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Employment transitions and COVID-19 containment measures: Evidence from a developing country

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Abstract

Containment measures implemented to curb the spread of coronavirus (COVID-19) disrupted labour markets across the world. While several studies focus on the impact of containment measures on job losses, this paper documents the effect of containment measures (specifically variation in the strictness of these measures) on employment patterns or transitions. COVID disruption can be viewed as multiple shocks to the labour market (as against a single shock). This is important because labour income is a key driver of aggregate inequality in developing countries, and such disruption has a knock-on effect on the achievement of the Sustainable Development Goals. Therefore, we estimate the causal relationship between coronavirus containment measures and employment dynamics in South Africa. Exploiting the timing of interviews and within individual variation, we find that containment measures impact employment transitions. Specifically, stricter containment measures have a positive effect on the transition into unemployment, and the converse is true for the transition into employment. The implication of this causal relationship for development, ongoing management of COVID-19 and future pandemics is discussed.

KEYWORDS
COVID-19, inequality, instrumental variable, South Africa, uncertainty shocks, unemployment dynamics

JEL CLASSIFICATION
E24, D04, I15, I18

1 | INTRODUCTION

The devastation caused by the COVID-19 pandemic and the associated lockdowns is well documented in the literature. The pandemic affected health outcomes directly, but also affected health and socioeconomic outcomes indirectly through government containment measures. The COVID-19 pandemic transformed from a health emergency to an economic and labour market shock through the containment measures that were put in place to curb the spread of the virus. The negative welfare outcomes of the containment measures arise mainly from the disruption to the labour market (ILO, 2020). Other negative welfare effects of the pandemic include an increase in psychological distress (Kim et al., 2022; Oyenubi et al., 2022; Oyenubi & Kollamparambil, 2022; Pfefferbaum & North, 2020; Posel et al., 2021; Rossi et al., 2020; Wanberg et al., 2020; Xiong et al., 2020), an increase in food insecurity (Abay et al., 2020; Ahmed et al., 2021; Nwosu et al., 2022a; Rudin-Rush et al., 2022; Tabe-Ojong et al., 2022; Tefera et al., 2022), problems with access to medication and health services (Choo & Rajkumar, 2020) and an increase in income inequality (Agrawal et al., 2021; Bundervoet et al., 2022; Darvas, 2021; Deaton, 2021; Duman, 2020; Oyenubi, 2023a).

The labour market effect of the pandemic has been argued to be stronger in developing countries because of the size of the informal economy in these countries. Pre-pandemic estimate suggests that as much as 90% of workers in developing countries rely on the informal economy (Bonnet et al., 2019). Work in the informal economy often involves face-to-face interaction and work tasks that cannot be performed remotely. Therefore, inequality in the ability to work from home has been identified as a factor that mediates the relationship between containment measures and the labour market effects of the pandemic (ILO, 2020; Jain et al., 2020; Nwosu et al., 2022b). The International Labour Organization reported that at the height of the pandemic, about 97% of the world's workers resided in countries where there was some sort of workplace closure (ILO, 2020). While several studies have shown that the lockdown was effective in curbing the spread of the virus (Alfano & Ercolano, 2020; Liu et al., 2021), others have suggested that less stringent containment measures would have been equally effective (Haug et al., 2020). These findings imply that a proper understanding of how the pandemic and resulting containment measures affected welfare and developmental efforts is important for the management of pandemics.[1]

COVID-19 restrictions varied over time (and in some cases spatially) across countries, mostly to allow national economies to open up while trying to contain the spread of the virus. This means that COVID disruption was not a single shock in time but is better viewed as multiple shocks in a short space of time. This is because changes in lockdown conditions have implications for who can work (essential workers could work even under the strictest lockdown conditions) and, in some cases, the duration of work. For example, the South African Government adjusted lockdown restrictions seven times[2] within the first 14 months of the pandemic (an average of once every 2 months). Apart from the negative employment effects of tighter measures on employment outcomes (Espi-Sanchis et al., 2022), the frequency of policy adjustment introduces uncertainty that might impact employment patterns. Specifically, the unpredictability and frequency of changes in containment measures are expected to have disproportionately affected developing countries and vulnerable workers in these countries because of the relationship between activity status and the ability to work remotely (Nwosu et al., 2022b; Rogan & Skinner, 2020a). The literature on uncertainty shocks and unemployment suggests that variations (over time) in lockdown restrictions may lead to job churning (Caggiano et al., 2017). This is important in the context of South Africa (and other developing countries in sub-Saharan Africa), given the high rate of job churning in the country even before the pandemic (Kerr, 2018).

While the analysis presented here focuses on South Africa, the findings have broader implications for developing countries in general since informality is a feature of the labour market in developing countries. A recent paper covering 160 economies over 67 years shows that economic informality is negatively correlated with several important indicators of sustainable development (Özgür et al., 2021). The implication is that, while informality constitutes a hindrance to sustainable development in normal times, a pandemic such as COVID-19 exacerbates this effect. Pre-pandemic literature suggests that informality is associated with lower levels of productivity, wages and investment and, consequently economic growth (Rada & von Arnim, 2014). Furthermore, pandemic-era literature suggests that informality is likely to aggravate the effects of the pandemic and, as a result, further slow down economic growth (Shulla et al., 2021). This finding is important because the literature suggests that a pandemic of similar impact to COVID-19 has a 2% probability of occurring in any one year (Marani et al., 2021). To put this in perspective, the implication is that someone born in the year 2000 would have about a 38% chance of experiencing such a pandemic by now (and this probability is increasing with time).[3] This suggests that the structure of the labour market in the developing world makes it more vulnerable to the negative economic effects of pandemics which could slow down Sustainable Development Goals (SDGs) progress. The main point is that the size and prevalence of the informal economy is a risk factor for the achievement of the SDGs in a world where the risk of pandemics is not negligible.

This paper documents the impact of containment measures on employment flows in South Africa during the first year of the COVID-19 pandemic. We combine data on pandemic-related variables (COVID-19 reproduction rate [R] and Containment and Health Index [CHI]) with panel survey data on South African adults during the pandemic. Using instrumental variable fixed effects (FE-IV) regressions, we show that containment measures positively impact employment flows. Specifically, variation in the CHI index increases employment transitions (although this result is not significant in the survey-weighted analysis). Furthermore, when the analysis is disaggregated by type of employment transition, the CHI index positively impacts negative employment transitions (transition from employed to unemployed), while it negatively impacts positive employment transitions (transition from unemployed to employed). Given that less stringent containment measures may have been equally effective in terms of curbing the spread of the virus (Haug et al., 2020), a more lenient approach to lockdown conditions may have been less disruptive. This is important for the management of future pandemics in developing countries.

2 | BRIEF REVIEW OF COVID-19 IN SOUTH AFRICA

The first case of COVID-19 in South Africa was reported on 5 March 2020.[4] This prompted the declaration of a state of emergency on 15 March 2020, with a nationwide lockdown enforced on

27 March 2020. The lockdown restrictions implemented on the 27th of March were designated Level 5 restrictions—with only essential travel and services allowed. This restriction lasted 5 weeks. South Africa then followed a risk-adjusted implementation of lockdown conditions that was guided by several criteria, including the level of infections, rate of transmission (that can be proxied by the variable R), the capacity of health facilities, the extent of the implementation of public health interventions and the economic and social impact of continued restrictions.[5] As a result, between March 2020 and May 2021, lockdown levels were adjusted seven times (see https://www.gov.za/Coronavirus, this period also coincides with the period covered by our data). Specifically, different stages of the pandemic had implications for who could work and for how long. Furthermore, there were three cases of a ban on the sale of alcoholic beverages within this period (Murhula & Nunlall, 2021), which disrupted the hospitality trade and other related businesses. Changes in lockdown restrictions were unpredictable and dictated by factors beyond the control of businesses. Business planning in this climate would, therefore, have been difficult. The likely consequence of this is increased volatility in hiring and letting go of workers, especially in informal environments (Oyenubi, 2023b).

In South Africa, by April 2020, a third of those who earned an income in February 2020 did not earn an income (Ranchhod & Daniels, 2020). Further pandemic-related job losses disproportionately affected already vulnerable groups (Rogan & Skinner, 2020b). Specifically, women, young and informal workers were disproportionately affected (Benhura & Magejo, 2020; Casale & Posel, 2021; Casale & Shepherd, 2020; Jain et al., 2020). While there were reports of some recovery by November 2020 (Jain et al., 2020), the employment rate had not returned to its pre-pandemic level by April–May 2021. Therefore, we expect there to be variation in employment status at the individual level within the period April 2020 to May 2021, especially for informal workers who will be more affected by changes in containment measures. This additional factor adds to the precarious nature of informal employment in a country where the labour market is characterised by a high level of job churning even before the pandemic (Kerr, 2018). This paper considers how much of the pandemic period changes in activity status can be explained by COVID-19 containment measures and variations in the measures.

3 | DATA

To answer this question, data on the COVID-19 CHI and estimated daily COVID reproduction rate (R) (Ritchie et al., 2020) is merged with survey data from South Africa. The survey data used is from the National Income Dynamic Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM, 2020a,b,c; NIDS-CRAM, 2021a,b). The data is merged by the interview date. This allows our analysis to exploit temporal variation in these COVID-19-related variables based on the day respondents were interviewed.

CHI is a country-level composite measure that captures policy response indicators that include school closures, workplace closures, travel bans, testing policies, contact tracing, face coverings, and vaccine policy rescaled to a value from 0 to 100 (100 = strictest). R is the estimate of the average number of new infections caused by a single infected individual (Ritchie et al., 2020); see Figure A1 for the trajectory of these variables over time. R is one of the factors that guided the risk-adjusted implementation of restrictions in South Africa and was often used to justify political strategies to control the COVID-19 pandemic (Linka et al., 2020). In the analysis, R is modelled as a dummy variable (i.e., is 1 if $R > 1$ and 0 otherwise). The motivation for this is that many of the changes in containment measures were influenced by changes in the value of R around the threshold of 1. This is because when R is greater than 1, the infection can spread in the population since one infected person will infect more than one person. However, when R is below the threshold of 1, the number of cases occurring in the population will gradually decrease since the rate of infection is on a downward trend. To get a sense of the strictness of containment measures around the time respondents were interviewed we estimate a 30-day moving average of CHI.

NIDS-CRAM is a five-wave telephone survey conducted in the period 2020–2021 using respondents drawn from the final (2017) wave of the National Income Dynamics Study (NIDS), a panel study conducted from 2008 to 2017 using a stratified sampling design. NIDS-CRAM provided sampling weights that adjusted for attrition over the waves of the data. That is, the weighted NIDS-CRAM data reflects the outcomes for a broadly representative sample of those 15 years and older from NIDS Wave 5 in 2017 who were followed up 3 years later (Ingle et al., 2021, p. 9). The NIDS-CRAM survey tracked socioeconomic and health outcomes of adult South Africans (18 years and older) between May 2020 and May 2021 (surveys were conducted approximately every 2 months). See Table A1 for details of survey dates. The survey weights supplied by the NIDS-CRAM team are used in the analysis presented in this paper.

The outcome variable is employment transition, this is a dummy variable that is equal to 1 if the respondent reports a change in employment status from the previous wave (and 0 otherwise).[6] While this combines positive and negative transitions in activity status, we also define negative and positive employment transitions separately, where the former is a dummy that indicates a change of status from employed to unemployed and the latter indicates a change in status in the opposite direction. The analysis also controls for various observed factors that may be correlated with employment transition. These include measures of socioeconomic status such as dwelling type, a dummy variable indicating whether the respondent has a tertiary education, and the receipt of social grants (i.e. child support grant and old age pension), including a dummy for whether the respondent personally receives a social grant. Controlling for socioeconomic status is important because it has been found that job and income losses are correlated with socioeconomic status, with those at the lower quantiles of the pre-pandemic income distribution being disproportionately affected (Oyenubi, 2023a). It is also important to control for social grant receipt because, during the pandemic, there were significant increases in the amounts paid out under various existing social grants and a new grant was also introduced to cushion the effect of the pandemic (Köhler & Bhorat, 2020). These increases may influence an individual's choice in terms of participation in the labour market. In the absence of a household income variable in the Wave 3 data, a dummy indicating loss of household income in the 4 weeks before the interview is included in the analysis.[7]

Further, we control for the state of hunger in the household (a dummy variable that was 1 if a household member had gone hungry in the last 7 days). We also control for demographic variables, including race (dummy for Black/African), gender (dummy for male), household size and age. We expect that this will capture demographic differences in labour market participation, for example, women are less likely to participate in the labour market even in non-pandemic times. Finally, the analysis is restricted to those who were between 18 and 59 years old. See Table 1 for the descriptive statistics for the four waves of the NIDS-CRAM data (Wave 1 was excluded since we are interested in transitions in activity status).

TABLE 1 Descriptive statistics (by wave).

	Wave 2	Wave 3	Wave 4	Wave 5
All job transitions	0.207	0.207	0.205	0.17
Transition into employment	0.116	0.163	0.097	0.097
Transition out of employment	0.091	0.044	0.108	0.073
Unemployed	0.557	0.479	0.499	0.47
Number of child support grants	1.565	1.569	1.541	1.519
Number of old age pension	0.347	0.301	0.285	0.276
Receipt of govt grant	0.33	0.426	0.385	0.391
Traditional (geolocation)	0.281	0.284	0.286	0.273
Urban (geolocation)	0.69	0.684	0.686	0.697
Farm (geolocation)	0.029	0.032	0.028	0.03
Age	36.041	35.845	36.167	36.38
Age^2	1414.456	1404.33	1425.649	1439.831
Male	0.378	0.387	0.381	0.385
African	0.866	0.885	0.888	0.88
House flat (housing)	0.739	0.763	0.758	0.766
Traditional/mud (housing)	0.134	0.113	0.111	0.109
Informal shack (housing)	0.1	0.105	0.107	0.103
Housing other (housing)	0.028	0.019	0.024	0.023
Hunger in household	0.188	0.216	0.194	0.194
Has tertiary education	0.278	0.272	0.265	0.274
Household size	5.439	5.505	5.316	5.296
containment index	78.321	54.128	66.056	52.951
Log of containment measure (CHI)	4.361	3.991	4.188	3.969
COVID reproduction rate > 1 (R)	0.402	0.991	0	0.983
Log of new deaths	5.388	4.508	0.205	3.956
Number of observations	4107	4783	4504	4617

4 | EMPIRICAL STRATEGY

The specification used for the analysis is as follows

$$\text{trans}_{i,w} = \alpha_i + \beta \text{MA\_CHI}_{i,w} + \delta X_{i,w-1} + \varepsilon_{i,t}, \tag{1}$$

where α_i represent individual fixed effects, $\text{trans}_{i,w}$ captures transition in employment status from wave $w-1$ to wave w, $\text{MA\_CHI}_{i,w}$ is the 30-day moving average of the containment index on the day individual i was interviewed (the logarithm of the variable is used), and $X_{i,w-1}$ is a vector of covariates of individual i in wave $w-1$ (wave lag values). In our base specification, Equation (1) is estimated using the fixed effect regression to control for α_i.

While variation in CHI may be exogenous to individual workers, it might suffer from possible feedback effects from the aggregate level of unemployment in the economy (possible reverse causality). For example, interest groups in South Africa were active in lobbying the government to strengthen or relax certain restrictions (Moultrie et al., 2021).[8] Therefore, government action as captured by CHI may not be purely exogenous. To address this concern, we instrument for CHI using *R*. This paper argues that the COVID-19 reproduction rate is a valid instrument because it is (i) exogenous since the reproduction rate is determined by a biological process, (ii) relevant because it correlates with the government's response since it was one of the factors that guided changes in containment measures and (iii) it satisfies the exclusion restriction since it is unlikely that the reproduction rate of the virus will directly affect employment or employment flows except through government regulations.[9]

Therefore, we also estimate Equation (1) using the instrumental variable fixed effects (FE-IV) regression to control for endogeneity. To be able to perform an overidentification test we use the log of new COVID-19-related deaths as an additional instrument. Like CHI, this variable satisfies the conditions mentioned above. Our model specification is similar to Cowan (2020); however, our analysis controls for time invariant and time varying heterogeneity. We define similar models for transition from employment to unemployment and transition from unemployment into employment. The first stage equation can be written as

$$\mathrm{MA\_CHI}_{i,w} = \alpha_i + \mu \mathrm{instruments}_{i,w-1} + \delta X_{i,w-1} + \varepsilon_{i,t}, \tag{2}$$

where $\mathrm{instruments}_{i,w-1}$ is the (wave) lag value of the instruments and other terms are as defined in Equation (1).

5 | RESULTS

5.1 | Descriptive analysis

Before presenting the main results, we explore heterogeneity in employment transitions. Figures 1–3 show heterogeneity in employment transitions by race, sector and type of employment relationship (defined as whether the employee has a temporary or permanent employment contract). A similar analysis is performed for gender, but we find no significant difference in transitions across gender (this result is not presented here but is available from the author). It is important to note that for job characteristics variables (sector and type of employment relationship) adjustments have to be made to the data. Specifically, those who are currently unemployed will not have a value for the type of employment relationship or sector. To deal with this, the last known sector/type of employment relationship is used if the respondent is unemployed or transitions into unemployment.[10]

Figure 1 shows the weighted proportion of individuals who experienced any type of transition aggregated over the four waves of data. The top three sectors in terms of transition in employment are construction, private households (domestic workers) and agriculture. This is not surprising since these sectors are some of the largest in terms of informal employment (Budlender, 2011). The result is, therefore, consistent with the extant literature on the impact of the pandemic, which suggests that informal workers were disproportionately affected (Oyenubi, 2023a, 2023b).

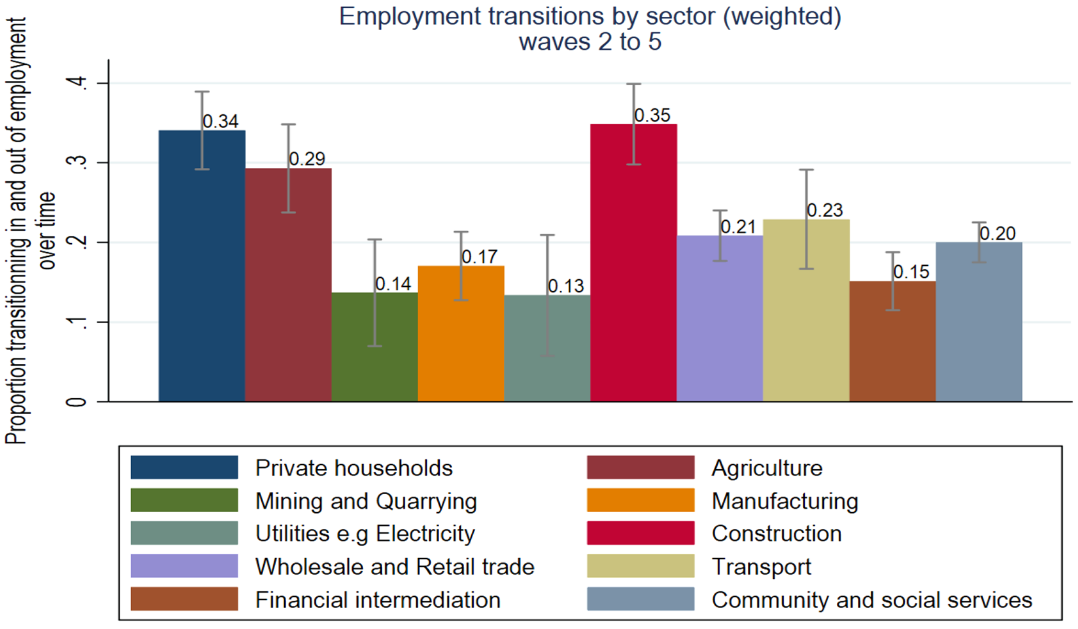

FIGURE 1 Employment transitions by sector (aggregated over survey waves). [Colour figure can be viewed at wileyonlinelibrary.com]

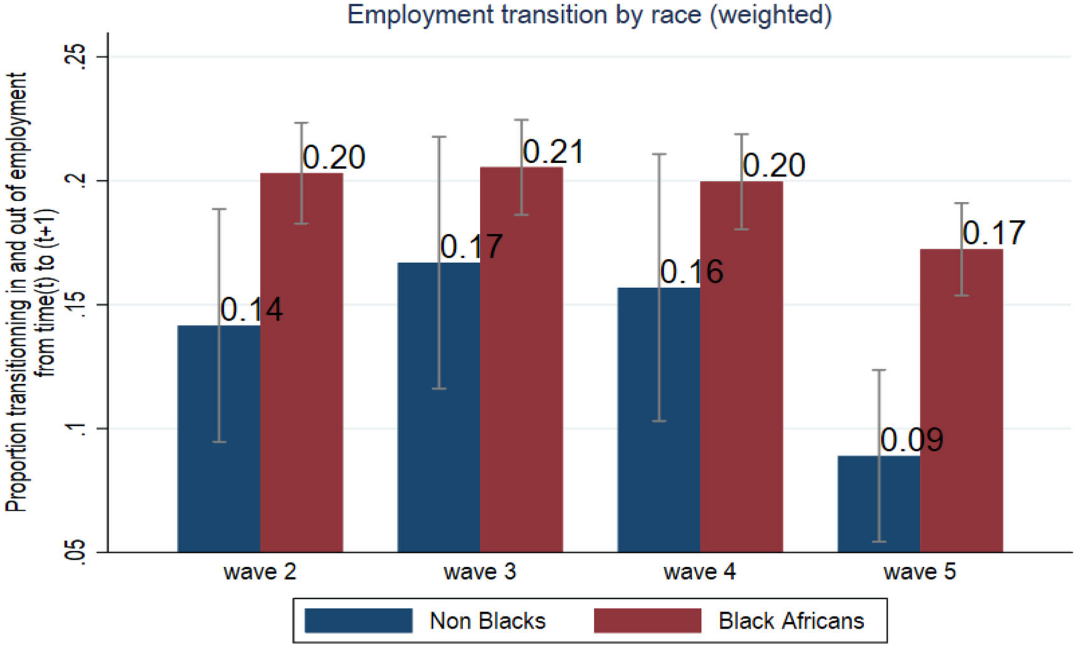

FIGURE 2 Employment transitions by race over time. [Colour figure can be viewed at wileyonlinelibrary.com]

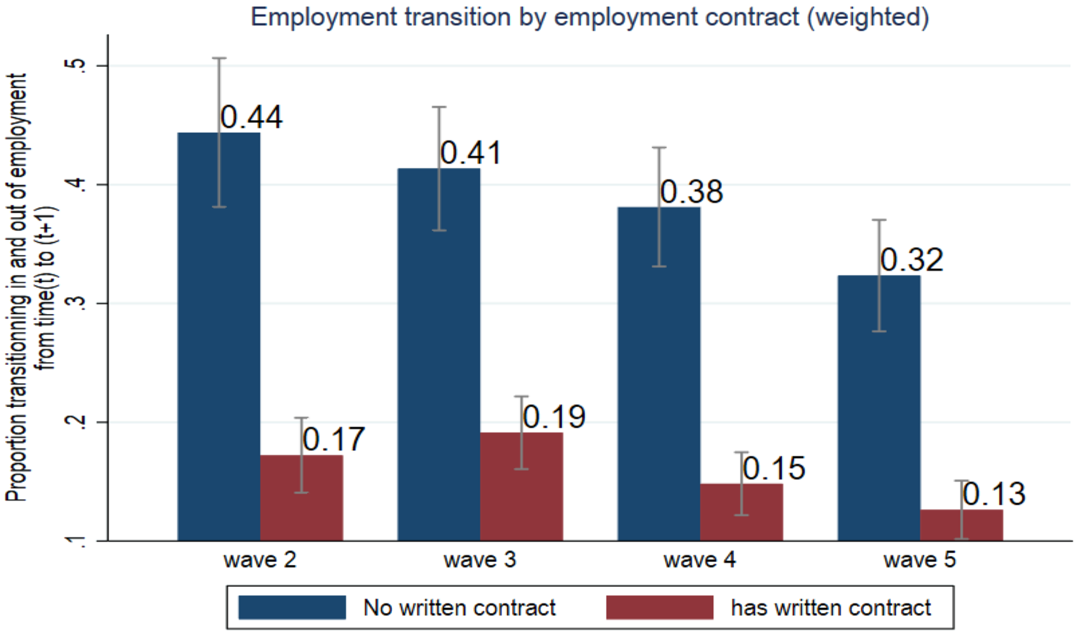

FIGURE 3 Employment transitions by type of employment over time. [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 2 shows the trend in employment transition over time by race (African). The results show that African workers were more likely to experience employment transitions across the four waves of data (although the difference is only statistically significant in Wave 5, that is, non-overlapping confidence intervals). Finally, Figure 3 shows that workers without permanent employment contracts are significantly more likely to experience employment transitions across time (note that the trends for the disaggregated employment transitions are not substantially different from those presented in Figures 1–3). The main inference here is that vulnerable workers were more likely to experience employment transitions during the COVID-19 pandemic in South Africa.

5.2 | Main results

The main results are presented in Tables 2–4. Table 2 presents the results when the independent variable is any transition in employment status. Tables 3 and 4 disaggregate the results into cases where the transition is into employment and out of employment, respectively. Column 1 (across tables) presents the fixed effects result, Columns 2 and 3 present the IV result using R alone as the instrument, while Columns 4 and 5 present the results using both R and log of new COVID deaths as instruments. The last four rows show the relevant tests performed to check our assumptions about the validity of the instrument(s). While the results presented show the weighted analysis, the unweighted results are presented in Appendix A.

The underidentification tests show that the instruments are relevant, the weak identification test suggests that the instruments are not weak, and further, the instruments show a significant correlation with the endogenous variable. Specifically, $R > 1$ in the previous wave (time lag of

TABLE 2 Fixed effects and fixed effects IV results (any transition, weighted).

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Instrument(s) used		*R* only		*R* and ln new deaths	
Log of 30-day moving average of (CHI)	0.019 (0.033)		0.046 (0.043)		0.030 (0.038)
Number of child support grants	0.026*** (0.009)	−0.001 (0.002)	0.026*** (0.008)	−0.001 (0.002)	0.027*** (0.008)
Number of old age pensions	−0.015 (0.017)	0.008 (0.006)	−0.016 (0.018)	0.001 (0.004)	−0.014 (0.018)
Receipt of govt grant	0.003 (0.016)	−0.021*** (0.004)	0.004 (0.016)	−0.005 (0.004)	0.002 (0.016)
Traditional (geolocation)[a]	−0.034 (0.056)	−0.009 (0.020)	−0.032 (0.054)	0.003 (0.015)	−0.038 (0.054)
Urban (geolocation)	−0.045 (0.055)	0.020 (0.020)	−0.045 (0.053)	0.015 (0.015)	−0.049 (0.053)
Age	−0.039 (0.044)	0.033** (0.014)	−0.037 (0.043)	0.031** (0.013)	−0.039 (0.043)
Age^2	0.000 (0.001)	−0.000* (0.000)	0.000 (0.001)	−0.000 (0.000)	0.000 (0.001)
House flat (housing)[b]	0.140** (0.058)	0.044*** (0.017)	0.139** (0.055)	0.021* (0.012)	0.141** (0.055)
Traditional/mud (housing)	0.097 (0.061)	0.020 (0.020)	0.096 (0.060)	0.001 (0.014)	0.101* (0.060)
Informal shack (Housing)	0.137** (0.068)	0.044** (0.022)	0.136** (0.065)	0.036** (0.016)	0.139** (0.065)
Household hunger	−0.005 (0.020)	0.024*** (0.006)	−0.006 (0.020)	0.006 (0.005)	−0.006 (0.020)
Has tertiary education	−0.034 (0.032)	0.019* (0.010)	−0.034 (0.028)	0.022*** (0.008)	−0.034 (0.028)
Household size	−0.003 (0.004)	0.001 (0.001)	−0.003 (0.004)	0.001 (0.001)	−0.003 (0.004)

(Continues)

TABLE 2 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Household lost income within the last 4 weeks	0.014 (0.013)	0.042*** (0.005)	0.012 (0.014)	0.024*** (0.004)	0.013 (0.014)
African		−0.020 (0.044)	0.505* (0.282)	−0.016 (0.044)	0.507* (0.284)
Dummy reproduction rate		0.249*** (0.003)		0.134*** (0.004)	
Log of new deaths				−0.119*** (0.003)	
Constant	0.911 (0.901)				
Observations	14,577	13,626	13,626	13,595	13,595
R^2	.008	.640	.008	.778	.008
Number of individuals	5424	4473	4473	4470	4470
Underidentification test (LM statistic)			1528.66		1802.07
LM statistic $\chi^2(1)$ p value			.00		.00
Weak identification test (Wald F statistic)			8459.20		6223.23
Stock–Yogo weak ID test critical values: 10% maximal IV size			16.38		8.68
Hansen J statistic (overidentification					0.65

TABLE 2 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
test of all instruments)					
χ^2 *p* value					.41
Endogeneity test			1.00		0.32
$\chi^2(1)$ *p* value			.32		.56

Note: Apart from CHI lag values are used for all covariates. This means the Wave 1 data is excluded from the analysis since there are no lag values for the Wave 1 data. Two IV results are presented. The first uses R alone as the instrument (Columns 2 and 3), while the second uses both R and log of new deaths as the instrument (Columns 4 and 5). Robust standard errors are in parentheses.

[a]Reference category farms.

[b]Reference category other housing.

***$p < .01$; **$p < .05$; *$p < .1$.

TABLE 3 Fixed effects and fixed effects IV results (positive transition, weighted).

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Instrument(s) used		R only		R and ln new deaths	
Log of 30-day moving average of (CHI)	−0.083** (0.032)		−0.061 (0.037)		−0.071** (0.033)
Number of child support grants	0.016** (0.007)	−0.001 (0.002)	0.016** (0.007)	−0.001 (0.002)	0.015** (0.007)
Number of old age pensions	0.005 (0.018)	0.008 (0.006)	0.005 (0.018)	0.001 (0.004)	0.010 (0.018)
Receipt of govt grant	−0.004 (0.014)	−0.021*** (0.004)	−0.003 (0.014)	−0.005 (0.004)	−0.005 (0.014)
Traditional (geolocation)[a]	0.003 (0.050)	−0.009 (0.020)	0.004 (0.050)	0.003 (0.015)	0.001 (0.050)
Urban (geolocation)	−0.010 (0.050)	0.020 (0.020)	−0.010 (0.049)	0.015 (0.015)	−0.010 (0.049)
Age	−0.047 (0.034)	0.033** (0.014)	−0.046 (0.038)	0.031** (0.013)	−0.047 (0.038)
Age^2	0.000 (0.000)	−0.000* (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
House flat (housing)[b]	0.107** (0.047)	0.044*** (0.017)	0.106** (0.049)	0.021* (0.012)	0.107** (0.049)
Traditional/mud (housing)	0.110** (0.050)	0.020 (0.020)	0.109** (0.053)	0.001 (0.014)	0.106** (0.053)
Informal shack (housing)	0.169*** (0.055)	0.044** (0.022)	0.168*** (0.056)	0.036** (0.016)	0.168*** (0.056)
Household hunger	−0.009 (0.017)	0.024*** (0.006)	−0.010 (0.018)	0.006 (0.005)	−0.009 (0.017)
Has tertiary education	−0.020 (0.022)	0.019* (0.010)	−0.021 (0.024)	0.022*** (0.008)	−0.021 (0.024)
Household size	−0.004 (0.003)	0.001 (0.001)	−0.004 (0.003)	0.001 (0.001)	−0.004 (0.003)

TABLE 3 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Household lost income within the last 4 weeks	−0.027** (0.012)	0.042*** (0.005)	−0.029** (0.012)	0.024*** (0.004)	−0.029** (0.012)
African		−0.020 (0.044)	−0.189 (0.183)	−0.016 (0.044)	−0.190 (0.182)
Dummy reproduction rate		0.249*** (0.003)		0.134*** (0.004)	
Log of new deaths				−0.119*** (0.003)	
Constant	1.663** (0.678)				
Observations	14,577	13,626	13,626	13,595	13,595
R^2	.010	.640	.010	.778	.010
Number of individuals	5424	4473	4473	4470	4470
Underidentification test (LM statistic)			1528.66		1802.07
LM statistic $\chi^2(1)$ p value			.00		.00
Weak identification test (Wald F statistic)			8459.20		6223.23
Stock–Yogo weak ID test critical values: 10% maximal IV size			16.38		8.68

(Continues)

TABLE 3 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Hansen J statistic (overidentification test of all instruments)					0.39
χ^2 p value					.53
Endogeneity test			0.71		0.41
$\chi^2(1)$ p value			.40		.52

Note: Apart from CHI lag values are used for all covariates. This means Wave 1 data is excluded from the analysis since there are no lag values for the Wave 1 data. Two IV results are presented. The first uses R alone as the instrument (Columns 2 and 3), while the second uses both R and log of new deaths as the instrument (columns 4 and 5). Robust standard errors are in parentheses.

[a]Reference category farms.

[b]Reference category other housing.

***$p < .01$; **$p < .05$; *$p < .1$.

TABLE 4 Fixed effects and fixed effects IV results (negative transition, weighted).

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Instrument(s) used		*R* only		*R* and ln new deaths	
Log of 30-day moving average of (CHI)	0.102*** (0.026)		0.107*** (0.033)		0.100*** (0.028)
Number of child support grants	0.010 (0.007)	−0.001 (0.002)	0.010 (0.006)	−0.001 (0.002)	0.011* (0.006)
Number of old age pensions	−0.021 (0.017)	0.008 (0.006)	−0.021 (0.017)	0.001 (0.004)	−0.023 (0.017)
Receipt of govt grant	0.007 (0.012)	−0.021*** (0.004)	0.007 (0.012)	−0.005 (0.004)	0.007 (0.012)
Traditional (geolocation)[a]	−0.037 (0.030)	−0.009 (0.020)	−0.037 (0.029)	0.003 (0.015)	−0.038 (0.029)
Urban (geolocation)	−0.035 (0.027)	0.020 (0.020)	−0.035 (0.026)	0.015 (0.015)	−0.038 (0.026)
Age	0.008 (0.038)	0.033** (0.014)	0.009 (0.038)	0.031** (0.013)	0.008 (0.038)
Age^2	0.000 (0.000)	−0.000* (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
House flat (housing)[b]	0.033 (0.021)	0.044*** (0.017)	0.033 (0.027)	0.021* (0.012)	0.034 (0.027)
Traditional/mud (housing)	−0.013 (0.033)	0.020 (0.020)	−0.013 (0.036)	0.001 (0.014)	−0.006 (0.036)
Informal shack (housing)	−0.032 (0.032)	0.044** (0.022)	−0.032 (0.036)	0.036** (0.016)	−0.030 (0.036)
Household hunger	0.004 (0.018)	0.024*** (0.006)	0.004 (0.017)	0.006 (0.005)	0.002 (0.017)
Has tertiary education	−0.014 (0.020)	0.019* (0.010)	−0.014 (0.021)	0.022*** (0.008)	−0.013 (0.021)
Household size	0.001 (0.003)	0.001 (0.001)	0.001 (0.003)	0.001 (0.001)	0.001 (0.003)

(Continues)

TABLE 4 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Household lost income within the last 4 weeks	0.041*** (0.012)	0.042*** (0.005)	0.041*** (0.011)	0.024*** (0.004)	0.042*** (0.011)
African		−0.020 (0.044)	0.694*** (0.203)	−0.016 (0.044)	0.697*** (0.204)
Dummy reproduction rate		0.249*** (0.003)		0.134*** (0.004)	
Log of new deaths				−0.119*** (0.003)	
Constant	−0.752 (0.763)				
Observations	14,577	13,626	13,626	13,595	13,595
R^2	.015	.640	.015	.778	.016
Number of individuals	5424	4473	4473	4470	4470
Underidentification test (LM statistic)			1528.66		1802.07
LM statistic $\chi^2(1)$ p value			.00		.00
Weak identification test (Wald F statistic)			8459.21		6223.23
Stock–Yogo weak ID test critical values: 10% maximal IV size			16.38		8.68

TABLE 4 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Hansen J statistic (overidentification test of all instruments)					0.11
χ^2 p value					.73
Endogeneity test			0.06		0.02
$\chi^2(1)$ p value			.81		.87

Note: Apart from CHI lag values are used for all covariates. This means Wave 1 data is excluded from the analysis since there are no lag values for the Wave 1 data. Two IV results are presented. The first uses R alone as the instrument (Columns 2 and 3), while the second uses both R and log of new deaths as the instrument (Columns 4 and 5). Robust standard errors are in parentheses.

[a]Reference category farms.

[b]Reference category other housing.

***$p < .01$; **$p < .05$; *$p < .1$.

about 2 months) translates into a higher average CHI index in the current wave. We note that the relationship between new COVID-19 deaths and containment measures is negative. This may be attributed to how deaths were reported (counts can include probable deaths) or the lag between when the deaths occur and the government response. The important point is that this variable can predict the value of the containment index. The Hansen *J* statistic (in the case where there are two instruments) suggests that the additional instrument is valid (assuming that the first instrument is valid), that is, uncorrelated with the stochastic error term. Finally, the endogeneity test is not statistically significant. Even though this suggests that the fixed effect regression will be appropriate, our argument about plausible endogeneity of the containment index remains valid (note that a similar pattern to that shown in Table 2 is observed for the IV tests in the disaggregated analysis depicted in Tables 3 and 4).

The survey-weighted fixed effects result suggests that the average of the CHI index around the time an individual is interviewed is uncorrelated with transition in employment status in general, and the result is confirmed by the FE-IV regressions. This may be because the general employment transition variable captures both the transition into and transition out of employment. However, for the unweighted analysis (see Table A2), the results are positive and statistically significant. Specifically, the unweighted analysis suggests that a unit change in the (average) CHI index increased employment transition by 5% (under the unweighted FE regression), 10% (under FE-IV regression with one instrument) and 8% (under the FE-IV regression with two instruments). This suggests that while the hypothesis that CHI induces employment transitions is valid in the sample, this cannot be generalised to the whole population (however, across Table 2, the estimates are positive even though they are not statistically significant).

Tables 3 and 4 disaggregate the analysis by depicting the transition into employment and transition out of employment, respectively. Table 3 shows a negative relationship between the average CHI index and the transition from unemployment to employment. This effect is not significant when only one instrument is used (Column 3) but significant at the 5% level under the FE and the FE-IV model with two instruments (Columns 1 and 5, respectively). This result suggests that stricter containment measure decreases the possibility of gaining employment during this period. Note that the unweighted analysis (Table A3) shows similar substantive results with comparable estimates.

Table 4 presents the result when the outcome captures the transition from employment to unemployment. The estimates are positive and statistically significant at the 1% level. Furthermore, the estimated impact does not vary significantly with the choice of method, suggesting that stricter containment measures positively impact the transition from being employed to being unemployed. This result is confirmed in the unweighted analysis with slightly higher coefficients (see Table A4). Perhaps the null result in Table 2 (general transition) can be explained by the opposing sign in Tables 3 and 4 cancelling each other out in the aggregate transition regression.

Results for the other covariates suggest that the number of child support grants received by a household and living in a flat or an informal dwelling is positively correlated with employment transition in general. Note that these results are inconclusive since it is unclear whether the transition is into employment or unemployment. Table 3 clarifies the results, and shows that the number of child support grants, and living in a flat or informal dwelling are positively correlated with the transition into employment (these variables are not significant for the regressions for the transition into unemployment). This may be an indication that individuals of lower socioeconomic status (who are more likely to receive grants and live in informal dwellings) may be less likely to withdraw labour supply given the high rate of unemployment in

South Africa. Furthermore, Table 3 shows that individuals who transition from unemployment to employment are less likely to report a decrease in or loss of household income, and Table 4 shows that individuals who transition from employment to unemployment are more likely to report a loss of household income, as we may expect.

6 | ROBUSTNESS CHECK

The exclusion restriction assumption may be problematic. As noted earlier (see Footnote 7), an increase in the COVID-19 reproduction rate (spread of the virus) may affect the health of individual workers and, consequently their employment transitions. Furthermore, workers may withdraw their labour participation as a result of observing an increase in the COVID-19 reproductive rate.[11] However, it is noted that this is unlikely in the context of South Africa because of the varied impact of the pandemic across the socioeconomic spectrum. Those of higher socioeconomic status are unlikely to withdraw their labour because they have the option of working from home (Nwosu et al., 2022b), while those who are at the lower end may not be able to afford to withdraw their labour supply. In other words, those who could afford to willingly withdraw their labour supply would not need to since they have the option to work remotely, while others may not be able to willingly withdraw because of the necessity to survive.

Nevertheless, this study conducts two falsification tests to check the robustness of the exclusion restriction assumption. The first test is an FE regression that includes the instruments as additional covariates, if the instruments are directly correlated with the outcome, we will expect significant estimates. However, the results (presented in Table A5) show that both the R and the log of new deaths are not correlated with the outcome (conditional on other covariates). While this is suggestive of the validity of the exclusion restriction, we conduct a more formal test using the method introduced by Nevo and Rosen (2012). The method allows for identification (of confidence intervals) when the exclusion restriction is not satisfied. Under this method, one can identify the confidence interval for the effect estimate under the following assumptions: (i) the instrument has (weakly) the same direction of correlation with the unobserved variable as the endogenous variable, (ii) the instrument is less endogenous than the endogenous variable (Nevo & Rosen, 2012). Note that the sign of the correlation between the instrument and the assumed omitted variable (health/health concern) is expected to be the same as the sign of the correlation between the instrument and the endogenous variable (i.e., both are expected to be positive). Furthermore, it is reasonable to assume that the containment index is more endogenous than the COVID-19 reproductive rate (since the former is controlled by the government and the latter is a biological process).

It is, therefore, possible to estimate the confidence interval for our effect (note we use the pooled OLS regression since the Nevo (2012) method does not allow for control for fixed effects estimation). Results are presented for the disaggregated analysis since the (weighted) undisaggregated result is not statistically significant (see Table 2). The estimated lower and upper bound estimators when the outcome is a transition from unemployment to employment are −0.11 and −0.13, respectively. The lower and upper confidence limits of these estimates are −0.18 and −0.06, respectively. When the outcome is a transition from employment to unemployment, the corresponding estimates are 0.19 and 0.18, and the confidence limits are 0.12 and 0.25 (for the lower and upper bounds, respectively). Since these estimates are consistent with the results in Tables 3 and 4 and they exclude zero, this suggests that the substantive results are valid even if the instrument does not satisfy the exclusion restriction assumption.

7 | DISCUSSION AND CONCLUSION

This paper establishes a causal link between COVID-19 containment measures and transition in employment status in South Africa. It is noted that while several papers have alluded to this relationship, to the best of our knowledge, this is the first study to empirically establish this relationship in a developing contry context. The findings are important in the context of developing countries since employment transitions were high in these countries even before the pandemic. Furthermore, the study shows that variations in containment measures are more likely to generate negative than positive employment transitions, as we would expect. A plausible explanation for this effect is that changes in containment rules constitute an uncertainty shock (particularly for firms), which is known to negatively impact employment (Caggiano et al., 2017). While containment measures are necessary, understanding this causal link and how it translates into changes in activity status is important for the management of future pandemics. We discuss some of these implications below.

The purpose of the SDGs was to produce a set of universal goals to combat the urgent environmental, political and economic challenges facing our world. The pandemic has revealed how tenuous the achievements towards these goals are. The pandemic has shown that it is indeed possible for decades of achievement to be wiped out in weeks. It has been argued that the pandemic has slowed down progress towards the SDGs (Shulla et al., 2021). The implication of this is that a future where pandemics cannot be ruled out (Marani et al., 2021) increases the possibility that developing countries will be left behind in sustainable development. The lesson from the first 2 years of the pandemic is that a more resilient labour market that can operate under unusual conditions such as the one precipitated by the pandemic is necessary for the achievement of developmental goals. The literature already suggests that progress towards SDG 8 (Decent Work and Economic Growth) (Shulla et al., 2021) and SDG 5 (Gender Equality) has been impacted by the COVID-19 pandemic (Casale & Posel, 2021; Casale & Shepherd, 2020; Shepherd, 2022).

It is also important to appreciate the cost of COVID-19 restrictions in terms of the economic consequences of the containment measures. This is especially important in developing countries where there is a high level of informality, a low share of jobs that can be performed from home, weak governance, and the absence of adequate social safety nets. It has been shown that in such environments, stringent lockdown restrictions are less effective since they involve a trade-off between health and economic survival (David & Pienknagura, 2021). This, coupled with the argument that a less stringent lockdown may have been as effective in controlling the spread of the virus (Haug et al., 2020), suggests that a less aggressive implementation of containment rules may have a less negative effect on employment patterns without necessarily resulting in worse health outcomes.

It is, therefore, important for policymakers to pay attention to what COVID-19 has revealed about the resilience of developing economies. The achievement of the SDGs depends on the ability of these economies to withstand unanticipated shocks such as the one brought about by COVID-19. Improvement in infrastructure is one way in which governments in developing countries can mitigate the effects of future COVID-19-like restrictions. This is likely to reduce the effect of the disruption on businesses since firms (including informal ones that are able to leverage the technology) can move their operations online. Oyenubi (2023b) argues that, in Zambia, firms that were able to move their business online were less affected by the pandemic. Therefore, the development of cheap and efficient internet infrastructure is one way to prepare for the next pandemic.

The government of South Africa increased the amount paid out under existing social grants and introduced the social relief of distress grant to cushion the effect of the pandemic. This was a welcome development since studies have suggested that social assistance did provide some relief (Gelo & Dikgang, 2022; Ohrnberger, 2022). It has also been shown that some of these grants can be repurposed as emergency relief for informal workers (Bassier et al., 2021). This is because grant receipt is correlated with informal employment. Despite these efforts, the literature finds that reports of hunger increased significantly during the pandemic (van der Berg et al., 2022). The implication is that these efforts did not cover all those negatively affected by the pandemic shock. This may be explained in part by informality since those who were affected but were not employed in the formal sector or on social assistance before the pandemic would have found it difficult to access assistance from the government. It has been suggested that a registry of informal firms and workers (as against firm registration, which involves taxation) could be one way to manage more targeted social assistance in times of uncertainty such as during the pandemic (Narula, 2020). Such a registry would have allowed the government to provide more accurately targeted social assistance by enabling them to reach individuals are in need but are not accounted for in the grant system.

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CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT

The data are held in a public repository and can be accessed at: https://cramsurvey.org.

ETHICS STATEMENT

Ethics approval for the NIDS-CRAM Survey was granted by the Commerce Faculty Ethics Committee of the University of Cape Town and the Research Ethics Committee: Social, Behavioral and Education Research, of the University of Stellenbosch.

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ENDNOTES

[1] Especially since future pandemics are likely https://www.chathamhouse.org/2022/02/next-pandemic-when-could-it-be.

[2] See https://www.gov.za/Coronavirus.

[3] https://globalhealth.duke.edu/news/statistics-say-large-pandemics-are-more-likely-we-thought.

[4] https://www.nicd.ac.za/first-case-of-covid-19-announced-an-update/.

[5] See https://www.gov.za/speeches/president-cyril-ramaphosa-developments-south-africa%E2%80%99s-risk-adjusted-strategy-manage-spread.

[6] Note that this definition can be broadened to include those who were furloughed (having an employment relationship but zero working days and pay) or paid leave, as done by Jain et al. (2020). However, the number of individuals in these categories decreased substantially from 2021 (Wave 3) (Espi-Sanchis et al., 2021, 2022). Therefore, these categories will have very small cell sizes which may not be meaningful for inference.

[7] Household income was not collected in Wave 3, so negative change in household income over the last 4 weeks was used as a proxy.

[8] See https://salba.co.za/new-data-analysis-reveals-surprising-insights-about-alcohol-harm-in-south-africa/.

[9] We note however that it is possible for the COVID reproduction rate to affect individuals' health and therefore the change in their activity status. We show that our substantive result is robust to this violation by using a method that allows us to recover the confidence interval for the effect estimate. Further in the analysis we augment the instrument with a log of new deaths, this instrument is not expected to have a direct effect on health.

[10] For example, if a respondent transitions from employment in Wave 1 to unemployment in Wave 2, the transition variable will be 1 in Wave 2 and the sector variable (for example) will be coded as the individual's sector variable in Wave 1. Note that this adjustment is not needed for those who transition into employment.

[11] We thank anonymous reviewers for pointing this out.

REFERENCES

Abay, K., Berhane, G., Hoddinott, J., & Tafere, K. (2020). *COVID-19 and food security in Ethiopia: Do social protection programs protect?* (IFPRI Discussion Paper 01972). International Food Policy Research Institute.

Agrawal, S., Cojocaru, A., Montalva, V., Narayan, A., Bundervoet, T., & Ten, A. (2021). *COVID-19 and inequality*. World Bank.

Ahmed, F., Islam, A., Pakrashi, D., Rahman, T., & Siddique, A. (2021). Determinants and dynamics of food insecurity during COVID-19 in rural Bangladesh. *Food Policy*, *101*, 102066. https://doi.org/10.1016/j.foodpol.2021.102066

Alfano, V., & Ercolano, S. (2020). The efficacy of lockdown against COVID-19: A cross-country panel analysis. *Applied Health Economics and Health Policy*, *18*, 509–517. https://doi.org/10.1007/s40258-020-00596-3

Bassier, I., Budlender, J., Zizzamia, R., Leibbrandt, M., & Ranchhod, V. (2021). Locked down and locked out: Repurposing social assistance as emergency relief to informal workers. *World Development*, *139*, 105271.

Benhura, M., & Magejo, P. (2020). *Differences between formal and informal workers' outcomes during the COVID-19 crisis lockdown in South Africa*.

Bonnet, F., Vanek, J., & Chen, M. (2019). *Women and men in the informal economy: A statistical brief (p. 20)*. International Labour Office.

Budlender, D. (2011). *Statistics on informal employment in South Africa*. WIEGO.

Bundervoet, T., Dávalos, M. E., & Garcia, N. (2022). The short-term impacts of COVID-19 on households in developing countries: An overview based on a harmonized dataset of high-frequency surveys. *World Development*, *153*, 105844.

Caggiano, G., Castelnuovo, E., & Figueres, J. M. (2017). Economic policy uncertainty and unemployment in the United States: A nonlinear approach. *Economics Letters*, *151*, 31–34. https://doi.org/10.1016/j.econlet.2016.12.002

Casale, D., & Posel, D. (2021). Gender inequality and the COVID-19 crisis: Evidence from a large national survey during South Africa's lockdown. *Research in Social Stratification and Mobility*, *71*, 100569.

Casale, D., & Shepherd, D. (2020). *The gendered effects of the ongoing lockdown and school closures in South Africa: Evidence from NIDS-CRAM Waves 1 and 2*. Department of Economics, University of Stellenbosch.

Choo, E. K., & Rajkumar, S. V. (2020). Medication shortages during the COVID-19 crisis: What we must do. *Mayo Clinic Proceedings*, *95*, 1112–1115.

Cowan, B. W. (2020). *Short-run effects of COVID-19 on US worker transitions* (No. 27315). National Bureau of Economic Research.

Darvas, Z. M. (2021). *The unequal inequality impact of the COVID-19 pandemic* (Working Paper). Bruegel.

David, A. C., & Pienknagura, S. (2021). On the effectiveness of containment measures in controlling the COVID-19 pandemic: The role of labour market characteristics and governance. *Applied Economics Letters*, *28*, 1641–1647.

Deaton, A. (2021). *Covid-19 and global income inequality*. National Bureau of Economic Research.

Duman, A. (2020). *Wage losses and inequality in developing countries: Labor market and distributional consequences of Covid-19 lockdowns in Turkey* (3645468).

Espi-Sanchis, G., Leibbrandt, M., & Ranchhod, V. (2021). *Employment dynamics in South Africa during the COVID-19 era: An update covering the second wave*. NIDS-CRAM Reports and Publications.

Espi-Sanchis, G., Leibbrandt, M., & Ranchhod, V. (2022). Age, employment and labour force participation outcomes in COVID-era South Africa. *Development Southern Africa*, *39*, 664–688.

Gelo, D., & Dikgang, J. (2022). Implications of COVID-19 labour market shock for child and household hungers in South Africa: Do social protection programs protect? *PLoS One*, *17*, e0269848.

Haug, N., Geyrhofer, L., Londei, A., Dervic, E., Desvars-Larrive, A., Loreto, V., Pinior, B., Thurner, S., & Klimek, P. (2020). Ranking the effectiveness of worldwide COVID-19 government interventions. *Nature Human Behaviour*, *4*, 1303–1312. https://doi.org/10.1038/s41562-020-01009-0

ILO. (2020). *ILO monitor: COVID-19 and the world of work. Updated estimates and analysis*. International Labour Organization.

Ingle, K., Brophy, T., & Daniels, R. C. (2021). *National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM) 2020–2021 panel user manual*. Southern Africa Labour and Development Research Unit.

Jain, R., Budlender, J., Zizzamia, R., & Bassier, I. (2020). *The labour market and poverty impacts of Covid-19 in South Africa* (NIDS-CRAM Report No. 5).

Kerr, A. (2018). Job flows, worker flows and churning in South Africa. *South African Journal of Economics*, *86*, 141–166.

Kim, A. W., Nyengerai, T., & Mendenhall, E. (2022). Evaluating the mental health impacts of the COVID-19 pandemic: Perceived risk of COVID-19 infection and childhood trauma predict adult depressive symptoms in urban South Africa. *Psychological Medicine*, *52*, 1587–1599.

Köhler, T., & Bhorat, H. (2020). *Social assistance during South Africa's national lockdown: Examining the COVID-19 grant, changes to the Child Support Grant, and post-October policy options* (Working Papers 202009). University of Cape Town, Development Policy Research Unit.

Linka, K., Peirlinck, M., & Kuhl, E. (2020). The reproduction number of COVID-19 and its correlation with public health interventions. *Computational Mechanics*, *66*, 1035–1050.

Liu, Y., Morgenstern, C., Kelly, J., Lowe, R., Munday, J., Villabona-Arenas, C. J., Gibbs, H., Pearson, C. A. B., Prem, K., Leclerc, Q. J., Meakin, S. R., Edmunds, W. J., Jarvis, C. I., Gimma, A., Funk, S., Quaife, M., Russell, T. W., Emory, J. C., Abbott, S., … CMMID COVID-19 Working Group. (2021). The impact of non-pharmaceutical interventions on SARS-CoV-2 transmission across 130 countries and territories. *BMC Medicine*, *19*, 40. https://doi.org/10.1186/s12916-020-01872-8

Marani, M., Katul, G. G., Pan, W. K., & Parolari, A. J. (2021). Intensity and frequency of extreme novel epidemics. *Proceedings of the National Academy of Sciences of the United States of America*, *118*, e2105482118.

Moultrie, T. A., Dorrington, R. E., Laubscher, R., Groenewald, P., Parry, C. D. H., Matzopoulos, R., & Bradshaw, D. (2021). Unnatural deaths, alcohol bans and curfews: Evidence from a quasi-natural experiment during COVID-19. *South African Medical Journal*, *111*, 834–837. https://doi.org/10.7196/SAMJ.2021.v111i9.15813

Murhula, P. B. B., & Nunlall, R. (2021). Covid-19 and the ban of alcohol sales in South Africa: A critical overview. *Acta Criminologica: African Journal of Criminology & Victimology*, *34*, 1–16.

Narula, R. (2020). Policy opportunities and challenges from the COVID-19 pandemic for economies with large informal sectors. *Journal of International Business Policy*, *3*, 302–310. https://doi.org/10.1057/s42214-020-00059-5

National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM). (2020a). Wave 1 [data set]. Version 3.0.0. Cape Town: Allan Gray Orbis Foundation [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2020. Cape Town: DataFirst [distributor], 2020. https://doi.org/10.25828/7tn9-1998

National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM). (2020b). Wave 2 [data set]. Version 3.0.0. Cape Town: Allan Gray Orbis Foundation [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [Implementer], 2020. Cape Town: DataFirst [distributor], 2020. https://doi.org/10.25828/5z2w-7678

National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM). (2020c). Wave 3 [data set]. Version 3.0.0. Cape Town: Allan Gray Orbis Foundation [funding agency]. Cape Town: Southern Africa

Labour and Development Research Unit [implementer], 2020. Cape Town: DataFirst [distributor], 2020. https://doi.org/10.25828/s82x-nx07
National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM). (2021a). Wave 5 [data set]. Version 1.0.0. Cape Town: FEM Education Foundation and Michael and Susan Dell Foundation [funding agencies]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2021. Cape Town: DataFirst [distributor], 2021. https://doi.org/10.25828/awhe-t852
National Income Dynamics Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM). (2021b). Wave 4 [data set]. Version 2.0.0. Cape Town: FEM Education Foundation and Michael and Susan Dell Foundation [funding agencies]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2021. Cape Town: DataFirst [distributor], 2021. https://doi.org/10.25828/y5qj-x095
Nevo, A., & Rosen, A. M. (2012). Identification with imperfect instruments. *Review of Economics and Statistics*, *94*, 659–671.
Nwosu, C. O., Kollamparambil, U., & Oyenubi, A. (2022a). Food insecurity and health outcomes during the coronavirus pandemic in South Africa: A longitudinal study. *Health Economics Review*, *12*, 32.
Nwosu, C. O., Kollamparambil, U., & Oyenubi, A. (2022b). Socio-economic inequalities in ability to work from home during the coronavirus pandemic. *The Economic and Labour Relations Review*, *33*, 290–307.
Ohrnberger, J. (2022). Economic shocks, health, and social protection: The effect of COVID-19 income shocks on health and mitigation through cash transfers in South Africa. *Health Economics*, *31*, 2481–2498. https://doi.org/10.1002/hec.4592
Oyenubi, A. (2023a). The COVID-19 pandemic and polarisation of income distribution in South Africa. *The Economic and Labour Relations Review*, *34*, 157–178.
Oyenubi, A. (2023b). Analysis of the labour market impacts of the coronavirus pandemic: Evidence from Zambia. *Development Southern Africa*, 1–24. https://doi.org/10.1080/0376835X.2023.2261977
Oyenubi, A., Kim, A. W., & Kollamparambil, U. (2022). COVID-19 risk perceptions and depressive symptoms in South Africa: Causal evidence in a longitudinal and nationally representative sample. *Journal of Affective Disorders*, *308*, 616–622.
Oyenubi, A., & Kollamparambil, U. (2022). Does socioeconomic status mediate the relationship between income loss and depression scores? *Evidence from South Africa. Current Psychology*, *42*, 1–12.
Özgür, G., Elgin, C., & Elveren, A. Y. (2021). Is informality a barrier to sustainable development? *Sustainable Development*, *29*, 45–65.
Pfefferbaum, B., & North, C. S. (2020). Mental health and the Covid-19 pandemic. *New England Journal of Medicine*, *383*, 510–512.
Posel, D., Oyenubi, A., & Kollamparambil, U. (2021). Job loss and mental health during the COVID-19 lockdown: Evidence from South Africa. *PLoS One*, *16*, e0249352.
Rada, C., & von Arnim, R. (2014). India's structural transformation and role in the world economy. *Journal of Policy Modeling*, *36*, 1–23.
Ranchhod, V., & Daniels, R. (2020). *Labour market dynamics in South Africa in the time of COVID-19* (NIDS-CRAM No. 9).
Ritchie, H., Mathieu, E., Rodés-Guirao, L., Appel, C., Giattino, C., Ortiz-Ospina, E., Hasell, J., Macdonald, B., Beltekian, D., & Roser, M. (2020). *Coronavirus pandemic (COVID-19). Our world in data*.
Rogan, M., & Skinner, C. (2020a). *The COVID-19 crisis and the south African informal economy: 'locked out' of livelihoods and employment*. National Income Dynamics Study–Coronavirus Rapid Mobile Survey (NIDS CRAM).
Rogan, M., & Skinner, C. (2020b). *The Covid-19 crisis and the south African informal economy 31*. NIDS-CRAM.
Rossi, R., Socci, V., Talevi, D., Mensi, S., Niolu, C., Pacitti, F., Di Marco, A., Rossi, A., Siracusano, A., & Di Lorenzo, G. (2020). COVID-19 pandemic and lockdown measures impact on mental health among the general population in Italy. *Frontiers in Psychiatry*, *11*, 790.
Rudin-Rush, L., Michler, J. D., Josephson, A., & Bloem, J. R. (2022). Food insecurity during the first year of the COVID-19 pandemic in four African countries. *Food Policy*, *111*, 102306.
Shepherd, D. L. (2022). Food insecurity, depressive symptoms, and the salience of gendered family roles during the COVID-19 pandemic in South Africa. *Social Science & Medicine*, *301*, 114830.
Shulla, K., Voigt, B.-F., Cibian, S., Scandone, G., Martinez, E., Nelkovski, F., & Salehi, P. (2021). Effects of COVID-19 on the Sustainable Development Goals (SDGs). *Discover Sustainability*, *2*, 15. https://doi.org/10.1007/s43621-021-00026-x

Tabe-Ojong, M. P., Jr., Nshakira-Rukundo, E., & Gebrekidan, B. (2022). *COVID-19 and food (in) security in Africa: Review of the emerging empirical evidence*. International Food Policy Research Institute.

Tefera, S. A., Tadesse, T. B., & Asmare, G. W. (2022). Prevalence of household food insecurity in Ethiopia during the COVID-19 pandemic: Evidence from panel data. *Scientific African*, *16*, e01141.

van der Berg, S., Patel, L., & Bridgman, G. (2022). Food insecurity in South Africa: Evidence from NIDS-CRAM wave 5. *Development Southern Africa*, *39*, 722–737.

Wanberg, C. R., Csillag, B., Douglass, R. P., Zhou, L., & Pollard, M. S. (2020). Socioeconomic status and well-being during COVID-19: A resource-based examination. *Journal of Applied Psychology.*, *105*, 1382–1396.

Xiong, J., Lipsitz, O., Nasri, F., Lui, L. M., Gill, H., Phan, L., Chen-Li, D., Iacobucci, M., Ho, R., & Majeed, A. (2020). Impact of COVID-19 pandemic on mental health in the general population: A systematic review. *Journal of Affective Disorders*, *277*, 55–64.

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APPENDIX A

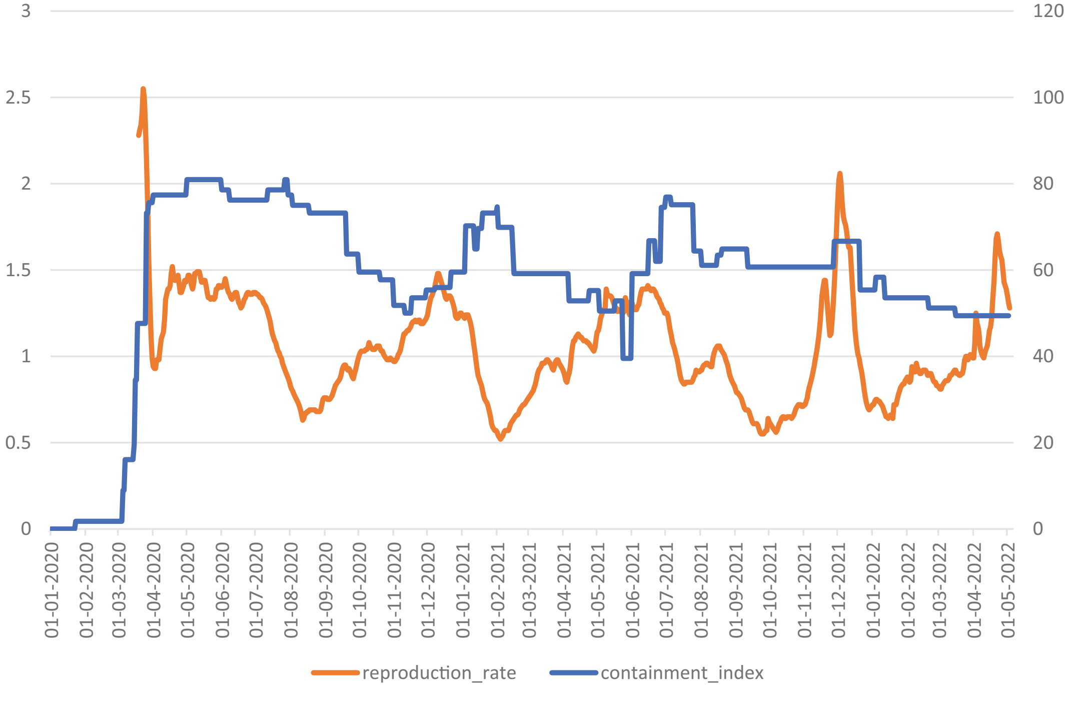

FIGURE A1 Evolution of COVID reproduction rate and containment index in South Africa. Data available at https://ourworldindata.org/coronavirus. Data from Wave 1 (before April) was excluded from the main analysis because both reproduction rate (R) and containment index (CHI) have just one jump in this period, that is, there is no systematic variation. This was the time the hardest lockdown in South Africa was in effect and it resulted in an abrupt jump in the evolution of the COVID-19 reproductive rate. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE A1 Survey data collection periods.

Wave	Start date	End date	Lockdown level
1	7 May 2020	27 Jun 2020	4 and 3
2	13 Jul 2020	13 Aug 2020	3
3	2 Nov 2020	13 Dec 2020	1
4	2 Feb 2021	10 Mar 2021	3 and 1
5	6 Apr 2021	11 May 2021	1 and 2

TABLE A2 Fixed effects and fixed effects IV results (any transition, unweighted).

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Instrument(s) used		R only		R and ln new deaths	
Log of 30-day moving average of (CHI)	0.049** (0.022)		0.096*** (0.028)		0.079*** (0.026)
Number of child support grants	0.007 (0.005)	−0.001 (0.002)	0.007 (0.005)	−0.001 (0.001)	0.007 (0.005)
Number of old age pensions	−0.010 (0.012)	0.003 (0.004)	−0.010 (0.013)	0.000 (0.003)	−0.009 (0.013)
Receipt of govt grant	0.022** (0.009)	−0.020*** (0.003)	0.024** (0.010)	−0.005** (0.002)	0.023** (0.010)
Traditional (geolocation)[a]	−0.024 (0.029)	−0.029*** (0.011)	−0.021 (0.032)	−0.010 (0.008)	−0.026 (0.032)
Urban (geolocation)	−0.023 (0.028)	0.006 (0.010)	−0.022 (0.031)	0.007 (0.008)	−0.026 (0.031)
Age	−0.028 (0.027)	0.019** (0.008)	−0.025 (0.030)	0.025*** (0.008)	−0.026 (0.030)
Age^2	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
House flat (housing)[b]	0.008 (0.030)	0.062*** (0.012)	0.005 (0.031)	0.039*** (0.008)	0.009 (0.031)
Traditional/mud (housing)	−0.004 (0.034)	0.024* (0.014)	−0.006 (0.037)	0.013 (0.009)	0.001 (0.037)
Informal shack (housing)	0.004 (0.038)	0.061*** (0.014)	0.000 (0.040)	0.047*** (0.010)	0.004 (0.040)
Household hunger	−0.008 (0.012)	0.025*** (0.004)	−0.010 (0.013)	0.010*** (0.003)	−0.010 (0.013)
Has tertiary education	0.009 (0.019)	0.008 (0.006)	0.009 (0.020)	0.013*** (0.005)	0.009 (0.020)
Household size	0.001 (0.003)	0.001 (0.001)	0.001 (0.003)	0.001* (0.001)	0.001 (0.003)

(Continues)

TABLE A2 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Household lost income within the last 4 weeks	0.002 (0.009)	0.053*** (0.003)	−0.004 (0.010)	0.034*** (0.002)	−0.001 (0.010)
African		−0.033 (0.073)	0.223 (0.177)	0.008 (0.060)	0.224 (0.178)
Dummy reproduction rate		0.246*** (0.002)		0.135*** (0.002)	
Log of new deaths				−0.114*** (0.002)	
Constant	0.668 (0.540)				
Observations	14,577	13,626	13,626	13,595	13,595
R^2	.002	.653	.002	.785	.002
Number of pid	5424	4473	4473	4470	4470
Underidentification test (LM ststistic)			3763.16		4317.64
LM statistic $\chi^2(1)$ p value			0.00		0.00
Weak identification test (Wald F statistic)			22000.00		15000.00
Stock–Yogo weak ID test critical values: 10% maximal IV size			16.38		8.68
Hansen J statistic (overidentification test of all instruments)					1.26

TABLE A2 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
χ^2 p value					0.26
Endogeneity test			6.45		5.89
$\chi^2(1)$ p value			.01		.01

Note: Apart from CHI lag values are used for all covariates, this means Wave 1 is excluded from the analysis since there are no lag values for Wave 1. Two IV results are presented the first use R alone as instrument (Columns 2 and 3) while the second use both R and log of new deaths as instrument (Columns 4 and 5). Robust standard errors are in parentheses.

[a]Reference category farms.

[b]Reference category other housing.

***$p < .01$; **$p < .05$; *$p < .1$.

TABLE A3 Fixed effects and fixed effects IV results (positive transition, unweighted).

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Instrument(s) used		R only		R and ln new deaths	
Log of 30-day moving average of (CHI)	−0.074*** (0.020)		−0.034 (0.0266)		−0.047** (0.023)
Number of child support grants	0.006 (0.005)	−0.001 (0.002)	0.006 (0.005)	−0.001 (0.001)	0.006 (0.005)
Number of old age pensions	−0.008 (0.011)	0.003 (0.004)	−0.008 (0.012)	0.000 (0.003)	−0.006 (0.012)
Receipt of govt grant	0.013 (0.009)	−0.020*** (0.003)	0.014 (0.009)	−0.005** (0.002)	0.014 (0.009)
Traditional (geolocation)[a]	−0.002 (0.026)	−0.029*** (0.011)	0.001 (0.030)	−0.010 (0.008)	−0.002 (0.030)
Urban (geolocation)	0.004 (0.025)	0.006 (0.010)	0.004 (0.029)	0.007 (0.008)	0.003 (0.029)
Age	−0.036 (0.025)	0.019** (0.008)	−0.033 (0.026)	0.025*** (0.008)	−0.035 (0.026)
Age^2	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
House flat (housing)[b]	0.005 (0.027)	0.062*** (0.012)	0.002 (0.029)	0.039*** (0.008)	0.003 (0.029)
Traditional/mud (housing)	0.030 (0.031)	0.024* (0.014)	0.028 (0.034)	0.013 (0.009)	0.030 (0.034)
Informal shack (housing)	0.033 (0.035)	0.061*** (0.014)	0.030 (0.038)	0.047*** (0.010)	0.030 (0.038)
Household hunger	0.006 (0.011)	0.025*** (0.004)	0.004 (0.012)	0.010*** (0.003)	0.005 (0.012)
Has tertiary education	0.020 (0.017)	0.008 (0.006)	0.020 (0.018)	0.013*** (0.005)	0.020 (0.018)
Household size	0.001 (0.002)	0.001 (0.001)	0.001 (0.003)	0.001* (0.001)	0.001 (0.003)

TABLE A3 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Household lost income within the last 4 weeks	−0.017** (0.008)	0.053*** (0.003)	−0.022** (0.009)	0.034*** (0.002)	−0.021** (0.009)
African		−0.033 (0.073)	−0.228 (0.199)	0.008 (0.060)	−0.227 (0.200)
Dummy reproduction rate		0.246*** (0.002)		0.135*** (0.002)	
Log of new deaths				−0.114*** (0.002)	
Constant	1.315*** (0.489)				
Observations	14,577	13,626	13,626	13,595	13,595
R^2	.004	.653	.004	.785	.004
Number of pid	5424	4473	4473	4470	4470
Underidentification test (LM ststistic)			3763.16		4317.64
LM statistic $\chi^2(1)$ p value			.00		.00
Weak identification test (Wald F statistic)			22000.00		15000.00
Stock–Yogo weak ID test critical values: 10% maximal IV size			16.38		8.68
Hansen J statistic (overidentification test of all instruments)					0.88

(Continues)

TABLE A3 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
χ^2 p value					.34
Endogeneity test			5.32		5.87
$\chi^2(1)$ p value			.02		.02

Note: Apart from CHI lag values are used for all covariates, this means Wave 1 is excluded from the analysis since there are no lag values for Wave 1. Two IV results are presented the first use R alone as instrument (Columns 2 and 3) while the second use both R and log of new deaths as instrument (Columns 4 and 5). Robust standard errors are in parentheses.

[a]Reference category farms.

[b]Reference category other housing.

***$p < .01$; **$p < .05$; *$p < .1$.

TABLE A4 Fixed effects and fixed effects IV results (negative transition, unweighted).

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Instrument(s) used		*R* only		*R* and ln new deaths	
Log of 30-day moving average of (CHI)	0.123*** (0.017)		0.130*** (0.022)		0.126*** (0.020)
Number of child support grants	0.001 (0.004)	−0.001 (0.002)	0.001 (0.004)	−0.001 (0.001)	0.001 (0.004)
Number of old age pensions	−0.002 (0.009)	0.003 (0.004)	−0.002 (0.010)	0.000 (0.003)	−0.002 (0.010)
Receipt of govt grant	0.010 (0.007)	−0.020*** (0.003)	0.010 (0.008)	−0.005** (0.002)	0.010 (0.008)
Traditional (geolocation)[a]	−0.022 (0.023)	−0.029*** (0.011)	−0.022 (0.025)	−0.010 (0.008)	−0.025 (0.025)
Urban (geolocation)	−0.027 (0.022)	0.006 (0.010)	−0.026 (0.024)	0.007 (0.008)	−0.029 (0.024)
Age	0.008 (0.021)	0.019** (0.008)	0.009 (0.023)	0.025*** (0.008)	0.008 (0.023)
Age^2	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
House flat (housing)[b]	0.004 (0.023)	0.062*** (0.012)	0.003 (0.022)	0.039*** (0.008)	0.007 (0.022)
Traditional/mud (housing)	−0.034 (0.027)	0.024* (0.014)	−0.034 (0.027)	0.013 (0.009)	−0.029 (0.026)
Informal shack (housing)	−0.029 (0.030)	0.061*** (0.014)	−0.030 (0.029)	0.047*** (0.010)	−0.026 (0.029)
Household hunger	−0.014 (0.009)	0.025*** (0.004)	−0.014 (0.010)	0.010*** (0.003)	−0.015 (0.010)
Has tertiary education	−0.010 (0.015)	0.008 (0.006)	−0.010 (0.016)	0.013*** (0.005)	−0.011 (0.016)
Household size	0.000 (0.002)	0.001 (0.001)	0.000 (0.002)	0.001* (0.001)	0.000 (0.002)

(Continues)

TABLE A4 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
Household lost income within the last 4 weeks	0.019*** (0.007)	0.053*** (0.003)	0.018** (0.008)	0.034*** (0.002)	0.019*** (0.008)
African		−0.033 (0.073)	0.451** (0.209)	0.008 (0.060)	0.451** (0.209)
Dummy reproduction rate		0.246*** (0.002)		0.135*** (0.002)	
Log of new deaths				−0.114*** (0.002)	
Constant	−0.647 (0.420)				
Observations	14,577	13,626	13,626	13,595	13,595
R^2	.010	.653	.011	.785	.011
Number of pid	5424	4473	4473	4470	4470
Underidentification test (LM ststistic)			3763.16		4317.64
LM statistic $\chi^2(1)$ *p* value			.00		.00
Weak identification test (Wald *F* statistic)			22000.00		15000.00
Stock–Yogo weak ID test critical values: 10% maximal IV size			16.38		8.68
Hansen *J* statistic (overidentification test of all instruments)					0.11

TABLE A4 (Continued)

Variables	(1) FE (employment transition)	(2) First (log containment index)	(3) Second (employment transition)	(4) First (log containment index)	(5) Second (employment transition)
χ^2 p value					.73
Endogeneity test			0.27		0.06
$\chi^2(1)$ p value			.60		.79

Note: Apart from CHI lag values are used for all covariates, this means Wave 1 is excluded from the analysis since there are no lag values for Wave 1. Two IV results are presented the first use R alone as instrument (Columns 2 and 3) while the second use both R and log of new deaths as instrument (Columns 4 and 5). Robust standard errors are in parentheses.

[a]Reference category farms.

[b]Reference category other housing.

***p < .01; **p < .05; *p < .1.

TABLE A5 Weighted fixed effects regression including instrument as covariates (falsification test).

Variables	(1) FE (transition)	(2) FE (positive transition)	(3) FE (negative transition)
Log of 30-day moving average of (CHI)	−0.014 (0.061)	−0.121* (0.062)	0.107** (0.049)
Number of child support grants	0.026*** (0.009)	0.015** (0.007)	0.011* (0.006)
Number of old age pensions	−0.013 (0.017)	0.010 (0.018)	−0.023 (0.017)
Receipt of govt grant	0.001 (0.016)	−0.005 (0.014)	0.007 (0.012)
Traditional (geolocation)[b]	−0.037 (0.057)	0.001 (0.051)	−0.038 (0.030)
Urban (geolocation)	−0.047 (0.055)	−0.009 (0.050)	−0.038 (0.027)
Age	−0.036 (0.045)	−0.044 (0.034)	0.008 (0.038)
Age^2	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
House flat (housing)[a]	0.143** (0.058)	0.109** (0.047)	0.034 (0.021)
Traditional/mud (housing)	0.101* (0.061)	0.107** (0.050)	−0.006 (0.033)
Informal shack (housing)	0.140** (0.068)	0.170*** (0.055)	−0.030 (0.031)
Household hunger	−0.005 (0.020)	−0.008 (0.017)	0.003 (0.018)
Has tertiary education	−0.033 (0.032)	−0.020 (0.022)	−0.014 (0.020)
Household size	−0.003 (0.004)	−0.004 (0.003)	0.001 (0.003)
Household lost income within the last 4 weeks	0.014 (0.013)	−0.028** (0.012)	0.042*** (0.012)
Dummy reproduction rate	0.016 (0.016)	0.014 (0.016)	0.002 (0.012)
Log of new deaths	0.001 (0.011)	−0.002 (0.009)	0.003 (0.009)
Constant	0.950 (0.915)	1.740** (0.688)	−0.790 (0.763)
Observations	14,547	14,547	14,547
R^2	.008	.011	.015
Number of pid	5422	5422	5422