SPECIAL ISSUE ARTICLE

The effect of shocks to GDP on employment in SADC member states during COVID-19 using a Bayesian hierarchical model

Ilan Strauss1 | Gilad Isaacs2,3 | Josh Rosenberg4

1Chair in Industrial Development, University of Johannesburg, Johannesburg, South Africa
2Institute for Economic Justice (IEJ), Johannesburg, South Africa
3School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa
4Airfinity LTD, West End, London, United Kingdom

Correspondence
Ilan Strauss, 267 Beach Rd Sea Point, Cape Town, South Africa, 8005.
Email: ilan.strauss@rice.edu

Abstract
Using a simple Bayesian 'mixed effects' hierarchical model we provide econometric estimates of annual 2020 employment losses in the context of the COVID-19 pandemic for 15 SADC member states on the basis of historical GDP data between 2000 and 2019 and 2020 forecasts. Our mixed effects model consists of country-varying coefficients, as well as 'fixed' (pooled) coefficients. This allows us to fully explore variation between countries. The model provides estimates for losses in total employment and women's employment, from which we infer income losses. We find that roughly half of estimated SADC countries have total employment losses below or approaching 25% of all jobs, while the other half have total losses exceeding 25%. Around one-third of all jobs for women risk being lost during 2020 for Madagascar, Comoros, Angola, Botswana, Namibia, and South Africa. Our model implies that most SADC countries will experience an equivalent loss of wage income in excess of 10% of GDP (whether through pure job losses and/or reductions in wages and working hours). Policy implications are briefly discussed.

1 | INTRODUCTION

COVID-19 has hit Africa's economies hard. The African Development Bank's (AfDB's) July 2020 Southern Africa Economic Outlook projects the region's baseline growth to be −4.9% with a worst-case scenario of −6.6% (African Development Bank, 2020). The global economic impact of COVID-19 has been transmitted rapidly and powerfully to the Southern African Development Community (SADC) due to their strong external integration. This integration reflects a reliance on global demand for domestic formal-sector employment, output, and foreign exchange earnings (World Bank, 2020a), and is captured by movements in domestic GDP. This allows changes in GDP to be an imperfect but useful proxy for changes in the viability of domestic employment (also known as Okun's Law).

Given limited data and poor data quality, employment losses can best be forecast using a panel model structure, where 2020 (annual) GDP forecasts from IMF data is used to produce a forecast for employment in 2020. Our model uses the historically estimated relationship between employment and GDP for each SADC economy between 2000 and 2019 as the basis for its forecasts. Predicted employment loss is equal to the difference between the actual 2019 employment level and 2020 employment predicted by the model. The Bayesian estimation, combined with the panel structure of the data, running across 15 countries and 20 years, is central to mitigating data quality issues which may be
present in one or more country. It does this by partially pooling estimates towards a grand mean estimate based on the average prediction across all countries (Gelman & Hill, 2007; Strauss & Yang, 2020). Despite this, our model has a number of limitations, including overfitting due to the nature of the data, and the tight historical relationship between employment and GDP. This highlights the need to develop longer time-series, with improved data integrity on employment for African economies.

Four key findings emerge: First, roughly half of SADC countries have total employment losses below or approaching 25% of all jobs, while the other half have losses exceeding 25%. Madagascar has the largest absolute and relative employment losses. Second, women are disproportionately impacted and around one-third of all female employment is at risk of being lost for Madagascar, Comoros, Angola, Botswana, Namibia, and South Africa. Third, our model’s findings imply that most SADC countries will experience an equivalent loss of wage income in excess of 10% of GDP (whether through pure job losses and/or reductions in wages and working hours). Fourth, for policy purposes we model which components of GDP most impact employment growth among SADC countries. We find fixed capital investment spending and government consumption as most important and as complementary, that is, they crowd each other ‘in’. We briefly reflect on the policy implications of these findings.

Our study is the first to use national accounts data to make employment forecasts across a large panel of African economies from COVID-19 impacts using a Bayesian partial pooling method. In contrast, existing employment impact studies from COVID-19 shocks tend to be country-specific and focus on advanced economies, where data is more detailed and current (Angelucci et al., 2020; Fana et al., 2020; Kurmann et al., 2020). This allows them to use recent quarterly labour market data for their assessments (as in the above studies), or real-time private (high frequency) data which is easily available (Chetty et al., 2020).

For developing economies, COVID-19 impact forecasts tend to rely on in-house models of the World Bank, IMF, or OECD where employment impacts are generally absent (Boone, 2020; International Monetary Fund, 2020b, 2020c). ILO employment forecasts exist but tend not to be country specific, given the high degree of noise in the data (International Labour Organisation, 2020). For developing economies, some employment impact studies exist but, like with South Africa in Africa, they tend to focus on the more developed examples, such as Brazil, with sufficiently detailed data that one can use input-output models or social accounting matrix models for employment impact assessment (Arndt et al., 2020; Barbosa & Prates, 2020; Boukar et al., 2021; Strauss et al., 2020).3

Few SADC countries’ employment impacts from COVID-19 have been studied. Those that have been studied often rely on unrepresentative high-frequency data which cover few countries and do not provide an annualised employment loss estimate. In Weber et al. (2020), rapid phone surveys were conducted by the World Bank in Ethiopia, Malawi, Nigeria and Uganda to assess labour market impacts. Such surveys have also been used to assess food security in Nigeria (Ibukun & Adebayo, 2021), and labour market dynamics in Cameroon (Djoumessi, 2021). Only Amare et al. (2020) use a difference-in-difference method on fairly representative household survey data combined with COVID-19 infection rates on a regional panel for Nigeria.

In contrast, this paper leverages existing historical national account’s GDP estimates that are widely available and improve forecast accuracy through applying a Bayesian partial pooling estimator to a panel data structure (in contrast to the complete pooling model as in Adegboye, 2020 or a non-Bayesian estimation of the same model, as in Chatri et al., 2021).

The rest of the paper is as follows. Section 2 provides an overview of our Bayesian multilevel/hierarchical regression model and motivates its use for our purposes. Section 3 shows the findings from our model. Section 4 concludes and discusses policy implications. The Appendix contains further technical details on our regression model.

## 2 | BAYESIAN MODEL OVERVIEW

### 2.1 | Model overview: GDP and employment

We use the historically estimated relationship between log(GDP) and log(employment) during 2000–2019 to provide econometric forecasts for employment changes for SADC countries for 2020. This is done by inserting into our already estimated econometric model IMF forecasts for SADC countries’ 2020 GDP (Figure 1). In this way, our model provides
Annual employment loss forecasts for 2020, arising from an annual expected shock to GDP in 2020. The exact time period of which these job losses manifests depends on country-specific labour market structures, government fiscal buffers, and any recovery in 2021.

We use the level of GDP to predict the level of the total number of employed workers, given that unemployment rates are not particularly informative for Africa (the traditional variable for Okun’s Law regression). This relationship is plotted in Figure 2, and shows a strong pre-existing relationship. This relationship holds across SADC countries, indicating that the relationship is unlikely to be ‘spurious’ (i.e., a false correlation).

In Figure 2 we see, for example, that Comoros has a very steep slope, while Mauritius has a much flatter slope. This slope governs the relationship between GDP and employment, such that GDP growth has a large impact on employment growth in Comoros, while in Mauritius this is not the case. The data trend for Mauritius is why our employment loss estimates for it are weak and unreliable. We know from the 1st round of the rapid continuous multipurpose household survey that relative to the first quarter of 2020, the number of employed declined in Mauritius by almost 129,400 or about 24%.

Figure 2 helps explain the rationale for our regression model, which allows for each country to have its own regression intercept and slope (our ‘random effects’), rather than assuming a single common intercept and slope for all SADC countries (a purely pooled regression).
2.2 Bayesian model

We estimate the above relationship using a Bayesian hierarchical model. This is also known as a ‘mixed-effects’ model and so combines fixed and random coefficients (Greene, 2003; Meager, 2019). In the Bayesian setting the degree of pooling in the random effects is decided by data rather than imposed by the researcher, such that these random coefficients can be equivalent to fixed effects (no pooling) or complete pooling (one coefficient for all countries), if this is what the data finds.

The model is run on 15 countries (Seychelles is excluded) between 2000 and 2019, \( t = 1 \ldots 20 \) (annual years), and \( c = 1 \ldots 15 \) (countries). With 300 data points we estimate 38 parameters concurrently.

2.2.1 Model regression

\[
\log(\text{Employment}_{t[c]}) = \log(\text{GDP}_{t[c]}) + \text{intercept}_{t[c]} + \epsilon_{t[c]} + \epsilon_{t-1[c]} - \text{Level 1(Pooled)}
\]
\[
+ \text{intercept}_c + \log(\text{GDP}_c) + \epsilon_c - \text{Level 2(Country)}
\]

Equation (1) is the ‘multilevel model’ with two levels (each has different subscripts) (Gelman & Hill, 2007). Level 1 runs a pooled, ‘fixed’, regression and estimates a single common intercept and GDP slope unchanging across countries. This is the average impact of GDP on employment across all SADC countries (and years). We have two error terms because Level 1 has an AR(1) error term \( \epsilon_{t-1[c]} \) to account for correlations over time between observations.

The country-level coefficients estimated in Level 2 can be thought of as ‘random effects’. Where Level 1 predicts variation between countries, Level 2 predicts variation within countries. Level 2 estimates two parameters per country: a GDP slope coefficient and an intercept coefficient (30 country-specific coefficients in total). It also estimates two standard deviation parameters that govern the degree of ‘partial pooling’ for each parameter, and one parameter that estimates the degree of correlation between different random effect parameters across countries (see the Appendix for further details, as in Strauss & Yang, 2020).
A range of other predictors (right-hand side variables) were tested in the model but were found to not improve the model’s performance. These included FDI inflows, US interbank rate, exports and investment spending to GDP, terms of trade, global GDP growth and GDP growth in China, the United States and Europe.

3 | ECONOMETRIC FORECASTS FOR EMPLOYMENT LOSSES: A BAYESIAN APPROACH

3.1 | Baseline model results

Our model converges properly and the Bayesian diagnostics are mostly good (Bayesian $\hat{R} = 1$) but with some divergent transitions. The Bayesian $R^2$ is above 0.9, indicating that the model overfits the data as a whole, despite our prior helping to regularise the estimates.

Figure 3 shows the model’s forecasts: each open circle reflects the model’s median forecast for employment loss (calculated as the model’s estimated 2020 forecast for employment less actual 2019 employment based on observed data). The light red dotted line shows the outer boundaries (the 95% ‘Bayesian credible interval’) of the forecast, encompassing 95% of all forecasts made for that country by our model. The model’s uncertainty is reflected by the red line, bigger implying more uncertainty in the forecast. Uncertainty can come from uncertainty in the coefficients or from the data itself. Our model ensures this uncertainty is propagated forward into the forecast itself.

Unsurprisingly, countries with smaller labour markets have smaller absolute (median) forecast employment losses. However, our model’s forecasts are more complex than that. Madagascar has the largest predicted median employment loss in the model, in relative terms ~44% (Table 1). This may reflect its more labour-intensive exports. In fact, Madagascar is one of the few countries in our data where export growth has a more pronounced impact on employment growth. This may relate to Madagascar’s more diversified economy and export structure, especially relative to single-commodity dependent economies, such as Angola and Botswana. This could allow for global shocks to transmit more rapidly to its domestic economy, though its more diversified economy can also help ensure its recovery is quicker. Mauritius stands out as having the lowest relative and absolute employment

![Figure 3](image_url)
impacts. Mauritius’s projections are hard to interpret at the median because of the extreme uncertainty in their results and so those should be set aside.

Our model results compare favourably with the limited existing knowledge of employment losses in SADC countries from COVID-19. The projected median employment loss for South Africa from our model is 3.65 million, with a 95% credible interval encompassing 2.4–4.7 million job losses (Table 1). In comparison, actual employment losses measured by the NIDS-CRAM survey, as of July 2020, are 2.5–3.6 million people job losses (95% confidence interval). The greater uncertainty in our model’s estimates makes sense, given that our forecasts are for the entire year—rather than just the first half—and that our estimates are projections rather than based on a household survey made representative using sampling weights.8

Tanzania and the DRC have the largest degree of uncertainty in their estimates for total employment losses, such that their 95% credible interval respectively range from less than 1 million to more than 8 million, and from around 3.5 million to almost 10 million (Table 1). Part of this uncertainty appears to be driven by its data and model estimates being outlying, but also perhaps by its labour market being much larger than other countries in our model. This may change how their labour markets function relative to others, according to our model. In addition, the DRC’s relationship between employment and GDP is highly nonlinear, even when logged. Our model may have trouble estimating this as a single relationship (coefficient).9

Figure 4 shows projected (median) total employment losses relative to total employment in 2019 (not accounting for forecast uncertainty). Roughly half of estimated SADC countries have total employment losses below or approaching 25%, while the other half have total job losses in excess of 25%. Lesotho and Mauritius are expected to have the lowest employment losses relative to their pre-existing level of employment (Table 1 above). Mauritius is also expected to have the lowest employment impact in absolute terms. This reflects the weaker historic relationship in Mauritius between GDP growth and employment growth, the reasons for which are uncertain. While Lesotho’s employment impacts are expected to be weaker at the median, we would caution against reading too much into this because of the fairly large 95% credibility interval. This large interval makes sense.

| Country   | Emp 2019 | Emp Loss (95-min) | Emp Loss (median) | Emp Loss (95-max) | Emp Loss (%) |
|-----------|----------|-------------------|-------------------|-------------------|--------------|
| Angola    | 12,257,769 | 3,967,515         | 4,710,126         | 5,405,423         | 38           |
| Botswana  | 884,021   | 257,340           | 315,042           | 368,803           | 36           |
| Comoros   | 213,900   | 64,687            | 78,698            | 90,862            | 37           |
| DRC       | 28,482,225 | 3,466,172         | 6,911,885         | 9,839,208         | 24           |
| Eswatini  | 292,004   | 37,347            | 59,999            | 83,164            | 21           |
| Lesotho   | 746,277   | 49,301            | 110,650           | 168,331           | 15           |
| Madagascar| 13,607,938 | 5,387,724         | 5,984,626         | 6,569,632         | 44           |
| Malawi    | 7,622,490 | 1,757,856         | 2,440,760         | 2,994,596         | 32           |
| Mauritius | 571,709   | –18,573           | 40,963            | 92,382            | 7            |
| Mozambique| 12,765,552 | 700,404           | 2,437,761         | 3,892,762         | 19           |
| Namibia   | 747,040   | 161,320           | 214,860           | 259,130           | 29           |
| South Africa | 16,734,037 | 2,419,320         | 3,658,888         | 4,688,496         | 22           |
| Tanzania  | 26,632,396 | 369,055           | 5,087,864         | 8,224,524         | 19           |
| Zambia    | 6,555,905 | 1,136,474         | 1,832,538         | 2,418,954         | 28           |
| Zimbabwe  | 6,690,726 | 1,328,519         | 1,570,306         | 1,799,539         | 23           |

Note: Emp 2019 shows 2019 employment levels, Emp Loss (min), Emp Loss, and Emp Loss (max) cover the summary statistics of the posterior total employment loss forecasts reflecting the median (Emp Loss), as well as the 95% credible interval of employment losses from the median absolute deviations of the posterior distribution. Emp Loss (%) shows median projected employment loss as a percentage of total employment in 2019.

Source: Authors’ econometric model.
given that the impact of COVID-19 on Lesotho is highly uncertain due to its dependence on the United States and South Africa for over 98% of exports by value.

3.2 | Model extension: Employment loss for women

We rerun the baseline model while changing the dependent variable from total employment to female employment. The relationship between female employment and GDP is plotted in Figure 5. 10 The changing slope of the red line reflects how responsive male employment is to changes in GDP over time, while the blue line reflects the same thing for female employment.

Countries with larger numbers of women employed in the workforce and larger labour markets tend to have more total job losses for women. Figure 6 shows absolute median projected job losses for women due to the pandemic-induced fall in GDP. Madagascar and South Africa, followed by Angola, have the largest median projected job losses for women. Greater losses for Madagascar might reflect a combination of factors, including strong female labour force participation rates and higher rates of female employment in services (World Bank, 2020b). It also might partly reflect different access to property rights for women and lower literacy rates. Women have higher rates of poverty in Madagascar (United Nations Women, 2020), as in most African countries, such that female job losses also likely entail disproportionate increases in poverty rates in the economy from COVID-19. Tanzania and the DRC projections are too uncertain to draw any firm inferences from them.

Figure 7 shows that around one-third of all jobs currently occupied by women risk being done away with during 2020 in Madagascar, Comoros, Angola, Botswana, Namibia, and South Africa. Only Lesotho and Mozambique see 'just' 15% of all jobs occupied by women being lost, at least initially.

For many countries, female job losses account for close to, or more than, half of total jobs (as shown in Figure 8), despite female employment comprising a proportionately smaller share of the workforce. Aside from Mauritius, South Africa, Namibia, and Zimbabwe show a large proportion of projected total job losses coming from female employment. The disproportionate impact on women is also visible when comparing the percentage of total job lost (Table 1) and the percentage of female jobs lost (Figure 8 and Table 2). For example, Angola, Botswana, Comoros, and Malawi are estimated to shed 32%–38% of total jobs, but 47%–51% of female jobs. The difference between total job losses as a percentage of pre-pandemic total employment and female job loss as a percentage of pre-pandemic female employment is highest in Eswatini, Lesotho, Namibia, South Africa, and Zimbabwe (interestingly, all countries tied
3.3 Impacts on incomes from COVID-19

In practice, not all of the impact of COVID-19 will be felt through job losses. Workers may instead be forced to work shorter hours or accept lower pay. Evidence shows a mixture of all three adjustments occur during recessions and COVID-19 (NIDS-CRAM Researchers, 2020). This has relevant implications for policy responses, where a combination of income transfers, unemployment insurance, and other support measures is required to mitigate the multi-faceted risks faced by labour during COVID-19.

We see from Table 3 and Figure 9 that most SADC countries will experience a loss of wage income in excess of 10% of GDP. Only Mauritius, South Africa and Eswatini experience less than this, with DRC and Namibia experiencing a loss around 10%. Madagascar and Zambia both are forecast to see a loss of wage income amounting to a bit less than one-third of GDP. The findings accord with estimates from others models for a given shock to GDP, though arguably with better employment impact estimates.

Significant wage loss is expected for women. The corresponding percentage contractions in wage income resulting from job losses experienced by women is shown in Figure 10. Around half of SADC counties see a 5% contraction in women’s wage income relative to GDP while the other half are in excess of this. Policies at the country level should look to mitigate these income losses through proportionate measures.
3.4 | Policy insights from our model

Next, we extend our model to assess how the different components of final demand (exports, investment, government spending and household consumption) impact employment levels differently across SADC countries. This can help us understand what governments should focus on in their expenditure, both direct and indirect, to best support a recovery in GDP and employment. For example, if government direct spending has little impact on employment then instead government might work to support household expenditure through transfers, or business investment through incentives and enhanced infrastructure.
To explore these questions, we use three new predictors which try and explain employment levels. These are investment (gross fixed capital formation), government consumption spending, and exports, all as a percentage of GDP. These variables are estimated as fixed effects (Level 1), and as random effects (Level 2). In addition, we estimate an intercept coefficient which is fixed and random. Data comes from UNCTADStat covering 2000–2018, except for Angola (2002–2018) and Comoros (2003–2018).

Figure 11 shows that the relative shares of the main components of GDP vary widely across SADC economies.
Despite our small sample we are able to estimate several parameters owing to the use of fairly informative ‘priors’. Our findings are robust to use of alternative priors though.

Equations (2) and (3) are the model regressions taking account of components of GDP.

Level 1—Across all countries (single set of fixed coefficients)

\[
\log(employment_{t[c]}) = \log(EX_{GDP_{t[c]}}) + \log(GOV_{GDP_{t[c]}}) + \log(INV_{GDP_{t[c]}}) + \text{intercept}_{t[c]} + \varepsilon_{t[c]} + \varepsilon_{t-1[c]} + \epsilon
\]  

\[(2)\]
**FIGURE 10** Annual loss of forecasted wage income relative to 2018 GDP (LCU), resulting from female job losses only. Source: Authors.

**FIGURE 11** GDP by component, SADC country, 2018. Note: inv_gdp includes gross fixed capital formation (public and private) plus change in inventories. Nx_gdp is exports plus imports. Source: UNCTADStat.
For SADC as a whole, we find that fixed capital investment spending drives employment growth. Its coefficient is 0.16 (0.04), with the standard error in brackets. Because this is a log-log regression, this coefficient is interpreted as an ‘elasticity’ such that if the ratio of investment to GDP increases by 100% (i.e., by 1 unit), going from say 15% of GDP to 30% of GDP, then employment increases by 16%, say from 10 million to 11.6 million. Government consumption also has a large coefficient size of 0.14 (0.05). The same interpretation as above stands. This implies that government spending has the potential to act as a significant stimulus to employment growth in COVID-19 economies on average. The standard error indicates quite a bit of variation, such that the fixed effect ranges from 0.5 to 0.24 for the 95% credible interval. By contrast, the export share of GDP has a low coefficient, of 0.02 (0.01), indicating that a higher export share in GDP does little to stimulate employment growth among SADC countries as a whole. This may indicate that export-led growth among SADC countries is often reliant on one or two commodities, which does little to create strong employment effects.

We observe variation in these findings across countries. In South Africa, in particular, both investment (0.34 coefficient) and consumption (0.3) has a strong impact on employment, such that the impact of these expenditures as a share of GDP is almost twice as large as in the other SADC countries. By contrast, all other countries show impacts somewhat less than the global mean (i.e., the fixed effect coefficients above). However, this does not change the relative positions of investment, consumption and exports in driving employment growth.

Lastly, our model estimates the correlation between the random effect coefficients. This helps us explore if government spending ‘crowds in’ or ‘crowds out’ investment spending, and in turn employment growth (since both are significantly and positively correlated with employment growth). We find a very strong relationship between cor (log(inv_gdp), log(govconsump_gdp)) = 0.92 (0.11). This implies that investment spending and government spending go together (are positively related), and so crowd each other ‘in’, though the direction and nature of the causality could run in either, or both, directions. Together, these findings have important implications for the policy measures that governments should take.

### 3.5 Model limitations and interpretation

A few provisos are in order when interpreting the model’s results. First, each country’s results should be interpreted in light of the unique economic characteristics and conditions of that country. Unfortunately, that is not possible here, given limited space. Second, while the strong correlation between GDP and employment allows us to get informative econometric forecasts for 2020 employment across SADC countries, this close correlation means that our model’s ‘fit’ is so tight that it struggles to incorporate other predictors and will not fully account for uncertainty in the data through alternative possible ‘fits’. Third, our analysis assumes that GDP impacts employment in a similar manner to its historical relationship for each country. We believe this assumption to be justified based on data coming out of economies across the world, including South Africa. But this is problematic for countries like Mauritius with a weak historical relationship between employment growth and GDP in our data set.

Fourth, our model uses expected changes to GDP as the main factor in estimating the impact on employment. This has two limitations: (1) factors other than the pandemic may influence changes to GDP; and (2) the pandemic may impact economies in novel ways. Neither dimension is a severe limitation. The consensus in the literature is that the pandemic is driving changes in GDP growth. Furthermore, even if the nature of the COVID-19 shock is unique, its impact on the economy (the first link in the causal chain) still manifests in the same way as other shocks: as a contraction in GDP as total spending, incomes and production contract. As a result, GDP still provides a highly informative summary measure of the severity of the impact of COVID-19 on the level of economic activity—including on employment—for SADC economies. It should also be recalled that our analysis is interested in the changes in employment in the COVID-19 context, as indicated by falling GDP, rather than in drawing a direct causal relation between a myriad of pandemic-induced economic changes and employment. Lastly, the analysis does indirectly take into account potentially mitigating government employment policies through the GDP forecasts. But still serves as a basis to inform the scale of the interventions required by governments given estimated GDP and employment falls.
CONCLUSION AND POLICY IMPLICATIONS

Applying a Bayesian multilevel model to developing economies we explore heterogeneity in employment outcome across SADC countries in response to (log) ‘changes’ in GDP. We use the historically estimated relationship between log(GDP) and log(employment) during 2000–2019 to provide econometric forecasts for employment losses for SADC countries for 2020 compared to 2019. We find that roughly half of estimated SADC countries have total employment losses below or approaching 25% of all jobs, while the other half have losses exceeding 25%. Our model shows that job losses are widespread and disproportionate for women workers. Around one-third of all female employment risks being lost during 2020 for Madagascar, Comoros, Angola, Botswana, Namibia, and South Africa. The model also shows the importance of fixed capital investment spending and consumption in driving employment growth and the complementarity between the two.

Despite the noted model limitations, the results have salient policy implications for SADC governments. First, they indicate the severity of potential job losses across the region and provide governments with a sense of the scope of support needed. This can be addressed through the now well-established package of COVID-19 relief measures used and tracked internationally (International Monetary Fund, 2020d, World Bank, 2020c, 2020d, 2020e). These policies consist of three key spheres: income support through social transfers to mitigate the income losses we estimate; wage support to help businesses retain and pay their workers to mitigate employment loss; and business and/or sector-specific support to prevent bankruptcies, including through subsidies, loans, and tax reductions and deferments. This must be complemented by specific measures targeted at the informal economy. All of these require accommodative macroeconomic policy measures. As the first regional study to systematically quantify potential employment loss, this study provides a basis for such planning and budgeting.

Second, our model results indicate the importance in the medium term of focusing on investment spending for stronger recoveries (given its high impact on employment), and that government investment spending complements private investment spending. South Africa for instance, has championed an infrastructure-led recovery in the medium term. This can best increase employment if government spending increases concurrently. Lastly, while impacts vary across countries, regional coordination will be important. Most importantly, the scale of the crisis indicated by this study should spur SADC governments to swift and bold action.

ACKNOWLEDGEMENTS

Thank you to feedback from ILO and SADC members on earlier drafts. All errors are our own.

ENDNOTES

1For ways of modelling the specific nature of the COVID-19 shock see, for example, Strauss et al. (2020).

2Though sometimes being too weak to get a useful inference, as for Mauritius.

3Constructing a regional input-output model to assess employment impacts, while possible, has considerable data requirements and would be a major undertaking for 15 SADC economies.

4We also log transform the variables to make the relationship linear and to improve interpretation as an elasticity. This also helps with the Bayesian sampling when running the actual regression.

5The ‘growth’ interpretation is justified by the use of log transformation.

6Between the first quarter of 2020 and May, 2020, over 2 in 3 jobs’ losses concern informal employment. Informal employment accounts for over 65% of the decline in wage employment and for about 76% of the decline in nonwage employment’ (World Bank and Statistics Mauritius, 2020).

7The intercept in this instance is the baseline/default level of employment when other predictors are at their mean value, since the predictors are mean centred for this regression. This helps in the computation as well as allows for the intercept to have a more meaningful interpretation.

8Note that many workers in South Africa were shown through the NIDS-CRAM survey to also still have a job technically but they were not earning any income. Our model does not account for this, as it assumes all adjustments occur through job losses. For more information, see NIDS-CRAM Researchers (2020).

9A more detailed investigation of these phenomena is not possible in this paper.

10Due to space limitations we do not discuss this figure further here.

11Using a 10% shock to final demand they find a 3.7% fall in wage income relative to GDP and 1.5 million job losses. We use a slightly lower shock at −8% for South Africa based on IMF forecast and find 3.1% of GDP loss in wages and 3.6 million job losses relative to 2019 (Strauss et al., 2020).
It uses an LKJ(1) prior for this. See Stan Manual. We interpret this as a weakly informative prior.

With a very high Bayesian $R^2$ coefficient above 0.9.

In South Africa the immediate employment contraction is roughly proportionate to the GDP shock. Three million jobs were immediately lost from a 40% annualised contraction to GDP after COVID-19. At an annual rate GDP is expected to contract by around 8% with our model predicting 2.4–4.6 million job losses.

ORCID
Ilan Strauss  http://orcid.org/0000-0002-6303-4107

REFERENCES
Adegboye, A. (2020). Macroeconomic policies and sustainable employment yields in sub-Saharan Africa. African Development Review, 32(4), 515–527.

African Development Bank (2020). Southern African Economic Outlook 2020: Coping with the COVID-19 Pandemic. Cote d’Ivoire: African Development Bank. https://www.afdb.org/en/documents/southern-africa-economic-outlook-2020-coping-covid-19-pandemic

Amare, M., Abay, K., Tiberti, L., & Chamberlin, J. (2020). Impacts of COVID-19 on food security: Panel data evidence from Nigeria (IFPRI discussion paper 01956, International Food Policy Research Institute). http://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/133866/filename/134078.pdf

Angelucci, M., Angrisani, M., Bennet, D. M., Kapteyn, A., & Schaner, S. G. (2020). Remote work and the heterogeneous impact of COVID-19 on employment and health (National Bureau of Economic Research online Working paper 27749). https://www.nber.org/papers/w27749

Ardnt, C., Davies, R., Gabriel, S., Harris, L., Makrelov, K., Robinson, S., Levy, S., Simbanevagi, W., van Sventer, D., & Anderson, L. (2020). Covid-19 lockdowns, income distribution, and food security: An analysis for South Africa. Global Food Security, 26, 100410. https://www.sciencedirect.com/science/article/pii/S221191242030064X

Barbosa, R., & Prates, I. (2020). Effects of unemployment, basic emergency income and the Emergency Employment and Income Preservation Program (MP 936) on income, poverty and inequality during and after the pandemic in Brazil. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3630693

Boone, L. (2020). Editorial: Turning hope into reality, OECDiLibrary. https://www.oecd-ilibrary.org/sites/39a88ab1-en/index.html?itemId=/content/publication/39a88ab1-en

Boukar, A. M., Mbock, O., & Kilolo, J. M. (2021). The impacts of the Covid-19 pandemic on employment in Cameroon: A general equilibrium analysis [Special issue]. African Development Review, 2021, 1–14.

Casale, D., & Posel, D. (2020). Gender & the early effects of the COVID-19 crisis in the paid and unpaid economies in South Africa. NIDS-CRAM Wave 1. https://cramsurvey.org/wp-content/uploads/2020/07/Casale-Gender-the-early-effects-of-the-COVID-19-crisis-in-the-paid-unpaid-economies-in-South-Africa.pdf

Chatri, A., Chahbi, I., & Snihji, M. (2021). The multilevel analysis of students’ achievement: Evidence from Morocco. African Development Review, 2021, 1–13.

Chetty, R., Friedman, J. N., Hendren, N., & Stepner, M. (2020). How did COVID-19 and stabilisation policies affect spending and employment? A new real-time economic tracker based on private data (Working paper 27431, National Bureau of Economic Research). https://www.nber.org/papers/w27431

Djoumessi, Y. F. (2021). The adverse impact of the Covid-19 pandemic on the labour market in Cameroon, [Special issue]. African Development Review, 2021, 1–14.

Fana, M., Perez, S. T., & Fernandez-Macias, E. (2020). Employment impact of Covid-19 crisis: From short term effects to long terms prospects. Journal of Industrial and Business Economics, 47, 391–410. https://link.springer.com/article/10.1007/s40812-020-00168-5

Gelman, A., & Hill, J. (2007). Data analysis using regression and multilevel/hierarchical models. Cambridge University Press.

Greene, W. H. (2003). Econometric analysis. Pearson Education.

Ibukun, C. O., & Adebayo, A. A. (2021). Household food security and the COVID
Greene, W. H. (2003). Econometric analysis. Pearson Education.

International Labour Organisation (2020). COVID-19 and the world of work: Impact and policy responses, ILO Monitor 1st ed. https://www., ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/documents/briefingnote/wcms_738753.pdf

International Monetary Fund (2020b). World Economic Outlook, October 2020: A long and difficult ascent. https://www.imf.org/en/Publications/WEO/Issues/2020/09/30/world-economic-outlook-october-2020

International Monetary Fund (2020c). World Economic Outlook Update, January 2020: Tentative stabilization, sluggish recovery? https://www.imf.org/en/Publications/WEO/Issues/2020/01/20/weo-update-january2020

International Monetary Fund (2020d). Policy responses to COVID-19: Policy tracker. https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19

Kurmann, A., Lale, E., & Ta, L. (2020). The impact of COVID-19 on U.S. employment and hours: Real-time estimates with homebase data. Drexel University. https://www.lebow.drexel.edu/sites/default/files/1588687497-hbdraft0504.pdf
Meager, R. (2019). Understanding the average impact of microcredit expansions: A Bayesian hierarchical analysis of seven randomized experiments. *American Economic Journal: Applied Economics, 11*(1), 57–91.

NIDS-CRAM Researchers. (2020). 2020 coronavirus rapid mobile survey: An overview of results and findings. Daily Maverick. https://www.dailymaverick.co.za/article/2020-07-15-overview-chapter-of-the-2020-coronavirus- rapid-mobile-survey-results-and-findings/

Schmidt-Catran, A., & Fairbrother, M. (2015). The random effects in multilevel models: Getting them wrong and getting them right. *European Sociological Review, 32*(1), 23–38.

Strauss, I., Isaacs, G., Rosenberg, J., & Passoni, P. (2020). Rapid country assessment: South Africa. The impacts from a COVID-19 shock to South Africa’s economy and labour market. ILO Country Report. https://www.ilo.org/empolicy/pubs/WCMS_754443/lang-en/index.htm

How to cite this article: Strauss, I., Isaacs, G., & Rosenberg, J. (2021). The effect of shocks to GDP on employment in SADC member states during COVID-19 using a Bayesian hierarchical model. *Afr Dev Rev, 33*, S221–S237. https://doi.org/10.1111/1467-8268.12524

**APPENDIX**

For further model details see Strauss and Yang (2020). For a discussion on the relationship between the Bayesian hierarchical estimator and the fixed effects and random effects estimators see Greene (2003, chapter 16.7). Our regression equations can formally be written in a hierarchical form as:

\[
\log(y_t) \sim \text{Normal}(\log(\mu), \sigma_y),
\]

\[
\mu_{ct} = \beta_0 + X_t \beta_c, \quad \text{for } t \in 1: T
\]

\[
\beta_c \sim \text{MVN}(M_\beta, \Sigma_\beta) \quad \text{for } c \in 1: C
\]

Equation A1 is a log-log model. This makes our dependent variable roughly normal, improves sampling efficiency, and reduces heteroscedasticity. We use a normal likelihood function. The mean of the employment function (Equation A2) is the location parameter \( \mu \) of the normal likelihood, and estimated as the combination of the fixed effect and random effect coefficients. GDP and the intercept are estimated as both fixed effects and random effects (Schmidt-Catran & Fairbrother, 2015). \( \beta_0 \) is the fixed effect intercept parameter estimated from the pooled, population-level regression across all countries. \( X_t \) is the random, group-level, predictor with parameter estimates \( \beta_c \), varying for each country. The country-level regression contain 15 clusters, with each country regression having such that \( T = 20 \) and \( C = 15 \). For each country, Equation A3 estimates the random effects of our model \( \beta_c \), as deviations around the grand mean effect of each parameter \( M_\beta = [\mu_{\text{var}}, \mu_{\text{gdp}}] \), resulting in them being drawn from a common multivariate normal (MVN) distribution. The variance-covariance matrix \( \Sigma_\beta \), is estimated separately for the group of random effect
parameters, with the two variance parameters in each group $\sigma_{\alpha, \text{gdp}}$ determining the extent of variability in parameter estimates across countries.

Variance-covariance structure

Our two random effects are drawn from a wider population distribution, governed by hyper-parameters $\left( \mu_{\beta}, \sum_{\beta} \right)$. Within our country-level regression, the variance-covariance matrix is $\Sigma_{\beta} = D(\sigma) \Omega D(\sigma)$, where $D(\cdot)$ has the standard deviation of each of the two random effect variables along the diagonal. $\Omega$ shows the correlation between the random effect coefficients for different variables.

Priors

We put a loose LKJ prior on the covariance matrix of the multivariate normal distribution, with $\eta = 5$. This means that prior independence between coefficients is assumed. Our list of hyper-priors are:

$$M_{\beta} \sim \text{N}(0.5, 0.1),$$ (A4)
$$\sigma_{\alpha c} \sim \text{Cauchy}(3, 1),$$ (A5)
$$\sigma_{\beta c} \sim \text{Cauchy}(0.2, 0.1),$$ (A6)
$$\Omega_{c} \sim \text{LKJcorr}(5).$$ (A7)

The prior for the variables’ population means $M_{\beta}$ is a normal distribution with mean 0.5 and a highly informative standard deviation of 0.1. Our model is not sensitive to the priors chosen and instead is done to assist with the converge properties of the model. Our other priors are:

$$\alpha^{0} \sim \text{N}(0, 2),$$ (A8)
$$\beta_{0}^{*} \sim \text{N}(0.5, 0.1),$$ (A9)
$$\sigma_{y} \sim \text{Cauchy}(0, 0.1).$$ (A10)