so far on the labour market impact of COVID-19 in low and middle-income countries is still sparse, the consequences could be much more severe. In developing countries, governments have fewer resources to support firms and workers through the crisis. Even when relief measures are implemented, since many businesses and workers are in the informal sector, they are harder to reach by targeted assistance (Bassier et al., 2020; Gerard, Imbert, and Orkin, 2020). Moreover, a greater share of workers are in occupations which cannot operate under conditions of social distancing or work from home (International Labour Organisation, 2020a; International Labour Organisation, 2020b; Kerr and Thornton, 2020).

Despite strategies for mitigating the economic impacts of the crisis, increases in unemployment are expected to lead to large increases in poverty across the world (Mahler et al., 2020; Parolin and Wimer, 2020; Sumner, Hoy, and Ortiz-Juarez, 2020). In developing countries, the poverty impact is expected to be especially severe. Mahler et al. (2020) estimate that between 71 and 100 million people, mostly in developing countries, will be pushed into extreme poverty ($1.90/day) while Sumner, Hoy, and Ortiz-Juarez (2020) estimate an increase in global extreme poverty between 85 and 135 million, assuming a global 5 percent contraction in per capita income. Both South Asia and Sub-Saharan Africa are expected to be particularly severely affected.

There are several reasons why the negative labour market effects of COVID-19 are likely to have especially severe poverty effects in developing countries, even abstracting from inadequate social assistance responses. First, household savings are generally very low and access to credit is limited, leaving households vulnerable to large income shocks Sarma and Pais (2011). Second, since insurance mechanisms are community-based and typically informal these insurance strategies are rendered ineffective when the shock is at the community level (Dercon, 2002). In the case of the global shock of COVID-19, this has also led to an unprecedented decline in international remittances – another source of emergency relief for many households and an important source of foreign exchange in many economies (The Economist, 2020). Finally, migration responses to economic shocks are constrained by the imposition of restrictions on free movement during periods of enforced social distancing.

To mitigate the effect that COVID-19-related job and earnings losses will have on individual welfare, almost all governments have implemented emergency social protection interventions to protect affected workers and their households with varying degrees of speed and creativity (Gentilini et al., 2020). Given the greater challenges that developing countries face in reaching vulnerable workers in informal sectors, (Gerard, Imbert, and Orkin, 2020) have argued for a “broader patchwork of solutions”.

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2.2 The South African context

South Africa went into lockdown on 26 March. Relief measures in response to the COVID-19 crisis have consisted of both social insurance measures, administered through the contribution-based Unemployment Insurance Fund (UIF), and social assistance interventions, administered through publicly funded cash grants. Social insurance relief measures were introduced first, with the Temporary Employee/Employer Relief Scheme (TERS) announced on 26 March 2020. TERS is an earnings relief benefit for employers unable to pay their employees due to the COVID-19 lockdown (Department of Labour, Republic of South Africa, 2020). The minimum payment was set at R3,500 per month ($205), equal to the National Minimum Wage, and the maximum payment was set at approximately R6,700 ($394). TERS benefits were initially restricted to workers who were contributing to UIF, but on 26 May 2020 a successful legal challenge expanded the scheme to any worker who could prove an employment relationship, whether registered with UIF or not.

On 21 April 2020 the South African government announced a set of social assistance measures aimed at delivering relief to those households which were not covered by the social insurance measures announced previously (The Presidency, Republic of South Africa, 2020). These consisted of: a) an increase to the Child Support Grant (CSG) of R300 ($17) for one month, followed by an increase of R500 ($30) per month from June to October (but limited during the latter period to one increase per caregiver); b) an increase to all other social grants (such as the Old Age Pension (OAP) and the the Disability Grant) of R250 ($15) per month until October, and; c) the installment of a new “COVID-19 Social Relief of Distress grant (SRD)" of R350 ($21) per month, introduced for people who are unemployed and not receiving any other grant or UIF.

The delivery of these relief measures has in many cases been poor, with the SRD grant in particular being widely considered an implementation failure. TERS payments were initially delayed due to large backlogs of applications and infrastructure breakdowns (Dept. of Employment and Labour, 2020), and double-payments of Old Age Pensions were made in some provinces in April, while elsewhere payments were not made at all (EWN, 2020). While eligibility for an SRD-like grant was previously estimated at approximately 15 million South Africans (Bassier et al., 2020), as of 11 June 2020, the South African Social Security Agency had received over 6.5 million applications but had only paid 600,000 grants (New Frame, 2020). The state has also revealed that 60% of rejected applicants actually qualified, leading to lengthy implementation delays for these individuals (SASSA, 2020).

However, without reliable survey data, it has been difficult to know how South African workers have been affected by COVID-19, how job and earning losses, to the extent that they have occurred, have translated to increases in poverty, and finally, the extent to which social protection interventions – despite delays and implementation bottlenecks – have reached those who have lost their jobs or household income. The release of NIDS-CRAM data allows us to undertake this analysis.

3. Data

3.1. Description of NIDS-CRAM and NIDS

This paper uses data from the National Income Dynamics Study (NIDS) (SALDRU, 2017) and the National Income Dynamics Study: Coronavirus Rapid Mobile Survey (NIDS-CRAM) (SALDRU, 2020). NIDS-CRAM uses a computer-assisted telephone interviewing (CATI) technique, with the first wave surveyed in May and June 2020. The NIDS-CRAM sample is drawn from a sub-sample of the fifth wave of NIDS, an existing South African longitudinal individual-level panel survey. The fifth wave of NIDS, surveyed in 2017, was the most recent survey round.

1 NIDS was an individual-level panel, but a household survey. That is, individuals were followed over time, but in each wave of data collection individual-level questionnaires were administered to each household member (or a proxy questionnaire on behalf of absent members). In addition, a household survey was administered to the eldest woman or household member most knowledgeable about household affairs. NIDS-CRAM, on the other hand, is both an individual level panel, and an individual-level survey.

2 3 of the 7074 respondents reported an age of 17
We use the employment, earnings and household-level economic outcomes data from NIDS-CRAM in our analysis. An important advantage of the longitudinal survey design is that NIDS-CRAM respondents can be linked back to their records in earlier NIDS waves. In addition to being useful for our econometric analysis, this also offers us the opportunity to report on the likely direction of over- or under-reporting of key variables in the NIDS-CRAM mobile survey, compared to the NIDS in-person survey. This is unlike many other recent rapid mobile surveys conducted to measure the impact of COVID-19, which in the absence of a longitudinal in-person survey as a pre-cursor cannot identify these potential biases.

However, there are a number of features of NIDS-CRAM that limit our analysis and compromise comparability to previous waves of NIDS and other sources of South African household survey data. First, NIDS-CRAM did not survey all individuals co-resident with the original sample member as in previous NIDS waves. As a result, unlike the previous waves of NIDS, we must use income reported from a one-shot question – the lack of a household roster means household income cannot be derived through aggregating individual item-responses as was done in NIDS (Brophy et al., 2018). Appendix Figure A1 shows that, using the NIDS 2017 results for the same adults in this NIDS-CRAM sample, the distribution of one-shot household income is substantially lower than the distribution of a derived household income. The variance decomposition in Appendix table A2 shows that there remain substantial differences in reported household income for individuals who are plausibly from the same household.

Second, household income was only reported for April and not for February. Third, while in NIDS household level questions were asked of the eldest woman or household member most knowledgeable about household affairs, in NIDS-CRAM each respondent was surveyed on household-level questions, such as household income. Fourth, while data collection happened over May and June, earnings and employment status are reported retrospectively for February and April. The methodological approach adopted in this paper attempts to deal directly with several of these limitations.

In all of our analysis here, we restrict the sample to working-age adults (18-64 years).

3.2. Sample
The NIDS-CRAM sampling frame is the NIDS Wave 5 sample, limited to those aged 18 years or older at the time of NIDS-CRAM data collection. The sample size selected to call for NIDS-CRAM was 17,568 out of approximately 30,000 individuals in NIDS Wave 5. The response rate was approximately 40%, where most of the non-response was from adults no longer reachable on the phone number provided in 2017 as opposed to refusals (Ingle, Brophy, and Daniels, 2020). The final sample consists of 7,074 successfully completed interviews. Non-response adjustments, however, were made both during the data collection, by oversampling strata with low response rates using a batch sampling method, as well as after data collection, by applying post-stratified weights.

3.3. Note on Representativeness
Weighted NIDS-CRAM estimates are representative of the 2017 NIDS sample, which itself followed individuals from a representative sample of the South African population in 2008. Post stratification weights on gender, race, age and province make NIDS wave 5 broadly representative of the South African population in 2017. Estimates from NIDS-CRAM should be therefore interpreted as broadly representative for a sample of South African adults from 2017, who were re-interviewed in 2020 (Ingle, Brophy, and Daniels, 2020). We were able to match all respondents in NIDS-CRAM to their

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3 In earlier waves, which were roughly two years apart, between-wave attrition was between 20-30 percent and the refusal rate was around 3% (Branson, 2018). We anticipate that the drivers of attrition in NIDS potentially differ systematically from NIDS-CRAM. In NIDS, while the source of attrition was mostly high income earners (Brophy et al., 2018), between Wave 5 of NIDS and NIDS-CRAM, we suspect attrition is likely to be higher among those who are harder to reach telephonically – a characteristic which is more likely to correlate with low income.

4 Using a “batch sampling” method, each stratum was defined by a combination of 2017 household per capita income decile, race, age and urban/rural to a total of 99 strata. Sampling from each stratum was adjusted flexibly in response to the response rate in the previous batch (Ingle, Brophy, and Daniels, 2020)
Wave 5 NIDS data. We note that NIDS-CRAM is not necessarily representative of the 2020 South African population and that neither NIDS nor NIDS-CRAM is designed to be representative at any geographical level below the national level.

Summary statistics of NIDS-CRAM and NIDS Wave 5 in Appendix Table A1 show an encouraging balance of raw sample statistics across most categories. The NIDS-CRAM sample is more urban than NIDS, and also notably more middle-aged. Middle-aged individuals were however intentionally over-sampled for better precision of labour market statistics – this is corrected by weights when estimating population level statistics.

4. Labour market impacts

4.1. Employment status definition

Standard employment definitions divide the working age population into 4 categories: (1) “Not economically active” if not employed and would not accept work if it were available, (2) “Unemployed” if not employed and actively searching for work, (3) “Discouraged unemployed” if not actively searching for work, but would accept work if it were available, and (4) “Employed” if undertaking any economic activity for profit or pay (International Labour Organisation, 2013). This categorization is used in the construction of internationally-comparable labour market statistics, such as the unemployment rate, employment rate, and labour force participation rate.

However a straightforward application of this categorization is prone to overlooking several important features of the COVID-19 labour market. In a context where in-person economic activity has largely ground to a halt and workers have been sent home from their workplaces, substantive labour market dynamics occur both across the standard employment categories (i.e. employment to unemployment transitions), but also within the standard employment categories (i.e. among the employed, transitions from actively working to paid leave or being temporarily laid-off). In the current situation it is also possible that survey respondents themselves are unsure of their employment status, and that their reported workdays and compensation are a more meaningful indicator of employment status.

For these reasons we develop a new employment typology designed for understanding the COVID-19 labour market and implementable with the NIDS-CRAM data, per the following mutually exclusive employment categories:

- **Not employed**: Not engaging in any economic activity for pay or profit, whether willing to accept work or not.
- **Temporary lay-off**: Reports an active employment relationship or job to return to, but works zero days and reports zero earnings.
- **Paid leave**: Reports an active employment relationship and earns a wage, but works zero days.
- **Active employed**: Engages in economic activity for profit or pay (reports positive workdays).

Ideally, we would have liked to distinguish between the “not economically active” and the “unemployed” who desire (and may search for) a job. However, while this is possible in NIDS-CRAM for April employment status, respondents were not asked to retrospectively report on willingness to work and job search activity in February. In order to maintain comparability between February and April, we collapse the unemployed and not economically active into the broader “Not employed” group.
4.2. Employment effects of the COVID-19 shock

We estimate that the number of actively employed adults in South Africa decreased by approximately 40% between February and April 2020. We find a 21 percentage point net decline in active employment as share of the working-age population, while there is a 9 percentage point net increase in the “Not employed” category, a 7 percentage point net increase in the “Paid leave” category, and a 4 percentage point net increase in the “Temporary layoff” category (Figure 1 Panel A). Just under half of the active employment decline is therefore attributable to increases in severed employment relationships rather than temporary unemployment, suggesting that the COVID-19 shock will likely have long-run impacts on the South African labour market.

Figure 1, Panel B shows percent changes in the net number of people employed in each category as a percent of February employment – for example, column one shows that net employment decreased by 41%, and then decomposes this into net increases in the “not employed” (18%), “temporary layoff” (9%), “paid leave” (14%) categories.

These employment decreases have disproportionately affected women, manual workers and those at the bottom of the earnings distribution. Women have seen a 49% reduction in active employment over the February-April period. This is 15 percentage points greater than for men, and over half of women’s net employment loss is attributable to severed employment relationships, compared to one third for men. The disparities are even more stark between occupation categories: manual workers have seen a 50% net decline in active employment, which is 30 percentage points more than professionals. Whereas only one sixth of the net employment losses are constituted by job severing for professionals, half of the active employment decreases for manual workers are made up of shifts into the “non-employed” category. These results regarding occupation and gender are related: women are much more likely to be in manual work (Table A3 in the Appendix) relative to men.

Those who were at the bottom half of the income distribution in 2017 have seen a 51% net decrease in active employment over the February-April period, and over half of that is a shift towards non-employment. The net employment loss is less dramatic for individuals further up the 2017 income distribution, and increasing shares of the loss of employment are constituted by “paid leave”. A similar pattern is observed with respect to educational attainment: those with tertiary education fare much better than those without. As expected, there is a much smaller net shift into non-employment for those who reported having a written contract in 2017 compared to those reporting a verbal contract – reflecting different impacts on formal and informal workers.

We also show the geographic distribution of the intensity of net employment loss in Figure A3 in the Appendix. While care must be taken when regionally disaggregating the NIDS-CRAM data, a pattern which emerges is that the metropolitan municipalities face relatively similar declines in active employment, compared to much more significant declines in the labour-sending regions of the Eastern Cape and Kwa-Zulu Natal.

As would be expected from the above results, we see a dramatic decrease in the proportion of individuals working full-time in April, as well as approximately a 20% reduction in the prevalence of part-time work (Table 1, Panel A).

5 Differences between the first and second quartiles are negligible. We use 2017 household per capita income quartiles because household income is not asked for February 2020.

6 We use 2017 contract status because in NIDS-CRAM this question is only asked of individuals who remain employed in April.
Figure 1: Employment Status for Working-Age Adults (18-64 years)
(a) Feb., Apr. and Net Change Over the Lockdown

Notes: Panel (a) shows the percentage of adults in the following employment status categories: "Working", "Paid leave", "Temporary layoff" and "Not employed". The left group of bars indicate the proportion of adults by their employment status for February (before the Lockdown), while the middle group of bars show the same for April (during the Lockdown). The right-most group of bars shows the net change (in percentage points) in jobs in each category between February and April (accounting for both inflows and outflows). Note that the "Not employed" category includes those not economically active. In Panel B, the sum total in each bar is the net percent decrease in the total number of people who were actively employed in Feb, and each sub-bar decomposes this by shifts into categories of "Paid Leave", "Temporary layoff" and "Not employed". Computationally, for example, the red "not employed" bars indicate the net increase in not employed, divided by total February active employment (by worker characteristic).
### Table 1: Earnings and Work-time Status

<table>
<thead>
<tr>
<th></th>
<th>Monthly Earnings (Rands)</th>
<th>Work-time status (prop)</th>
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<th></th>
<th></th>
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<tr>
<td></td>
<td>Freq (mil)</td>
<td>(mean)</td>
<td>(p10)</td>
<td>(p50)</td>
<td>(p90)</td>
<td>No days</td>
<td>Part time</td>
</tr>
<tr>
<td>Panel A: Unconditional</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Feb</td>
<td>31.5</td>
<td>3,953</td>
<td>-</td>
<td>90</td>
<td>11,958</td>
<td>50</td>
<td>13</td>
</tr>
<tr>
<td>Apr</td>
<td>31.2</td>
<td>3,561</td>
<td>-</td>
<td>-</td>
<td>11,958</td>
<td>70</td>
<td>10</td>
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<td>Change (%)</td>
<td>-10</td>
<td>-100</td>
<td>-100</td>
<td>0</td>
<td>42</td>
<td>-23</td>
<td>-47</td>
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<tr>
<td>Panel B: Conditional on positive wage</td>
<td></td>
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<td></td>
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<tr>
<td>Feb</td>
<td>16</td>
<td>7,847</td>
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<td>3,887</td>
<td>18,934</td>
<td>5</td>
<td>24</td>
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<tr>
<td>Apr</td>
<td>11.7</td>
<td>9,673</td>
<td>997</td>
<td>4,983</td>
<td>21,924</td>
<td>26</td>
<td>23</td>
</tr>
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<td>Change (%)</td>
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<td>Panel C: Change w/in individuals</td>
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</tbody>
</table>

**Notes:** Panel A reports earnings and work-time status for individuals without conditioning on them being employed (missing earnings and hours are re-coded to zeros). Panel B reports statistics conditional on individuals being employed and receiving a positive wage. Column 1 of the table reports the number of people in each group (weighted using NIDS-CRAM panel weights). The mean, median, 10th and 90th percentile of the relevant earnings distributions are shown in Columns 2-5. Columns 6-8 report work-time status. Rows 1 and 2 of panels A and B give the raw levels (in Rands or proportion of individuals in work-time categories) while the subsequent rows report percent changes from February to April. A dot indicates when February values are zero and no percentage change can be calculated. Panel C shows the proportion of individuals, conditional on reporting positive earnings in both February and April, which reported a decrease, no change or increase in earnings and workdays respectively.

#### 4.3 Effects on earnings and hours

Average earnings in our sample decline by 10% when we do not condition on employment or positive earnings (Table 1, Panel A). It is unsurprising that unconditional earnings decrease given the employment shock, but it is notable that there is little effect at the 90th earnings percentile.

Earnings conditional on positive wage however increase substantially, across the distribution (Table 1, Panel B). This can be explained by selection issues: far fewer individuals are employed in April than in February, and it is the lowest earners who disproportionately lose their jobs and thus fall out of the employed sample in April. To examine changes for the same individuals over the intensive margin, Table 1 Panel C shows that, conditional on receiving positive wages in both periods, the greatest proportion of workers saw no earnings change over the lockdown.

Looking at employment changes along the intensive margin – i.e. for those who have positive earnings – Table 1 Panel B shows that there was a greater than 4-fold increase in those reporting no workdays in April compared to February – clearly reflecting the move into paid leave. We find a 29% decline in the prevalence of full-time work, while part-time work prevalence stays stable. This latter finding may very well reflect moves both into and out of part-time work. For individuals who remained employed with positive earnings, a much larger proportion decreased work-time compared to those who experienced increases (Panel C).
Table A4 in the Appendix shows the unconditional changes by group. Women’s mean earnings declined by two times that of men (14% and 7% respectively). Reflecting the employment patterns, full time work declined most for women, manual workers, lower household quartiles, and the informally employed.

Overall these findings present a picture of massive disruption to the South African labour market. The lockdown induced a dramatic drop in employment, earnings, and work-time. While this was expected, it is concerning that a large proportion of the net employment loss is made up by shifts into non-employment – that is, where employment relationships have been terminated rather than temporarily suspended. This suggests that changes to the South African labour market will be persistent. Existing social inequalities were deepened as women, lower household income adults, and manual and informal workers bore the brunt of the labour market shock. Our estimates suggest that over the February-April period, on net about 1 in 5 workers suddenly found themselves without a wage or even the prospect of a job to return to.

5. Social protection

Labour market income has an instrumental value in sustaining individual-level welfare – both directly for the worker, and indirectly for that workers’ dependents. The COVID-19 labour market shock will be detrimental to welfare to the extent that this shock is transmitted into falling household incomes. The motivation for emergency social protection interventions has been to protect workers and their dependents from the effects of this shock.

Realised changes in household income will be jointly determined by the negative earnings shock as well as the compensatory social protection benefit. Therefore before moving to our analysis of poverty impacts of the COVID-19-related labour market shock, we discuss here the reach of social protection among affected workers. As discussed in Section 2, the main form of emergency social insurance implemented for workers in April was the Temporary Employee/Employer Relief Scheme (TERS). Additional emergency social assistance interventions – that is, the social grants expansions – were only introduced in May. Therefore during the period of our data collection, social assistance remained unchanged relative to February. Nevertheless, the existing social grant system would have provided some cushioning of the COVID-19 labour market shock.

We find that 37% of those who were “temporarily laid-off” or put on “paid leave” in April were not covered by any kind of social protection measure (Figure 2, Panel (a)). Only around one in five of these workers received TERS, and for about half of these TERS recipients this was the only form of social assistance they received – they did not report any grant recipients in their household. However, household grants do reach a substantial share of the temporarily unemployed – over 50% receive a grant in their household. The vast majority of these recipients rely solely on the grant for social protection. TERS seems to have its greatest coverage in the upper-middle parts of the distribution – the Service/Operators occupational group and the third quartile of February 2020 earnings. Grants are however consistently progressively targeted.

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We follow Ranchhod and Daniels (2020) in disaggregating by February earnings quartiles.
**Figure 2: Social Protection Coverage for Job losers**

*a) Workers who were working in Feb but temporarily laid-off or on paid leave in April*

The figure shows the extent to which individuals not in active employment are protected by various forms of social insurance. Panel (a) plots the coverage of social protection for those who were employed in February and are either “temporarily laid-off” or on “paid leave” in April. The red bars show the percentage of those in each category who are not reached by any type of grant and do not receive TERS, blue shows those who receive TERS but have no social grant receipt in their household, purple shows those who receive a grant in their household but do not receive TERS, and green shows individuals who receive TERS and have a social grant recipient in their household. TERS is the social insurance scheme implemented for workers in response to Covid. Panel (b) plots the coverage of social protection for those who were employed in February and are not in employment in April. As in Panel (a), the sub-bars distinguish between social assistance from having a child support grant recipient in the household versus some other social grant.

**Notes:** The figure shows the extent to which individuals not in active employment are protected by various forms of social insurance. Panel (a) plots the coverage of social protection for those who were employed in February and are either “temporarily laid-off” or on “paid leave” in April. The red bars show the percentage of those in each category who are not reached by any type of grant and do not receive TERS, blue shows those who receive TERS but have no social grant receipt in their household, purple shows those who receive a grant in their household but do not receive TERS, and green shows individuals who receive TERS and have a social grant recipient in their household. TERS is the social insurance scheme implemented for workers in response to Covid. Panel (b) plots the coverage of social protection for those who were employed in February and are not in employment in April. As in Panel (a), the sub-bars distinguish between social assistance from having a child support grant recipient in the household versus some other social grant.
TERS is not applicable in cases where the employment relation is completely severed. For job losers who shift into non-employment, we therefore examine social protection coverage by looking at co-residency with different types of household grant receipt, distinguishing between CSG receipt and other grant receipt (Figure 2, Panel (b)). We find that close to 1 in 3 of these workers are not covered by any kind of social protection measure while 39% receive only the Child Support Grant (CSG) in their household, 9% receive other household-level grants but no CSG, while 1 in 5 of these workers receive the CSG and some other grant in their household. Across different groups of job-losers, household grant receipt is clearly progressive, with women, those at the bottom of the February earnings distribution, and informal workers being much more likely to have a grant recipient in the household. This progressivity in grant coverage is mainly driven by the pattern of household CSG receipt – consistent with Bassier et al. (2020).

That two thirds of non-employed job-losers have a grant in their household reflects both the progressivity of the grant system and the regressivity of the labour market shock (e.g. see larger net job loss for lower household income quartiles in 1). However it should be kept in mind that being "covered" by household grant receipt will frequently not preclude descent into poverty – the vast majority of these grant recipients live in multi-member households (Bassier et al., 2020), and the monetary value of each grant is small compared to the magnitude of the labour market shock, especially for the CSG. The patterns of grant receipt at the extensive margin nevertheless give some idea of how grant top-ups may mitigate the inequality-enhancing aspect of the labour market shock, though again the magnitude of their effect still remains to be evaluated. For direct replacement of labour income lost, one would hope for better coverage of the TERS benefit. Unfortunately, it has particularly poor coverage among the most vulnerable job-losers.

6. Welfare impacts

6.1. Empirical strategy

The poverty impact of COVID-19 and the associated lockdown is a central question of interest. However because household income in NIDS-CRAM was only asked for April 2020, and not for February, we cannot directly observe income changes from before lockdown. Additionally, as discussed in Section 3, the household income variable in NIDS-CRAM is not comparable to household income in NIDS 2017, rendering direct comparisons of poverty rates in 2017 and 2020 untenable. Poverty comparisons also cannot be made between NIDS-CRAM and Statistics South Africa’s Q1:2020 Quarterly Labour Force Survey (QLFS) due a lack of household income questions in the QLFS and general comparability issues as discussed in Ranchhod and Daniels (2020).

However, we can see which individuals in NIDS-CRAM have lost their jobs between February and April, and respondents also report whether their household has lost income since the lockdown started. Cross-sectionally comparing the April 2020 household incomes of job-losers and job-retainers, (and household income losers and retainers), we can estimate the poverty impact of these COVID-19-induced shocks. However, a clear problem with a naive comparison of incomes of these two groups of workers is that job-losers are likely to be systematically different from job-retainers.

8 While the SRD Grant was introduced explicitly to target otherwise unprotected job-losers, too few respondents report receiving this grant to merit its inclusion as a stand-alone category. Instead, it is included within the "other grants" category.

9 We present evidence on the quality and comparability of the NIDS-CRAM household income variable in Appendix Table A1.

10 For analysis of the poverty impact of job loss, "job loss" means a shift from active employment into either a temporary lay-off or a fully severed employment relationship, while "job retention" means staying actively employed. Those shifting into paid leave are omitted.

For analysis of the poverty impact of household income loss analysis, we define "household income" loss as a binary variable equal to one if one reports that their household has lost their main or any source of income, and equal to zero otherwise. When this is zero and an individual reports they have lost their job, we set this variable to missing in order to reduce inconsistencies due to reporting errors. We do so in order to have the counterfactual as a "no income loss" group, and the loss of income questions by themselves appear to be somewhat inconsistently answered. If, however, these corrections are not made, and one simply uses the main household income source question, the poverty increase associated with income loss is 510,000 and 1 million people rather than the 1.1 million and 1.9 million people as reported here, for the food and upper bound poverty line respectively. While leaving in inconsistent responses in the counterfactual would seem clearly wrong, our unease with the inconsistent answering of the income loss questions is one reason we prefer our job-loss specification for assessing poverty impacts.

11 The same issues and approach apply to income losers and income retainers, but for clarity of exposition we refer solely to job losers and job retainers in this discussion.
As our analysis in Section 4 shows, low-income workers face disproportionately higher rates of job loss. Therefore while the April food poverty rate amongst job-losers is 63% and the equivalent poverty rate for job-retainers is 22%, it would be misleading to conclude that COVID-19-induced job-loss has increased poverty by 41 percentage points amongst job-losers. Some of this difference in poverty rates is due to comparing different types of workers to begin with, and not job loss – that is, these groups would have different poverty rates even if job-losers had not actually lost their jobs.

In order to estimate a true job loss “treatment effect”, we adjust for this selection issue by re-weighting the job-retainers sample such that it is rendered comparable to the job-losers sample. Intuitively, this allows us to compare household incomes between observably similar job-losers and job-retainers, thus removing the selection effect and isolating the treatment effect of job loss. Specifically, we use DiNardo-Fortin-Lemieux (DFL) re-weighting: we estimate a propensity score for treatment of “job loss”, use these scores to construct weights for the job-retainers sample, and then compare the un-adjusted income distribution of the job-losers with the re-weighted income distribution of the job-retainers. If this estimation strategy is successful, differences between these distributions identify treatment effects of job loss.

The DFL procedure is only effective to the extent that we successfully identify the relevant individual characteristics which predict job-loss, and therefore match people across these characteristics in the re-weighting procedure (and therefore remove differences in incomes driven by selection). Additionally, these characteristics need to be “pre-treatment” – we do not want to control for post-treatment outcomes. Fortunately, the longitudinal nature of NIDS-CRAM means that we have a rich set of 2017 individual-level characteristics to draw from. Combining hundreds of these 2017 characteristics as well as pre-treatment NIDS-CRAM 2020 characteristics (such as demographic characteristics and education), we use an adaptive logit LASSO regression to select variables which predict job loss, and then use these variables to predict our propensity scores.

This procedure, applied to job loss and analogously to income loss, seems to work well. Estimated propensity scores are well-balanced across job-losers and job-retainers (or income losers and income retainers), and only a few job-retainer (income retainer) observations are dropped due to propensity scores below the 1st or above the 99th percentiles of job-losers’ (income losers’) propensity scores (left hand panels of Figure 3).

The right panels of Figure 3 present a type of “placebo” test for our procedure. We repeat the LASSO DFL procedure outlined above, but do not include NIDS 2017 household income (or its major components) in the set of variables from which the LASSO regression selects. We then compare the 2017 income distribution of 2020 job losers with the income distribution of job retainers. Comparing the un-adjusted densities in Panel (b) of Figure 3 – red for job losers and blue for job retainers – the selection issue is clear: 2020 job losers were generally poorer in 2017 than 2020 job retainers. However after we re-weight the job-retainers according to our DFL weights, the re-weighted job-retainer 2017 income density (green) is remarkably similar to the un-adjusted job-loser 2017 income density, especially in the regions to the left of the two indicated poverty lines. The same results apply to the loss of household income “treatment”. These results suggest that the re-weighting successfully accounts for selection, giving us confidence that differences between 2020 income densities of job-losers (or income losers) and re-weighted job-retainers (or income retainers) will approximate poverty treatment effects. It remains possible that the re-weighted job retainers are different to job losers along other unobservable margins that are independent of observable margins, such as aspects of vulnerability, but the propensity score overlap and placebo test results end credibility to our counterfactual exercises.
Figure 3: DFL Re-weighting: Diagnostics Tests

Notes: The figure presents evidence on the quality of our re-weighting procedures, where we (separately) DFL re-weight job-retainers to match job-losers, and household income retainers to household income losers. Panel (a) shows the overlap in job-loss propensity scores for job-losers and job-retainers, while Panel (c) shows the analogous figure for household income loss. Empty bars show job-retainers (or main income retainers) who are dropped from our matched sample because their propensity scores are below the 1st percentile or above the 99th percentile of propensity scores for job-losers (or main income losers). Panels (b) and (d) present a type of placebo test, showing how our job-loss and household income loss re-weighting procedures successfully re-weight job-retainers and household income retainers (from 2020) such that their re-weighted 2017 income distribution closely matches the 2017 income distributions of job losers and household income losers.
6.2. Results

Our results are presented in Figure 4, with job loss versus job retention in Panels (a) and (b), and income loss versus income retention in Panels (c) and (d). We show the poverty headcount ratio using two poverty lines: the Statistics South Africa “upper-bound” line (R1265 per person per month) and “food poverty” line (R580 per person per month) (Statistics South Africa, 2019). While the former is often taken to indicate “poverty” and the latter “extreme poverty”, we are hesitant to ascribe such precise interpretations, as our household income variable may be significantly under-reported (see Figure A1 in the Appendix for details). We instead use these lines to present a range of plausible poverty impact estimates.
Figure 4: Impact on Household Income and Poverty due to Job Loss and Household Income Loss

Notes: Household income is only reported for April, but individuals report whether they have lost their job and/or a household income. Figure shows changes in poverty associated with job loss (Panels (a) and (b)) and loss of household income (Panels (c) and (d)) between February and April. Poverty is measured using household per-capita income being below one of two - StatsSA food poverty line and StatsSA upper poverty line respectively - indicated poverty lines which are shown as vertical dotted lines in panels a) and c). The left panels show in maroon the raw April household income distributions for job-losers (or losers of household income), and in blue the equivalent distribution for job-retainers (or retainers of household income). The green line is household income of the job-retainers (or retainers of household income) after DFL re-weighting so that their covariates match those of the job-losers (or household income losers). The difference between the red and green lines reflects the treatment effect of job loss (or household income loss).

The red bars in the right panels (b) and (d) show the proportion of job losers and losers of household income respectively in poverty in April, by the two different poverty measures. The green bars show the proportion of job-retainers (or retainers of household income) in poverty, after DFL re-weighting to match job-losers (losers of household income). The difference between the red and green bars – shown by the pink bars – is therefore the increase in poverty associated with losing a job or household income. Note that we define household income loss as a binary variable equal to one if one reports that their household has lost their main or any source of income, and equal to zero otherwise. As we note in our exposition, if this is zero and an individual reports they have lost their job, we set this variable to missing in order to reduce inconsistencies due to reporting errors.
Figure 4 Panel (a) shows that the job-losers’ 2020 income density (red) is substantially to the left of the reweighted job-retainers income density (green), and that therefore job loss did indeed decrease household income in 2020. The figure also shows why a naive comparison of job-loser income to job-retainer income would be ill-advised, and how the DFL procedure significantly adjusts the job-retainer density sample for selection. The maroon bars in Panel (b) show the poverty headcount ratios of job-losers in April, which are to be compared against the headcount ratios of the re-weighted job-retainers – shown as green bars. Per our DFL procedure, the differences in these bars (shown in pink) reflect the percentage point increase in poverty for job-losers which is induced by job-loss.

We therefore find that poverty among job-losers increased by 29 and 17 percentage points using the food poverty and upper bound poverty lines respectively. Multiplying this increase by the number of job-losers (5.23 million), this suggests that COVID-19-induced job loss thrust an additional 1.5 million and 0.9 million job-losers into food poverty and upper bound poverty respectively.

Broadly similar magnitudes are evident in the case of income source loss, though the treatment (and selection) effect appear less dramatic (Panel (c)), and the percentage point increases in poverty for income losers are accordingly smaller than they are for job losers (Panel (d)). However many more individuals report losing household income than there are job-losers, so the effect must be scaled up to the population level to meaningfully compare to the estimate from job loss. With 18.59 million household income losers, the 6 and 10 percentage point increases in poverty associated with household income source loss imply 1.1 million and 1.9 million household income losers falling into food poverty and upper bound poverty respectively.

6.3. Interpretation and robustness checks

While the poverty impacts estimated above seem roughly similar in terms of numbers of individuals pushed into poverty, they in fact measure quite different local treatment effects. The job loss specification allows an estimate of the number of working-age workers who are pushed into poverty because they lose their job. The income loss specification allows an estimate of the number of working-age adults who are pushed into poverty because there is some decrease in income in their household.

While the local treatment effect of the income loss specification may seem preferable as a poverty effect baseline, we prefer the job-loss specification. The household income loss questions appear to be quite noisy and are sometimes inconsistent with each other, or with other survey questions (as noted in footnote 10), and we therefore prefer to use our cleaner job loss versus job retainer comparison.

The diagnostics tests of Figure 3 give us confidence in our poverty-impact results, and we undertake additional robustness tests shown in the appendix. Given concerns about possible under-reporting of household income and over-reporting of household size in NIDS-CRAM (Figure A1 in the Appendix), we also check for increases in food-insecurity, as per answers to the NIDS-CRAM question of whether households ran out of money to buy food during April. Using the same DFL re-weighting procedure, we compare the prevalence of the food-insecurity among job-losers (or income losers) versus re-weighted job keepers (or income keepers). As per the left group of bars in Figure A4, both job-losers and income-losers report greater food-insecurity than the re-weighted job-retainers and income retainer, with the effect size being especially large for the latter comparison. For our baseline poverty estimates we also implement a version of matched difference-in-differences, across NIDS 2017 and NIDSCRAM, which compares the change in income between 2017 and 2020 for job losers (and income losers) versus re-weighted job retainers (and income retainers). We find roughly similar results using this approach as we do with our baseline DFL re-weighting procedure (centre and right bars of Figure A4).

The results in this section suggest that poverty increased substantially over the initial part of the COVID-19 lockdown period in South Africa. While we refrain from directly calculating a poverty change number (due to data limitations and comparability issues noted previously), the results of
diagnostics and robustness tests leave us reasonably confident in the results from our preferred specification comparing job-losers versus job-retainers: job-loss caused an increase in poverty for job losers in the range of roughly 15 to 30 percentage points. In terms of individuals, this is a dramatic poverty increase, corresponding to around 1 million job losers falling into poverty.

It is important, however, to note that our poverty impact estimates are still approximations. In addition to unavoidable imprecision, there are also other factors which could make our results an over- or under-estimate of the realized impact. To the extent that our re-weighting approach does not fully control for selection bias along unobservable worker characteristics in the relevant region of the income distribution, our poverty estimate will be upward-biased. If it over-corrects, the poverty estimate will be downward-biased. Our poverty estimates will also be downward-biased by job-retainers experiencing per capita household income decreases which push them into poverty, and the same issue applies to the income loss specification if income retainers experience unreported income losses. The net effect of these factors cannot be determined a priori, and we interpret them simply as more reason to view our estimates as approximate.

7. Discussion

While the poverty estimation in the previous section is certainly an approximate exercise, it has plausible econometric foundations and we are reasonably confident in the results. In this section we present a more speculative extension of the poverty analysis in two areas: accounting for dependents in the workers’ household, and a counterfactual simulating a more immediate delivery of social assistance relief following the imposition of lockdown.

7.1. Accounting for dependents

While the poverty estimates of the previous section suggest substantial COVID-19-associated poverty increases for job-losers, they do not capture the total poverty impact of COVID-19 job losses. In particular, workers typically support many dependents. In a usual household survey, one can easily infer household impacts from labour market shocks, because the household is observed. However in NIDS-CRAM, there is no household identifier and the sample does not include children. In order to very roughly infer the broader social impact of job-loss-induced poverty estimated in the previous section, we estimate the average number of dependents each job-loser supported in NIDS 2017. We do this by dividing each job-loser’s 2017 household size by the total number of workers in the household. Taking the average across all job losers in NIDS-CRAM, we find an average dependency ratio of 3.2. This means that for our estimate of COVID-19-related job loss pushing 1 million job-losers into poverty, we speculatively estimate a broader job-loss effect which increases the total poverty headcount by just over 3 million people when accounting for the dependents of job-losers. This number closely matches the COVID-19 poverty prediction of Bassier et al., 2020, of 2.5 to 3 million more individuals falling into poverty as a result of the lockdown labour market shock.

This exercise comes with important caveats. We estimate the dependency ratio across all job-losers, while the relevant group is those shifted into poverty. Household structure may have changed significantly for job-losers between 2017 and 2020, and indeed it would be surprising if it had not, given that our NIDS-CRAM respondents are three years older than they were in 2017. This figure is therefore a speculative extension of our poverty impact estimate.

7.2. Expanded social protection

As detailed in Section 2, South Africa went into lockdown at the end of March 2020, but only announced additional social assistance measures – in the form of social grant expansions – at the end of April. Social grant top-ups were only introduced from the beginning of May, while implementation of the new COVID-19 Social Relief of Distress Grants has taken even longer. Here we present a counterfactual poverty simulation where we estimate how the grant top-ups would have mitigated the poverty of job-losers and income losers if they had been implemented from the beginning of April. Reflecting the grant top-up values, we add R250 per Old Age Pension and R300 per Child
Support Grant to April household income. We then compare headcount ratios for job losers under this counterfactual scenario to the headcount ratios actually observed. We find that the grant top-ups would decrease job-loser poverty by 12 and 3 percentage points for the food and upper bound poverty lines respectively. While job-loss-induced poverty (29 and 17 percentage points) is on net larger than the protection offered by the grant top-ups, the grants would mitigate the poverty increase associated with job-loss by roughly between 20 and 40%. Although speculative, based as it is on an imposed counterfactual, the exercise still provides a rough guide as to the extent to which expanded social protection could have mitigated these estimated poverty impacts further if they were implemented shortly after the lockdown was first implemented in South Africa.

8. Conclusion

The COVID-19 crisis has resulted in a large negative labour market shock globally. While the data on the economic impact of this shock is steadily emerging for developed countries, evidence is still lacking for developing countries.

In this paper we use newly released South African panel data, specifically designed for assessing the impact of COVID-19, in order to provide some of the first pieces of evidence on the impact of COVID-19 on employment and poverty in the developing world.

We observe a large 40% decline in net active employment between February (pre-lockdown) and April (during lockdown) of 2020, with approximately half of this decline composed of complete job terminations. Alarmingly, the incidence of employment losses has been much greater among female workers, manual workers, informal workers, and those at the bottom half of the income distribution, thereby exacerbating existing inequalities. We also provide a plausible estimate of the poverty impact of this shock: 15 - 30% of those who have lost jobs over the lockdown period fall into poverty, which translates to approximately 1 million job losers. More speculatively, accounting for dependents of these job-losers, we estimate a total impact of COVID-19-associated job loss of over 3 million people falling into poverty.

Governments across the world have responded by introducing unprecedented expansions in emergency social protection interventions. We document that, in the South African case, approximately one third of those who lost active employment by April did not receive any household-level social protection. The bulk of the social protection they did receive was from the already-existing social grant system, and in particular, the receipt of the child support grant in the household. Despite the existing social protection being progressively targeted, COVID-19 still led to large increases in poverty.
### 9. Appendix Tables & Figures

#### Table A1: Sample summary Statistics, NIDS vs NIDS-CRAM

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<td>Quartile 2</td>
<td>0.28</td>
<td>0.447</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 3</td>
<td>0.26</td>
<td>0.439</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quartile 4</td>
<td>0.20</td>
<td>0.397</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>7072</td>
<td></td>
<td></td>
<td>24600</td>
</tr>
</tbody>
</table>

**Notes:** The table gives the mean and standard deviation for the NIDS-CRAM and NIDS Wave 5 (2017) sample (over the age of 18). Earnings figures are expressed in February 2020 Rands ($1 is roughly 17 Rands) All figures reflect unweighted sample statistics.
### Table A2: Variance decomposition of NIDS-CRAM reported household income

<table>
<thead>
<tr>
<th></th>
<th>Raw</th>
<th>No outliers</th>
<th>With imputations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total variance</td>
<td>1.545</td>
<td>1.531</td>
<td>1.346</td>
</tr>
<tr>
<td>Within HH variance</td>
<td>0.175</td>
<td>0.166</td>
<td>0.183</td>
</tr>
<tr>
<td>Between HH variance</td>
<td>1.334</td>
<td>1.326</td>
<td>1.123</td>
</tr>
<tr>
<td>$2\times$Cov</td>
<td>$3.03E-08$</td>
<td>$2.37E-08$</td>
<td>$3.16E-08$</td>
</tr>
<tr>
<td>Observations</td>
<td>772</td>
<td>769</td>
<td>800</td>
</tr>
</tbody>
</table>

**Notes:** In order to check the internal consistency of the one-shot household income reported in NIDS-CRAM we construct a best guess of whether any two of the respondents in NIDS-CRAM belong to the same household using their Wave 5 Household ID, total number of children under 18 they report in NIDS-CRAM and their current district council. Using this best guess of the household ID, we decompose the variance in reported household income into within household and between household variance. Column 1 shows the decomposition for the raw reported household income, Column 2 shows this with correction for outliers, and Column 3 shows this with imputations (imposing a lower bound for household income constructed using reported earnings, reported number of household grants and the amounts for these).

### Table A3: Gender & Occupation

<table>
<thead>
<tr>
<th></th>
<th>Professionals</th>
<th>Service or Operators</th>
<th>Manual</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>%</td>
<td>%</td>
<td>%</td>
<td>%</td>
</tr>
<tr>
<td>Male</td>
<td>23.1</td>
<td>58.2</td>
<td>18.7</td>
<td>100.0</td>
</tr>
<tr>
<td>Female</td>
<td>30.1</td>
<td>40.5</td>
<td>29.4</td>
<td>100.0</td>
</tr>
<tr>
<td>Total</td>
<td>26.4</td>
<td>49.7</td>
<td>23.8</td>
<td>100.0</td>
</tr>
</tbody>
</table>

**Notes:** The table gives a breakdown of the working age population by gender and occupation category in the NIDS-CRAM sample. For those who were working in April, this reflects their current occupation and for those who were no longer working in April, this reflects their usual occupation. Source: Authors’ calculations using NIDS-CRAM with NIDS-CRAM panel weights.
**Table A4: Changes in Earnings and Work-time Status, by group**

<table>
<thead>
<tr>
<th></th>
<th>Freq</th>
<th>Change in Earnings (%)</th>
<th>Change in Work-time Status (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(millions)</td>
<td>(mean)</td>
<td>(p10)</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Men</td>
<td>14.9</td>
<td>-7</td>
<td>.</td>
</tr>
<tr>
<td>Women</td>
<td>16.3</td>
<td>-14</td>
<td>.</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Matric or less</td>
<td>22.7</td>
<td>-1</td>
<td>.</td>
</tr>
<tr>
<td>Tertiary</td>
<td>8.39</td>
<td>-15</td>
<td>.</td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Professionals</td>
<td>5.80</td>
<td>-12</td>
<td>.</td>
</tr>
<tr>
<td>Service/operator</td>
<td>11</td>
<td>0</td>
<td>.</td>
</tr>
<tr>
<td>Manual</td>
<td>5.24</td>
<td>-8</td>
<td>.</td>
</tr>
<tr>
<td><strong>HH income quartile (2017)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q1-2</td>
<td>13.80</td>
<td>13</td>
<td>.</td>
</tr>
<tr>
<td>Q3</td>
<td>7.83</td>
<td>-2</td>
<td>.</td>
</tr>
<tr>
<td>Q4</td>
<td>9.61</td>
<td>-15</td>
<td>.</td>
</tr>
<tr>
<td><strong>Contract</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Verbal</td>
<td>2.41</td>
<td>-25</td>
<td>.</td>
</tr>
<tr>
<td>Written</td>
<td>9.32</td>
<td>-6</td>
<td>.</td>
</tr>
</tbody>
</table>

**Notes:** Earnings and work-time status are reported for individuals without conditioning on them being employed (missing earnings and hours are re-coded to zeros). Column 1 of the table reports the number of people in each group in April (weighted using NIDS-CRAM panel weights). The percent change in mean, 10th, median and 90th percentile of the relevant earnings distributions are shown in Columns 2-5. Columns 6-8 report the change in the proportion of the group in each work-time status category. Only percent changes from February to April are reported, by different worker characteristics. A dot indicates when February values are zero and no percentage change can be calculated.
Figure A1: Household Income and Size: NIDS Wave 5 and NIDS-CRAM

(a) Quality of household income variable in CRAM

(b) Household size as reported by individuals by wave

Notes: Panel (a) shows the densities of household income in NIDS Wave 5 (2017) and NIDS-CRAM (2020). Solid lines show the density using the raw one-shot reported income from the survey, while dashed lines show densities after imputations. Red lines show CRAM, while blue lines show NIDS. The NIDS Wave 5 derived variable adds up the component parts of household income using the household co-resident roster, in addition to imputations for outliers. The imputation we use for NIDS-CRAM is replacing household income with a lower bound constructed by summing across an individual’s reported earnings, and income due to social grants they report receiving individually or by a household member. Panel (b) shows household size as reported by individuals in NIDS Wave 5 and NIDS-CRAM.
**Figure A2: Individual Employment Status Change Over Lockdown**

**(A) Individual Employment Transitions from Feb. to Apr.**

![Bar chart showing employment status transitions over lockdown from February to April](chart)

**(b) April employment status for Feb actively employed, by worker characteristics**

![Bar chart showing employment status by various characteristics](chart)

**Notes:** Panel (a) shows the job status transition patterns of individuals who were actively employed in Feb (left group of bars) and who were “Not Employed” in Feb (right group of bars) into the four employment categories in April. Panel (b) plots the change in individual-level employment status over Feb and April along various worker characteristics for workers who were actively employed in Feb. In Panel (b), the sum total in each bar is the percent of Feb actively employed who were no longer actively employed in April. Each sub-bar decomposes these shifts out of employment into categories of “Paid Leave”, “Temporary layoff” and “Not employed”. Note that the “Not employed” category includes those not economically active. While Figure 1 shows the net change in employment, this figure focuses on job losers and does not account for job finders.
Figure A3: Geographical Distribution of Net Employment Loss
Provinces and Metropolitan Municipalities

Notes: Figure shows the net employment decrease as a percent of those employed in February across South Africa’s provinces and Metropolitan Areas.
Figure A4: DFL Re-weighting: Additional Checks

(a) Food affordability and Matched DiD for poverty due to Job Loss.

Notes: The figure presents further crude checks for the quality of our re-weighting procedures, where we (separately) DFL re-weight job-retainers to match job-losers, and household income retainers to household income losers. Figure Panel (a) shows changes in reported food affordability (left-most set of bars), where the proportion of job losers that could not afford food (red bars) are compared to the DFL re-weighted proportion of job keepers that could not afford food (green bars). It also shows poverty associated with job loss (middle and right-most set of bars). Poverty is measured using household per capita income being below one of two - StatsSA food poverty line and StatsSA upper poverty line respectively. The Matched DiD estimates show the difference for job losers in poverty between 2020 compared to 2017 (red bars), the difference for DFL re-weighted job retainers in poverty between 2020 compared to 2017 (green bars), and the difference in these differences (pink bars). Panel (b) shows the analogous figure for household income loss. Note that we define household income loss as a binary variable equal to one if one reports that their household has lost their main or any source of income, and equal to zero otherwise. As we note in our exposition, if this is zero and an individual reports they have lost their job, we set this variable to missing in order to reduce inconsistencies due to reporting errors.
REFERENCES


EWN. “SASSA: Grant beneficiaries who got double payments won’t be paid in June”. In: *EWN* (May 5, 2020). url: https://ewn.co.za/2020/05/05/sassa-grant-beneficiaries-who-got-double-payments-won-t-be-paid-in-june (visited on 05/05/2020).


