# SOCIAL DISTRESS AND (SOME) RELIEF. ESTIMATING THE IMPACT OF PANDEMIC JOB LOSS ON POVERTY IN SOUTH AFRICA

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## ABSTRACT

Up-to-date, nationally representative household income/expenditure data are crucial to estimating poverty during the COVID-19 pandemic and to policy-making more broadly, but South Africa lacks such data. We present new pandemic poverty estimates, simulating incomes in pre-pandemic household surveys using contemporary labour market data to account for job losses between 2020 Q1 and 2021 Q4. Improving on much of the existing literature, we use observed rather than simulated shocks and allow for uneven impacts of the pandemic by employment sector and demographic characteristics. We present three updating methods, using the National Income Dynamics Study (NIDS) Wave 5, the Living Conditions Survey 2014/15, and the Quarterly Labour Force Survey (QLFS). Giving primacy to NIDS Wave 5 produces the largest estimate of pandemic-period job-loss-induced poverty: a headcount ratio increase at the upper-bound poverty line of 5.2 percentage points (3.1 million people/13 per cent) and poverty gap increase of 3.8 percentage points (21 per cent). Giving primacy to QLFS data produces the lowest estimated change: a headcount ratio increase of 3.0 percentage points (1.8 million people/7 per cent) and poverty gap increase of 2.5 percentage points (12 per cent). Simulating receipt of the Special COVID-19 Social Relief of Distress social grant substantially mitigates poverty effects, with a poverty headcount increase of 1.1–3.4 percentage points and a poverty gap increase of 0.2–1.5 percentage points.

**JEL Codes:** E24, E27, I31, I38

**Key words:** COVID-19, job loss, poverty, social grants, labour market, simulation, South Africa

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# Social distress and (some) relief

## Estimating the impact of pandemic job loss on poverty in South Africa

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July 2022

**Abstract:** Up-to-date, nationally representative household income/expenditure data are crucial to estimating poverty during the COVID-19 pandemic and to policy-making more broadly, but South Africa lacks such data. We present new pandemic poverty estimates, simulating incomes in pre-pandemic household surveys using contemporary labour market data to account for job losses between 2020 Q1 and 2021 Q4. Improving on much of the existing literature, we use observed rather than simulated shocks and allow for uneven impacts of the pandemic by employment sector and demographic characteristics. We present three updating methods, using the National Income Dynamics Study (NIDS) Wave 5, the Living Conditions Survey 2014/15, and the Quarterly Labour Force Survey (QLFS). Giving primacy to NIDS Wave 5 produces the largest estimate of pandemic-period job-loss-induced poverty: a headcount ratio increase at the upper-bound poverty line of 5.2 percentage points (3.1 million people/13 per cent) and poverty gap increase of 3.8 percentage points (21 per cent). Giving primacy to QLFS data produces the lowest estimated change: a headcount ratio increase of 3.0 percentage points (1.8 million people/7 per cent) and poverty gap increase of 2.5 percentage points (12 per cent). Simulating receipt of the Special COVID-19 Social Relief of Distress social grant substantially mitigates poverty effects, with a poverty headcount increase of 1.1–3.4 percentage points and a poverty gap increase of 0.2–1.5 percentage points.

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# 1 Introduction

The COVID-19 pandemic has had a devastating economic impact in South Africa, with a global economic contraction, behavioural changes, and strict local lockdown measures severely restricting economic activity. However, while effects on production and employment can be estimated fairly easily, limited pandemic-period data on incomes and consumption means little is known about the effects on poverty. In this paper, we seek to fill this gap by combining various data sources to estimate the impact of employment loss on poverty from the first quarter of 2020 (2020 Q1) to the fourth quarter of 2021 (2021 Q4).

South Africa introduced a strict physical one-and-a-half-month lockdown on 15 March 2020, and subsequent economic restrictions lasted until October 2021.[1] The Quarterly Labour Force Surveys (QLFS; Statistics South Africa 2020a; 2021c) report a drop in the 18–60 employment rate from 46.7 per cent to 40.7 per cent over the course of 2020 and 2021, and the South African Reserve Bank (SARB) reports a decrease in gross national income (GNI) of 17.9 per cent.[2] However, the last official South African poverty estimates come from the 2015 Living Conditions Survey (LCS), and the latest broadly representative national survey with reliable household income measures—the National Income Dynamics Study (NIDS)—last provided an unofficial estimate in 2017 (SALDRU 2018).[3] The 2020/21 round of the official Income and Expenditure Survey (last conducted in 2010/11) was postponed due to budget shortfalls and other difficulties associated with the pandemic (Wilkinson 2020), while an unofficial rapid telephone survey used an income measure that was not comparable with that of previous surveys and was discontinued due to quality concerns.[4]

We provide estimates of pandemic-period poverty by updating the 2015 LCS and 2017 NIDS household income data using contemporary labour market data from the QLFS, the source of official labour market statistics. The QLFS is collected at a quarterly frequency, which has been sustained during the pandemic. At the time of writing, the latest dataset released was for 2021 Q4, which follows the ending of the stricter lockdown measures. While there are many aspects to our updating procedure, the core of the approach is changing individual employment statuses in the

[1] The beginning of the COVID-19 pandemic in South Africa saw the declaration of a 'National State of Disaster' on 15 March 2020, and a strict lockdown and the closure of all non-essential economic activity from 17 March. Prior to the lockdown, the impact on the economy was felt most strongly through a sudden reduction in exports and international tourism. With the initial 'level 5' strict restrictions, all non-essential economic activity that could not be done virtually ceased. Measures were lowered progressively from 1 May 2020, allowing some industries to reopen, to the exclusion of all sporting, religious, and cultural events. Where possible, businesses were required to operate from home and respect different curfews and social distancing measures. Restrictions reached their lowest level, 'level 1', on 1 September 2020. They then tightened again with the second wave, before easing back to level 1 on 1 March 2021. With the third wave they tightened once more, and they only eased back to level 1 again on 1 October 2021. For details, see The Presidency (2020a, b, c, 2021).

[2] There was a 7 per cent decrease in gross domestic product (GDP) in 2020—mainly due to the initial impacts of the pandemic and strict lockdown, and despite growth in the third and fourth quarters of the year. To put this in context, in 2009 GDP decreased by a comparatively small 1.5 per cent due to the global economic recession. Only the agriculture and government sectors experienced some growth over the year (Statistics South Africa 2021a).

[3] Note that the first wave of NIDS in 2008 was nationally representative, and representativity has been maintained in subsequent waves as best as possible. See Section 2.1 for more details.

[4] This was the National Income Dynamics Study—Coronavirus Rapid Mobile Survey (NIDS-CRAM). See Jain et al. (2020b) for discussion of the income measure and an attendant attempt to measure some poverty impacts in the first wave of the survey.

LCS and NIDS to match the pandemic employment effects evident in the QLFS, and then applying attendant changes in incomes. Such data updates necessarily come with assumptions and uncertainty, and so we conduct several sensitivity tests and comparisons to get a sense of the size of the uncertainty.

We estimate the change in poverty between 2020 Q1 and 2021 Q4. We give primacy to each of the three different datasets in turn and compare the results. The first estimates assume the NIDS Wave 5 to be the best source of data and use the QLFS only to forecast percentage changes in employment. The second method assumes the LCS 2014/15 to be primary and again uses the QLFS only to forecast percentage changes in employment. The third method assumes the QLFS to be the best source of data and forces the NIDS to match the QLFS *levels* of employment.[5]

This paper makes several contributions. First, we provide a new set of poverty estimates for South Africa during the pandemic. Our estimates also go up to the fourth quarter of 2021, while much of the international and South African literature estimating the poverty impact of the pandemic focuses on immediate impacts or at most extends to the end of 2020.

Second, we simulate receipt of the state's attempt to mitigate the shock to the vulnerable by means of an extensive support package (the Special COVID-19 Social Relief of Distress grant, or Special COVID-19 SRD). This allows us to approximately estimate the poverty-reducing effect of the policy.

Third, our updating methodology is an improvement over much of the existing work, in that we do not impose that the pandemic shock be distribution-neutral, and we apply observed rather than simulated employment shocks. Existing work using observed and forecasted shocks to GDP growth typically estimates poverty effects after applying a uniform shock to incomes or consumption (Bhalla et al. 2022; Decerf et al. 2021; Diop and Asongu 2021; Mahler et al. 2020; Sumner et al. 2020). This is likely to significantly understate poverty effects, as the pandemic employment effects have been found to be highly regressive across diverse contexts (Adams-Prassl et al. 2020; Basole et al. 2021; Higa et al. 2022; Jain et al. 2020b).

Other work which simulates the poverty effect of the pandemic typically does take into account the uneven effects of the pandemic, but does not use observed shocks (typically due to data constraints), and must make assumptions about pandemic impacts across different sectors (Barletta et al. 2021; Bengoechea 2020; Brum and De Rosa 2021; Cuesta and Pico 2020; Lustig et al. 2021; Suryahadi et al. 2020; Younger et al. 2020). In contrast, our use of observed shocks not only likely improves accuracy in general, but in particular allows us to incorporate employment growth in some sectors and demographic groups. This may be quantitatively important for a shock like the pandemic that, while employment-reducing in aggregate, also induces significant sectoral reallocation (Barrero et al. 2020, 2021).

There is other work which applies heterogenous employment shocks using observed data to estimate poverty. Wheaton et al. (2021) do so in the United States, while Barnes et al. (2021) and Van den Heever et al. (2021) do so for South Africa. We describe our own method in detail, perform a variety of robustness and diagnostic checks, and discuss and compare our results (Section 6.3) and methodology (Appendix 6 to Barnes et al. (2021) and Van den Heever et al. (2021). We also make our datasets and programs available for other researchers who may wish to

[5] Note that we also run the method giving primacy to the QLFS data on the LCS 2014/15 dataset, and we find that the results are very similar to those of the LCS method. For simplicity we do not discuss the method or results here.

use them, critique them, or improve on them. This is important given that our estimates vary substantially with variations in assumptions.

Our results vary depending on the dataset and updating methodology used. When not taking into account the poverty-mitigating effect of the Special COVID-19 SRD grant, we estimate that the headcount ratio at the upper-bound poverty line (UBPL) increases by between 3 and 5.2 percentage points (equivalent to 1.8–3.1 million people, or 6.8–12.9 per cent) between the first quarter of 2020 and the last quarter of 2021. The lowest estimate is produced by matching to QLFS levels, and the highest by giving primacy to the NIDS Wave 5 data. The poverty gap at the same poverty line increases by between 2.5 and 3.8 percentage points (equivalent to 11.7–20.9 per cent). These estimated poverty increases are solely due to income changes caused by employment changes—we do not adjust for factors such as government relief programmes, changes in household composition, or behaviour. The employment loss over the same period in the QLFS, which drives these poverty results, is a drop in the 18–60 employment rate from 46.7 per cent in 2020 Q1 to 40.7 per cent in 2021 Q4.

Our simulation of the December 2021 receipt of the Special COVID-19 SRD by 10 million recipients suggests that the programme substantially mitigates pandemic employment-induced poverty.[6] The rise in the upper-bound headcount ratio between 2020 Q1 and 2021 Q4 is reduced to between 1.1 and 3.4 percentage points (0.7 to 2 million people), depending on updating method, while the poverty gap increase is now between 0.2 and 1.5 percentage points.

While the simulated SRD grant substantially mitigates poverty, it does not restore people to pre-pandemic income levels, with most of its effect taking place at the bottom of the income distribution. This is evident from how much more effective the simulated grant is at reducing poverty at the food poverty line (FPL) compared with the UBPL. Without the simulated SRD grant, the FPL headcount ratio increases by between 3.3 and 4.7 percentage points (equivalent to 2.0–2.8 million people, or 16.8–30.1 per cent) between 2020 Q1 and 2021 Q4, while the poverty gap increases by between 1.7 and 2.6 percentage points (equivalent to 21–45.6 per cent). With the simulated SRD, the headcount ratio change ranges from a decrease of 0.3 percentage points (200,000 people) to an increase of 1.4 percentage points (800,000 people), while the poverty gap change ranges from a decrease of 0.3 percentage points to an increase of 0.7 percentage points.

Existing estimates in the literature during the pandemic period from Barnes et al. (2021) set the upper-bound poverty headcount ratio at 52.5 per cent in April 2020, while accounting for employment loss but not employment gains, and Van den Heever et al. (2021) estimate poverty at 48.9 per cent in Q4 of 2020, accounting for both employment loss and gains but with important differences to our methodology in other ways (see Section 6.3 and Appendix 6 for a more detailed discussion).[7] In Q4 of 2021, we estimate the upper-bound poverty headcount ratio to be between 45.6 and 48.5 per cent depending on the method. Differences in results are due to differences in both methodology (discussed in Appendix 6) and time period.

Using the NIDS dataset and matching on employment levels in the QLFS, we produce estimates for Q2 of 2020 (though not strictly comparable with the April 2020 estimate of Barnes et al. 2021)

[6] Note that we do not simulate the impacts of other relief programmes such as the Presidential Employment Stimulus, the Unemployment Insurance Fund COVID19 Temporary Employment Relief (UIF COVID19 TERS), or various 'top-ups' to existing grants which were implemented during 2020. While this means that our poverty estimates will be somewhat overestimated during periods when these policies were in effect, the UIF COVID19 TERS and grant top-ups had been discontinued by the period of our main results, 2021 Q4.

[7] We compare with their estimates without the Special COVID-19 SRD policy included.

and Q4 of 2020. These show job-loss-induced poverty to be roughly constant over the less than two-year portion of the pandemic captured here, if one excludes the effect of the SRD (and other pandemic-period relief policies; see Section 5.3), with the upper-bound poverty headcount ratio being 46.7 per cent in Q2 of 2020 and 47.0 per cent in Q4 of 2021 (using the NIDS levels method). This is consistent with the lack of labour market recovery over this period in the QLFS data.

The paper is structured as follows: we begin by describing the data in Section 2 and the updating methodology in Section 3. Section 3 is divided into Section 3.1, which describes the income inflation process; Section 3.2, which describes the demographic updating procedure; and Section 3.3, which describes how the changes in employment are taken into account. While we implement and describe three different combinations of base datasets and employment-updating methodologies in this paper, in order to simplify the exposition in Sections 4 and 5 we choose to focus on one dataset and method that happens to produce the largest increase in poverty over the period. In Section 4 we present a set of diagnostic results which compare changes in baseline to post-simulation employment rates in the NIDS data with changes in the QLFS from 2017 to 2021, to get a sense of how well the employment-updating method performs and its idiosyncrasies. In Section 5 we produce substantive results regarding poverty over the pandemic period using the same data and method. In Section 6 we present the full range of poverty estimates across the different datasets and updating methodologies, as well as a comparison with existing estimates in the literature. Section 7 concludes.

## 2 Data

We work with a combination of three household surveys, namely the NIDS Wave 5, the LCS 2014/15, and the QLFS for several years and quarters, supplemented by other non-survey data.

### 2.1 National Income Dynamics Study, Wave 5, 2017

The NIDS is the first broadly representative national longitudinal study. It is commissioned by the Department of Planning, Monitoring and Evaluation within the South African Presidency, and undertaken by SALDRU. The survey measures, among other things, income, expenditure, assets, demographics, education and employment, and access to cash transfers and social services (Brophy et al. 2018). The first wave, collected in 2008, was a nationally representative sample of over 28,000 individuals in 7,300 households. In subsequent waves, non-response, attrition, and population trends were taken into account as best as possible through a combination of temporary respondents (who are not tracked over time), the recalibration of cross-sectional weights, and in the most recent wave, Wave 5, a top-up sample of 2,775 respondents. We work with Wave 5 only, collected from January to December 2017, which consists of 40,944 individuals in 13,719 households (Brophy et al. 2018; SALDRU 2018).

### 2.2 Living Conditions Survey 2014/15

The LCS 2014/15 is a cross-sectional survey undertaken by Statistics South Africa and consisting of data on household composition and structure; demographics; and education and employment, expenditures, and incomes. The most recent iteration was conducted from October 2014 to October 2015. The survey is designed to be representative at the national and provincial levels and consists of 88,906 individuals in 23,380 households.

The labour market module is less comprehensive than that in NIDS. It lacks categorical variables on occupation and sector and data on whether a worker has a formal contract and benefits from labour market protections such as annual leave, sick leave, or maternity leave (Statistics South Africa 2017a, b).

### 2.3 Quarterly Labour Force Survey

The QLFS is a rotating panel survey undertaken by Statistics South Africa. The scope is narrower than that of the NIDS and the LCS and consists of data on labour market activity, history, and preferences, demographic characteristics, marital and employment status, education, grants, and tax. The QLFS is undertaken quarterly; as of writing, the most recently available data were for the fourth quarter of 2021 (Statistics South Africa 2021d). We use the first quarters of 2015 and 2017 (Statistics South Africa 2015, 2017c); the first, second, and fourth quarters of 2020 (Statistics South Africa 2020b, c, d); and the fourth quarter of 2021 (Statistics 2022b). See Appendix 1 for information on sample size.

### 2.4 Other data sources

We work with official poverty lines, mid-year population estimates, and consumer price indices released by Statistics South Africa (2020a, 2021b, 2022a). We calculate growth in yearly per capita GNI based on statistics released by the SARB in the *Quarterly Bulletin*.[8]

## 3 Methodology

### 3.1 Income forecasting

We use gross income per person as the welfare indicator in the surveys.[9] We forecast household incomes from the original survey year to December 2021. As per a number of studies similarly estimating the impact of COVID-19 on poverty (for example Lustig and Pabon 2020; Younger et al. 2020), to forecast income increases for the pre-pandemic period (from the original survey year up to December 2019) we use the growth in nominal per capita GNI from the national accounts.[10] However, while the above-mentioned studies assume no growth in income in sectors over the subsequent mid-pandemic period, the evidence from South Africa is that for those individuals who retained employment, earnings kept pace with inflation (Bassier et al. 2021b). From January 2020 to December 2021 we therefore assume wage and income growth equivalent to the growth in the

[8] The information is retrievable as a time series using the code KBP6271 in an online statistical query on the SARB website (SARB 2022).

[9] Income sources in the NIDS Wave 5 survey include labour market income (main and second job, casual wages, self-employment income, piece-rate income, bonus payments); government grant and other income (state old-age pension, disability grant, child support grant, foster care grant and care dependency grant, Unemployment Insurance Fund and workmen's compensation); investment income from interest and dividends, rent, and private pensions and annuities; remittances; income from subsistence agriculture; and the value of own production consumed (Brophy et al. 2018). Income sources in the LCS 2014/15 dataset include salaries and wages; income from business activities and subsistence farming; rental income; royalties; interest and dividends on shares and income from share trading; receipts from pension, social welfare grants, and other annuity funds; and alimony, maintenance, and other allowances (Statistics South Africa 2017).

[10] We use nominal values in order to produce a dataset that in 2021 will be comparable with 2021 poverty lines and administrative values for grants and income tax brackets, for example. The studies mentioned here use GDP while we use GNI; however, the differences are negligible. We also considered using private disposable income as an alternative, and again find the differences in growth rates to be small enough to ignore.

consumer price index (CPI) of 8.85 per cent (authors' calculations based on Statistics South Africa 2022a; see Appendix 1 for more details).

One of the well-known challenges for forecasting survey incomes is that not all the growth in the national accounts is passed through to growth in household welfare in surveys (Ravallion 2001).[11] The studies above adjust for this by applying a 0.85 'pass-through' rate, estimated by Lakner et al. (2020) to be the global average. However, in the same study the authors also implement two different machine learning methods to determine the relevant variables that affect this pass-through rate—in theory allowing for a refined pass-through parameter.

Lakner et al. (2020) detect a substantial difference in the pass-through rate for surveys using an income aggregate (1.01) as opposed to surveys using a consumption aggregate (0.72). However, while one method generates a pass-through factor of 0.86 for countries in South Africa's subgroup, the other generates a pass-through factor of 1.39.[12] Given the large range in these estimates, the variable nature of the ratio of survey to national accounts income even within the same survey series over time (Van der Berg et al. 2007), the fact that we are working with an income aggregate, and the authors' acknowledgement that 'a shortcoming of this method is that its coarseness means that small changes in underlying data could change the predictions', we prefer to work with a pass-through factor of 1—equivalent to the average pass-through rate for surveys using income welfare aggregates.[13]

### 3.2 Demographic updating

The second stage of the updating process is to account for population growth, which varies across demographic groups. We reweight the underlying dataset to reflect changes in the demographic profile of the South African population that occurred between the time of the original survey and the updating year.

Specifically, we reweight the underlying data so that weighted population proportions for each province and each age-race-gender interaction match those given in the relevant year's Statistics South Africa mid-year population estimates (MYPE). Following the grouping in the MYPE, age is divided into 17 categories. Together with four racial groups and two genders, this implies 136 interacted age-race-gender cells. This gives 145 dimensions along which population proportions are adjusted—the 136 age-race-gender cells and the nine provincial categories—plus the

[11] Ravallion (2001) identifies four reasons for the divergence, namely: (i) problems in measuring illegal, informal, household-based, and subsistence outputs in the national accounts; (ii) difficulties in separating out certain elements in the national accounts that do not belong under household income, such as spending in the not-for-profit sector; (iii) underestimation of top incomes in household surveys; and (iv) the use of different deflators.

[12] That is, countries using an income aggregate, with a median income above US$172 in 2011 purchasing power parity (PPP), with a Gini index higher than 32.246, and which are not in the Europe and Central Asia region.

[13] Note that one possible extension to this income inflation method would be to estimate an index of distributional changes in household income growth per decile or quintile based on previous survey datasets or secondary surveys and apply these to the GNI growth factor used to inflate income (see, for example, Van der Berg et al. 2007, who use a similar technique for adjusting surveys to be consistent with the national accounts). For this paper, in the spirit of keeping our method simple enough to be able to isolate the changes due to datasets versus method versus additional assumptions, we do not apply this technique here.

requirement that in absolute terms, the weighted national population total in the survey be inflated to match the total given in the MYPE.[14]

Demographic reweighting along these dimensions is fairly common in the production of South African household survey data—for example, it is used in the calibration of weights for the underlying LCS, QLFS, and NIDS datasets, as well as in the SAMOD (South African tax-benefit Microsimulation Model) dataset updating procedure (Barnes et al. 2021). In terms of the specific procedure used to accomplish this reweighting, we use the minimum cross-entropy estimation technique of Wittenberg (2010).[15]

## 3.3 Employment updating

The employment-updating procedure introduces changes in individual employment status, individual employment sector, individual earnings, and thus household incomes.

The centrepiece of our dataset-updating methodology is to account for the dramatic employment changes associated with the pandemic. We do this by imposing employment status changes in the (pre-pandemic) base data (e.g., NIDS 2017). To this end, we use the QLFS as the benchmark indicator of the contemporaneous state of the labour market. This has the advantage of providing regular quarterly surveys both before and during the pandemic.[16]

*Overall objective and two approaches*

We use two different methods of adjusting employment. Before getting into the details of how we make the adjustments, we explain the two different approaches. The objective of the exercise is to adjust employment in the base data to 2021 rates.

In the first method, which we call *matching on changes*, we start by calculating percentage changes in employment in the QLFS over time, from the survey year of the base data up until 2021 Q4.[17] This gives us the change in employment over the period according to the QLFS. We then adjust employment in the base data so that the percentage change in employment over time between the base data (NIDS 2017 or LCS 2014/15) and our new 'updated' base data ('NIDS 2021 Q4' or 'LCS 2021 Q4') matches the change in the QLFS over the same period.

[14] We also require that recalibrated weights be constant within households, as in the underlying surveys, and do not allow missing item response in any of these demographic variables, as we need to use these same categories for the employment-updating process discussed below. If any individual is missing one of these characteristics, we impute it at random (with probabilities in proportion with the distribution of non-missing responses). This affects very few observations in practice.

[15] Wittenberg (2010) provides a Stata program 'maxentropy', which we use for this purpose. The minimum cross-entropy procedure is the same as is used to post-stratify weights in NIDS (Wittenberg 2009), with the only substantive difference being that we do not allow missing item response in demographic variables, as noted above. Wittenberg (2010) shows that this cross-entropy technique is equivalent to the iterative proportional fitting or 'raking' procedure which is often used for this kind of weight calibration.

[16] Questions have been raised about the accuracy of the pandemic-period QLFS (Paton 2022; Simkins 2021), and our use of the data should not be seen as an endorsement of the QLFS over alternatives such as NIDS-CRAM. In our view there are few technical reasons to prefer one dataset over the other; our use of the QLFS is necessitated by our requiring a consistent labour market series pre- and post-pandemic, which is available from no other source. The QLFS also has the advantage of being the official source of labour statistics in South Africa. We discuss potential issues with the QLFS and its divergences from NIDS-CRAM in Section 4.2, under 'Household disposable income'.

[17] When updating NIDS, we use 2017 as the base year, and when updating LCS we use 2015.

In the second method, which we call *matching on levels*, we start by calculating employment levels in the QLFS in 2021 Q4. This gives us up-to-date employment levels that incorporate the pandemic shock, according to the QLFS. We then adjust employment in the base data (e.g., NIDS 2017) so that the employment levels match those in the 2021 Q4 QLFS.

The more appropriate method will depend on how one evaluates the underlying NIDS, LCS, and QLFS data sources. This is because the base datasets differ from the QLFS dataset even when they represent the same survey year. The NIDS 2017 and LCS 2015 employment rates are higher than the employment rates in the QLFS 2017 and 2015 respectively.[18]

If matching on *levels*, the implicit assumption is that the QLFS is a superior employment data source. Therefore, it is most useful to force the data to 'look like' the QLFS in terms of employment, even though this will impose changes in the base data beyond those changes associated with the passage of time between the base period (e.g., 2017) and 2021 Q4.

If matching on *changes*, the characteristics of the base data are better preserved. In this case, the base data is not made to 'look like' the QLFS (e.g., NIDS updated to 2021 will still have higher employment rates than the 2021 Q4 QLFS) but only to reflect changes over time which are estimated from the QLFS.

In our view, neither method is obviously superior. In this paper we use matching on changes as our baseline approach when presenting results, which provides our largest estimates of poverty increases. We then compare to matching on levels in Section 6, which presents the full range of our poverty estimates. This should not be understood as a substantive endorsement of one approach over the other.

*Accounting for heterogenous employment rates and changes*

Individual employment probabilities vary by demographic characteristics, and the probability of employment transition over the period of the pandemic has similarly been heterogenous across these groups, with more-vulnerable groups consistently found to have higher rates of job loss (Casale and Posel 2021; Jain et al. 2020b; Rancchod and Daniels 2021). The distribution of jobs has also changed, with some industries disproportionately disrupted by the pandemic, for example (Bassier et al. 2021b). Therefore, when adjusting employment rates in the base data to match the QLFS levels or changes, we aim to ensure that after the adjustments, the base data matches the QLFS employment levels or changes over time *for each salient demographic type and employment type*.

To take a simplified example, consider matching on levels in NIDS, using gender as a demographic characteristic and formal/informal employment as employment sector. We interact demographic characteristics (such as area and gender) into demographic-characteristic combinations (hereafter demographic 'groups') and we interact employment sectors (such as formal/informal employment and industry) into employment sector combinations (hereafter employment 'groups'). In this simplified example there are only three different possible employment groups—formally employed, informally employed, and non-employed—and only two different demographic groups—female and male.[19] Our matching algorithm does not directly adjust employment rates in

[18] For the age 25–55 employment rates we use in Section 4 below, NIDS 2017 has an employment rate of 63 per cent versus 58 per cent in the 2017 Q2 QLFS (see Table 2), while the LCS 2015 has an employment rate of 61 per cent versus 57 per cent in the 2015 Q2 QLFS (see Table A5.2 in Appendix 5).

[19] In our actual implementation, demographic and employment groups are much more detailed than in this simplified example and are created by interacting the various demographic characteristics and separately the various employment

NIDS so that the *aggregate* NIDS employment rate matches the *aggregate* 2021 Q4 QLFS employment rate; rather, it matches the distribution of employment groups *for each demographic group* so that women (and men) have the same proportion of individuals in formal employment (and informal employment, and non-employment) in NIDS as in the QLFS. This ensures that aggregate employment rates approximately match while reflecting the prevailing labour market structure, which is essential for poverty outcomes.

Of course, the question of what defines a 'salient characteristic' in terms of the South African labour market structure is disputable. In our actual implementation, for demographic characteristics we use age (six categories), gender (two categories), education (three categories), urban/rural (two categories) and race (two categories),[20] which collectively makes 144 demographic groups ($6 \times 2 \times 3 \times 2 \times 2 = 144$).[21] For employment sectors we use formal/informal (two categories) and industry (six categories), plus a non-employed category, which generates 13 employment groups ($2 \times 6 + 1 = 13$).[22]

If we were to use too few characteristics or sectors, we would inadequately reflect the heterogeneity of employment probabilities and employment transitions and create a dataset which understated the true extent of labour market stratification and inequality.[23]

However, we have a limited number of observations in each survey, and each additional characteristic and sector that we add increases the number of groups multiplicatively.[24] Too many groups would increase overfitting error, resulting in increasingly matching on idiosyncratic features of the data (the 'irreducible error') rather than reflecting core features of the labour market data generating process. In this case the updated base data would match the QLFS very well on the characteristics and sectors we use for matching but perform poorly 'out of sample' on other characteristics or sectors.

Another reason that the matching process is approximate and will contain noise is that many groups can also create problems when it comes to matching the QLFS even for characteristics or sectors explicitly used in the matching process. Consider, for example, the case where we choose

sectors. For example, consider the case where we use gender (two categories reported in the data) and urban/rural (two categories) as demographic characteristics. We would then have four demographic *groups*: urban women, rural women, urban men, and rural men. The same logic applies to employment types. If we use formal/informal employment (two categories) and industry (six categories) as employment sectors, we will have 13 different employment groups: the product of six industry categories and the two formality/informality categories, plus a non-employed category.

[20] In order to reduce dimensionality, we define race as a binary variable for the purposes of our matching algorithm, collapsing the standard African, coloured, and Indian/Asian classifications in South Africa into one category, with white as the other category. In our diagnostic section we nonetheless present results for each of the standard four racial typologies.

[21] See footnote 19 for an explanation of how characteristics and sectors are multiplicatively converted into types. These categories are selected from a review of the NIDS-CRAM literature, in particular Casale and Posel (2021), Jain et al. (2020b), and Rancchod and Daniels (2021).

[22] Industry classification is not available in the LCS, so we use only formal/informal and a non-employed category when it comes to employment sectors, leading to three employment groups. The formal/informal definition in the LCS is also a little different to the NIDS definition. For each matching process we create an analogous formal/informal variable in the QLFS.

[23] Indeed, our results do suggest that the method creates datasets which understate inequality, and for this reason we avoid reporting inequality statistics such as the Gini coefficient.

[24] Even with the perhaps relatively minimal characteristics and sectors we use in our implementation, we end up with 1,872 employment-demographic combinations ($144 \times 13$).

characteristics and sectors so as to define a category of female urban agricultural workers. If individuals who fall into this category are observed in the QLFS sample and lose employment between 2017 and 2021, but they are not represented in the NIDS 2017 sample due to random sampling variation, the aggregate female employment rate in NIDS will then not match the QLFS rate, as there will be no group in NIDS on which to apply the female-urban-agricultural-worker employment change.

*Changing employment status*

With these overarching objectives and considerations in mind, we now turn to the actual implementation of our employment status adjustments. We directly change individuals' employment status in the base data to match QLFS changes or levels. As mentioned above under 'Overall objectives and two approaches', employment and employment transition probabilities for each individual, benchmarked from the QLFS, are based on combinations of various demographic characteristics into demographic groups and combinations of employment sectors into employment groups.

One natural approach to implementing these changes is to directly estimate employment status or employment transition probabilities in the QLFS in a regression framework, and then use the coefficients and covariates from that model to predict employment status or transitions for individuals in the base data. Instead, we use an analogous but more manual approach, which more easily lends itself to the hot-deck wage imputation performed at a later stage (see the end of this subsection).

We use the 144 demographic groups and 13 employment groups to create 1,872 exhaustive and mutually exclusive demographic and employment 'cells'. For each of the 144 demographic groups, we calculate either:

1. how its members are proportionally distributed across the 13 employment groups in the 2021 Q4 QLFS (if matching on levels); or
2. how the distribution of members has changed across the 13 employment groups in the QLFS over time (if matching on changes).

Then, in the base data we change the employment groups of individuals randomly chosen from the relevant demographic-employment cell, so that for each of the 144 demographic groups, the distribution of individuals across employment groups or the change in distribution in employment groups matches the QLFS.

Because the pandemic was a large negative employment shock, this exercise mostly consists of shifting individuals from one of the 12 employed groups to the non-employment group, until the proportion of individuals within each employment group (for the demographic group) matches the level or change in the QLFS. Individuals shifted to non-employed status then have their earnings reduced to zero, while their non-earnings income is left intact.[25]

The proportion of individuals in some employed groups *increases* for particular demographic groups, and in these cases, we assign people to employment. The non-employed sector is somewhat coarse: it includes the unemployed, the not economically active (NEA), and those who

[25] Note that when an individual is shifted into non-employment, we reduce their entire earnings to zero regardless of what type of work they are in. This is different to some other updating exercises, such as that of Younger et al. (2020), who define different types of 'risky income' which are reduced to different degrees: for example, self-employed have only a proportion of their income reduced. In both NIDS and LCS, all incomes are net of tax.

are moved from an employed sector to the non-employed sector via the first stage of the employment-updating procedure above.

If an individual was originally non-employed in the base data and therefore does not have a wage, we use hot-deck imputation to provide a wage for them by randomly duplicating a wage from another person in the demographic-employment cell to which they are newly assigned.[26] If the person does have earnings in the base data, was only initially shifted into non-employment by our algorithm, and is now shifted back into employment, albeit into a different employment sector, they keep their original earnings.

It is worth noting that our algorithm is likely more robust when shifting people into non-employment than into employment, and so we expect our updating procedure to work better during times of net employment loss (such as the pandemic) than during periods of net gain. This is because the probability of a shift to non-employed status for any individual is determined by both their demographic characteristics and their employment sector, whereas the probability of an individual shifting to employed status in our algorithm does not account for the nature of their non-employment (unemployed, NEA). We impute an employment group for those shifting into employment purely on the basis of their demographic characteristics.

*Adjusting incomes*

After the employment-updating process above, updating household incomes is relatively simple. For any individual whose employment status has changed as a result of the updating procedure, we subtract their initial earnings from their household's income if they are moving into non-employment, and add in their new earnings if they are moving out of non-employment. For those who are shifted to non-employed status, this simply means subtracting their earnings, as their new earnings are zero; for those shifted to an employed status from a non-employed status, this is done by adding their new earnings to household income.

## 4 Diagnostic results

In this section we look at a set of diagnostic results to determine how well our method achieves its objectives. For the results presented here, our baseline methodology is updating the NIDS 2017 data by matching employment changes in the QLFS ('matching on changes'). As noted above, this is for simplicity of presentation and is not an endorsement of this dataset or updating method. Section 6 compares these results to the results of (a) updating LCS 2014/15 data and (b) updating NIDS 2017 data but matching employment levels in the QLFS ('matching on levels').[27] For all three approaches, the income forecasting and demographic updating methods remain the same, with the employment-updating method or underlying data being the points of difference.

To make the employment rates examined here focused on those most likely to be economically active, throughout the sections on diagnostic results and sensitivity tests we look at results for ages

[26] Hot-deck imputation is a method for imputing item non-response by substituting in the item value from a 'similar' observation which has a non-missing response in this item. In our case, 'similarity' is defined by being in the same demographic-employment cell.

[27] Appendix 6 compares our method and results with the alternative SAMOD updating method used in Barnes et al. (2021).

25–55. This narrows our focus to a population likely to be working and avoids ages where some demographics groups are especially likely to be studying or otherwise out of the labour force.

## 4.1 Demographic proportions

Table 1 shows that in terms of demographic characteristics, the QLFS, LCS, and NIDS of each year match each other extremely well, both before and after our weight recalibration. This is gratifying but not very surprising, given that all of the surveys are calibrated to the Statistics South Africa MYPE of the relevant year, though using slightly different techniques.

Table 1: Population and demographic distribution by dataset

| Demographic characteristics | QLFS 2015 | LCS 2014/15 | QLFS 2017 | NIDS 2017 | QLFS 2021 | LCS 2021* | NIDS 2021* |
|---|---|---|---|---|---|---|---|
| Total population (millions) | 54.2 | 54.8 | 55.6 | 53.6 | 58.7 | 60.1 | 58.4 |
| % employed, by: | | | | | | | |
| *Age* | | | | | | | |
| Age 0–17 | 34.2 | 35.9 | 33.3 | 35.2 | 31.8 | 33.3 | 33.7 |
| Age 18–35 | 32.4 | 32.2 | 32.0 | 32.9 | 31.2 | 31.0 | 31.2 |
| Age 36–45 | 13.4 | 12.3 | 13.7 | 12.6 | 14.2 | 14.2 | 14.0 |
| Age 46–59 | 11.9 | 11.6 | 12.4 | 11.4 | 13.3 | 12.3 | 12.1 |
| Age 60+ | 8.1 | 8.0 | 8.5 | 7.9 | 9.4 | 9.2 | 9.0 |
| *Gender* | | | | | | | |
| Female | 51.2 | 51.1 | 51.1 | 51.5 | 51.1 | 51.1 | 51.0 |
| *Race* | | | | | | | |
| African | 80.1 | 80.4 | 80.5 | 82.8 | 81.3 | 80.9 | 81.4 |
| Coloured | 8.9 | 8.8 | 8.9 | 8.7 | 8.7 | 8.8 | 8.7 |
| Indian/Asian | 2.5 | 2.5 | 2.5 | 1.9 | 2.5 | 2.6 | 2.5 |
| White | 8.4 | 8.3 | 8.1 | 6.6 | 7.5 | 7.8 | 7.4 |
| *Urban/rural* | | | | | | | |
| Urban | 65.0 | 63.5 | 65.5 | 62.9 | 64.9 | 65.8 | 63.5 |
| *Education* | | | | | | | |
| Less than matric | 73.2 | 74.9 | 71.9 | 70.2 | 68.9 | 73.7 | 69.4 |
| Matric | 19.3 | 17.7 | 20.0 | 18.2 | 23.1 | 18.2 | 18.4 |
| Tertiary | 7.5 | 7.4 | 8.0 | 11.6 | 8.1 | 8.1 | 12.2 |

Note: * LCS 2021 and NIDS 2021 are datasets derived by updating the base datasets LCS 2014/15 and NIDS 2017 respectively.

Source: authors' estimates based on QLFS 2015, 2017, 2021; LCS 2014/15; NIDS 2017.

In Table 1 we also include the proportion of the population by urban/rural and education categories, which are not dimensions we explicitly reweight on. It is reassuring that the urban-rural proportion remains very well matched after reweighting, though there are some mild yet still surprising divergences when it comes to the distribution of educational outcomes. In the underlying data the LCS has an over-representation of those with 'less than matric' compared with the QLFS, while NIDS has the same with respect to tertiary education.[28] These differences are accentuated in the reweighing process, so that the 2021 QLFS has a larger proportion of individuals with matric than in the reweighted LCS and NIDS.

### 4.2 Employment

As a check on how well the employment-updating process works, we present various employment statistics for the benchmark QLFS data as well as the original NIDS 2017 and NIDS 2021 data-updating by matching on changes. We first do this for the demographic characteristics and employment sectors used in the employment-updating process—e.g., the female employment rate and the proportion of informal employment. We then also examine how well employment rates in our updated NIDS data match the QLFS by province—a demographic characteristic we do not use in the matching algorithm.

While the updating method matches the QLFS employment rate changes by demographic characteristic fairly well (with some notable divergences discussed in the first subsection below), the method matches the changes to employment sectors very closely. Table 2 shows employment rates by demographic characteristics and Table 3 the sector of the employed individual.

Note that while Table 2 shows the proportion of employed individuals within each demographic characteristic, Table 3 shows the proportion of employed individuals working within the various sectors. For example, we can read from Table 2 that 65 per cent of women are employed, and from Table 3 that 19 per cent of all workers are employed in the trade sector.

*Employment rates by demographic characteristics*

Reassuringly, the percentage change in employment rate in NIDS between 2017 and 2021 matches the employment change in the QLFS reasonably well (19 per cent and 16 per cent respectively). The slight divergence is likely due to lumpiness inherent in matching on survey weights and the issues associated with matching on many groups discussed in Section 3.3.2. The first row of Table 2 shows that in 2017, the overall employment rate (for those aged 25–55) in the underlying NIDS base data (63 per cent) was higher than that of the contemporaneous QLFS data (58 per cent). As expected (and indeed implicit) when matching on changes, this is reflected in the updated NIDS 2021 data, which show a marginally higher (51 per cent) employment rate than the QLFS (49 per cent).

Given that the NIDS 2021 data produce larger estimates of the aggregate employment loss, the implied employment loss for each demographic group is typically slightly higher in the NIDS 2021 data than in the QLFS. Table 2 shows changes in employment rates for each demographic group.

The NIDS update (hereafter NIDS 2021) does not fully capture patterns of socioeconomic security and vulnerability in the labour market. For Africans, we match the employment loss reasonably well (21 per cent in NIDS 2021 vs 17 per cent in the QLFS), but our updating method dramatically overstates the extent of white unemployment loss (11 per cent in NIDS 2021 vs 1 per cent in the QLFS) because it does not fully capture the impact on job loss of systemic inequalities in the labour market.

[28] Matric is the 12th and final grade of formal schooling in South Africa, signifying the completion of high school. ‘Less than matric’ refers to anyone without a matric qualification.

This is likely a general issue: because the markers of labour market security are both too numerous to include in our matching and also sometimes simply unobservable in survey data, the updating procedure will tend to do poorly for extremely vulnerable or secure groups, assigning labour market changes more like the 'group average' and thus understating inequality. The updated data similarly misrepresent labour market stratification in the changes in employment rates by gender (to a limited extent), though in this case our updating method overestimates female employment loss relative to the QLFS and in fact suggests higher employment loss than for men, contrary to the QLFS.

Table 2: Employment rates by demographic characteristic in QLFS and NIDS, matching on changes

| Demographic characteristics | Employment | | | | | |
|---|---|---|---|---|---|---|
| | a. 2017 rates | | b. 2021 rates | | c. 2017–21 (% change) | |
| | **QLFS** | **NIDS** | **QLFS** | **NIDS** | **QLFS** | **NIDS** |
| *All* | **58.0** | 63.2 | **48.5** | 51.0 | **−16.4** | −19.3 |
| *Race* | | | | | | |
| African | **54.9** | 61.8 | **45.5** | 49.0 | **−17.1** | −20.7 |
| Coloured | **62.7** | 63.6 | **52.2** | 51.9 | **−16.7** | −18.4 |
| Indian/Asian | **68.0** | 66.5 | **51.6** | 58.0 | **−24.1** | −12.8 |
| White | **79.6** | 79.0 | **78.9** | 70.4 | **−0.9** | −10.9 |
| *Gender* | | | | | | |
| Female | **65.0** | 72.9 | **55.1** | 58.1 | **−15.2** | −20.3 |
| Male | **51.1** | 53.8 | **41.9** | 44.0 | **−18.0** | −18.2 |
| *Rural/urban* | | | | | | |
| Rural | **44.9** | 52.3 | **37.2** | 42.9 | **−17.1** | −18.0 |
| Urban | **63.1** | 68.1 | **53.4** | 54.6 | **−15.4** | −19.8 |
| *Education* | | | | | | |
| Less than matric | **48.8** | 54.1 | **40.4** | 42.3 | **−17.2** | −21.8 |
| Matric | **62.9** | 64.1 | **50.4** | 49.7 | **−19.9** | −22.5 |
| Tertiary | **81.9** | 82.0 | **73.9** | 71.2 | **−9.8** | −13.2 |

Note: supercolumn (a) shows the employment rates in the original 2017 data, for NIDS and QLFS, supercolumn (b) the employment rates for 2021 Q4 in the updated dataset, and supercolumn (c) the % change in the QLFS and NIDS from 2017 to 2021 Q4; we disaggregate into the usual four racial groups rather than the aggregated two we use for the updating algorithm; restricted to ages 25–55.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017.

*Proportion employed by sector*

The change in employment types in the NIDS data matches the QLFS changes very well. Table 3 shows the percentage of the employed who are informally employed, and separately their industry, as well as how these proportions change over time in the QLFS and in the updated NIDS data. Table 3 shows how closely the NIDS data matches the QLFS when it comes to employment sectors, and the changing composition of the workforce over the pandemic.

Table 3: Employment sectors in QLFS and NIDS, matching on changes

| Employment sector | Employment | | | | | |
|---|---|---|---|---|---|---|
| | a. 2017 rates (%) | | b. 2021 rates (%) | | c. 2017–21 (% change) | |
| | QLFS | NIDS | QLFS | NIDS | QLFS | NIDS |
| *Formal/informal* | | | | | | |
| Informal | 28.3 | 32.5 | 28.0 | 31.9 | −1.1 | −1.8 |
| *Sector* | | | | | | |
| Agriculture | 8.1 | 10.9 | 8.4 | 11.9 | 3.7 | 9.2 |
| Util./fin. | 21.8 | 18.3 | 24.2 | 20.3 | 11.0 | 10.9 |
| Industry | 20.3 | 19.0 | 17.0 | 15.4 | −16.3 | −18.9 |
| Trade | 19.4 | 16.3 | 19.7 | 15.9 | 1.5 | −2.5 |
| Services | 22.2 | 25.3 | 22.2 | 25.6 | - | 1.2 |
| Private households | 8.2 | 10.2 | 8.6 | 11.0 | 4.9 | 7.8 |

Note: supercolumn (a) shows the proportions of employed in the original 2017 data, for NIDS and QLFS, supercolumn (b) the proportions of employed for 2021 Q4 in the updated dataset; and supercolumn (c) the % change in the QLFS and NIDS from 2017 to 2021 Q4; data restricted to ages 25–55.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017.

Note that whether we vary the base dataset (using LCS 2014/15 instead of NIDS 2017) or the method (matching to QLFS employment levels rather than changes), we find the diagnostic changes to be broadly similar. See Appendix 5 for more detail.

*Employment rates by province*

Tables 2 and 3, while fairly reassuring, show only how well our updated NIDS data compares with the QLFS changes in aggregate and *for the categories we use in our matching procedure*. As mentioned in Section 3.3, however, *overfitting* is a major concern, and for this we need to look at how well our updating method works for characteristics which we do not directly match on. Table 4 shows employment rates and employment changes over time by province, a demographic characteristic not used in the matching procedure.

Table 4 presents a mixed picture. Overall, NIDS changes in employment rates by province match QLFS changes about as well as our matching on variables used in the updating process (Table 2). It is gratifying that the updating works well for the main economic centre of Gauteng as well as for the province with the lowest baseline employment rate, the Eastern Cape.

However, the NIDS updating substantially overestimates the employment decline in the Western Cape, Free State, and Northern Cape compared with the benchmark QLFS data. In the case of the Western Cape this may be explained by its racial composition: it is the province with the largest proportion of white people (for whom our updating procedure performs poorly) and the lowest proportion of African people (for whom the updating process does seem to work well). The Northern Cape is the most sparsely populated province, and the difference may reflect noise and sample size issues.

Another cause may be that these are the three provinces with the lowest employment declines according to the QLFS. In general, the employment declines implied by our NIDS data are much more uniform across provinces than in the QLFS—the coefficient of variation of the NIDS employment changes is approximately one-third that of the QLFS changes. This again likely reflects the fact that our updating procedure cannot fully capture the stratification and heterogeneity of the labour market and thus understates inequality in employment vulnerability.

Table 4: Employment rates by province in QLFS and NIDS, matching on changes

| | Employment | | | | | |
|---|---|---|---|---|---|---|
| Province | a. 2017 rates | | b. 2021 rates | | c. 2017–21 (% change) | |
| | QLFS | NIDS | QLFS | NIDS | QLFS | NIDS |
| Eastern Cape | **49.5** | 55.6 | **40.5** | 46.1 | **−18.2** | −17.1 |
| Free State | **52.9** | 62.1 | **50.1** | 48.9 | **−5.3** | −21.3 |
| Gauteng | **64.6** | 69.5 | **53.1** | 55.9 | **−17.8** | −19.6 |
| KwaZulu-Natal | **52.1** | 61.6 | **44.8** | 52.0 | **−14.0** | −15.6 |
| Limpopo | **53.7** | 57.0 | **42.0** | 45.4 | **−21.8** | −20.4 |
| Mpumalanga | **58.0** | 62.9 | **46.7** | 49.1 | **−19.5** | −21.9 |
| Northern Cape | **50.6** | 62.2 | **45.1** | 50.4 | **−10.9** | −19.0 |
| North West | **53.5** | 60.2 | **43.3** | 49.2 | **−19.1** | −18.3 |
| Western Cape | **67.4** | 63.1 | **58.9** | 48.6 | **−12.6** | −23.0 |

Note: supercolumn (a) shows the employment rates in the original 2017 data, for NIDS and QLFS, supercolumn (b) the employment rates for 2021 Q4 in the updated dataset, and supercolumn (c) the % change in the QLFS and NIDS from 2017 to 2021 Q4; data restricted to ages 25–55.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017.

*Household disposable income*

There are substantial differences between the change in GNI growth observed in the national accounts from 2017 to 2021 and the change in incomes in the NIDS survey from 2017 to 2021 (Table 5).

From 2017 to 2019, after taking into account growth in GNI, CPI, and changing incomes due to the change in employment over the period, growth in per capita disposable income in the survey is 95 per cent of growth in per capita GNI. The total average change in per capita household disposable income in the NIDS data drops from a 7 per cent nominal increase in income with the income forecasting procedure to a 2 per cent nominal increase once we apply the employment shock.

From 2020 to 2021, growth in per capita disposable income in the survey is 87 per cent of growth in per capita GNI, and the total average change in per capita household disposable income in the NIDS data is a *decrease* of 6 per cent over the 2020–21 period compared with a 9 per cent *increase* in per capita GNI over the same period.

Table 5: Income growth in NIDS and national accounts

| Year | Per capita national income | | |
|---|---|---|---|
| | GNI in national accounts | Matching on changes | Matching on levels |
| *Rand values* | | | |
| 2017 | 86,633 | 4,410 | 4,055 |
| 2020 Q1 | 93,072 | 4,486 | 4,190 |
| 2021 Q4 | 101,241 | 4,223 | 4,059 |
| 2021 Q4 + SRD | | 4,219 | 4,136 |
| Growth | | | |
| 2017 to 2019 | 1.07 | 1.02 | 1.03 |
| 2020 Q1 to 2021 Q4 | 1.09 | 0.94 | 0.97 |
| 2020 Q1 to 2021 Q4 + SRD | | 0.94 | 0.99 |

Source: authors' calculations based on SARB (2022) and NIDS 2017.

This substantial pandemic-period discrepancy between per capita incomes in the updated NIDS data and the national accounts is illustrative of difficulties and pitfalls when it comes to drawing conclusions about pandemic poverty changes without contemporaneous data.

While the QLFS has shown almost no employment recovery over the pandemic period, and the updated NIDS data reflects the QLFS, other sources differ. In particular, the NIDS-CRAM (National Income Dynamics Study—Coronavirus Rapid Mobile) survey has shown very quick employment recoveries outside of hard lockdown periods, and national accounts and industry-level sales data similarly show large recoveries and even growth over the period of the pandemic (Bassier et al. 2021b; Simkins 2021). The Quarterly Employment Statistics (QES), on the other hand, agree with the large employment declines in the QLFS (Simkins 2021). In Simkins' (2021) words: 'When it comes to employment, the national accounts and NIDS-CRAM are in one corner, and the QLFS and QES are in the other'.

The reasons for these discrepancies are not clear, especially when it comes to divergences between NIDS-CRAM and the QLFS (Bassier et al. 2021a). However, one possible factor when it comes to the national accounts data may be the 2020/21 commodity boom, which saw a substantial increase in prices and sales in sectors like mining, but which may not translate into equivalent employment or earnings increases for workers (Bassier et al. 2021b). This points to the potential problems of reaching conclusions about the poverty effects over the course of pandemic by extrapolating from national accounts growth rather than using real-time survey data, as has been used for other countries (Bhalla et al. 2022). The *distribution* of growth is of critical importance for poverty results, and applying a uniform rate of growth, especially over such a tumultuous period as the pandemic, may lead to spurious results.

# 5 Poverty increase

## 5.1 Employment-loss-induced poverty

We now turn from a diagnostic exercise to what we can *substantively learn* from updating NIDS and LCS: poverty changes over the pandemic period, which are not available in the QLFS. In this section we look at *employment-induced* poverty in the absence of government pandemic-related income support or changes in household composition, changing incomes in response to employment loss, or employment gain only. In the next section, we look at the capacity of the Special COVID-19 SRD to mitigate the poverty impact of the employment loss.

This section, continuing from the previous section, presents results from the NIDS data updated by matching on changes—which produce the largest poverty increases out of our various updating methods and changes. In this section, aside from the income inflation, only earnings incomes have been adjusted for employment loss, as we do not yet increase non-earnings income by simulating allocation of the Special COVID-19 SRD grant. Estimates including the latter exercise are presented in Section 5.3, and the full range of poverty estimates are discussed in Section 6.

We consider the increase in the poverty rate between 2020 Q1 and 2021 Q4 our 'best guess' at unemployment-induced poverty of the pandemic. This is because the 2020 Q1 update mostly reflects the 'pre-pandemic' state of the labour market, while 2021 Q4 represents the end of the most severe lockdown policy thus far and incorporates the effects of the pandemic at that point in time. We therefore update the 2017 NIDS data to two different periods—2020 Q1 and 2021 Q4—using the relevant QLFS datasets and measure the change in poverty between these periods.

There is only a marginal increase in employment-induced poverty before the pandemic, but there is a notable increase due to pandemic-period job loss. Figure 1 shows these poverty rates and changes for the poverty headcount ratio, and the poverty gap for the FPL and UBPL respectively.[29]

Over the pandemic period, 90 per cent of the 3.1 million individuals that we simulate to fall below the UBPL (a 5.2 percentage point increase in poverty at the headcount ratio), also fall below the FPL (2.8 million individuals, and a 4.7 percentage point increase in the poverty headcount ratio). For those individuals who remain above the FPL while becoming newly poor at the UBPL, their earnings constitute a smaller percentage of total household income.

According to this set of results, poverty was also increasing in the pre-pandemic period, more slowly, with a 1.5 percentage point increase in the UBPL headcount ratio over the 2017–2020 period and a 1.2 percentage point increase in the FPL headcount ratio. Eighty per cent of those newly poor individuals at the UBPL also fell below the FPL, resulting in a 1.2 percentage point increase in the poverty headcount ratio. However, these pre-pandemic estimates need to be interpreted cautiously. As discussed in Section 3.3, we expect our updating method to work less well outside of periods with large employment shocks such as the pandemic, and indeed Section 6 shows that these particular results are highly sensitive to the updating method used.

The increase in the UBPL headcount ratio over the less than two years of the pandemic period is 13 per cent, while that in the FPL headcount ratio is 30 per cent. These are both substantial

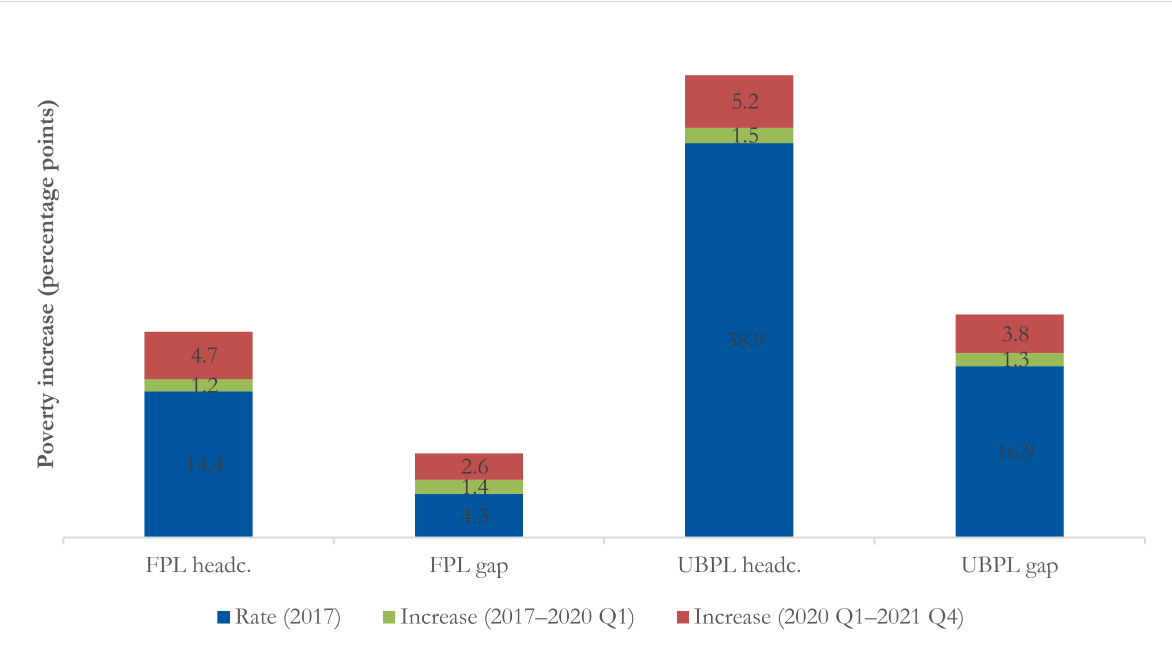
[29] The poverty lines are published by Statistics South Africa. The 2021 FPL was ZAR624 (rands) per month while the UBPL was ZAR1,335 per month.

increases, with the relative change in the FPL headcount ratio much larger because the pre-pandemic 2020 poverty headcount ratio at the UBPL is much higher in 2020 than at the FPL.

There is a similarly large increase in the poverty gap over the pandemic period, of 3.8 percentage points at the UBPL, and 2.6 percentage points at the FPL. In the pre-pandemic period, from 2017 to 2020, the poverty gap increased by a smaller 1.3 percentage points at the UBPL (from a 2017 level of 17 per cent), with a slightly larger increase of 1.4 percentage points at the FPL (from a 2017 level of 4 per cent) (caveats again apply to our estimates of these pre-pandemic poverty changes).

The pandemic-period increase in the poverty gap constitutes a substantial increase relative to pre-pandemic 2020 rates: a 21 per cent increase at the upper-bound poverty line and a 45 per cent increase at the FPL.

Figure 1: Poverty increase in NIDS by matching QLFS employment changes




Note: the total height of each bar represents the 2021 Q4 poverty rate for the particular poverty measure and poverty line in our updated NIDS 2021 Q4 data, which is then disaggregated into the original 2017 poverty rate, the increase between 2017 and 2020 Q1, and the increase between 2020 Q1 and 2021 Q4; the 2021 FPL was ZAR624 per month and the UBPL ZAR1,335 per month.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017.

## 5.2 Employment loss and poverty

Given that these poverty results are directly due to the employment changes we impose in the data, it is useful to examine the employment–poverty relationship in a bit more detail. In Table 6 we compare NIDS updated 2021 Q4 employment and poverty rates to NIDS updated 2020 Q1 employment and poverty rates, because we are interested in the increase in pandemic-related poverty. To simplify matters we use one poverty measure, the upper-bound poverty gap.

Note that whether employment loss and the loss of earnings income translate directly into an increase in poverty depends on the amount of other income which households have access to, such as inter-household transfers, remittances, passive income from investments and capital, and social grants. We therefore expect employment loss to increase poverty more for more-vulnerable groups which cannot absorb the negative labour market shock without falling into poverty.[30] Across the groups shown in Table 6, the correlation between the percentage point decrease in employment and equivalent increase in poverty is 0.92.

The table shows, for example, that African employment in NIDS decreases from 45 per cent to 39 per cent between 2020 Q1 and 2021 Q4, while the African upper-bound poverty gap increases from 21 per cent to 25 per cent over the same period.

Table 6: Employment and poverty rates in NIDS 2020 Q1 and 2021 Q4, matching on changes

| Demographic characteristics | a. Employment rate (%) | | b. Poverty at the UBPL (%) | |
|---|---|---|---|---|
| | 2020 Q1 | 2021 Q4 | 2020 Q1 | 2021 Q4 |
| *All* | 47.7 | 40.8 | 18.2 | 22.0 |
| *Race* | | | | |
| African | 45.4 | 38.5 | 20.7 | 24.6 |
| Coloured | 50.9 | 40.9 | 11.8 | 18.7 |
| Indian/Asian | 57.0 | 48.6 | 1.2 | 4.7 |
| White | 67.0 | 65.2 | 3.8 | 2.8 |
| *Gender* | | | | |
| Female | 54.8 | 46.9 | 17.0 | 20.8 |
| Male | 40.7 | 34.8 | 19.3 | 23.2 |
| *Rural/urban* | | | | |
| Rural | 38.7 | 32.3 | 26.0 | 29.2 |
| Urban | 52.1 | 45.0 | 13.7 | 17.8 |
| *Education* | | | | |
| Less than matric | 37.3 | 30.2 | 21.9 | 25.9 |
| Matric | 50.9 | 43.6 | 12.3 | 15.9 |
| Tertiary | 74.4 | 69.1 | 5.8 | 8.8 |

Note: supercolumn (a) shows the employment rates in 2020 Q1 and 2021 Q4, supercolumn (b) the upper-bound poverty gap in 2020 Q1 and 2021 Q4; we disaggregate into the usual four racial groups rather than the aggregated two we use for the updating algorithm; restricted to ages 25–55.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017.

### 5.3 Special COVID-19 SRD grant

The Special COVID-19 SRD grant is a ZAR350 per month grant (56 per cent of the FPL) first introduced in May 2020 by the Department of Social Development and digitally administered by the South African Social Security Agency (SASSA). Despite initially being conceived of as a temporary measure, it was first extended to the end of January 2021, and then to April 2021. From

[30] Some households are also more or less likely to be vulnerable to employment shocks in particular. For example, rural households are more likely to receive social grants, and are also more likely to support themselves from own-production, which mitigates the poverty effect of the unemployment shock.

May to July 2021 it was suspended, and it was then reinstated in August 2021, with all applicants required to reapply (Gronbach et al. 2022). As of the time of writing, it is still in operation.

Eligible applicants had to be older than 18, unemployed, and not receiving any income from pensions, Unemployment Insurance Fund (UIF) payments, or the National Student Financial Aid Scheme. While the grant was designed to target those with no means of supporting themselves, in reality it was provided to all those not formally employed, with the means test of ZAR585 per month (the 2020 FPL) applied only to individuals who appealed their grant denial (Goldman et al. 2021).[31] Initially the grant excluded individuals receiving caregiver grants (the foster care grant, child support grant, or care dependency grant), but this criteria was challenged and removed from August 2021 (Zulu 2021).

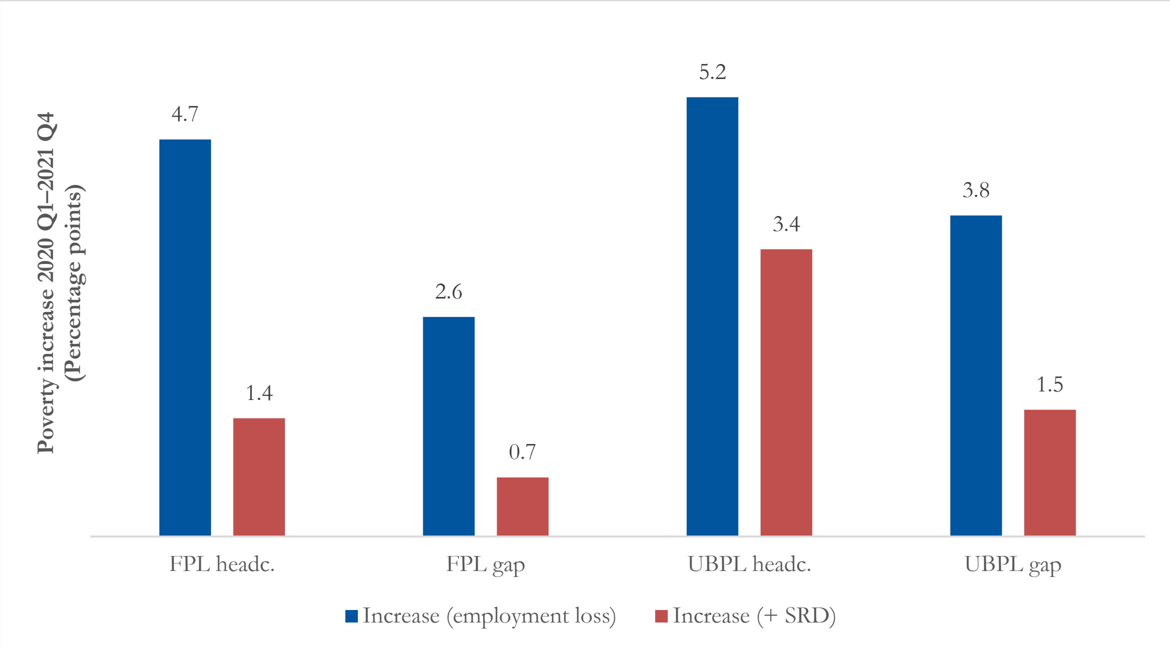
We model the grant by means of a simulation, given that we do not observe Special COVID-19 SRD recipients in the QLFS. While some 21.5 million individuals are *technically* eligible for the grant, 10.5 million were approved for payment in December 2021, and only 9.7 million received a pay-out (SASSA 2022). We select 10 million recipients from the pool of eligible individuals according to the proportional distribution observed in the National Income Dynamics Study—Coronavirus Rapid Mobile Survey (NIDS-CRAM), namely: 12 per cent of recipients are drawn from each of the first seven deciles, 8 per cent are drawn from deciles 8 and 9, and 2 per cent are drawn from decile 10 (Bassier et al. 2021b). We include recipients of caregiver grants (child support, foster care, and care dependency grants) as per the phase two eligibility criteria. Note that while we take into account actual disbursement in the simulation, the distribution of the grant may differ from actual distributional allocation of the grant, particularly given issues with the NIDS-CRAM data of reliability, granularity, and representativity, the fact that individuals had to reapply for the latest phase of the grant, and the timing of the NIDS-CRAM data collection (Wave 3, October 2020) compared with our Q4 2021 estimates.

The Special COVID-19 SRD grant appears to have reached the non-employed and informally employed, and to have supported the newly unemployed either directly or via their households and other support networks. We know that large numbers of those who should have qualified for receipt were not approved or did not receive payment (Goldman et al. 2020). Nonetheless, for the first time, many unemployed South Africans who had previously not been eligible for a grant have begun receiving one—even if they were unemployed prior to the pandemic—and frequently more than one individual in a household is eligible for receipt.

While the size of the grant is small at R350 per month—only 26 per cent of the 2021 UBPL—it was received by close to 10 million people in December 2021, while our highest estimates are that 3.1 million individuals became poor at the UBPL during the pandemic due to job loss. As a result, our simulations suggest the grant was effectively able to mitigate 35 per cent of the poverty headcount increase at the UBPL (61 per cent of the poverty gap) and 70 per cent of the poverty headcount increase at the FPL (73 per cent of the poverty gap).

[31] ZAR350 per month as of 22 April 2022 (Heywood 2022). The size of the means test is incorrectly reportedly by various sources. The figure of ZARR585 per month was provided directly to us in a meeting with SASSA representatives.

Figure 2: Poverty increase 2020 Q1 to 2021 Q4 with and without SRD, in NIDS by matching on employment changes




Note: figure shows estimated poverty increase between 2020 Q1 and 2021 Q4 taking into account the decrease in employment only (blue), and mitigated by simulated receipt of a Special COVID-19 SRD grant by 10 million claimants (red); methodology applies percentage change in employment in QLFS from 2017 to 2021; the 2021 FPL is ZAR624 per month and the UBPL is ZAR1,335 per month.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017.

## 6 Range of poverty estimates

As noted above, our main results are presented using just the NIDS dataset, updated to match percentage changes in employment in the QLFS, to simplify the presentation. This does not reflect a substantive preference for the NIDS 2017 survey over the LCS 2014/15 survey or for matching QLFS employment changes over matching employment levels.

In this section, therefore, we compare the main results from the above analysis with the results when using different updating methods or datasets. We show both the FPL and the UBPL results in the tables and figures, although we report only on the UBPL results in the text for simplicity. We begin the section by comparing the three results, shown in Table 7. In the sections that follow we discuss first the LCS vs NIDS results and then the NIDS levels vs NIDS changes results in greater detail.

Updating for employment loss using the NIDS dataset and matching changes in the QLFS employment rates produces the highest estimated increases in poverty. Table 7 shows our baseline method estimates that from 2020 Q1 to 2021 Q4 there was a 5.2 percentage point increase in the poverty headcount (3.1 million individuals or an 11.4 per cent increase), and a 3.8 percentage point increase in the poverty gap (a 17.3 per cent increase). This decreases to 3.4 percentage points (2.0 million individuals and 8.4 per cent) in the poverty headcount and 1.5 percentage points (8.2 per cent) in the poverty gap once we take the simulated Special COVID-19 SRD into account.

When we vary the method, matching QLFS employment levels in 2017 and 2021, we find that the estimates are substantially lower, at 3.0 percentage points for the poverty headcount (1.8 million individuals, 6.4 per cent increase), and 2.5 for the poverty gap (10.5 per cent increase). This decreases to 1.1 percentage points (0.7 million and 2.5 per cent) in the poverty headcount and 0.2 percentage points (0.9 per cent) in the poverty gap once we take the simulation of the Special COVID-19 SRD into account.

Applying the changes method to the LCS dataset produces estimates in-between the NIDS changes and NIDS levels method. There is a 4.0 percentage point increase in the poverty headcount (2.4 million individuals, 8.2 per cent increase), and a 3.0 change in the poverty gap (11.9 per cent increase).[32]

In summary, whether we look at the results with or without the simulated Special COVID-19 SRD, there is a substantial level of uncertainty in these poverty estimates, with a grey area of about 1.3–1.4 million individuals who may or may not have been impoverished by the pandemic. The upper-bound poverty headcount increases by between 7 and 13 per cent and the poverty gap between 12 and 21 per cent taking only employment loss into account. Once we take into account the simulated Special COVID-19 SRD, we find that the upper-bound poverty headcount increases by between 2.5 and 8.4 per cent, the poverty gap between 0.9 and 8.2 per cent. These results are described in greater detail in the subsections below.

[32] Note that unlike the NIDS dataset, whether we apply the changes or levels method to the LCS dataset produces fairly similar results, with a 4.0 percentage point increase in the poverty headcount for both methods (2.4 million individuals, or an 8.2 and 7.7 per cent increase respectively), and a 3.0–3.1 change in the poverty gap (11.9 and 11.2 per cent increase respectively).

Table 7: Poverty estimates by method, 2020 Q1 to 2021 Q4

| Increase in poverty rates | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Data and method | | Baseline | | Employment loss only | | | SRD | | | |
| | | Headcount (%) | Gap (%) | Headcount (percentage points) | Gap (percentage points) | Population (million) | Headcount (percentage points) | Gap (percentage points) | Population (million) | |
| *Upper-bound poverty line* | | | | | | | | | | |
| NIDS | Changes | 40.4 | 18.2 | 5.2 | 3.8 | 3.1 | 3.4 | 1.5 | 2.0 | |
| | Levels | 44.0 | 21.4 | 3.0 | 2.5 | 1.8 | 1.1 | 0.2 | 0.7 | |
| LCS | Changes | 44.5 | 22.2 | 4.0 | 3.0 | 2.4 | | | | |
| *Food poverty line* | | | | | | | | | | |
| NIDS | Changes | 15.6 | 5.7 | 4.7 | 2.6 | 2.8 | 1.4 | 0.7 | 0.8 | |
| | Levels | 19.6 | 8.1 | 3.3 | 1.7 | 2.0 | −0.3 | −0.3 | −0.2 | |
| LCS | Changes | 21.5 | 8.6 | 3.4 | 2.0 | 2.0 | | | | |

Note: the 2021 FPL is ZAR624 per month and the UBPL is ZAR1,335 per month.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017; LCS 2014/15

## 6.1 LCS vs NIDS changes

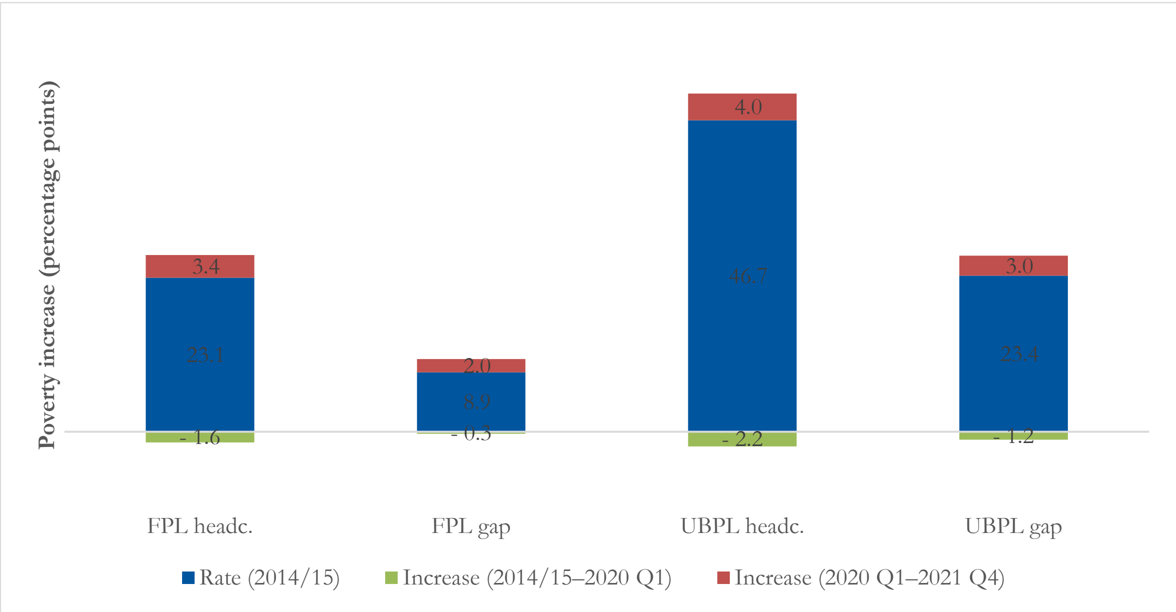
The LCS estimates are more difficult to interpret than the NIDS estimates. Updating over the pre-pandemic period (from 2015 to 2020 Q1), we find a *decline* in poverty before an increase over the period of the pandemic. This initial poverty decrease is shown by the negative bars in Figure 3.

In order to read the total 2021 Q4 poverty level, one needs to subtract the negative component from the total bar height, but one can read the bar sections directly to understand changes. For example, the LCS upper-bound poverty gap was 23 per cent in 2015 (the blue main section of the bar) which then drops to 22 per cent in 2020Q1 (the negative green bar section is one percentage points in size). Over the pandemic period the poverty gap increases to 25 per cent in 2021Q4—a three-percentage-point increase (the uppermost red section of the bar).

In general, the pandemic employment-induced poverty increases from the LCS changes method are still large, but they are smaller in both absolute and relative terms than is the case with the NIDS changes method. The poverty headcount ratio at the UBPL increases by 4.0 percentage points—compared with the 5.2 percentage points in the NIDS changes method. This is a 9 per cent increase relative to 2020 Q1.

The poverty gap ratio increases by 3.0 percentage points at the UBPL over the pandemic, lower than the 3.8 and 2.6 percentage points estimated using the NIDS changes method. This is a 13.5 per cent increase compared with 2020 Q1 levels.

Figure 3: Poverty rates in LCS, matching on changes




Note: the total height of each bar represents the 2021 Q4 poverty rate for the particular poverty measure and poverty line in our updated NIDS 2021 Q4 data, which is then disaggregated into the original 2017 poverty rate, the increase between 2017 and 2020 Q1, and the increase between 2020 Q1 and 2021 Q4; the 2021 FPL is ZAR624 per month and the UBPL is ZAR1,335 per month.

Source: authors' estimates based on QLFS 2015, 2020 Q1, 2021 Q4; LCS 2014/15.

## 6.2 NIDS levels vs changes

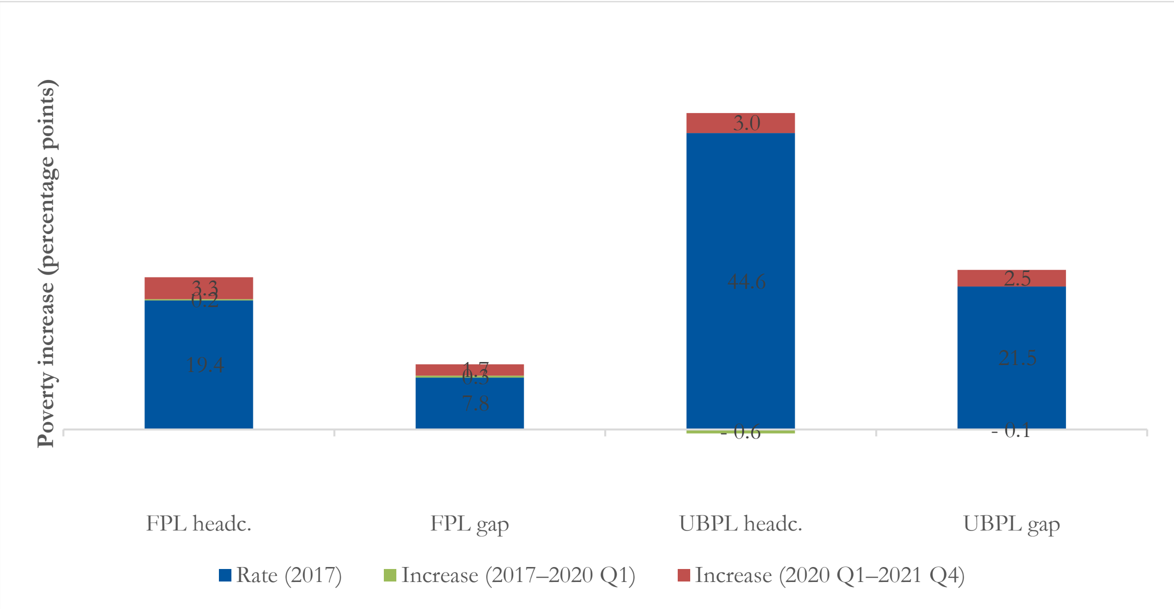
When matching the NIDS 2017 data to QLFS employment *levels* rather than percentage employment changes over time, a different method is needed for making substantive conclusions about poverty over time (see Appendix 5 for employment diagnostic results). It is no longer useful to interpret the entirety of the changes from NIDS 2017 to 2021 as a substantive result, as these changes are driven by a combination of a real evolution of poverty between 2017 and 2021 and the methodological adjustment of employment levels in NIDS 2017 to 'look like' the QLFS.

Therefore, when looking at poverty changes from 2017, we first adjust the 2017 NIDS data to match the 2017 QLFS on levels (NIDS-QLFS 2017) and make comparisons with this baseline. As would be expected, this adjustment increases the baseline poverty rate because the QLFS implies a lower employment rate. This is evident from the higher poverty rates in Figure 4 than Figure 3. Once this adjustment has been made, we can compare poverty changes over time across methods, with the results for NIDS matched on levels in Figure 4. Matching on levels implies essentially no poverty change between 2017 and 2020, presenting a middle ground between the LCS results matched on changes which suggested poverty decreases over the pre-pandemic period, and NIDS results matched on changes which suggested poverty increases over the pre-pandemic period.

The size of the pandemic employment-induced poverty increase is lower than with both the NIDS and the LCS matched on employment changes. The increase in the headcount ratio at the UBPL is 3.0 percentage points (compared with 5.2 and 4.0 for NIDS and LCS matched on employment changes respectively). This is an increase of 7 per cent on 2020 Q1 levels.

The increase in the poverty gap is 2.5 percentage points (compared with 3.8 and 3.0 for NIDS and LCS matched on employment changes respectively). This is an increase of 12 per cent on 2020 Q1 levels.

Figure 4: Poverty rates in NIDS, matching on levels




Note: the total height of each bar represents the 2021 Q4 poverty rate for the particular poverty measure and poverty line in the updated NIDS 2021 Q4 data, which is then disaggregated into the original 2017 poverty rate, the increase between 2017 and 2020 Q1, and the increase between 2020 Q1 and 2021 Q4; the 2021 FPL is ZAR624 per month and the UBPL is ZAR1,335 per month.

Source: authors' estimates based on QLFS 2017, 2020 Q1, 2021Q4; NIDS 2017.

## 6.3 Comparison with existing estimates in the literature

We further compare our poverty results with two other estimates of mid-COVID-19 poverty in the literature. Barnes et al. (2021) estimate job-loss-induced poverty for April 2020, and Van den Heever et al. (2021) present an estimate of employment-change-related poverty in Q4 of 2020 (we compare with their estimates without the Special COVID-19 SRD policy included). We consider these estimates to be broadly comparable: these papers use related but different methods, and in both cases their methodologies also differ from our own in important ways. See Appendix 6 for a detailed discussion of their methods and potential strengths and weaknesses. In this section, we briefly present their headline poverty results and compare them with our own.

The Barnes et al. (2021) estimates are for April 2020 (they update NIDS 2017 using NIDS-CRAM) and therefore are not directly comparable to any estimates we can produce using the quarterly data of the QLFS. Our closest comparison is updating NIDS 2017 (by matching on levels) to QLFS 2020 Q2, but Jain et al. (2020a) show that there was non-negligible employment recovery and poverty reduction over the second quarter of 2020, from April to June. We would therefore expect the Barnes et al. (2021) April estimates to show higher poverty than our 2020 Q2 equivalent, because our quarterly data incorporates some April–June recovery.

Indeed, this is exactly what we see: for 2020 Q2 our estimated headcount ratios are 22.5 and 46.7 per cent at the FPL and UBPL respectively, while the equivalent April 2020 estimates from Barnes et al. (2021) are 26.3 and 52.5 per cent. However, we are wary of attributing all of the substantial difference in our results to different time periods; as discussed in Appendix 6, we believe that poverty may be overestimated in Barnes et al. (2021).

Van den Heever et al. (2021) present poverty results for 2020 Q4 by updating NIDS to match the QLFS. While their method is substantively different from ours, in this case a direct comparison of the results to our own is possible (for this comparison we update NIDS to 2020 Q4 by matching on levels). Our headline poverty results are fairly similar. While we estimate UBPL and FPL headcount ratios of 21.6 and 46.0 per cent respectively in 2020 Q4, Van den Heever et al. (2021) estimate headcount ratios of 21.2 and 48.9 per cent.

Table 8: Comparison with existing poverty estimates

| | Poverty headcount ratio estimates (%) | | | | | | |
|---|---|---|---|---|---|---|---|
| Poverty line | | Barnes et al. | Van den Heever et al. | | | | NIDS levels |
| | Mar 2020 | April 2020 | 2020 Q4 | 2020 Q1 | 2020 Q2 | 2020 Q4 | 2021 Q4 |
| FPL | 20.6 | 26.3 | 21.2 | 19.6 | 22.5 | 21.6 | 22.9 |
| UBPL | 48.2 | 52.5 | 48.9 | 44.0 | 46.7 | 46.0 | 47.0 |

Note: authors' estimates calculated here using most comparable method (NIDS levels); authors' estimates and 2020 Q2 broadly comparable estimates not including simulated allocations of the Special COVID-19 SRD; broadly comparable poverty rate estimates modelled using income aggregate; authors' estimates based on 2021 poverty lines; broadly comparable estimates based on 2019 lines adjusted using CPI to 2021; differences likely to be minimal.

Source: author's estimates based on QLFS 2017, 2020 Q4, 2021 Q4; NIDS 2017; broadly comparable estimates for April 2020 based on Barnes et al. (2021) (including simulated TERS receipt) and for 2020 Q4 on Van den Heever et al. (2021).

Conducting this analysis provides us with a set of estimates over time. Our method suggests that in the absence of the Special COVID-19 SRD grant, there was no employment-induced poverty reduction over the period of the pandemic, with employment-related poverty essentially remaining constant. This is consistent with the QLFS data, which report no substantive employment recovery over the period of 2020 Q2 to 2021 Q4. This is a particularly stark finding, which must be considered alongside the active debate about whether the QLFS might understate employment recovery in the pandemic period (see Section 4.2).

## 7 Conclusion

The contribution of this paper is to estimate the impact on poverty rates of the COVID-19 employment loss and subsequent allocation of the Special COVID-19 SRD grant, between the first quarter of 2020 and the fourth quarter of 2021. This is challenging in the absence of up-to-date income and expenditure household surveys, and we generate synthetic datasets for NIDS 2017 and LCS 2014/15 surveys updated to the fourth quarter of 2021, using the QLFS. This allows us to take into account the distribution of incomes in the household survey and to account for heterogeneity in employment changes across demographic groups.

We generate the synthetic 2021 household datasets in three steps: we forecast incomes using per capita GNI from the national accounts, we reweight the dataset to take demographic changes into account, and we simulate employment losses and gains. This procedure matches employment rates or employment rate changes for a set of demographic characteristics and employment sectors.

A set of diagnostic checks confirms that the method works fairly well for poverty, but we suspect not as well for inequality. The method tends to smooth out divergences from the mean in the data—for example, white employment is revised downwards, while female employment is revised upwards. We therefore do not report inequality estimates in the paper.

To account for differences in official sources of data, we run our estimates using three different updating methods. The first method matches the employment *change* in the NIDS data to the employment change in the QLFS data, while the second matches the employment *levels* in the NIDS data to the employment levels in the QLFS data. The third matches the LCS employment change to the QLFS employment change.

The variation based on methods is fairly large. A main reason for uncertainty in these numbers is the disagreement in employment rates across the three survey datasets, with the LCS and NIDS producing higher employment rates than the QLFS. For ages 25–55, we find the NIDS 2017 survey has an employment rate of 63 per cent, while the QLFS 2017 dataset has an employment rate of 58 per cent. Similarly in the LCS 2014/15 household survey we observe an employment rate of 61 per cent, while the QLFS 2014/15 data has an employment rate of 57 per cent.

We find the increase in poverty due to employment change to be substantial. Taking into account only changes to earnings income (and not the mitigating effects of the simulated Special COVID-19 SRD), at the upper-bound poverty line of ZAR1,335 per month, our largest estimate of the poverty headcount increase, produced by the NIDS changes method, is 5.2 percentage points, from a rate of 40.4 in 2020 Q1 (an increase of 13 per cent, or 3.1 million individuals), and our smallest estimate, produced using the NIDS levels method, is 3.0 percentage points (an increase of 7 per cent, or 1.8 million individuals). The poverty gap increases at the UBPL by between 3.8 percentage points, from a rate of 18.2 in 2020 Q1 (an increase of 21 per cent), and 2.5 percentage points (an increase of 12 per cent on 2020 Q1).

The resultant poverty headcount ratio without the inclusion of the Special COVID-19 SRD grant for 2021 Q4 is between 45.6 and 48.5 per cent. Compared with existing estimates for March 2020 and April 2020 (Barnes et al. 2021) and 2020 Q4 (Van den Heever et al. 2021) our estimates suggest a lower increase in poverty in the initial period of the pandemic than Barnes et al. (2021) but we have a headcount ratio for 2020 Q4 similar to that of Van den Heever et al. (2021).

Encouragingly, when we simulate provision of the Special COVID-19 SRD grant to 10 million recipients, our new estimates of the poverty increase are considerably lower. The 2020 Q1 upper-bound poverty headcount increase is reduced to between 3.4 percentage points (an increase of 8 per cent on 2020 Q1 poverty rates, or 2.0 million individuals) and 1.1 percentage points (an increase of 2.5 per cent, or 0.7 million individuals). The upper-bound poverty gap increase is reduced to between 1.5 and 0.2 percentage points (an increase of 8 per cent and 1 per cent respectively).

Using the NIDS dataset and matching on employment levels in the QLFS, we produce estimates for Q2 and Q4 of 2020, and Q4 of 2021. These show job-loss-induced poverty to be roughly constant over the less than two-year portion of the pandemic captured here if one excludes the effect of the SRD. This is consistent with the lack of labour market recovery over this period in the QLFS data.

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## Appendix 1: Quarterly Labour Force Survey Data

The number of individuals and households in each dataset is detailed in Table A1.1. Importantly the QLFS data collection during the COVID-19 era was done telephonically, which resulted in the exclusion of households without telephones. The data was then adjusted for the resultant bias (Statistics South Africa 2022b).

Table A1.1: Number of individuals and households, by QLFS dataset

| QLFS dataset | Individuals | Households |
|---|---|---|
| 2015 Q1 | 72,561 | 20,828 |
| 2017 Q1 | 69,353 | 20,529 |
| 2020 Q1 | 66,657 | 19,913 |
| 2020 Q2 | 47,103 | 13,408 |
| 2020 Q4 | 48,990 | 14,242 |
| 2021 Q4 | 39,073 | 11,502 |

Source: authors' calculations based on QLFS 2015 Q1, 2017 Q1, 2020 Q1, 2021 Q4.

## Appendix 2: LCS 2014/15 household disposable income

Table A2.1: Income growth in LCS and national accounts

| Year | Per capita national income | | |
|---|---|---|---|
| | GNI in national accounts | Matching on changes | Matching on levels |
| *Rand values* | | | |
| 2015 | 78,086 | 4,293 | 3,988 |
| 2020 Q1 | 93,072 | 4,436 | 4,178 |
| 2021 Q4 | - | 4,122 | 3,903 |
| *Growth* | | | |
| 2017 to 2020 Q1 | 1.19 | 1.03 | 1.05 |
| 2020 Q1 to 2021 Q4 | - | 0.93 | 0.93 |

Source: authors' calculations based on SARB (2022) and LCS 2014/15.

## Appendix 3: Variable list

Table A3.1: Variable list for updating procedure

| Var name | Label | Description |
|---|---|---|
| hhid | Household ID | Unique household identifier |
| hhsizer | Household size | Number of people belonging to unique household identifier |
| pid | Individual ID | Unique personal identifier; ensure that this variable provides a unique identifier across the dataset, and not only within households |
| wgt | Household weight | Survey weight provided in the dataset; the weighted total of all survey respondents should be close to the full population count of South Africa |
| age | Age | Age in years of respondent |
| emp | Employed [1 = yes, 0 = no] | Indicator for employment status of respondent; employment is broadly defined, including informal and part time; in the LCS, includes anyone who is working for a wage, running a business, working without pay, or has a job to return to, OR reports a sector that they are working in |
| totwage | Wages | Total gross/net wages of respondent, including all sources of employment; missings or unemployed are set to 0; whether the variable is gross or net must correspond to the hhincome variable (i.e. if hhincome is net of taxes then totwage should be net of taxes); in the case of the dataset used here, for both NIDS and LCS the variables are net of taxes and contributions |
| hhincome | Household net income | Total gross/net household income of respondent, including all sources of income; whether the variable is gross or net must correspond to totwage variable (i.e. if totwage is net of taxes then hhincome should be net of taxes); in the case of the dataset used here, for both NIDS and LCS the variables are net of taxes and contributions |
| female | Female [1 = yes, 0 = no] | Indicator for gender of respondent, defined as 0: man, 1: woman |
| nea | Not economically active [1 = yes,0 = no] | Indicator for whether respondent is economically active or not |
| race_cat | Race category | Race of respondent, defined as 1: African/black, 2: coloured, 3: Indian/Asian, 4: white |
| province | Province | Province of respondent's current residence, defined as 1: Eastern Cape, 2: Free State, 3: Gauteng, 4: KwaZulu-Natal, 5: Limpopo, 6: Mpumalanga, 7: Northern Cape, 8: North West, 9: Western Cape |
| urban | Urban [1 = yes,0 = no] | Indicator for respondent's settlement type defined as: 0: rural, 1: urban |
| educ_cat | Level of education attained | Category of respondent's highest level of education, defined as 1: less than matric, 2: Matric/less than tertiary, 3: tertiary |
| black | African/black [1 = yes, 2 = no] | Indicator for African black, derived from the race variable, defined as 0: non-black, 1: black |

| | | |
|---|---|---|
| informal | Informal employment | Indicator for informal employment, defined in NIDS as not having a written contract and in LCS as working in the informal sector or in a private household, and excluding anyone with medical aid paid by their employer |
| indus_cat | Industry category | Industry of respondent's current employment, defined as 1: agriculture/mining, 2: utilities and finance, 3: industry, 4: trade, 5: services, 6: private households; these are not available in LCS |
| occup_cat | Occupational category | Respondent's current occupational category, broadly defined as 1: professional, 2: service and other, 3: manual; these are not available in LCS |

Source: authors' construction.

## Appendix 4: Income inflation growth rate

In this appendix we show how we estimated the income inflation growth rate for both the LCS and the NIDS surveys.

We inflate income from 2015 (LCS) and 2017 (NIDS) to 2021 using a combination of growth in per capita nominal GNI and CPI. We do this by calculating the growth from the survey year to June 2018/19 (LCS) or December 2019 (NIDS), and then using CPI growth to calculate the counterfactual GNI for 2021, in the absence of the COVID-19 pandemic.

### A4.1 Living Conditions Survey 2014/15

The LCS (Statistics South Africa 2017a, b) was conducted from October 2014 to October 2015. We use an annual per capita GNI weighted by 0.25 for the previous year and 0.75 for the following year.

From 2014/15 to 2018/19, we see a per capita GNI growth rate of 1.21 (ZAR92,309 million/ZAR77,062 million). If we extend this growth by the 8.85 per cent growth in CPI from January 2020 to December 2021, we estimate a total counterfactual growth in per capita GNI, in the absence of the COVID-19 pandemic, from the survey year to 2020/21 of 1.32 (1.21*(1 + 0.085)) (see Table A4.1).

Table A4.1: Year-on-year GNI growth (LCS)

| Year | Per capita GNI | Year-on-year growth |
|---|---|---|
| 2014/15 | 77,062 | |
| 2015/16 | 81,474 | 1.06 |
| 2016/17 | 85,626 | 1.05 |
| 2017/18 | 89,172 | 1.04 |
| 2018/19 | 92,309 | 1.04 |
| 2019/20 | 91,681 | 0.99 |
| 2020/21 | 96,229 | 1.05 |

Source: authors' estimates based on SARB (2022).

### A4.2 National Income Dynamics Study 2017

The NIDS was conducted from January 2017 to December 2017. From 2017 to 2019, we see a per capita GNI growth rate of 1.07 (ZAR93,072 million/86,633 million).

If we extend this by the 8.85 per cent growth in CPI from January 2020 to December 2021, we estimate a total counterfactual growth in per capita GNI, in the absence of the COVID-19 pandemic, from the survey year to 2020/21 of 1.17 (1.07*(1 + 0.085)) (see Table A4.2).

Table A4.2: Year-on-year GNI growth (NIDS)

| Year | Per capita GNI | Year-on-year growth |
|---|---|---|
| 2017 | 86,633 | |
| 2018 | 90,018 | 1.04 |
| 2019 | 93,072 | 1.03 |
| 2020 | 91,217 | 0.98 |

Source: authors' estimates based on SARB (2022).

## Appendix 5: Diagnostic results for sensitivity tests

### A5.1 LCS vs NIDS changes

Table A5.1 shows employment rates by demographic groups when the 2015 LCS rather than the 2017 NIDS is the underlying dataset, but still matching on changes. As is the case with NIDS, the LCS has higher baseline employment rates than the contemporaneous QLFS. The matching process seems to work well for the demographic categories we match on, as the implied changes over time in the LCS match the QLFS better than is the case for NIDS. Contributing factors for this may be that the larger sample size of the LCS and the lack of industry information means matching with substantially fewer cells, thus leading to less noise from matching on small cell sizes and distortions caused by empty cells in the QLFS or base data. The trade-off of less industry information is that the updated LCS likely does not reflect changing industrial structure—types of jobs—as well as NIDS does.

Table A5.1: Employment rates in QLFS and LCS, matching on changes

| Demographic characteristics | a. 2015 rates (%) | | b. 2021 rates (%) | | c. 2017–21 (% change) | |
|---|---|---|---|---|---|---|
| | QLFS | LCS | QLFS | LCS | QLFS | LCS |
| *All* | 57 | 61 | 49 | 53 | −15 | −14 |
| *Race* | | | | | | |
| African | 54 | 58 | 46 | 50 | −16 | −13 |
| Coloured | 63 | 68 | 52 | 55 | −17 | −19 |
| Indian/Asian | 65 | 70 | 52 | 61 | −20 | −14 |
| White | 78 | 83 | 79 | 77 | 1 | −7 |
| *Gender* | | | | | | |
| Female | 65 | 68 | 55 | 59 | −15 | −14 |
| Male | 50 | 55 | 42 | 47 | -16 | -14 |
| *Rural/urban* | | | | | | |
| Rural | 45 | 46 | 37 | 40 | -17 | -14 |
| Urban | 62 | 68 | 53 | 58 | -14 | -14 |
| *Education* | | | | | | |
| Less than matric | 49 | 52 | 40 | 45 | −17 | −14 |
| Matric | 62 | 67 | 50 | 56 | −19 | −15 |
| Tertiary | 81 | 87 | 74 | 78 | −9 | −10 |

Note: supercolumn (a) shows the employment rates in the original 2015 data, for LCS and QLFS, supercolumn (b) the employment rates for 2021 Q4 in the updated dataset, and supercolumn (c) the % change in the QLFS and LCS from 2015 to 2021 Q4; we disaggregate into the usual four racial groups rather than the aggregated two we use for the updating algorithm; restricted to ages 25–55.

Source: authors' estimates based on QLFS 2015, 2021 Q4; LCS 2014/15.

### A5.2 NIDS levels vs changes

When matching on levels rather than changes, a different focus is needed when reading the diagnostics tables. It is no longer useful to substantively interpret changes from 2017 to 2021 Q4 as a 'change over time', as these changes are driven by a combination of a real evolution of employment between 2017 and 2021, which is substantively interesting, and the one-time adjusting of the NIDS data to 'look like' the QLFS in levels.

When looking at the employment rates by demographic group in Table A5.2 it is therefore informative to look not at how the QLFS and NIDS rates change 'over time' between 2017 and 2021, but rather at how employment rates match in 2021 Q4, which is the objective of the matching-on-levels approach. It is apparent that generally, the updating procedure works very well when it comes to creating a NIDS dataset which looks like the QLFS in 2021 Q4—at least for the variables we match on. Again, however, our process potentially understates the true racial stratification and inequality of the labour market, with whites imputed a much lower employment rate than is reflected in the underlying NIDS and QLFS data.

Table A5.2: Employment rates in QLFS and NIDS, matching on levels

| Demographic characteristics | a. 2017 rates (%) | | b. 2021 rates (%) | | c. 2017–21 (% change) | |
|---|---|---|---|---|---|---|
| | QLFS | NIDS | QLFS | NIDS | QLFS | NIDS |
| All | 58 | 63 | 49 | 47 | −16 | −26 |
| *Race* | | | | | | |
| African | 55 | 62 | 46 | 44 | −17 | −29 |
| Coloured | 63 | 64 | 52 | 48 | −17 | −24 |
| Indian/Asian | 68 | 67 | 52 | 63 | −24 | −5 |
| White | 80 | 79 | 79 | 68 | −1 | −14 |
| *Gender* | | | | | | |
| Female | 65 | 73 | 55 | 51 | −15 | −30 |
| Male | 51 | 54 | 42 | 42 | −18 | −22 |
| *Rural/urban* | | | | | | |
| Rural | 45 | 52 | 37 | 37 | −17 | −30 |
| Urban | 63 | 68 | 53 | 51 | −15 | −25 |
| *Education* | | | | | | |
| Less than matric | 49 | 54 | 40 | 37 | −17 | −31 |
| Matric | 63 | 64 | 50 | 46 | −20 | −28 |
| Tertiary | 82 | 82 | 74 | 68 | −10 | −18 |

Note: supercolumn (a) shows the employment rates in the original 2017 data, for NIDS and QLFS, supercolumn (b) the employment rates for 2021 Q4 in the updated dataset, and supercolumn (c) the % change in the QLFS and NIDS from 2017 to 2021 Q4; we disaggregate into the usual four racial groups rather than the aggregated two we use for the updating algorithm; restricted to ages 25–55.

Source: authors' estimates based on QLFS 2017, 2021 Q4; NIDS 2017.

## Appendix 6: Benchmarking against SAMOD datasets

As noted in the introduction, two papers perform a similar task to what we do in our analysis here: Barnes et al. (2021) and Van den Heever et al. (2021). The papers have authors in common and the SAMOD is an important component of both papers, but there are substantive differences in their overall methods. Below we discuss each paper in turn.

### A6.1 Barnes et al. (2021)

Barnes et al. (2021) perform a very similar dataset updating procedure to us, and also benchmark the 2017 NIDS data to the QLFS. Their implementation does, however, have some important differences from our own. They start by reweighting NIDS to create a 'pre-pandemic' March 2020 dataset.[33] However, in addition to reweighting to match the Statistics South Africa MYPE, as we do, they also reweight NIDS to match the QLFS 2020 Q1 employment profiles with regard to the detailed employment status variable interacted with occupation.[34] This component of their procedure is conceptually comparable to our 'matching on levels', though reweighting is substantively different to direct changing of employment statuses, as we discuss in the subsection below.

Barnes et al. (2021) do change employment statuses directly in the second stage of their procedure, where they impose employment losses in the pre-pandemic data that match employment loss in the first wave of the NIDS-CRAM data, which is for April 2020. In a regression framework, they estimate the probabilities of different kinds of employment and earnings losses, with various demographic and employment predictors.[35] They then assign individuals to different employment states based on these probabilities.

This aspect of their process is more comparable to our matching on *changes*, with an important difference: they only model job *loss* probabilities, and do not complement this with concurrent job *gain* probabilities. The South African labour market in general has a high rate of employment churn (Kerr, 2018), and this continued throughout the pandemic (Espi-Sanchis et al. 2021; Jain et al. 2020b). Jain et al. (2020b) show that 9 per cent of those who were not employed in February 2020 (pre-pandemic) were actively employed or on paid leave in April, with a further 2 per cent having some kind of other employment relationship and being 'temporarily laid off' in April. Only imposing employment losses is likely to lead to a potentially substantial overstatement of the net employment loss over the February–April period, and indeed Barnes et al. (2021) do note this as a likely part of the explanation for the much lower employment rate in their updated data (33 per cent) than in the NIDS-CRAM data (45 per cent).

### A6.2 Van den Heever et al. (2021)

Dataset updating is not a focus of Van den Heever et al. (2021), but it does form part of their analysis. They implement the reweighting method of Barnes et al. (2021) to adjust the 2017 NIDS data to match the employment profiles in the QLFS in 2020 Q4, rather than 2020 Q1. They then

[33] Rather than using Wittenberg's (2010) minimum cross-entropy estimation, they calibrate weights using iterative proportional fitting (raking). We do not expect these methods to lead to substantively different results.

[34] It is worth noting that their employment status variable is much more detailed than our own, with particular detail on different kinds of non-employment which we coarsely group together.

[35] These types of employment and earnings states are again substantially more detailed than our own, for example including a category for furloughed workers.

do not further adjust employment statuses or incomes (other than inflation adjustments). This is a substantive difference, as it means that unlike Barnes et al. (2021) and unlike our methodology here, they account for the pandemic employment shock by adjusting sample weights rather than directly changing individual employment statuses and incomes. In effect, to increase aggregate unemployment they increase the weights of those who were unemployed in the 2017 data and reduce the weights of those who were employed.

The potential drawback of this method, as opposed to direct employment status adjusting as in Barnes et al.'s (2021) and our own methods, is that it implicitly assumes that those newly unemployed over the period of the pandemic will be similar in characteristics to those unemployed in 2017, which is likely to be erroneous to some degree. Direct employment adjusting, in contrast, only affects employment status and incomes, leaving other characteristics of the sample unchanged.

The potential problem can be illustrated with an example. Receipt of social grants in 2017 is higher among the non-employed than the employed. Reweighting to increase unemployment will therefore also increase social grant receipt in the data, because the existing unemployed, who are up-weighted, disproportionately receive grants. However, in reality, those who became unemployed over the pandemic would be unlikely to increase their grant receipt—indeed, SASSA offices were frequently closed and the social grant application process takes time in any case. This means the reweighting may erroneously increase grant receipt in 2020, or other characteristics associated with non-employment.

These problems will be mitigated, perhaps substantially, by the simultaneous demographic reweighting of Van den Heever (2021), which ensures that their 2020 demographic profile matches the Statistics South Africa MYPE (as is also the case in Barnes et al., 2021). But this is an empirical question, and the demographic reweighting is unlikely to fully resolve this issue.

It is worth noting that this reweighting approach may be superior to our method of directly updating employment statuses during 'normal' times, when we may expect increases in unemployment to be accompanied by changes such as increases in social grant receipt. However, it does seem problematic when attempting to adjust for a dramatic shock such as the COVID-19 pandemic. Indeed, this is probably why Barnes et al. (2021) use reweighting to adjust to 2020 Q1, and then direct adjusting of employment statuses for the pandemic period.

A related issue is what to do about the changing distribution of grant eligibility in the 'normal' times leading up to the pandemic. We do not adjust grant receipt from what is reported in NIDS 2017 (and LCS 2015), and to the extent that the distribution of grant receipt changed in the years preceding the pandemic this may cause some inaccuracies in our analysis. In contrast, Barnes et al. (2021) and Van den Heever et al. (2021) simulate grant receipt based on *de jure* eligibility, which may account for some changes in grant receipt over time but then risks introducing simulation errors. These decisions in turn raise the question of how grant values are adjusted over time. Because we do not separate grant income out from disposable income at large, we inflate grant values by the same factor as market incomes, as discussed in Section 3.1. This could create inaccuracies, but we do not expect it to be particularly consequential because grant increases over these periods were roughly in line with headline inflation.[36]

[36] From 2017 to 2021 (or 2015 to 2021) the Old Age Grant value increased by 18 per cent (or 34 per cent), the Child Support Grant value increased by 21 per cent (or 39 per cent), while the headline CPI increased by 16.5 per cent (or 32.5 per cent).