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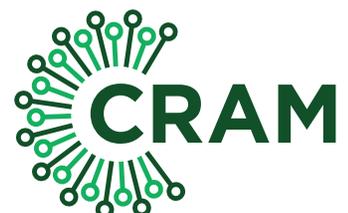
Gabriel Espi - University of Cape Town

Murray Leibbrandt - University of Cape Town

Vimal Ranchhod - University of Cape Town

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The relationship between employment history and COVID-19 employment outcomes in South Africa

Gabriel Espi, SALDRU Researcher, School of Economics, University of Cape Town[1]

Murray Leibbrandt, SALDRU Researcher and Professor, School of Economics, University of Cape Town[2]

Vimal Ranchhod, SALDRU Researcher and Professor, School of Economics, University of Cape Town[3]

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Abstract

Future employment outcomes are believed to be strongly determined by an individual's past employment experience (or lack thereof). We investigate the relationship between individuals' labour market experience over the decade covered by NIDS (2008-2017) and their contemporary employment outcomes under the COVID-19 pandemic and lockdown as captured by NIDS-CRAM waves 1 and 2. Restricting to a balanced panel of prime-age (25 to 50) individuals who have employment status information across all periods of NIDS and NIDS-CRAM, we assign individuals to three groups on the basis of their employment history: the stable employed, the transient employed, and the persistent non-employed. We find that pre-lockdown employment status in February 2020 correlated strongly with this employment history. Nonetheless, a substantial proportion (45%) of the historically persistent non-employed were employed going into lockdown. This group was found to be young and thus more likely to have previously been engaged in education rather than labour activities. This highlights the need for care in interpreting employment history for individuals with different ages. Under lockdown, those with transient employed or persistent non-employed histories were more likely to have lost work and to be excluded from employment opportunities relative to the historically stable employed, with job loss consistently the highest for the persistent non-employed in both April and June 2020. Job gain also followed clearly differentiated lines, with a third of the historically stable employed who were without work in February finding employment by April, relative to only 8% of the persistent non-employed (although this discrepancy was less pronounced between April and June). Those with the least recorded employment were mostly younger, rural African women, while among the stable employed (who were all much more likely to be male), those who lost work in the lockdown were more likely to be African and have a rural background relative to those who retained work. These findings suggest that people's long-term employment histories have been influential in determining their employment outcomes during COVID-19, and that understanding these histories can tell us more about the capacities and needs for intervention of those who have been affected by the lockdown.

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1 Gabriel.espi-sanchis@uct.ac.za.

2 Murray.leibbrandt@uct.ac.za

3 Vimal.ranchhod@uct.ac.za.

Executive summary

Future employment outcomes are believed to be strongly determined by an individual's past employment experience (or lack thereof). We investigate the relationship between individuals' labour market experience over the decade covered by NIDS (2008-2017) and their contemporary employment outcomes under the COVID-19 pandemic and lockdown as captured by NIDS-CRAM waves 1 and 2. This analysis is based on a balanced panel of individuals who were prime-age (25 to 50) in 2020 and who had employment status information across all periods.

Substantial differences in employment history underlie individuals' pre-lockdown employment status. 41.5% of individuals in our balanced panel had a history of persistent non-employment between 2008 and 2017, compared to 32% who were transient employed, moving in and out of employment frequently, and 27.5% who were stably employed in the period. Employment status immediately preceding lockdown, as captured by the February 2020 information in NIDS-CRAM, was highly correlated with this employment history. In our balanced panel 83% of the stably employed were employed in February; the respective figures for the transient employed and the persistent non-employed were 66% and 45% respectively.

Job loss under lockdown correlated strongly with employment history. 86% of the historically stable employed retained employment between February and April, compared with only 72% of the transient employed and 67% of the persistent non-employed who were employed in February.

The risk of job loss remained persistently high for many workers in the later stage of the lockdown. 87% of the historically stable employed who had retained their employment between February and April remained employed in June, compared to 87% and 70% of the transient employed and persistent non-employed, respectively. The increase in the job retention rate among the historically transient employed meant that the higher risk of job loss faced by the persistent non-employed was unique in this later period of the lockdown.

Job finding rates reflected employment history, particularly in April. In both April and June there was substantial churning underlying overall employment rates, including some movement into employment. The historically stable employed were more likely to move into employment between February and April, with 34% finding work, relative to the transient employed, 25% of whom found work, and the persistent non-employed, 8% of whom found work. Job finding rates between April and June were not as clearly correlated with employment history.

We conduct an exploratory description of four groups, two each from opposite ends of the labour market: those with a stable employment history who remained employed in February, April and June; those with a stable employment history who were employed in February but lost work during the lockdown; those with a persistent non-employed history who remained non-employed in February, April and June; and those with a persistent non-employed history who were not employed in February but found work during the lockdown. This revealed that those with the least recorded employment were mostly younger, rural African women, while among the stable employed (who were all much more likely to be male), those who lost work in the lockdown were more likely to be African and have a rural background relative to those who retained work. Interesting to note, though, is that a group of mostly young, African males with rural backgrounds and negligible employment histories found work during the lockdown.

Those in the labour market have carried into the COVID-19 pandemic and lockdown their long-term labour market experience and their associated capacities to withstand employment shocks or gain employment. This research has shown that these historical factors have mediated labour market outcomes under lockdown, albeit within a very unstable labour market. For now, these findings are indicative, but they make the case that considering employment histories holds significant

implications for understanding whose employment has been jeopardised by the COVID-19 pandemic, who needs targeted short-term assistance and who requires more structured labour market interventions.

1. Introduction

The COVID-19 pandemic and ensuing lockdown have shaken the South African economy, leading to unprecedented closures of large portions of the economy and dramatic increases in unemployment, income loss and temporary lay-offs. Previous research has found that these employment shocks have followed clear race, gender, age, and class lines. Africans, women, the young, and low-income workers have been disproportionately likely to bear the burden of job and income loss, leading to an entrenching and deepening of existing inequalities (Jain et al., 2020; Ranchhod & Daniels, 2020a; Casale & Posel, 2020).

Any modelling of COVID-19 lockdown employment dynamics is incomplete without an understanding of an individual's conditions going into the lockdown. Someone's employment status immediately preceding the lockdown clearly matters in determining how they were subsequently affected. But those who were employed immediately preceding the lockdown are not a homogenous group. For some, employment was the norm, while for others, work experience had been limited or made up of temporary, short-term spells of employment. These differences are likely to be relevant in determining the likelihood of their keeping the job they have, their means to withstand an employment shock, and their capacity to bounce back from any loss of work. Likewise, treating the pre-lockdown non-employed as a homogenous group fails to distinguish between those experiencing a temporary spell out of employment and those who have faced chronic exclusion from the labour market. Any analysis of their movement into employment during the lockdown is incomplete without accounting for and understanding this history. The paths that different individuals took in arriving at their pre-lockdown state is best understood in as long-term a perspective as possible.

In this paper we seek to make a contribution in this regard and to show that these different labour market pathways leading into the COVID pandemic are important in understanding subsequent labour market outcomes. We link the National Income Dynamics Study – Coronavirus Rapid Mobile survey (NIDS-CRAM; 2020) and the National Income Dynamics Study (NIDS; 2008 – 2017) to provide the historical context for the contemporary, post-lockdown changes in employment. We distinguish between three groups with different employment histories: the stable employed – those consistently employed across the observed periods, the transient employed – those who have moved between employment and non-employment, and the persistent non-employed – those with very limited recorded employment, and then interrogate the relationship between this employment history and their movements into and out of employment during COVID-19.

Section 2 discusses the South African labour market context and reviews the relevant literature on employment dynamics and precarious work, and their relation to COVID-19. In Section 3 we present the data sources and balanced panel used for analysis, made up of individuals who were successfully interviewed and had employment status information across all time periods and were of prime working age in 2020. Section 4 briefly presents employment levels and transitions for 2020 in order to anchor our analysis in the COVID-19 labour market transitions that we are seeking to understand. In Section 5 we examine February 2020 employment outcomes for groups with different employment histories. We then interrogate the relationship between the COVID-19 employment transitions and these longer-term employment histories. This is the central contribution of this paper. In Section 6 we profile a subset of groups who we identified in the previous analysis as significant, both in terms of the share of individuals following that path and because of the implied dynamics. Finally, in Section 7 we consolidate and conclude.

2. Background and Literature

South Africa is characterised by chronic large-scale unemployment and an informal sector that is small relative to its continental neighbours (Theron, 2010). Early anecdotal accounts of the effect of the South African lockdown from civil society organizations emphasized its effect on informal traders, who were prohibited from working and excluded from compensatory mechanisms such as the Temporary Employer/Employee Relief Scheme (TERS) (Labour Research Service, 2020), and on casualised workers who faced disproportionate job loss or unpaid leave facilitated in many cases by a lack of contractual commitment to a minimum number of hours on the part of their employers (CWAO, 2020). Early national estimates found that the lockdown disproportionately affected already disadvantaged groups, including informal workers (those working without a contract or running unregistered businesses) who faced some of the biggest net job losses (mainly through terminated employment relationships rather than temporary lay-offs) between February and April (Jain et al., 2020).

Research focused on dynamics in South Africa has repeatedly revealed the limitations of using cross-sectional snapshots to understand individuals and households. For example, with regard to understanding poverty in South Africa, not all households that are able to buy a certain basket of goods, or that fall below a poverty line, are alike, and a single snapshot provides insufficient evidence of their likelihood of staying in that state in the future (Finn & Leibbrandt, 2017; Schotte et al., 2017). Similarly, a focus on employment status immediately before the lockdown generates an incomplete picture of an individual's history of employment, and yields an imprecise measure of their chances of gaining (or losing) employment in the future. This is especially true in the light of studies finding high churning (Kerr, 2018) and employment volatility (Cichello et al., 2005; Zizzamia & Ranchhod, 2019) in the South African labour market.

Employment losses are significant in themselves in understanding the economy, but a large part of the significance of employment shocks derives from the implications of these shocks for welfare, and the importance of employment losses as trigger events for households falling into poverty (Schotte et al., 2017). Jain et al. (2020) made an explicit link between lockdown-associated job-loss, income-loss, and poverty; estimating that as many as 3 million people fell into poverty in April due to early lockdown job loss.

Another danger with COVID-19 is that the poor labour market conditions that it creates can lead to entrenched outcomes (such as persistent unemployment, lower wages and benefits). This risk is especially acute among those with relatively new careers, in line with the wage scarring literature that has found future outcomes to be significantly affected by individuals' early labour market experience (von Fintel & Black, 2007).

3. Data

3.1. NIDS, NIDS-CRAM and the link between the two

The data for this paper come from two different but related data sources: the first two waves of the NIDS-CRAM panel (May and July 2020) and all five waves of the NIDS panel (2008 to 2017).

NIDS was a household panel survey that started in 2008 with a sample of just over 28,226 people who were re-interviewed (along with anyone that they lived with) every two or three years for five waves up to 2017 (when close to 40,000 were interviewed) (Brophy et al., 2018). NIDS-CRAM is a follow-up individual-level survey implemented using Computer Assisted Telephone Interviewing (CATI) and focusing on adult individuals' responses to the COVID-19 pandemic and national lockdown (Ingle et al., 2020). The NIDS-CRAM sampling frame came from the NIDS wave 5 sample, and so (after weighting) it is meant to estimate outcomes in 2020 for a broadly representative sample of South African adults from 2017.

To appropriately interpret the data one needs to understand the relation between the dates of data collection and the events taking place in the country. The first wave of NIDS-CRAM (interviews conducted between 7 May and 27 June 2020) asked respondents about employment outcomes in February and April, i.e., before the lockdown (which started on 26 March 2020) and then in the midst of the national level 5 'hard' lockdown. The second wave of data collection occurred between 13 July and 13 August 2020, and asked retrospectively about employment in June, a period in which lockdown restrictions had been relaxed to level 3 but there remained substantial restrictions on certain sectors of the economy and social distancing regulations.

3.2. The balanced panel across NIDS and NIDS-CRAM

Owing to the use of NIDS wave 5 as the sampling frame for NIDS-CRAM, NIDS potentially provides a decade of historical data on individual employment dynamics that can be connected with the picture of the unfolding COVID-19 labour market that is provided by NIDS-CRAM.

The wave to wave attrition in NIDS was in line with good international comparators. However, there was substantial cumulative attrition between waves of NIDS (Brophy et al., 2018; Branson & Wittenberg, 2019)[4]. A balanced panel of 15,673 NIDS respondents were successfully interviewed across all 5 waves of NIDS. Of these, 3,674 (23.27%) were interviewed in wave 1 of NIDS-CRAM, reflecting the much smaller sample and different mode and circumstances of data collection of NIDS-CRAM as compared to NIDS (Ingle et al., 2020)[5]. A high proportion of these respondents will be relevant to our study of employment due to the special targeting of working-age individuals in NIDS-CRAM. Of these, 2,976 (81.6%) were successfully interviewed in wave 2 of NIDS-CRAM, constituting the total interviewed balanced panel sample across all seven waves of data.

South Africans have been found to have gradually declining labour force participation rates in the years preceding retirement age (Lam et al., 2006). To raise the probability that the transitions out of employment that we observe are involuntary and do not represent retirement effects, we restrict all analysis of employment transitions in this paper to the sample of prime-age individuals between the ages of 25 and 50. For the central analysis of this paper linking NIDS-CRAM employment transitions to NIDS employment history we restrict to the sample of individuals who were prime-age in 2020, and had employment status information at all points in time from the first wave of NIDS (2008) to the last period of NIDS-CRAM (June 2020)[6]. This yields a sample of 1,530 individuals that we refer to as our 'prime-age balanced panel' throughout the paper. This sample is distinguished from the total interviewed balanced panel (N = 2,976) described above and the 'NIDS-CRAM prime-age balanced panel' (that we define as those prime-age in 2020 with employment status information across February, April and June 2020, N = 3,388).

The fact that our prime-age balanced panel covers such a long period (12 years) and so many waves of data collection means that it is important to think very carefully about who makes it into this panel and who does not[7]. To obtain some sense of who made it into our prime-age balanced panel, *Table 1* compares unweighted summary statistics for this seven-wave panel to the NIDS wave 1 cross-section for 2008, and to the NIDS-CRAM wave 1 cross-section for 2020, with the age range restricted in both cases so that the cross-sections reflect the same age range covered by the balanced panel at that point in time.

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4   To address this attrition and make the sample more representative, a top-up sample was added to NIDS wave 5 (Brophy et al., 2018).

5   Ardington (2020) found rates of item non-response for NIDS-CRAM to be comparable to those from face-to-face interviews, and that the estimates it generates for key descriptives and associations between key outcomes and demographic variables were broadly in line with appropriate benchmark datasets.

6   The 'employment status information present across all waves' condition means that the effective minimum age of our balanced panel in 2020 is 27, because only those who were aged 15 and older had employment status information for NIDS wave 1 (2008).

7   As has been documented, there was selective non-random attrition between each wave of NIDS (Branson & Wittenberg, 2019), between NIDS and NIDS-CRAM, and between waves of NIDS-CRAM (Ingle et al., 2020).

Table 1: Unweighted comparison of key statistics between the prime-age balanced panel, NIDS wave 1 cross-section and NIDS-CRAM wave 1 cross section

	2008 (NIDS wave 1)		2020 (NIDS-CRAM wave 1)	
	NIDS cross-section aged 15-38	**Balanced panel aged 15-38**	**NIDS-CRAM cross-section aged 27-50**	**Balanced panel aged 27-50**
African (%)	80.28	90.85	86.99	90.85
Female (%)	53.62	62.42	60.93	62.42
Urban (%)	50.47	39.02	77.41	74.67
Youth (15-24) (%)	53.55	48.04	0	0
Prime-age (25-50) (%)	46.45	51.96	100	100
Less than matric	68.03	64.03	51.28	53.47
Matric	20.8	22.76	23.23	24.44
Tertiary	11.17	13.21	25.49	22.08
Employed (%)	36.1	35.49	60.65	59.8
Mean earnings	2495.78	1781.89	5668.52	4514.17
N	10630	1530	4121	1530

Notes:
1. Unweighted descriptive statistics are presented for our prime-age balanced panel at two time points (2008 and 2020) along with the NIDS wave 1 cross section and the NIDS-CRAM wave 1 cross section with the age range restricted in both cases so that the cross-sections reflect the same age range covered by the balanced panel at that point in time.
2. Since descriptive statistics are presented for the same prime-age balanced panel in 2008 and 2020, time invariant characteristics will necessarily be the same across years.
3. For this sample comparison the minimum age used for the NIDS-CRAM sample comparisons is 27 rather than 25 because only respondents 15 and older had employment status information for NIDS wave 1 and could potentially make it into our balanced panel.

Comparison of the statistics for 2008 between the NIDS wave 1 cross-section and our prime-age balanced panel (both aged 15-38) can give us an indication of differences in sample characteristics brought about by attrition. The high probability of attrition among white respondents and male respondents is reflected in the much higher proportion of the balanced panel that is African and female relative to the cross-section in 2008. Higher attrition among urban dwellers is reflected in the lower urban proportion in our balanced panel. Within the restricted age range the balanced panel was slightly older than the NIDS cross-section, as seen in the higher proportion of prime-age adults (and the smaller proportion of youths). This age distribution is also reflected in the slightly higher rates of matric and tertiary education in the balanced panel.

Since a large part of the NIDS-CRAM sample was made up of those from the original NIDS sample who were still present in wave 5 (2017), many of the figures for our balanced panel are much closer to those from NIDS-CRAM in 2020, including gender, race and urban proportions. However, tertiary education rates and mean earnings are lower in the balanced panel. The proportion employed in our balanced panel is slightly lower but similar to the proportion in the cross-section in both 2008 and 2020.

Thus, in interpreting estimates of the contemporary situation based on the balanced panel, we must bear in mind that these are based on a sample with characteristics that are different to the original NIDS sample (and to a lesser degree the NIDS-CRAM sample) in some important ways. We create balanced panel weights that are adjusted for respondents' probabilities of remaining in the sample between waves (see Appendix 1 for a full explanation of the weight creation process). These go some way towards correcting for these differences (and bringing sample characteristics closer to those of NIDS wave 1). However, they will not change the fact that all estimates are based on a highly selected sample on the attributes identified above, as well as other unobservable factors.

4. NIDS-CRAM employment dynamics

In this section we look at employment outcomes and transitions among our NIDS-CRAM prime-age balanced panel with employment status information for February, April and June. This gives us an understanding of the COVID-19 labour market transitions that we will then seek to understand in terms of individuals' longer-term employment histories.

Table 2 presents employment rates (the proportion of working age individuals that are employed) and various percentiles of the earnings distributions for February, April and June for our NIDS-CRAM prime-age balanced panel[8].

Table 2: Employment and earnings in February, April and June 2020 among the NIDS-CRAM prime-age balanced panel.

		February	April	June
Employed (%)		**65.87**	**56.57**	**56.85**
Earnings percentiles	10%	700	1200	1200
	25%	1500	2598	2500
	50%	4000	5200	5000
	75%	8300	12600	12000
	90%	17000	21000	20000

Notes:
1. Earnings percentiles are based on the sample of workers with positive earnings in each period.
2. Point values were imputed for bracket responses by taking the mean earnings of individuals who gave point values falling within the range of each bracket.
3. Estimates weighted using NIDS-CRAM wave 2 panel weights.

A dramatic drop in the employment rate was observed among prime-age adults between February and April, from 65.9% to 56.6%, and there was no real sign of employment recovery observed between April and June (56.9%). Among those with positive earnings there was a large increase in earnings at each percentile of the distribution between February and April, probably reflecting composition effects due to the disproportionate loss of work among lower-income workers[9] (Ranchhod & Daniels, 2020a). This was followed by a small decrease in earnings across the distribution (with the exception of the 10th percentile) between April and June.
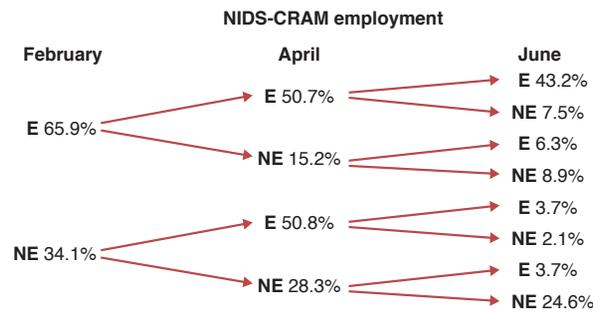
It has been well documented that the phenomenon of furloughed workers became highly relevant during the lockdown, with many workers being nominally employed but not working any hours or receiving any pay in April (Jain et al., 2020; Ranchhod & Daniels, 2020a). Since we are interested in longer-term determinants of employment gain and loss we do not give specific attention to furloughed workers, who are likely to be in an exceptional, temporary state lasting only for the duration of the more severe lockdown. Nonetheless, it is important to keep in mind that we include these groups in our employment figures throughout this paper.

We now turn our attention towards the transitions made between employment and non-employment in February, April and June. *Figure 1* presents an employment transition tree for prime-age adults in February, April and June 2020, showing that there was substantial churning in both transition periods, including the period between April and June when the overall employment rate remained nearly unchanged.

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8   This includes some people who are not present (or do not have employment status information) across all waves of NIDS and is therefore a broader sample than our prime-age balanced sample across all periods.

9   Similar increases in wages based on composition effects have been observed in the US (Cajner et al., 2020)

Figure 1: Employment transition tree for the NIDS-CRAM balanced panel

NIDS-CRAM employment

February	April	June

E 65.9%
→ E 50.7%
→ E 43.2%
→ NE 7.5%
→ NE 15.2%
→ E 6.3%
→ NE 8.9%

NE 34.1%
→ E 50.8%
→ E 3.7%
→ NE 2.1%
→ NE 28.3%
→ E 3.7%
→ NE 24.6%

Notes:
1. Estimates weighted using NIDS-CRAM wave 2 panel weights. N = 3,388

Transition trees give the proportion of individuals at each node for a given time period, with nodes in later periods (i.e. April and June) reflecting not just an individual's state at that time but also their previous states[10]. In this transition tree individuals are categorized as either employed **- E -** or non-employed – **NE –** at each point in time, and the proportion of individuals following a given path can be labelled using their sequence of states up to that point[11]. For example, the **NE,E** node tells us that 5.8% of prime-age adults were not employed in February but had gained employment in April, while the **E,E,NE** node tells us that 7.5% of prime-age adults were employed in both February and April but fell out of employment in June.

The first column shows that 65.9% of prime-age individuals were employed in February. The second column describes movements into employment and out of employment following the imposition of the lockdown and shows that there was substantial job loss along with some relatively small job gain. From the third column we can see that 6.3% of individuals lost their job in April but had regained it by June, and that 3.7% of individuals had been non-employed in both February and April but found work in June. However, this was offset by further job loss affecting 9.6% of individuals, including many who had originally maintained work between February and April.

5. The relationship between employment history from NIDS and employment patterns in NIDS-CRAM

The previous section outlined both the dramatic and (so far) persistent job loss brought about by the national lockdown, and the fact that there was substantial churning underlying these net employment changes. It also shows that there was substantial churning in the labour market between April and June, when net employment rates remained similar. It is therefore important to know who these individuals are that are making these transitions and are being affected by the crisis in different ways. Initial NIDS-CRAM papers (e.g. Jain et al., 2020; Ranchhod & Daniels, 2020a; Casale & Posel, 2020) have shed light on this issue by decomposing transitions using factors such as race, gender and class. We now take a different approach in seeking to explain and understand these transitions in relation to individuals' longer-term employment history.

5.1. Describing the balanced panel

For a start we examine how key characteristics varied for our prime-age balanced panel over all the waves of NIDS and NIDS-CRAM. Descriptive statistics are presented for key demographic and socioeconomic characteristics in *Table 3*.

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10 Previous research using NIDS has used transition trees to model employment transitions (Zizzamia & Ranchhod, 2019) and poverty transitions (Finn & Leibbrandt, 2017).

11 In this and future transition analyses we assume that individuals' movements into and out of employment are fully captured by the information that we have in NIDS-CRAM. We will miss some very short-term transitions in and out of employment in the periods between data points, but this risk is attenuated given the short duration between periods (2 months).

Table 3: Descriptive statistics for the balanced panel across waves and data sources (weighted)

		NIDS					NIDS-CRAM	
		Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Wave 1	Wave 2
Race (%)	African				89.02			
	Coloured				7.48			
	Asian/Indian				0.35			
	White				3.15			
Gender (%)	Male				45.77			
	Female				54.23			
Age (mean)		24.7	27.16	28.94	31.45	33.74	36.81	36.95
Education (%)	None	1.5	1.64	1.76	1.37	1.51	1.07	1.09
	Primary	11.34	8.59	8.47	8.28	8.07	8.64	8.69
	Incomplete secondary	50.53	48.34	45.15	39.75	36.95	37.44	37.42
	Matric	21.93	24.59	27.31	22.69	20.74	24.83	24.71
	Tertiary	14.7	16.84	17.3	27.9	32.73	28.02	28.11
Labour force participation (%)		55.77	55.62	70.84	74.1	74.4	90.51	91.36
Household size (mean)		5.23	5.45	5.14	4.69	4.61	5.15	5.14
Urban (%)		50.66	50.76	55.43	57.74	58.64	79.35	70.69

Notes:
1. Estimates are weighted using balanced panel weights created by the authors.
2. Estimates based on the prime-age balanced panel of individuals between the ages of 25 and 50 with employment status information across all periods (N = 1,530).

The aging of our prime-age balanced panel as they approach prime-age in 2020 is reflected in the increasing labour force participation rate, which jumps upwards in both wave 3 of NIDS and wave 1 of NIDS-CRAM. Substantial increases in the attainment of matric and tertiary education are observed across waves of NIDS before a decrease in reported tertiary educational attainment in NIDS-CRAM[12] (with many more individuals classified as having incomplete secondary education). The low mean age of our prime-age balanced panel in wave 1 and wave 2 of NIDS means that many individuals will be far less likely to be employed in the early waves of NIDS because of their young age and the associated chance that they are engaged in non-labour market activities, an issue we return to later in this paper. A clear upward trend of urbanisation is visible in the prime-age balanced panel over NIDS before a dramatic increase in NIDS-CRAM that is likely to reflect the fact that classification of geolocation in NIDS-CRAM was based on a self-reported location rather than being based on GPS coordinates (Ingle et al., 2020). This meant that in many cases someone living on a farm gave a nearby town as the reference point for their location and was classified as urban on the basis of that town.

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12 This decrease could partly be explained by the less extensive questioning about different forms of tertiary education in NIDS-CRAM relative to NIDS.

5.2. Distinguishing between groups with different employment histories and evaluating their pre-lockdown employment status

In this section we define the grouping that we use to capture long-term employment history and evaluate how pre-lockdown employment status varied according to this history.

To capture long-term employment history over the entire period of NIDS (2008-2017) we follow Zizzamia and Ranchhod (2019) in distinguishing between three groups:

- the **'stable employed'** who were employed in 4 or 5 waves,
- the **'transient employed'** who were employed in 2 or 3 waves, and
- the **'persistent non-employed'** who were employed in 0 or 1 of the 5 waves of NIDS.

All analysis using these groups is restricted to our prime-age balanced panel, so we know for all five waves whether someone was employed or not[13]. This provides us with a simple three-group division that represents the stability or precariousness of an individual's employment history over a decade of labour market experience. The distribution of the prime-age balanced panel across the three groups is shown in *Figure 2*, showing that 27.5% of individuals were stably employed, 31.9% were transient employed and 40.65% were persistently non-employed between 2008 and 2017.

Figure 2: Distribution of employment history from five waves of NIDS among the prime-age balanced panel
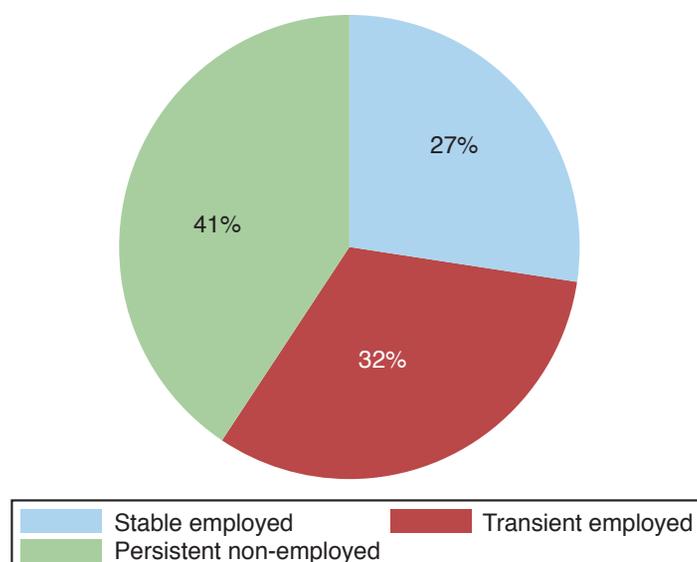
Notes:
1. Estimates based on employment status in NIDS wave 1 to 5 for the prime-age balanced panel of individuals between the ages of 25 and 50 with employment status information across all periods (N = 1,530).
2. Estimates are weighted using balanced panel weights created by the authors.
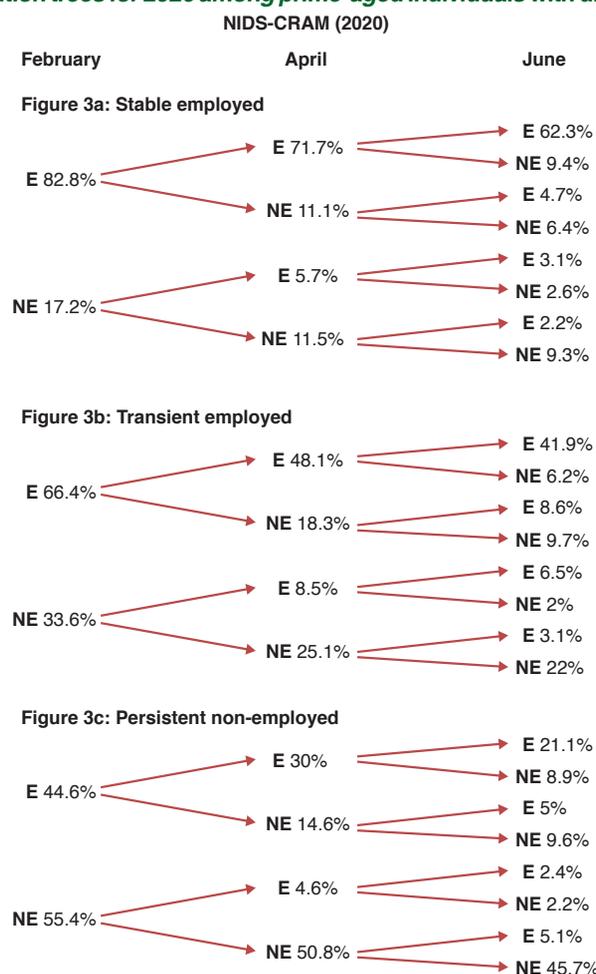
The NIDS-CRAM measure of employment for February 2020, before the lockdown and employment shocks associated with COVID-19 came into effect, allows us to examine pre-lockdown employment for these groups, and to see how it varied as a function of employment history.

Figure 3 presents employment transition trees covering the three periods with employment information in NIDS-CRAM (February, April and June 2020) for individuals in our prime-age balanced panel divided into the three employment history groups defined above[14]. Each of the columns of the tree provides percentages of each group (summing to 100) that were in a particular state (**E** – employed or **NE** – not employed) and (in later columns) had followed a particular path to arrive there (e.g. **E**,**NE** - employed in February and non-employed in April).

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13 Even with such a long-term panel, we only know individuals' employment status at five discrete time points and there always exists the possibility that there was substantial fluctuation in employment status in the periods between waves that is not captured by our estimate. However, the fact that we are aiming to provide a general measure of long-term employment history rather than pinpoint specific continuous spells of employment (or non-employment) means that we are not overly concerned with this issue.

14 These trees are similar to that in *Figure 1*, but now presented separately for the different employment history groups. A similar transition tree is presented in Appendix 2 but with cells representing the proportion of all prime-age adults falling within a particular employment history group and 2020 employment path for our prime-age balanced panel, rather than proportions within employment history groups.

Figure 3: Employment transition trees for 2020 among prime-aged individuals with differing employment histories

NIDS-CRAM (2020)

February	April	June

Figure 3a: Stable employed

E 82.8%
→ E 71.7%
→ E 62.3%
→ NE 9.4%
→ NE 11.1%
→ E 4.7%
→ NE 6.4%

NE 17.2%
→ E 5.7%
→ E 3.1%
→ NE 2.6%
→ NE 11.5%
→ E 2.2%
→ NE 9.3%

Figure 3b: Transient employed

E 66.4%
→ E 48.1%
→ E 41.9%
→ NE 6.2%
→ NE 18.3%
→ E 8.6%
→ NE 9.7%

NE 33.6%
→ E 8.5%
→ E 6.5%
→ NE 2%
→ NE 25.1%
→ E 3.1%
→ NE 22%

Figure 3c: Persistent non-employed

E 44.6%
→ E 30%
→ E 21.1%
→ NE 8.9%
→ NE 14.6%
→ E 5%
→ NE 9.6%

NE 55.4%
→ E 4.6%
→ E 2.4%
→ NE 2.2%
→ NE 50.8%
→ E 5.1%
→ NE 45.7%

Notes:
1. E = employed. **NE** = non-employed. Based on the prime-age balanced panel of individuals between the ages of 25 and 50 with employment status information across all periods (N = 1,530).
2. Estimates are weighted using balanced panel weights created by the authors.
3. For each figure all numbers show the percentage of individuals in that state (summing to 100 by column). Later columns show the percentage of individuals in an employed or non-employed state and that have followed the path showed in previous columns.

The first column gives the percentage of each employment history group that was in employment in February (later columns will be analysed in the following section). Pertinently, between 2017 and 2020 there had already been some substantial diversion from historically stable states, with 44.6% of the persistent non-employed in employment (node **E** in *Figure 3c*) and 17.2% of the stable employed in the not-employed group going into the lockdown (node **NE** in *Figure 3a*). 66.4% of the transient employed were working in February (node **E** in *Figure 3b*).

The low mean age of our prime-age balanced panel in early waves of NIDS (see *Table 3*), along with the division in the panel between youths and prime-age individuals in 2008 (see *Table 1*) means that part of the lack of historical employment observed among the persistent non-employed could reflect age effects and involvement in non-labour market activities such as education rather than exclusion from the labour market. Individuals in this group may have higher chances of employment in 2020 than their employment history suggests if they are younger and are entering more stable employment as they age, a proposition that is supported by the high rate (44.6%) of employment among this group in February 2020. Appendix 3 presents the NIDS-CRAM wave 1 age distribution (in 5-year age brackets) for this historically persistent non-employed group, both in total and separately by February employment status. It shows that the historically persistent non-employed are generally on the younger side of the prime-age range and that those who were employed in February were substantially younger than those who were not. This means that amongst the persistent non-employed there will be many younger individuals with potentially good chances of finding (or maintaining) employment and we should be cautious in identifying persistent non-employment with *exclusion* from the labour market.

5.3.   Employment dynamics under lockdown for groups with different employment histories

The combination of February employment status and the classification based on long-term employment history together provide us with a deeper understanding of individuals' initial states before COVID-19. In this section we turn our attention to the central focus of our study: how these employment histories determined employment outcomes under the extreme conditions of the COVID-19 pandemic and lockdown.

Although we can pinpoint the beginning of the lockdown and large regulatory changes that have occurred since then, the lockdown is not a single event and has remained in place with unfolding degrees of coverage and severity. The transition trees in *Figure 3* allow us to examine the relationship between long-term employment history and a range of dynamics at different points of the lockdown: did job loss under lockdown level 5, or recovery from initial job loss, vary as a function of employment history? Did later employment losses as the lockdown progressed affect groups differently to initial job losses? In brief, we find that employment losses affected all groups but that those with more stable employment were less likely to have been adversely affected, and that those with inconsistent or negligible histories of employment were more likely to have lost work and to be excluded from employment opportunities.

The uppermost branch (node **E**,**E**,**E** of *Figure 3a*) tells us that 62.3% of prime-age adults with a stable employment history remained employed throughout the lockdown, implying the presence of a hyper-stable group with near unbroken employment histories that were insulated from the shock of the lockdown.

In contrast, 45.7% of prime-age adults who were historically persistently non-employed were not employed in any of the three periods the lockdown (node **NE**,**NE**,**NE** of *Figure 3c*), a group that will contain those most excluded from the workforce (among other people, e.g. some younger individuals, as discussed). They can be contrasted with the 9.7% who were historically persistently non-employed and went into the lockdown without work but subsequently gained employment (sum of nodes **NE**,**E** and **NE**,**NE**,**E**), potentially working for the first time during lockdown.

The April column **NE** cells that are preceded by **E** cells tell us the percentage of prime age adults in each employment history group that lost work between February and April (covering the imposition of social distancing measures and the national lockdown). Comparing transitions into and out of employment between the three figures shows us that job loss was strongly correlated with employment history.

By taking the percentage in the **E**,**NE** node as a fraction of the **E** node we can derive the percentage of the February employed who had lost employment for each group. For example, 82.8% of the historically stable employed were employed in February (**E**), while 11.1% were employed in February but not employed in April (**E**,**NE**). Dividing the latter by the former tells us that 13.6% lost work between the two periods. In contrast, among those with transient employed or persistent non-employed histories who were employed in February, 27.5% and 32.7% had lost work by April respectively.

Workers with transient employment histories who kept their jobs in April faced a much diminished risk of falling out of employment in June, with only 12.9% losing employment (calculated by dividing node **E**,**E**,**NE** by node **E**,**E**). In contrast both the historically stable employed and persistent non-employed faced strikingly similar rates of job loss between April and June – 13.1% and 29.7% respectively – as they had suffered between February and April. This suggests that for a large portion of workers the risk of losing employment remained at a consistent and perilous level even as the lockdown eased. The increase in the job retention rate among the historically transient employed (to similar levels as the stable employed) meant that the higher risk of job loss faced by the persistent non-employed was unique in this later period of the lockdown.

Job gain between February and April followed similarly unequal lines. The historically stable employed were more likely to move into employment, with 34% finding work in the period, relative to the transient employed, 25% of whom found work, and the persistent non-employed, 8% of whom found work. Job finding rates between April and June were not as clearly correlated with employment history.

6. Profiles of groups whose employment has been affected in different ways during lockdown

To close out this analysis, we seek to understand more about the characteristics of those undertaking the employment transitions that we document above. In the following table, a subset of the noteworthy groups that emerged from the employment transition tree are profiled in terms of their key demographic characteristics. This improves our understanding of who followed which paths, and allows us to speculate as to why these particular patterns have been observed. We profile four groups that provide us with meaningful contrasts at opposite ends of the labour market. These profiles remain exploratory and are not exhaustive of the entire sample.

First, we look at those prime-age individuals with a stable employment history who were employed in all three periods in 2020. Second, we look at those individuals with a stable employment history who were employed in February but lost employment during the lockdown (either April or June), contrasting them with the first group. Mirroring these groups at the opposite end of the labour market we look at prime-age individuals with a history of persistent non-employment who remained non-employed in all three periods in 2020, as well as those persistent non-employed who found employment during the lockdown. In so doing we can begin to understand the characteristics of the highly stable workers who have been unaffected by the lockdown are, and contrast them with those for whom the lockdown brought what looks like unprecedented job loss. In addition, we get a profile of those who have almost no record of employment, both before and during the lockdown, along with those who may be finding work for the first time during the lockdown.

Table 4 presents the mean age and the proportion of each of these groups that is female, African and had a long-term rural history[15]. All analyses are restricted to our prime-age balanced panel.

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15 If an individual had been recorded as being rural in all five waves of NIDS they are considered long-term rural. Given issues with the rural classification in NIDS-CRAM based on self-report that led to an artificial spike in urban proportions (62.08% of the long-term rural were recorded as urban in NIDS-CRAM wave 1), long-term rural history may be a better indicator of geolocation.

Table 4: Characteristics of groups following particular paths through the lockdown

Historical employment record in NIDS	Contemporaneous employment path	Mean age	Female (%)	African (%)	Long-term rural (%)	Proportion of prime-age adults in this group	N
Stable employed	Employed in February, April and June	42.55 (.59)	44.74 (4.85)	81.48 (4.73)	18.46 (4.44)	17.1	246
Stable employed	Employed in February but lost employment in April and/or June	41.65 (.94)	34.51 (6.53)	89.95 (6.37)	32.63 (6.83)	5.7	90
Persistent non-employed	Non-employed in February but found employment in April and/or June	34.64 (1.13)	57.4 (9.91)	100 (0)	58.85 (8.89)	3.8	59
Persistent non-employed	Non-employed in February, April and June	35.24 (.65)	71.48 (4.43)	93.48 (3.38)	46.91 (5.21)	18.8	280
Total sample of prime-age (25-50) adults		36.81 (.31)	54.23 (1.95)	89.02 (2.08)	33.65 (2.75)	-	1530

Notes:
1. Estimates are weighted using balanced panel weights created by the authors.
2. Estimates are based on the prime-age balanced panel of individuals between the ages of 25 and 50 with employment status information across all periods (N = 1,530).
3. Standard errors in parentheses.
4. The four groups profiled are not exhaustive of the prime-age balanced panel used for analysis.

Those with stable long-term employment who remained employed throughout the lockdown were substantially older than the average prime-age adult, were disproportionately more likely to live in urban areas, to be male, and to be Coloured or white. Interestingly, those with stable employment histories who lost their jobs during the lockdown were of a similar age to those who maintained employment, but were substantially more likely to be male, African and rural.

Those persistently non-employed both before and during the lockdown were young (relative to the mean age for prime-age adults and especially compared to the historically stable employed groups) and disproportionately rural. This group makes up a substantial percentage of prime-age adults (18.8%) and it stands out that the overwhelming majority are female (71.5%) and African (93.5%). Although this group will include some people, such as younger students, who do not want to be employed, it will also include those facing the most chronic exclusion from the labour market. Those who were historically non-employed but found a job (what could be their first) during the lockdown were similarly young and African but were much more likely to be male and to have a long-term rural background relative to those who remained without employment during the lockdown. The high presence of youth within these groups echoes the earlier finding that the persistent non-employed were on the younger side of the age distribution. Both the very high rate of youth unemployment in South Africa (De Lannoy et al., 2020) and voluntary non-employment while pursuing education could contribute to the historical lack of employment among these groups.

The use of a long-term measure of rural inhabitance covering 2008-2017 means that some respondents who had in fact urbanized by 2020 will not be correctly categorized. The high representation of those with long-term rural backgrounds among the persistent non-employed could therefore capture a combination of joblessness in rural areas and outcomes for recent immigrants to urban areas (both issues that are worthy of attention). There is a possibility that this is driving the entry into employment observed among the historically persistent non-employed but this remains speculation without more accurate contemporary geographic data[16].

7. Concluding discussion

These results provide evidence that past inequalities in the attainment of employment have been exacerbated by the lockdown. Those with more stable employment were less likely to have been adversely affected and those with inconsistent or negligible histories of employment were more likely to have lost work or be excluded from employment opportunities. Nonetheless, we found substantial job loss even among the historically stable employed. Job loss and job gain were particularly strongly determined by employment history at the beginning of the lockdown (between February and April), and those with a stable history of either employment or non-employment faced similar additional job loss between April and June.

Our profiles of groups with particular combinations of employment histories and contemporaneous employment patterns revealed that those with the least recorded employment were mostly younger, rural African women, while among the stable employed (who were all much more likely to be male), those who lost work in the lockdown were more likely to be African and have a rural background relative to those who retained work. Interesting to note, though, is that a group of mostly young, African males with rural backgrounds and negligible employment histories found work during the lockdown.

The younger age distribution of the historically persistent non-employed, and in particular of those among them who were employed going into the lockdown, highlighted the challenge of making broad employment history groupings when there are varying underlying reasons why individuals are in these groupings. Being persistent non-employed is very different for a chronically unemployed 50 year old and for a 25 year old who has been largely focussed on education. The persistent non-

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16 In the NIDS-CRAM geolocation data this group is still more rural than others but is much closer to the persistent non-employed in urban rate.

employed group will contain many of those who face the most chronic exclusion from the labour market, as was reflected in many of the inferior outcomes for this group found in this paper. If these people can be differentiated from others who are in this group by virtue of their age then the effect of the lockdown on their employment, and the relationship between their previous employment and their current outcomes, can be understood in a much more specific and meaningful way. This is important in sharpening policy targeting as these two groups of persistently non-employed require different labour market interventions.

Generally, we have focused on employment transitions as the central outcome. This is a meaningful but limited measure, as we have not said anything about the nature of the work nor how well remunerated it is. In addition, in the time of COVID-19, differentiations between those actively working and those who are furloughed (or on paid leave) have important implications for both worker welfare and economic activity. The dramatic increase in the number of furloughed workers in April, and the subsequent return of many to active employment in June (as found by Ranchhod & Daniels, 2020b), will not be captured by our employment transition analysis.

The use of a simple employed – non-employed dichotomy also means that certain meaningful questions surrounding the lockdown remain unexplored. For example, what is the nature and remuneration of the employment found by those who are working for the first time during the exceptionally poor labour market conditions of the lockdown, and is there the potential for wage scarring later in their careers (von Fintel & Black, 2007; Regan, 2020)? Additionally, if social exclusion is based not on job loss alone but also on the disempowering effect of past work experiences (Atkinson & Hills, 1998), as has been observed in South Africans' recounting of their experiences (Mncwango, 2016; Zizzamia, 2020), there is a need for future research to understand employment history not only in terms of patterns of employment and non-employment but also in terms of the nature of that employment. Likewise, there will be a diversity of experiences within the historically stable employed, and some people would have been employed in a long-term but precarious manner, lacking job security or a guaranteed number of working hours. If we are able to account for these differences in historical precariousness and go beyond mere stability we may be able to understand who among the stable employed lost work or was furloughed in the lockdown, and why.

The fact that we are using such a limited sample because of our balanced panel and age restrictions means that there is a chance that the employment transitions that we are estimating and predicting may not reflect those in the entire NIDS-CRAM sample. Weighting up of certain groups that have a high probability of attrition between waves means that some individuals with several characteristics that are associated with attrition may have very high weights and a disproportionate effect on the dynamics observed. For example, our lack of high earnings individuals may result in the few we do have having very large weights. Our prime age restriction means that we miss employment effects among a large share of working age individuals, but also increases the likelihood that the transitions that we describe are in fact involuntary job losses.

We have sought to explain and predict heterogeneity in 2020 employment outcomes principally in terms of employment history, but our message is not that stability of previous employment is the only cause of contemporary employment loss. Clearly the nature of the lockdown meant that workers in certain sectors and occupations that were forced to cease or limit operations faced disproportionate employment losses. Likewise, we acknowledge and emphasise that stability or precariousness of previous employment is not an independent cause of future employment loss; it is based on and constantly interacting with several factors such as race, class, education and location.

As more waves of NIDS-CRAM become available, spanning the easing of lockdown (including the move to level 2 in mid-August) and the return to more 'regular' economic activity, it will become possible to study the extent to which different measures return to baseline level. However, what baseline level is can only be properly understood by looking at pre-lockdown trends (Spurk & Straub, 2020). We have made the case for a lens that focusses on whether people return to their pre-lockdown labour market state (in terms of historical stability or mobility) by reference to their long-term labour market experience as reflected in NIDS.

This work has significant implications for the framing of other research based on NIDS-CRAM, which has generally framed statistics relative to February 2020, implicitly assigning pre-lockdown employment status a dominant role in representing what economic participation was like for people before the pandemic struck. This is appropriate for assessing aggregate labour market changes due to the pandemic and the lockdown. However, it has limitations in ascertaining which individuals made these transitions and understanding why. The extensive heterogeneity in employment history that we found among both the employed and non-employed in February 2020, and the significance of this heterogeneity for the way that individuals were affected by the lockdown, suggests that this understanding can be enriched by incorporating employment histories.

These findings provide sufficient evidence that the relationship between long-term employment history and employment outcomes during COVID-19 are worth studying in more detail. In particular, within the broad employment history groups we used there may be subgroups, such as the chronic unemployed, for whom contemporary employment effects are even more strongly and uniquely determined by employment history. Understanding how these employment histories interact with other factors to determine contemporary outcomes could provide valuable insight into the capacities and needs of different groups who have been affected by the crisis.

8.   Appendices

8.1.   Appendix 1: Creating balanced panel weights

The fact that there were so many iterations of non-random attrition between periods means that those who remain in the sample in the final period (wave 2 of NIDS-CRAM) and make it into the balanced panel will be a highly selected sample and that some kinds of individuals belonging to groups who are more likely to attrite will be severely under-represented.

To account for this non-random attrition, we follow Finn and Leibbrandt (2017) in running probits estimating the probability of remaining in the sample in each wave conditional on being successfully interviewed in the previous wave and based on a range of characteristics from the previous wave (similar adjustments for attrition were made for the official NIDS panel weights, see Branson & Wittenberg, 2019). The inverse of this conditional probability of re-interview is then taken as a weight adjustment applied to the 2008 NIDS post-stratified design weight for those who remain in the sample in the next wave. The application of high sequential weight adjustments to already high wave 1 weights resulted in some extremely high weights and so balanced panel weights were trimmed at the 1st and 99th percentiles following the precedent of Branson and Wittenberg (2019).

In choosing the explanatory variables predicting re-interview we largely followed the precedent of Branson and Wittenberg (2019[17]) and sought to account for the variables that have been found to correlate with attrition. Explanatory variables covered race, gender, province, urban location, age categories (younger than 30, 30-39, 40-50 and above 50), an indicator for employment and household per capita income quartile (with a separate category for missing household income). These weight adjustments will not correct for any selection on unobservable characteristics that occurs between waves, however.

Because we are analysing such a specific and selected sample, the cohort who were present in all waves of data collection, we do not calibrate to later population totals. This means that our balanced panel is only broadly representative of the South African population in 2008, and does not factor in migration in and out of the country or the birth of new inhabitants over the period[18]. If the employment shock has been particularly bad for migrants, as has been found elsewhere (Borjas & Cassidy, 2020) and observed anecdotally in South Africa (LRS, 2020), then these dynamics will present an overly optimistic picture of overall employment effects.
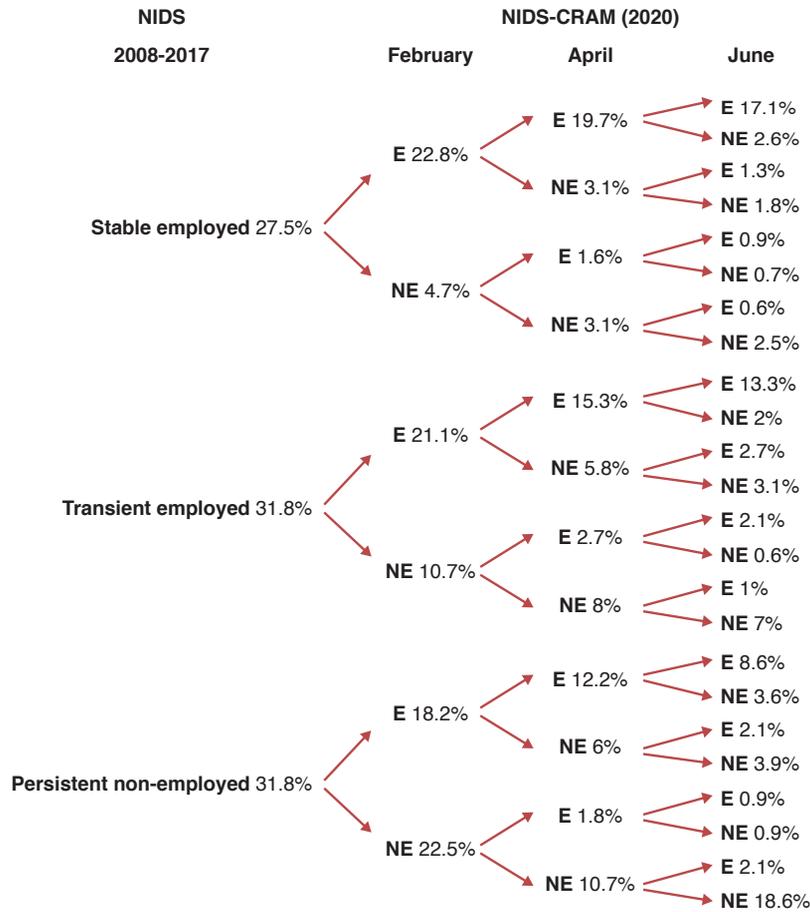
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17 Similar explanatory variables were used by Kerr et al. (2020) for the estimation of NIDS-CRAM attrition and by Finn and Leibbrandt (2017) in creating balanced panel weights.

18 There is also some indication that NIDS employment rates were higher in wave compared to other estimates from 2008, although this was more of an issue in later waves (Ranchhod & Daniels, 2020).

8.2.   Appendix 2: Proportions of all prime-age adults in our balanced panel in each combination of employment history group and 2020 employment transitions

*Appendix Figure 1: Employment history and 2020 employment transition tree for the prime-aged balanced panel*

NIDS	NIDS-CRAM (2020)		
2008-2017	**February**	**April**	**June**

Stable employed 27.5%
- **E** 22.8%
  - **E** 19.7%
    - **E** 17.1%
    - **NE** 2.6%
  - **NE** 3.1%
    - **E** 1.3%
    - **NE** 1.8%
- **NE** 4.7%
  - **E** 1.6%
    - **E** 0.9%
    - **NE** 0.7%
  - **NE** 3.1%
    - **E** 0.6%
    - **NE** 2.5%

Transient employed 31.8%
- **E** 21.1%
  - **E** 15.3%
    - **E** 13.3%
    - **NE** 2%
  - **NE** 5.8%
    - **E** 2.7%
    - **NE** 3.1%
- **NE** 10.7%
  - **E** 2.7%
    - **E** 2.1%
    - **NE** 0.6%
  - **NE** 8%
    - **E** 1%
    - **NE** 7%

Persistent non-employed 31.8%
- **E** 18.2%
  - **E** 12.2%
    - **E** 8.6%
    - **NE** 3.6%
  - **NE** 6%
    - **E** 2.1%
    - **NE** 3.9%
- **NE** 22.5%
  - **E** 1.8%
    - **E** 0.9%
    - **NE** 0.9%
  - **NE** 10.7%
    - **E** 2.1%
    - **NE** 18.6%

Notes:
1. E = employed. **NE** = non-employed. Based on the prime-age balanced panel of individuals between the ages of 25 and 50 with employement status information across all periods (N = 1,530).
2. Estimates are weighted using balanced panel weights created by the authors. For each figure all numbers show the percentage of individuals in that state (summing to 100 by column).
3. Later columns show the percentage of individuals in an employed or non-employed state and that have followed the path showed in previous columns.

8.3.   Appendix 3: Age distribution in NIDS-CRAM wave 1 of the historically persistent non-employed

Appendix Figure 2: Distribution of age (in wave 1 of NIDS-CRAM) among the historically persistent non-employed in our prime-age balanced panel

Appendix Figure 2a: Total historically persistent non-employed

Appendix Figure 2b: Employed in February subgroup

Appendix Figure 2c: Non-employed in February subgroup
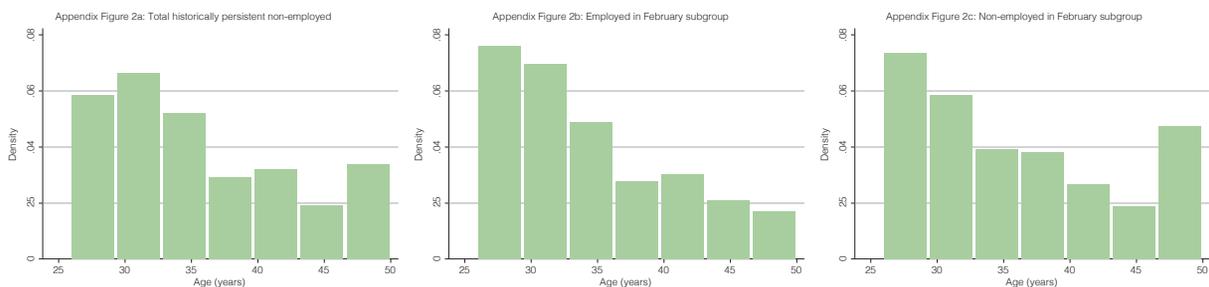
Notes:
1. Unweighted distribution based on our 2020 prime-age balanced panel of individuals with employment status information across all waves (N = 1,530)

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