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# The Governance and Disclosure of IFRS 9 Economic Scenarios

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**Abstract:** Extraordinary economic conditions during the COVID-19 pandemic caused many IFRS 9 impairment models to produce unreliable results. Severe market reactions, resulting from unprecedented events, prompted swift action from the regulatory authorities to maintain the financial system's stability. Banks managed the uncertainty and volatility in the models with expert overlays, increasing the risk of biased outcomes. This study examines new ways of enhancing the governance and transparency of the IFRS 9 economic scenarios within banks and suggests additional financial disclosures. Benchmarking is proposed as a useful tool to evaluate the IFRS 9 economic scenarios and ensure effective challenge as part of a model risk governance framework. Archimedean copulas are used to generate objective economic benchmarks. Ideas around benchmarking are illustrated for a set of South African economic variables, and the outcomes are compared to the IFRS 9 scenarios published by the six biggest South African banks in their annual financial statements during the pandemic.

**Keywords:** IFRS 9 impairments; procyclicality; Archimedean copulas; d-vine; economic scenarios; ARIMA–GARCH; spurious correlation; model risk management; financial disclosures; automation

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## 1. Introduction

The International Financial Reporting Standards (IFRS) 9 and the corresponding Generally Accepted Accounting Principles (US GAAP) accounting standards have been developed in response to the Financial Stability Financial Stability Forum's (2009) findings that early recognition of loan losses could have decreased the impact of procyclicality during the global financial crisis of 2009. The term procyclicality refers to variables that move with the financial cycle in a highly correlated manner, reinforcing the cycle and amplifying fluctuations, increasing the risk of financial instability. IFRS 9 was introduced with the expectation that banks would recognise higher expected credit losses (impairments) in good times to prepare for economic downturns, which then would smooth the financial cycle. The early recognition of impairments is achieved by incorporating forward-looking information in the form of economic scenarios into the calculation, which leads to impairments that are sensitive to the economic cycle and more volatile (International Accounting Standards Board 2014; Stander 2021).

Events during the COVID-19 pandemic confirmed that there is still significant risk of procyclicality. Market uncertainty led to economic outcomes never experienced before. Regulatory authorities had to issue guidance on how to handle the macroeconomic assumptions to avoid impairment volatility and ensure the stability of the financial system (European Central Bank 2020; SARB 2020a). Volatile impairments have a negative impact on the earnings quality of a bank.

The extraordinary economic conditions caused many of the econometric models used in the derivation of the IFRS 9 impairments to become unreliable and not fit for use (El Barnoussi et al. 2020; Breeden et al. 2021). Uncertainty around economic outcomes, structural correlation breaks, and unreliable econometric models caused banks to use post-model adjustments (expert overlays) to ensure the appropriate levels of impairments. The overlays refer to the adjustments to the modelled impairment outcome (European Banking Authority 2021; Marlin 2021).

Supervisory authorities require strong governance around the use of expert overlays (European Banking Authority 2021). Expert overlays have the potential to produce biased outcomes, which is contrary to the intent of accounting standards. The purpose of the accounting standard is to ensure reliable and consistent accounting policies, that financial statements are neutral, and that financial results and disclosures are comparable (International Accounting Standards Board 2018). Where expert judgement is used to override economic outcomes, there is a further risk of forced breaks in the econometric models, which may have downstream implications as the models are simplistic representations of very complex interrelated systems.

Based on the importance of the scenarios in determining impairments, the study explores greater governance around economic scenarios in the IFRS 9 framework. A robust model risk framework increases confidence in the modelled outcomes and reduces the need for expert overrides in future stress periods. It is also a useful tool to provide assurance to the audit function concerned about material judgments in the financial statements (European Securities and Markets Authority 2020; Caruso et al. 2021). The current IFRS disclosure requirements around the economic assumptions in the annual financial statements are considered, and further disclosure is proposed.

An important contribution of this study is to illustrate how economic benchmarks can be derived and used to assess the suitability of IFRS 9 scenarios. This study extends existing research by introducing a copula vine algorithm that considers causality and the optimal lag at which to link variable pairs into a d-vine structure. Research has shown the benefit of using vine structures instead of more simplified approaches such as Gaussian dependence structures (Semenov and Smagulov 2019). The d-vine is very flexible and captures many different types of dependence structures. In this study, 22 different copulas sourced from Nelsen (2006) are considered in the derivation of the d-vine. The proposed approach helps to identify the instances where expert judgement led to broken economic relationships and to generate events that have not occurred historically.

It is challenging to obtain appropriate economic benchmarks as there is no standard economic narrative used by all banks. The published benchmarks generally only contain a select set of key variables and usually only for a baseline scenario (IMF 2022; World Bank 2022).

The remainder of the paper is organised as follows. Section 2 provides a literature review around economic forecasting, and Section 3 explores approaches to evaluate the economic forecasts. Section 4 provides a brief overview of multivariate copulas and the copula vine algorithm used to produce economic benchmarks. In Section 5, the expected trends between the economic variables and non-performing loans (NPLs) are established. The proposed approach is illustrated by deriving benchmarks for a set of South African economic variables, and the outcomes are compared to the IFRS 9 economic scenarios published by the six biggest South African banks in their annual financial statements. The results are summarised in Section 6. Financial disclosures are considered in Section 7. The contributions of this paper and the final remarks are summarised in Section 8.

## 2. Literature Review

The international benchmark studies indicate that the IFRS 9 economic scenarios are usually the responsibility of the bank's economics unit. The economics unit formulates scenario stories based on current political and economic events, which are then extrapolated to impacts on specific economic variables. Generally, three to five scenarios are generated, and each scenario is assigned a probability of being realised (Global Credit Data 2019).

Economic forecasters apply expert overrides when they do not agree with a modelled outcome. Analytical models developed on historical relationships often break down in times of economic stress. It is difficult to capture structural breaks, and the historical data are generally not adequate to develop bespoke models for the different phases of the economic cycle (Kenny and Morgan 2011; Arnold 2018).

The model forecast errors are significant when there are market shocks never experienced historically. During the COVID-19 pandemic, researchers attempted to predict the economic recovery process by drawing lessons from the previous pandemic, the Spanish flu in 1918–1920, but acknowledged that the 2020 economic environment was very different (Bishop 2020).

Macroeconomic forecast models are generally divided into two broad categories: structural models and reduced-form models (Lewbel 2019). Structural models explain economic behaviour based on economic theory which, given the complexity of the economy, leads to intricate systems of equations. The reduced-form models make use of causal relationships to model the observed behaviour over time, instead of using pre-defined economic theory to inform the equations. Reduced-form models often produce more accurate forecasts, but they are more difficult to interpret (Carriero et al. 2019; Lewbel 2019). Lewbel (2019) argues that techniques such as machine learning uncover previously unknown relationships between economic variables and will increase the demand for structural models to make sense of the observed relationships.

There are many economic scenario generation approaches. Dynamic stochastic general equilibrium (DSGE) models have been proven successful, especially when incorporating stochastic volatility (Diebold et al. 2017). Abe et al. (2019) propose Markov-switching DSGE models to allow for changes in monetary/fiscal policy.

Factor models are reduced-form models that summarise information from big datasets. Techniques such as principal component analysis are used to summarise a big dataset into a smaller set of factors which is then used in a regression model for each economic variable (Groen and Kapetanios 2016; Carriero et al. 2019; Chudy and Reschenhofer 2019).

Hirano (2018) applies a filtered historical simulation, sampling from the estimated residual vectors when simulating paths for the economic time series.

Elshendy and Colladon (2017) suggest including big data analysis in the form of news sourced from social network sites. They consider news-related variables, such as volume and tone, and show how these variables improve econometric models.

Vector autoregressive (VAR) models are multivariate time series models, where the relationships between the set of variables and all the lagged variables are simultaneously estimated. These models are usually highly parameterised, depending on the number of variables and the lags included, which may be a problem when there are limited historical data. Too many lags inflate the standard errors of the time series coefficients and increase the forecast errors, while omitting lags may lead to biased estimates. Bayesian VAR is an extension of the VAR model where the parameters are treated as random variables with prior information on the parameters incorporated in the model estimation (Miranda-Agrippino and Ricco 2018).

Brechmann and Czado (2015) note that VAR models only capture linear and symmetric dependence and propose copulas as a useful alternative.

Copulas are more parsimonious functions and allow for great flexibility in the modelling of multivariate distribution functions as they allow for asymmetric relationships where upper- or lower-tail dependence may be present; additionally, they capture positive and negative relationships (Nelsen 2006). Copulas allow for the marginal distributions to be specified separately from the dependence structure that links the variables to form the joint distribution function (Patton 2013). The flexibility of copulas in time series models has been explored by many researchers, who have considered the link with VAR models or the models that simultaneously consider serial dependence and interdependence between time series (Remillard et al. 2012; Brechmann and Czado 2015; Zhao et al. 2021).

This study extends the existing research by introducing an algorithm to first filter the time series for non-stationarity and serial correlation and then considering the causality and the optimal lag at which to link the variable pairs in multivariate dependence structures. Economic benchmarks are constructed from the dependence structures. The proposed approach is a reduced-form model where the relationships are modelled based on the multivariate dependence structure, instead of applying economic theory in a structural framework.

## 3. The Governance of Economic Forecasts

The importance of model risk management was highlighted during the pandemic when extraordinary economic conditions caused many of the econometric models used to derive the IFRS 9 impairments to produce unreliable results. As many banks resorted to the use of management overlays to manage market volatility, care had to be taken to ensure the accounting standard's continuing neutral application to offer objective and decision-useful information (El Barnoussi et al. 2020).

Table 1 summarises the economic outlook for a select set of economic variables as disclosed by the six biggest South African banks in their annual financial statements. The banks do not disclose information on the same set of economic variables. The forecasts are as published at each financial year-end (FYE) from 2019 to 2021 and cover a one-year period. It is not possible to go back further because IFRS 9 only came into effect in 2018, with very little disclosure around the economic scenarios at that time. Comparing the economic forecasts of the banks is challenging due to differences in FYE, the scenario narratives, the number of scenarios, and the probabilities assigned to each scenario.

**Table 1.** Economic outlook over a 1-year period for select economic variables as disclosed by six South African banks in their annual financial statements.

| Bank | FYE | Scenario | Scenario Probability Range | FYE 2019 SA Real GDP YoY | FYE 2020 SA Real GDP YoY | FYE 2021 SA Real GDP YoY | FYE 2019 SA Repo Rate | FYE 2020 SA Repo Rate | FYE 2021 SA Repo Rate |
|---|---|---|---|---|---|---|---|---|---|
| Bank 1 | 31-Dec | Upside | 20% to 21% | 1.40% | 3.85% | 3.08% | 5.90% | 3.50% | 4.00% |
| | | Baseline | 50% | 0.70% | 3.04% | 1.75% | 6.30% | 3.50% | 4.75% |
| | | Downside | 10% to 21% | 0.30% | 2.84% | −0.09% | 6.80% | 3.75% | 5.00% |
| | | Severe Stress | 8% to 20% | n.a. | 2.14% | −1.41% | n.a. | 3.92% | 5.25% |
| | | Weighted Average | | n.a. | 3.10% | 1.39% | n.a. | 3.59% | 4.69% |
| Bank 2 | 31-Dec | Upside | 16% to 25% | 1.96% | 6.52% | 2.87% | 6.00% | 3.25% | 4.25% |
| | | Baseline | 55% | 1.33% | 4.79% | 2.05% | 6.25% | 3.75% | 4.50% |
| | | Downside | 20% to 28% | 0.18% | 5.87% | 1.36% | 7.19% | 4.75% | 5.25% |
| | | Weighted Average | | 1.26% | 5.38% | 2.00% | 6.38% | 3.96% | 4.67% |
| Bank 3 | 31-Dec | Upside | 30% | 2.90% | 3.20% | 2.20% | 4.60% | 2.90% | 4.30% |
| | | Baseline | 40% | 1.50% | 3.20% | 1.70% | 6.50% | 3.30% | 3.90% |
| | | Downside | 30% | −1.40% | 3.00% | 0.80% | 9.00% | 3.90% | 4.10% |
| | | Weighted Average | | 1.05% | 3.14% | 1.58% | 6.68% | 3.36% | 4.08% |
| Bank 4 | 30-Jun | Upside | 12% to 23% | 2.83% | −0.60% | 4.20% | 6.19% | 2.75% | 3.25% |
| | | Baseline | 56% to 59% | 1.05% | −0.60% | 3.10% | 6.75% | 3.25% | 3.50% |
| | | Downside | 18% to 32% | 0.31% | −2.00% | −1.90% | 8.19% | 6.00% | 6.35% |
| | | Weighted Average | | 1.33% | −1.05% | 1.79% | 6.88% | 4.07% | 4.29% |
| Bank 5 | 31-Mar | Positive Outcome | 1% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Upside | 2% to 10% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Baseline | 42% to 48% | n.a. | −4.40% | 4.50% | n.a. | 4.80% | 3.60% |
| | | Downside | 37% to 44% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Severe Stress | 5% to 10% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Weighted Average | | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| Bank 6 | 28-Feb | Upside | 5% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Baseline | 60% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Downside | 35% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Weighted Average | | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |

**Table 1.** *Cont.*

| Bank | FYE | Scenario | Scenario Probability Range | FYE 2019 SA Inflation Rate | FYE 2020 SA Inflation Rate | FYE 2021 SA Inflation Rate | FYE 2019 Exchange Rate USD/ZAR | FYE 2020 Exchange Rate USD/ZAR | FYE 2021 Exchange Rate USD/ZAR |
|---|---|---|---|---|---|---|---|---|---|
| Bank 1 | 31-Dec | Upside | 20% to 21% | 4.20% | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Baseline | 50% | 4.30% | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Downside | 10% to 21% | 5.20% | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Severe Stress | 8% to 20% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Weighted Average | | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| Bank 2 | 31-Dec | Upside | 16% to 25% | 4.38% | 3.68% | 4.30% | 13.70 | 14.50 | 14.43 |
| | | Baseline | 55% | 4.60% | 4.06% | 4.72% | 14.83 | 15.46 | 15.03 |
| | | Downside | 20% to 28% | 6.03% | 5.42% | 5.18% | 16.44 | 17.50 | 15.58 |
| | | Weighted Average | | 4.83% | 4.39% | 4.78% | 12.67 | 15.90 | 15.08 |
| Bank 3 | 31-Dec | Upside | 30% | 3.50% | 4.10% | 4.40% | n.a. | n.a. | n.a. |
| | | Baseline | 40% | 5.20% | 3.90% | 4.40% | n.a. | n.a. | n.a. |
| | | Downside | 30% | 8.20% | 3.60% | 5.20% | n.a. | n.a. | n.a. |
| | | Weighted Average | | 5.59% | 3.87% | 4.64% | n.a. | n.a. | n.a. |
| Bank 4 | 30-Jun | Upside | 12% to 23% | 3.99% | 3.30% | 3.10% | 12.60 | 12.30 | 12.00 |
| | | Baseline | 56% to 59% | 4.89% | 3% | 4.10% | 14.50 | 15.40 | 15.20 |
| | | Downside | 18% to 32% | 6.89% | 4.70% | 7.20% | 16.45 | 17.30 | 19.70 |
| | | Weighted Average | | 5.04% | 3.58% | 4.87% | 14.41 | 15.64 | 16.09 |
| Bank 5 | 31-Mar | Positive Outcome | 1% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Upside | 2% to 10% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Baseline | 42% to 48% | n.a. | n.a. | n.a. | n.a. | 16.60 | 15.40 |
| | | Downside | 37% to 44% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Severe Stress | 5% to 10% | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| | | Weighted Average | | n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| Bank 6 | 28-Feb | Upside | 5% | n.a. | 4.10% | 2.60% | n.a. | n.a. | n.a. |
| | | Baseline | 60% | n.a. | 4.60% | 2.90% | n.a. | n.a. | n.a. |
| | | Downside | 35% | n.a. | 5.20% | 3.10% | n.a. | n.a. | n.a. |
| | | Weighted Average | | n.a. | 4.79% | 2.96% | n.a. | n.a. | n.a. |

The scenario probabilities are usually high for the baseline case and then more evenly distributed amongst the others, except for the severe stress, which generally has a low probability. During the pandemic, the likelihood of a negative outcome increased.

It is noteworthy how the economic outlooks of the banks evolved during 2019–2021. The volatility in the economic forecasts between the years is indicative of the level of uncertainty. An interesting line of research would be to consider the extent to which sentiment affects economic outcomes. Behavioural finance theory postulates that emotion and cognitive biases may lead to irrational decisions with disastrous consequences to the market (Paule-Vianez et al. 2020). Reichmann (2020) highlights the role of emotion in economic forecasting and suggests that forecasters are influenced by social interaction and general news. By developing a feeling for economic trends, forecasters attempt to overcome shortcomings in economic theory and models. A way to manage the subjectivity in economic forecasts is to combine the results from different forecasters and models (McAlinn et al. 2019; Montero-Manso et al. 2020). If the regulatory authorities had not provided guidelines to lessen the impact, the volatility of the economic forecasts presented in Table 1 may have been much worse (European Central Bank 2020; SARB 2020a).

Evaluating the economic forecasts is not only important as part of the model risk framework, it also ensures the appropriateness of the IFRS 9 impairments derived from them. There are various approaches to the evaluation of economic forecasts. Model risk governance requires effective challenge and the demonstration of conceptual soundness. Sensitivity analyses in the form of attribution reports are useful to understand the key drivers of risk (Stander 2021).

A common approach to evaluate economic scenarios is to benchmark with consensus forecasts or third-party scenarios. The published benchmarks typically only capture a select set of variables and are only for a baseline case that may not be consistent with the scenario narrative of the bank. It is important to understand how the benchmarks were derived to ensure they are used appropriately (Financial Reporting Council 2019). This study addresses these shortcomings by illustrating how benchmarks can be derived that capture the economic outlook of the specific bank and enhance the economic review process.

The backtesting of economic forecasts is important. Backtests show whether the scenarios accurately predicted the market outcomes and can reveal areas where approaches need to be revised (IFRS Foundation 2016).

In summary, the events during the pandemic highlighted the need for greater transparency around economic scenarios given the impact on impairments. This study provides a way to improve the governance process by ensuring effective challenge in the form of benchmarks designed specifically for the bank.

## 4. Methodology

The copula vine algorithm is introduced as a tool to construct economic benchmarks for the IFRS 9 scenarios. The copula vine is constructed by first finding the variable pairs that exhibit the strongest correlation at the optimal lag and then iteratively building a multivariate copula based on those variable pairs.

### *4.1. Overview of Copulas*

A copula is a multivariate distribution function defined by:

$$H(x_1, \cdots, x_n) = C(F_1(x_1), \cdots, F_n(x_n))$$

where $H$ denotes the $n$-dimensional distribution function with margins $F_1, \cdots, F_n$, and $C$ denotes the copula function (Sklar 1959). A copula allows for the marginal distributions to be specified separately from the dependence structure (Patton 2013).

In this study, Archimedean copulas are used. Archimedean copulas are constructed with a generator function $\varphi$ that is continuous and strictly decreasing from $I = [0, 1]$ to $[0, \infty]$. The bivariate Archimedean copula is defined by

$$C(u_1, u_2) = \varphi^{-1}(\varphi(u_1) + \varphi(u_2)) \tag{1}$$

where $\varphi^{-1}$ denotes the pseudo-inverse function and $u_1$, $u_2$ in $I$ (Nelsen 2006). Kimberling (1974) shows that, for a strict generator function, multivariate copulas can be constructed by applying Equation (1) repeatedly:

$$C(u_1, u_2, u_3) = C(C(u_1, u_2), u_3) = \varphi^{-1}(\varphi(u_1) + \varphi(u_2) + \varphi(u_3))$$

so that in general the $n$-dimensional copula can be constructed using

$$C(u_1, \cdots, u_n) = \varphi^{-1}(\varphi(u_1) + \cdots + \varphi(u_n))$$

The conditions to ensure the validity of $C(u_1, \cdots, u_n)$ are explored in Nelsen (2006) and McNeil and Neslehová (2009). Copula vines extend the Kimberling construction by relaxing the assumption of using the same generator function in each step (Savu and Trede 2006). The fully nested copula is constructed using $\varphi_1$ to model the dependence between the first two variables and then using $\varphi_2$ when adding the third variable:

$$C(u_1, u_2, u_3) = \varphi_2^{-1}\left(\varphi_2 \circ \varphi_1^{-1}(\varphi_1(u_1) + \varphi_1(u_2)) + \varphi_2(u_3)\right)$$

and continuing this way with a new generator function for each additional variable added.

In this study, the d-vine copula structure is used. Aas et al. (2009) show how to use bivariate Archimedean copulas to build a multivariate structure by fitting bivariate copulas iteratively to different variable pairs. The d-vine structure for four variables is illustrated in Figure 1. The second level indicates that the bivariate copulas are fitted to the variable pairs {1;2}, {2;3}, and {3;4}, respectively. The third level shows that the bivariate copulas are fitted to {1 | 2; 3 | 2} and {2 | 3; 4 | 3} using the conditional copula function. Finally, in level four, the bivariate copulas are fitted to {1 | 2,3; 4 | 2,3}. The algorithm is easily scalable to many variables.

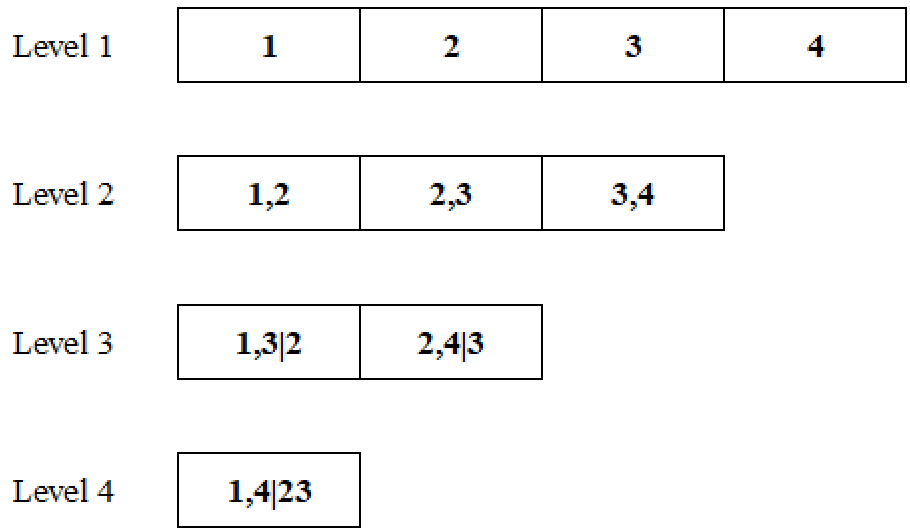


**Figure 1.** Example of a d-vine copula structure for four variables.

In constructing the d-vine, the 22 Archimedean copulas, as outlined in Nelsen (2006), are considered for each variable pair. The generator functions are summarised in Table 2. At each node on the d-vine, the 22 Archimedean copulas are fitted, and the best fit is selected based on the Kolmogorov–Smirnov test statistic that compares the distribution function $K_c(t)$ of the random variable $C(U_1, U_2)$ with its nonparametric counterpart. For Archimedean copulas, the distribution function $K_c(t)$ can be derived from the generator function $K_c(t) = t - \frac{\varphi(t)}{\varphi'(t)}$. Please refer to Genest and Remillard (2005), Genest et al. (2006), and Genest et al. (2007) for detailed discussions.

**Table 2.** Summary of the Archimedean copulas and their generating functions considered in constructing the d-vine.

| No. | Copula Name | Generator Function $\varphi_\alpha(t)$ | Copula Parameter Range |
|---|---|---|---|
| 1 | Clayton | $\frac{1}{\alpha}(t^{-\alpha}-1)$ | $[-1,\infty)\backslash\{0\}$ |
| 2 | N2 | $(1-t)^{\alpha}$ | $[-1,\infty)$ |
| 3 | Ali-Mikhail-Haq | $\ln\frac{1-\alpha(1-t)}{t}$ | $[-1,1)$ |
| 4 | Gumbel | $(-\ln t)^{\alpha}$ | $[1,\infty)$ |
| 5 | Frank | $\ln\frac{e^{-\alpha t}-1}{e^{-\alpha}-1}$ | $(-\infty,\infty)\backslash\{0\}$ |
| 6 | Joe | $-\ln\left(1-(1-t)^{\alpha}\right)$ | $[1,\infty)$ |
| 7 | N7 | $-\ln(\alpha t+(1-\alpha))$ | $(0,1]$ |
| 8 | N8 | $\frac{1-t}{1+(\alpha-1)t}$ | $[1,\infty)$ |
| 9 | Gumbel–Barnett | $\ln(1-\alpha\ln t)$ | $(0,1]$ |
| 10 | N10 | $\ln\left(2t^{-\alpha}-1\right)$ | $(0,1]$ |
| 11 | N11 | $\ln(2-t^{\alpha})$ | $\left(0,\frac{1}{2}\right]$ |
| 12 | N12 | $\left(\frac{1}{t}-1\right)^{\alpha}$ | $[1,\infty)$ |
| 13 | N13 | $(1-\ln t)^{\alpha}-1$ | $(0,\infty)$ |
| 14 | N14 | $\left(t^{\frac{-1}{\alpha}}-1\right)^{\alpha}$ | $[1,\infty)$ |
| 15 | Genest–Ghoudi | $\left(1-t^{\frac{1}{\alpha}}\right)^{\alpha}$ | $[1,\infty)$ |
| 16 | N16 | $\left(\frac{\alpha}{t}+1\right)(1-t)$ | $[0,\infty)$ |
| 17 | N17 | $-\ln\frac{(1+t)^{-\alpha}-1}{2^{-\alpha}-1}$ | $(-\infty,\infty)\backslash\{0\}$ |
| 18 | N18 | $e^{\frac{\alpha}{(t-1)}}$ | $[2,\infty)$ |
| 19 | N19 | $e^{\frac{\alpha}{t}}-e^{\alpha}$ | $(0,\infty)$ |
| 20 | N20 | $exp\left(t^{-\alpha}\right)-e$ | $(0,\infty)$ |
| 21 | N21 | $1-\left[1-(1-t)^{\alpha}\right]^{1/\alpha}$ | $[1,\infty)$ |
| 22 | N22 | $arcsin(1-t^{\alpha})$ | $(0,1]$ |

The algorithms used to estimate the copula parameters and simulate the values from the copula vines can be found in Aas et al. (2009) and Kurowicka and Joe (2011). In this study, canonical maximum likelihood estimation is used to estimate the copula parameters (Cherubini et al. 2004). The algorithms used in this paper have been developed and implemented in Python (Python Core Team 2019).

### *4.2. Spurious Correlation and Stationarity*

In 1897, Karl Pearson highlighted the dangers of spurious correlation. Spurious correlation arises where two uncorrelated series have a significant correlation coefficient, which is typically due to a different common factor that affects both (Pearson 1897; Aldrich 1995). It is important to first handle non-stationarity and serial correlation before attempting a correlation analysis of a time series. Most economic and financial data are non-stationary, with means and variances that fluctuate over time (Hendry and Juselius 2000; Granger et al. 2001; Hendry and Pretis 2016).

The ARIMA–GARCH models are used to allow for non-stationary trends and time-dependent volatility in the data. The ARIMA($p_A, d, q_A$)–GARCH($p$,$q$) model for a stationary time series $y_t$ with $d = 0$ is defined as follows (Ruppert 2011):

$$y_t = \lambda_0 + \sum_{i=1}^{p_A} \lambda_i y_{t-i} + \sum_{i=1}^{q_A} \psi_i \varepsilon_{t-i} + \varepsilon_t \tag{2}$$

$$\varepsilon_t = \eta_t \sqrt{h_t} \tag{3}$$

$$h_t = \omega + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{4}$$

where $\eta_t = \varepsilon_t / \sqrt{h_t} \sim F(0, 1)$, $p_A \geq 0$, $q_A \geq 0$, $|\lambda_i| < 1$, $|\psi_i| < 1$, $p \geq 0$, $q > 0$, $\omega > 0$, $\gamma_i \geq 0$, and $\beta_i \geq 0$. The $p_A$ and $q_A$ denote the order of the autoregressive and moving average components, respectively. In the GARCH model, $p$ denotes the number of lag variances, and $q$ is the number of lag residual errors. When $p = 0$, the GARCH model reduces to the ARCH($q$) model.

The stationarity of the economic variable is first established by using the autocorrelation (ACF) and partial autocorrelation (PACF) plots and then confirmed with the augmented Dickey–Fuller (ADF) test. In most cases, the first differences of the economic variable lead to stationarity and are denoted as ARIMA($p_A, d, q_A$), where $d$ denotes the order of the differencing applied. Where seasonality was detected, the model was extended to ARIMA$(p_A, d, q_A)(p_S, d_S, q_S)_S$, where $p_S$, $d_S$, and $q_S$ denote the order of the seasonal components at a lag of $s$. For example, for a stationary time series $y_t$ modelled by ARIMA$(3, 0, 0)(2, 0, 0)_4$, the representation is

$$\left(1 - \lambda_1 B^1 - \lambda_2 B^2 - \lambda_3 B^3\right)\left(1 - \Lambda_4 B^4 - \lambda_8 B^8\right)(y_t - \lambda_0) = \varepsilon_t$$

where $\Lambda_i$ denotes the autoregressive parameters of the seasonal components with $s = 4$, and $B$ denotes the differencing operator defined as $(1 - B^n) y_t = y_t - y_{t-n}$. All the other symbols are as defined before.

The ARIMA–GARCH model coefficients are estimated by the *Statsmodels* and *ARCH_model* software libraries in Python. Maximum likelihood estimation is used.

The multivariate copula is fitted to the set of residuals $\{\eta_{1t}, \eta_{2t}, \cdots, \eta_{nt}\}$, where $\eta_{jt}$ denotes the residuals from the ARIMA–GARCH model for variable $j$.

### 4.3. Copula Vine Algorithm

The copula vine algorithm is used to find the optimal order in which to link the economic variables by starting with the variable pairs with the highest correlation. The algorithm is as follows:

The copula vine is constructed on $n$ economic variables denoted by $\eta_1, \cdots, \eta_n$.

1. Convert all the variables to standard uniform variables using the probability integral transform and empirical marginal distribution functions (Angus 1994). The uniform variables are denoted as $U_1, \cdots, U_n$ where $U_j$ corresponds to $\eta_j$.
2. Calculate the correlation between each variable pair at monthly or quarterly lags out to $m$ years. Typically, lags out to one year were considered in this study.
3. Look up the correlation and lag at which each variable pair displays the highest correlation with the correct sign based on the predefined expected trend (discussed in Section 5). Say, for instance, that the highest correlation is observed between (lagged) $U_1$ and $U_n$. In the next step, consider all the remaining variables, $U_2, \cdots, U_{n-1}$, and find which one is most correlated with the (now lagged) $U_n$. This process is repeated until all the variables have been processed or when there are no variables left exhibiting a significant correlation. This process creates lists of ordered variables based on the strength of the correlation and causal links.
4. Construct the d-vine multivariate copula from the list of ordered variables, where the underlying dataset has been adjusted to incorporate the lags.

In using empirical marginal distribution functions, no assumptions are necessary around the parametric distribution functions of the economic variables. The cross-correlation function is used to test the significance of the correlations observed. The dependence structure between each variable pair is modelled with a bivariate Archimedean copula.

*4.4. Generating Scenarios Using Conditional Copulas*

The economic scenarios are generated using conditional copulas. Let $U_1^*, \cdots, U_n^*$ denote the set of ordered uniform variables from the copula vine algorithm. The variables $U_1^*, \cdots, U_n^*$ have a joint distribution function $C$, and the conditional distribution of the $U_k^*$ given values of $U_1^*, \cdots, U_{k-1}^*$ is given by (Cherubini et al. 2004):

$$C_k(u_k|u_1, \cdots, u_{k-1}) = \frac{\left[\partial^{k-1} C_k(u_1, \cdots, u_k)\right] / [\partial u_1 \cdots \partial u_{k-1}]}{\left[\partial^{k-1} C_{k-1}(u_1, \cdots, u_{k-1})\right] / [\partial u_1 \cdots \partial u_{k-1}]} \tag{5}$$

where $C_k$ denotes the conditional distribution function. The procedure for generating values using the conditional copula function is:

- Generate $u_1$ from the uniform distribution $U(0, 1)$.
- Generate $u_2$ from $C_2(\cdot|u_1)$.
- Generate ...
- Generate $u_n$ from $C_n(\cdot|u_1, \cdots, u_{n-1})$.

The algorithms used to simulate values from the copula vines were implemented in Python. The simulated variables are converted back to the original distribution functions using

$$\eta_j^* = F_j^{-1}(u_j) \tag{6}$$

where $\eta_j^*$ denotes the simulated variable and $F_j^{-1}$ denotes the inverse of the marginal distribution function for variable $j = 1, \cdots, n$.

## 5. Economic Data and Trends

The economic scenarios provide the forward-looking information required in the derivation of the IFRS 9 probability-of-default (PD), loss-given-default (LGD), and exposure-at-default (EAD), which in turn are used to calculate the impairments. Incorrect scenario trends will feed through to the IFRS 9 risk parameters and in turn lead to inappropriate impairments. In this section, the expected trend between each economic variable and the NPL is established based on the published economic studies.

*5.1. Data*

The economic benchmarks are derived for a set of South African variables. The economic variables were selected to cover different market aspects such as monetary policy (inflation rate and interest rate), labour markets (Gross Domestic Product (GDP) and unemployment rate), consumption, and business confidence (currencies and investment). The dependence structures between the following variables are analysed:

- GDP: SA real GDP year-on-year;
- PDI: Personal disposable income year-on-year;
- BOND: Annual moves in the long-term nominal bond yield;
- CPI: SA inflation rate calculated as the consumer price index year-on-year;
- PPI: Producer price index year-on-year;
- USDZAR: USD/ZAR year-on-year;
- GBPZAR: GBP/ZAR year-on-year;
- EURZAR: EUR/ZAR year-on-year;
- GDE: Real gross domestic expenditure year-on-year;
- HCE: Household consumption expenditure year-on-year;
- HCEG: Household consumption expenditure over GDP year-on-year;

- HHDI: Household debt to disposable income year-on-year;
- UNEMP: SA unemployment rate year-on-year;
- PCE: Private sector credit extension year-on-year;
- FIR: Residential fixed investment year-on-year.

Please refer to Appendix A for the details on the data sources. Quarterly data from 2000 to 2020 were sourced.

### 5.2. Expected Trends

The following expected trends are built into the copula vine algorithm:

- A negative relationship between real GDP growth and NPLs. Positive GDP growth is generally associated with higher household income and lower HHDI (Messai and Jouini 2013; Ghosh 2015; Kuzucu and Kuzucu 2019; Olarewaju 2020).
- A positive relationship between UNEMP and NPLs. Unemployment reduces the purchasing power of households and increases the debt burden. It leads to a decline in effective demand and lower GDE. Higher unemployment implies lower PDI (Rinaldi and Sanchis-Arellano 2006; Messai and Jouini 2013; Kuzucu and Kuzucu 2019; Syed and Aidyngul 2022).
- Increasing interest rates lead to higher NPLs (Messai and Jouini 2013; Kuzucu and Kuzucu 2019; Syed and Aidyngul 2022).
- The relationship between inflation and NPLs is not always straightforward, but in this study, a positive relationship is implemented given the negative impact of inflation on economic growth (Hodge 2006; Rinaldi and Sanchis-Arellano 2006; Nkusu 2011; Ghosh 2015; Olarewaju 2020).
- Sanusi and Meyer (2018) show a positive relationship between inflation and the exchange rate. A depreciation of the exchange rate is correlated with higher NPLs due to the impact on imports and the higher costs involved.
- Low economic growth and a decline in business confidence reduce the demand for credit. Nkusu (2011) shows that a decrease in credit extension is correlated with an increase in NPLs.
- Declines in real estate investment are correlated with economic downturns and implicitly higher NPLs (Żelazowski 2017; Kohlscheen et al. 2018).

## 6. Results

### 6.1. Handling Non-Stationarity and Serial Correlation

The economic data are filtered for non-stationarity and serial correlation using the ARIMA–GARCH structure. The quarterly data from March 2000 to December 2018 are used to estimate the parameters of the ARIMA–GARCH models, except for UNEMP and PCE, where the data from 2010 are used to capture the structural break observed for the two series since 2010. The 2019–2020 data are used in the out-of-sample test.

The best model for each economic variable was selected by ensuring statistically significant parameters, no remaining autocorrelation, and the lowest AIC test statistic, as discussed in Section 4.2. The first differences ($d$ = 1 in the ARIMA($p_A, d, q_A$) model) were calculated for all the variables to establish stationarity. No seasonal differencing was required ($d_S = 0$).

The estimated parameters of the ARIMA–GARCH model are shown in Table 3, using the notation defined in Section 4.2. The estimated coefficients are significant at the 5% confidence level, except for the ARIMA model constant $\lambda_0$ that does not differ significantly from zero in all the fitted models. The estimated models capture seasonal effects as well as changes in volatility over time.

**Table 3.** Summary of the estimated coefficients of the ARIMA$(p_A, d, q_A)(p_S, d_S, q_S)_S$–GARCH$(p,q)$ models.

| Variable | $\lambda_0$ | $\lambda_1$ | $\lambda_2$ | $\lambda_3$ | $\Lambda_4$ | $\Lambda_8$ | $\sigma^2$ | $\omega$ | $\gamma_1$ | $\beta_1$ |
|---|---|---|---|---|---|---|---|---|---|---|
| USDZAR | 0.00 | 0.00 | 0.00 | 0.00 | −0.55 | −0.32 | 104.36 | 0.00 | 0.00 | 0.99 |
| GBPZAR | −0.01 | 0.00 | 0.00 | 0.00 | −0.63 | −0.39 | 76.33 | 0.00 | 0.00 | 0.99 |
| EURZAR | 0.00 | 0.00 | 0.00 | 0.26 | −0.73 | −0.44 | 81.12 | 0.00 | 0.00 | 0.99 |
| BOND | 0.00 | 0.00 | −0.38 | 0.00 | −0.66 | 0.00 | 0.36 | 0.00 | 0.00 | 0.98 |
| CPI | 0.00 | 0.47 | 0.00 | 0.00 | −0.49 | 0.00 | 0.94 | 0.00 | 0.00 | 0.98 |
| PPI | 0.00 | 0.38 | 0.00 | 0.00 | −0.70 | −0.35 | 3.26 | 1.99 | 0.49 | 0.00 |
| GDP | 0.00 | 0.45 | 0.00 | 0.00 | −0.55 | −0.40 | 0.35 | 0.11 | 0.00 | 0.71 |
| GDE | 0.00 | 0.00 | 0.00 | 0.00 | −0.57 | −0.25 | 1.92 | 0.72 | 0.22 | 0.42 |
| HCE | −0.0004 | 0.7117 | 0 | 0 | −0.3828 | −0.3277 | 0.3756 | 0.1154 | 0 | 0.7124 |
| HCEG | 0.0005 | −0.2172 | 0 | 0 | −0.5191 | −0.3356 | 1.7211 | 0.5888 | 0.0918 | 0.5743 |
| PDI | 0.00 | 0.00 | 0.00 | 0.00 | −0.56 | 0.00 | 1.66 | 0.00 | 0.00 | 0.95 |
| HHDI | 0.00 | 0.33 | 0.38 | 0.00 | −0.78 | −0.41 | 2.54 | 0.00 | 0.00 | 0.97 |
| UNEMP | 0.00 | 0.00 | 0.00 | 0.00 | −0.40 | −0.37 | 6.98 | 0.90 | 0.00 | 0.86 |
| PCE | 0.00 | 0.00 | 0.00 | 0.37 | −0.49 | 0.00 | 1.26 | 0.00 | 0.00 | 0.96 |
| FIR | 0.00 | 0.42 | 0.00 | 0.00 | −0.44 | 0.00 | 17.90 | 3.29 | 0.08 | 0.74 |

The ARIMA parameters $\lambda_1$, $\lambda_2$, and $\lambda_3$ indicate the autoregressive components included in the model up to order three. The inflation variables (CPI, PPI), economic growth (GDP), consumption (HCE, HCEG), and GDE have a statistically significant first-order autoregressive component, as denoted by $\lambda_1$. BOND and HHDI have statistically significant second-order autoregressive components ($\lambda_2$), and EURZAR and PCE have statistically significant third-order autoregressive components ($\lambda_3$).

The seasonal components are denoted by $\Lambda_4$ and $\Lambda_8$ and capture the seasonal effects up to order $p_S = 2$ with $s = 4$ (quarterly data) in the ARIMA$(p_A, d, q_A)(p_S, d_S, q_S)_S$ model. Most of the economic variables have statistically significant seasonal autoregressive components out to order two.

The GARCH(1,1) model captures the changes in volatility over time. High $\beta_1$-parameters show a relatively slow decay in volatility over time for most variables; only GDE and HCEG show faster decay. The ARCH(1) model fitted best for PPI.

The residuals are derived from Equations (2)–(4) and are denoted by $\{\eta_1, \eta_2, \cdots, \eta_n\}$ for each of the $n$ economic variables in the dataset. The residuals from the ARIMA–GARCH models are used in the remainder of the analyses.

### 6.2. Leading and Lagging Relationships

The causality between variables is established with a cross-correlation function (CCF). The CCF shows the optimal lag and the highest statistically significant correlation. Figure 2 shows the CCFs for a subset of the variables. The data from 2010 to 2018 are used to estimate the dependence structures. The CCFs are derived from the residuals of the ARIMA–GARCH models as they are stationary and do not exhibit any serial correlation, and thus, they minimise the risk of spurious correlations.

The CCFs show that the currencies are most highly correlated when not incorporating any lag. The lag between interest rates and unemployment is six months. This means that rising interest rates are correlated with higher unemployment six months later.

### 6.3. Multivariate Dependence Structures

The copula vine algorithm discussed in Section 4.3 is applied to the residuals $\{\eta_1, \eta_2, \cdots, \eta_n\}$ to find the best order in which to combine the variable pairs, based on the strength of the relationships between them. A correlation cut-off of 40% is used, which means the algorithm continues to link new variable pairs until the remaining correlation is lower than 40%, then the algorithm starts with a new vine. The copula vine algorithm produced two vines:

- Vine Structure 1: {USDZAR, GBPZAR, EURZAR, HHDI, PDI, HCEG, BOND, UNEMP};
- Vine Structure 2: {CPI, PPI, HCE, GDP}.

The remaining variables did not exhibit any significant correlation and are modelled individually.

Figure 3 illustrates the d-vine structure for the currencies; the numbers correspond with the order in which the variables were linked. The copulas are estimated as discussed in Section 4.1. At each node on the d-vine, the 22 Archimedean copulas are fitted, and the best-fit copula is selected based on the Kolmogorov–Smirnov test statistic.

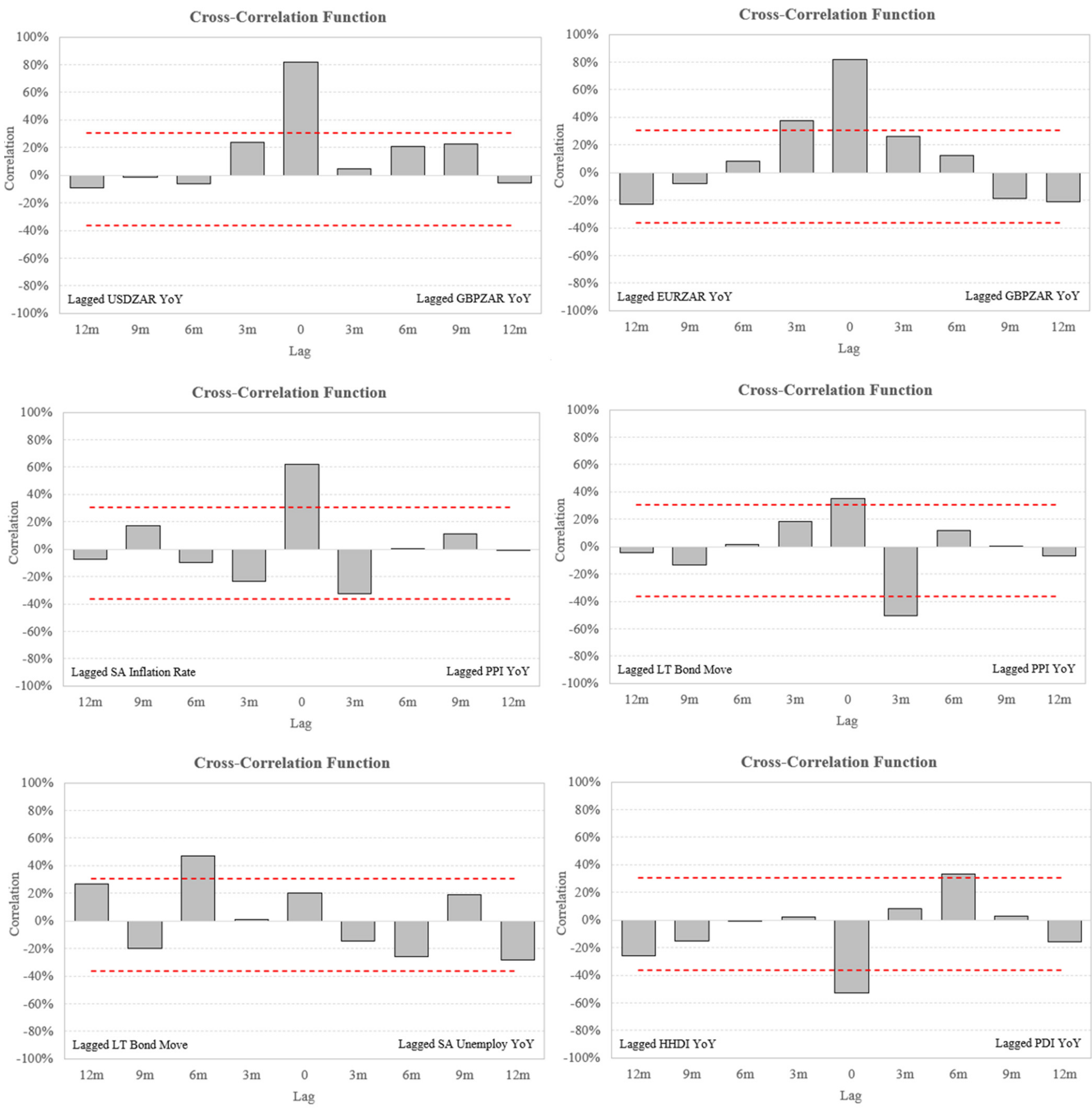


**Figure 2.** Cross-correlation graphs between selected variable pairs based on quarterly historical data from March 2010 to December 2018.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Level 1** | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| | Variable | USDZAR | GBPZAR | EURZAR | HHDI | PDI | HCEG | BOND | UNEMP |
| **Level 2** | Variable-Pair | 1,2 | 2,3 | 3,4 | 4,5 | 5,6 | 6,7 | 7,8 | |
| | Copula Number | 4 | 20 | 3 | 5 | 6 | 3 | 21 | |
| | Estimated Parameter | 2.464 | 0.515 | 0.971 | −3.426 | 1.51 | −1 | 2.33 | |
| **Level 3** | Variable-Pair | 1,3\|2 | 2,4\|3 | 3,5\|4 | 4,6\|5 | 5,7\|6 | 6,8\|7 | | |
| | Copula Number | 6 | 6 | 5 | 3 | 6 | 5 | | |
| | Estimated Parameter | 1 | 1.733 | −0.1 | 0.699 | 1 | 2.319 | | |
| **Level 4** | Variable-Pair | 1,4\|23 | 2,5\|34 | 3,6\|45 | 4,7\|56 | 5,8\|67 | | | |
| | Copula Number | 6 | 1 | 3 | 5 | 1 | | | |
| | Estimated Parameter | 1 | 0.01 | −0.85 | −0.277 | 0.01 | | | |
| **Level 5** | Variable-Pair | 1,5\|234 | 2,6\|345 | 3,7\|456 | 4,8\|567 | | | | |
| | Copula Number | 5 | 5 | 1 | 5 | | | | |
| | Estimated Parameter | −0.685 | −1.311 | 0.515 | 0.057 | | | | |
| **Level 6** | Variable-Pair | 1,6\|2345 | 2,7\|3456 | 3,8\|4567 | | | | | |
| | Copula Number | 3 | 5 | 6 | | | | | |
| | Estimated Parameter | −1 | 2.334 | 1 | | | | | |
| **Level 7** | Variable-Pair | 1,7\|23456 | 2,8\|34567 | | | | | | |
| | Copula Number | 4 | 4 | | | | | | |
| | Estimated Parameter | 1.078 | 1.053 | | | | | | |
| **Level 8** | Variable-Pair | 1,8\|234567 | | | | | | | |
| | Copula Number | 3 | | | | | | | |
| | Estimated Parameter | 0.387 | | | | | | | |

**Figure 3.** D-vine copula fitted to the economic variables {USDZAR, GBPZAR, EURZAR, HHDI, PDI, HCEG, BOND, UNEMP} with quarterly data from 2010 to 2018.

The strongest correlation is captured by the Gumbel copula fitted to the USDZAR-GBPZAR variable pair and is shown in Figure 4. It captures upper-tail dependence, which means that a large ZAR depreciation against the USD and GBP is more highly correlated than a ZAR appreciation. The two histograms illustrate the shape of the conditional distribution functions at high percentiles. There is a direct relationship between the copula parameter and the correlation between the two series, where a higher copula parameter indicates higher correlation.

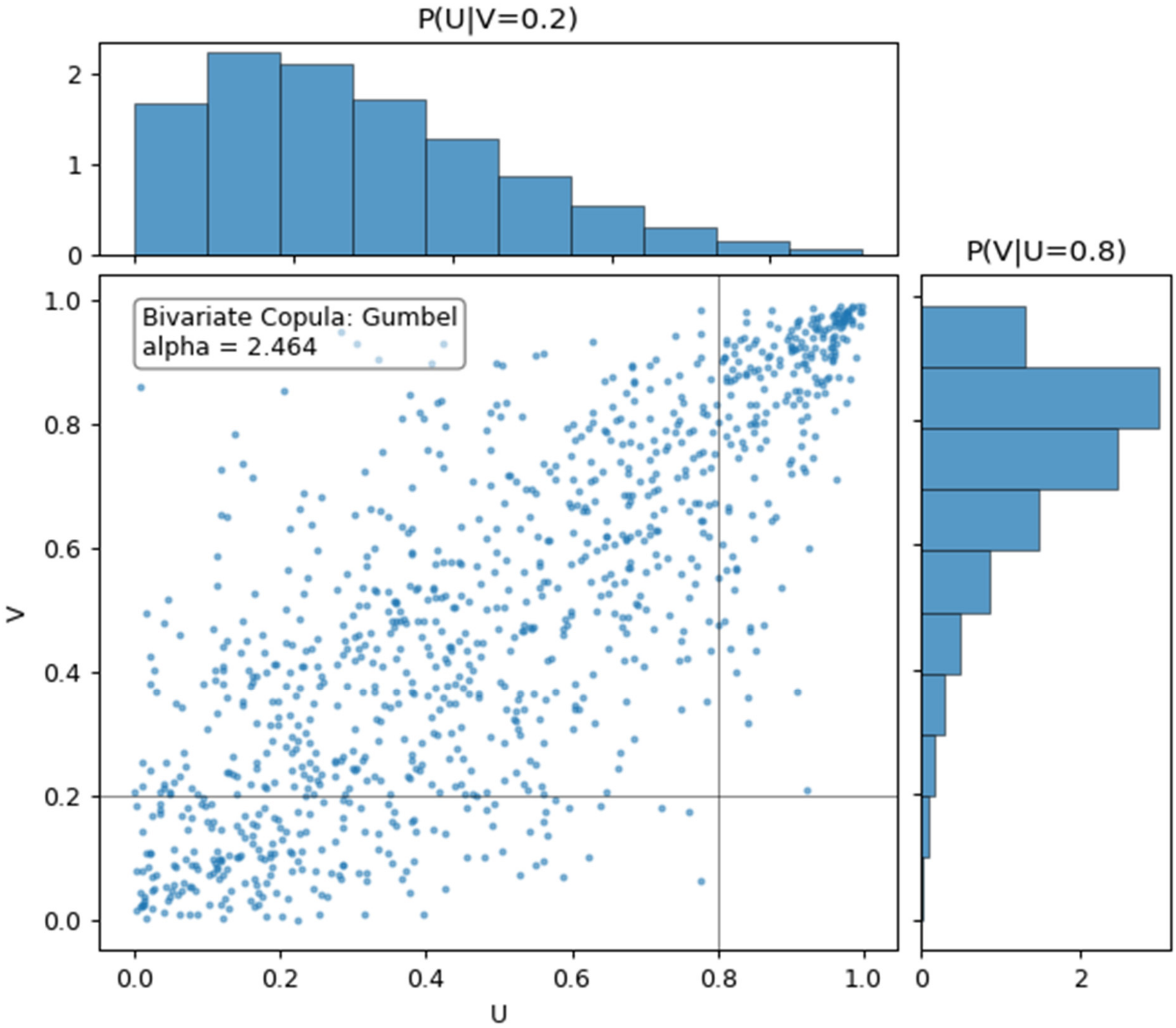


**Figure 4.** Bivariate Gumbel copula fitted to the {U: USDZAR, V: GBPZAR} variable pair and an example of the histograms of the conditional distributions.

Currency depreciation leads to higher import costs (Sanusi and Meyer 2018), which explain the link to lower PDI and consumption and higher household debt in the d-vine. Lower consumption is linked to higher interest rates, which in turn are linked to higher unemployment.

The second vine captures inflation and the link to economic growth. Higher inflation leads to lower consumption and economic growth. The d-vine structure is shown in Figure 5. The Frank copula captures the relationship between CPI and PPI and is shown in Figure 6. The Frank copula allows for both positive and negative dependence, and the copula parameter indicates the strength of the relationship. Higher (lower) values of the copula parameter indicate a higher positive (negative) correlation between the variable pairs.

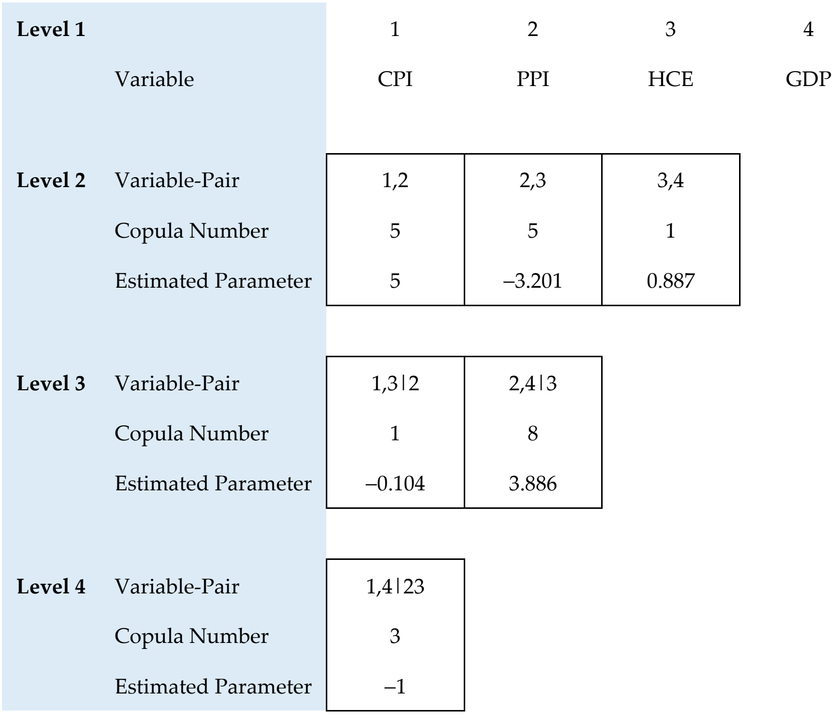


**Figure 5.** D-vine copula fitted to the economic variables {CPI, PPI, HCE, GDP} using quarterly data from 2010 to 2018.

The estimated copula parameters and lags at which the variables were linked are shown in Table 4.

**Table 4.** Estimated parameters of the multivariate d-vine dependence structures.

| d-Vine No. | Variable Pair | Correlation | Lag in Quarters | Copula No. | Copula Parameter |
|---|---|---|---|---|---|
| 1 | USDZAR; GBPZAR | 83% | 0 | 4 | 2.464 |
| 1 | GBPZAR; EURZAR | 79% | 0 | 20 | 0.515 |
| 1 | EURZAR; HHDI | 50% | 0 | 3 | 0.971 |
| 1 | HHDI; PDI | −49% | 0 | 5 | −3.426 |
| 1 | PDI; HCEG | 43% | 0 | 6 | 1.51 |
| 1 | HCEG; BOND | −42% | 0 | 3 | −1 |
| 1 | BOND; UNEMP | 50% | 2 | 21 | 2.33 |
| 2 | CPI; PPI | 65% | 0 | 5 | 5 |
| 2 | PPI; HCE | −46% | 0 | 5 | −3.201 |
| 2 | HCE; GDP | 47% | 0 | 1 | 0.887 |

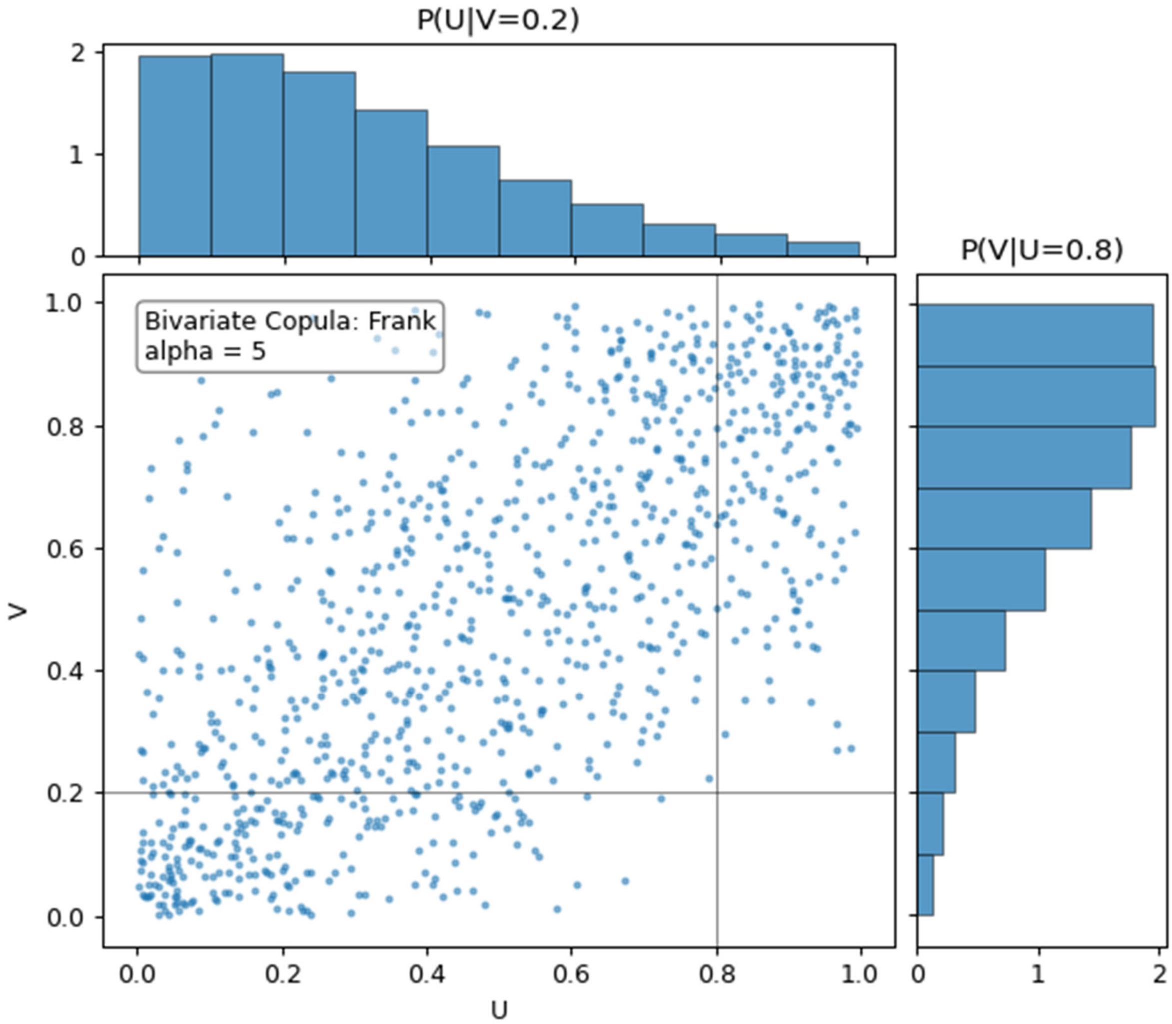


**Figure 6.** Bivariate Frank copula fitted to the {U: CPI, V:PPI} variable pair and an example of the histograms of the conditional distributions.

*6.4. Benchmarking the IFRS 9 Economic Scenarios*

The multivariate copulas are used to generate the economic benchmarks for the IFRS 9 scenarios. It is intended to be a more objective process, independent of the economics unit responsible for the IFRS 9 scenarios. The benchmarks are derived based on observed relationships instead of applying economic theory in a structural framework.

The $\left\{\tilde{\eta}_{1t}, \tilde{\eta}_{2t}, \cdots, \tilde{\eta}_{nt}\right\}$ are generated from the multivariate d-vine structures and then plugged into Equations (2)–(4) to obtain the economic benchmarks.

Table 1 has shown that banks usually have at least three economic scenarios, which cover a baseline, an upside, and a downside. The baseline scenario carries the highest weight, between 40% and 60%. The downside scenarios' probabilities are lower because they capture periods of stress.

The benchmarks for the baseline scenarios are generated for 2019 to 2020. The period from 2019 to 2020 was a challenging time in South Africa. Over the period, structural issues inhibited economic growth. Risks around state-owned enterprises materialised, which needed government bailouts. Higher expenditure and weak revenues led to increased government debt and a sovereign downgrade to a sub-investment grade. On top of that, COVID-19 further damaged the economy in 2020 with a sharp decrease in economic activity caused by the lockdown restrictions. Negative business sentiment led to lower investment and capital spending. Unemployment increased significantly (IMF 2020; SARB 2020b, 2020c).

The benchmarks produce confidence intervals as illustrated in Figure 7 and are then compared to the published baseline scenarios of the South African banks for FYE 2019 (please refer to Table 1). The published scenario values for USDZAR and CPI generally fall within the 50% confidence interval, which indicates that the IFRS 9 scenarios are in line with the benchmarks. The scenarios for GDP will trigger further discussions in an economic review because in most cases they fall outside the 50% confidence interval. This indicates that the published baseline scenarios may overstate economic growth.

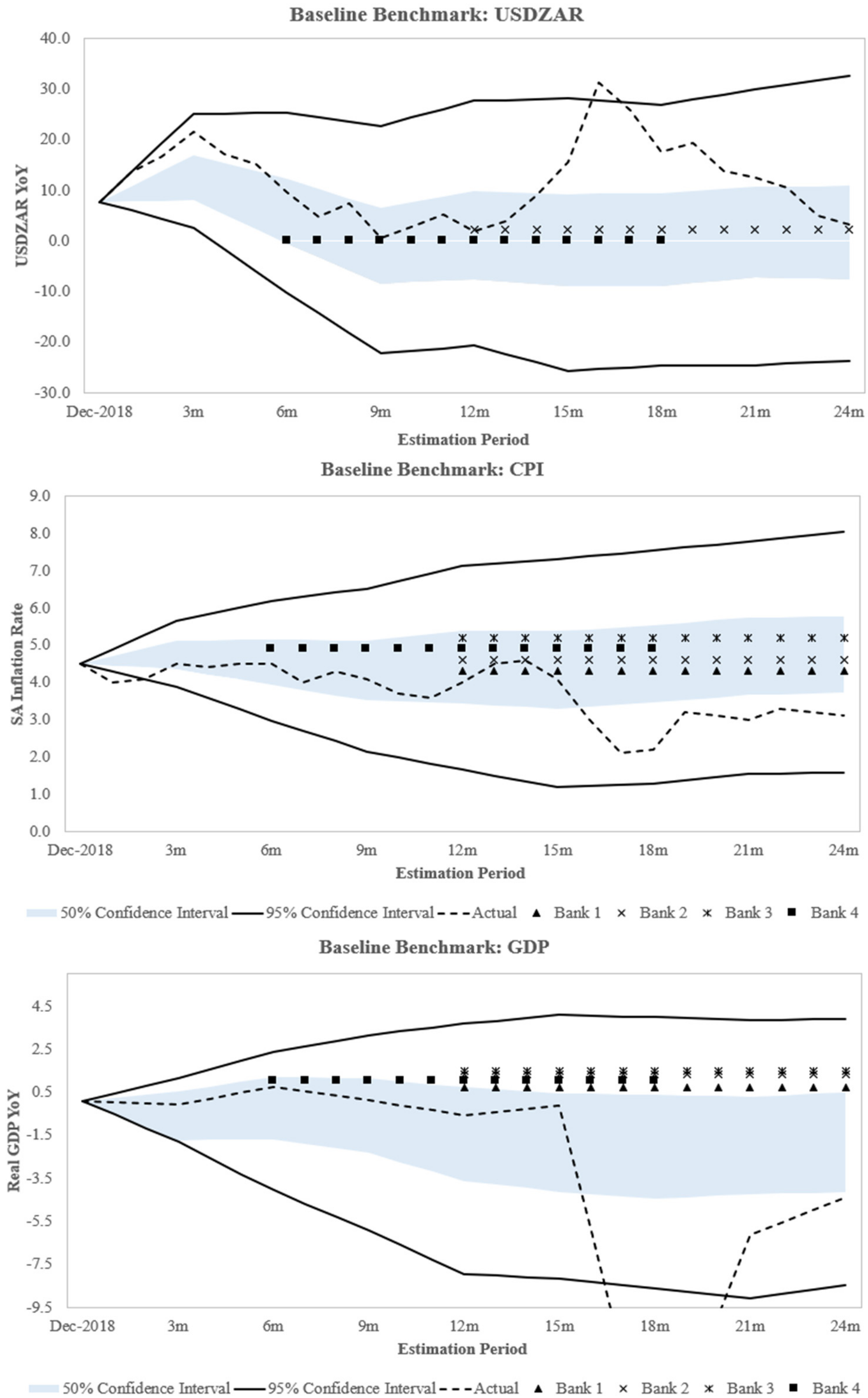


**Figure 7.** Illustrating the benchmark approach for the baseline scenarios as published in the annual financial statements of the South African banks for FYE 2019.

### *6.5. Benchmarking the IFRS 9 Economic Scenario Narrative*

The proposed benchmark approach can also be applied to test a specific scenario narrative. To illustrate this, consider, for instance, a narrative around a currency depreciation and a significant increase in inflation. This is a downside scenario and is assigned an assumed probability of 10%. Table 1 has shown that lower probabilities are assigned to downside scenarios. The scenario narrative is tested by deriving benchmarks from the d-vines by conditioning on the USDZAR and CPI at a 10% confidence level. The generated benchmarks are compared to the downside scenario values published by the South African banks for FYE 2019 in Figure 8.

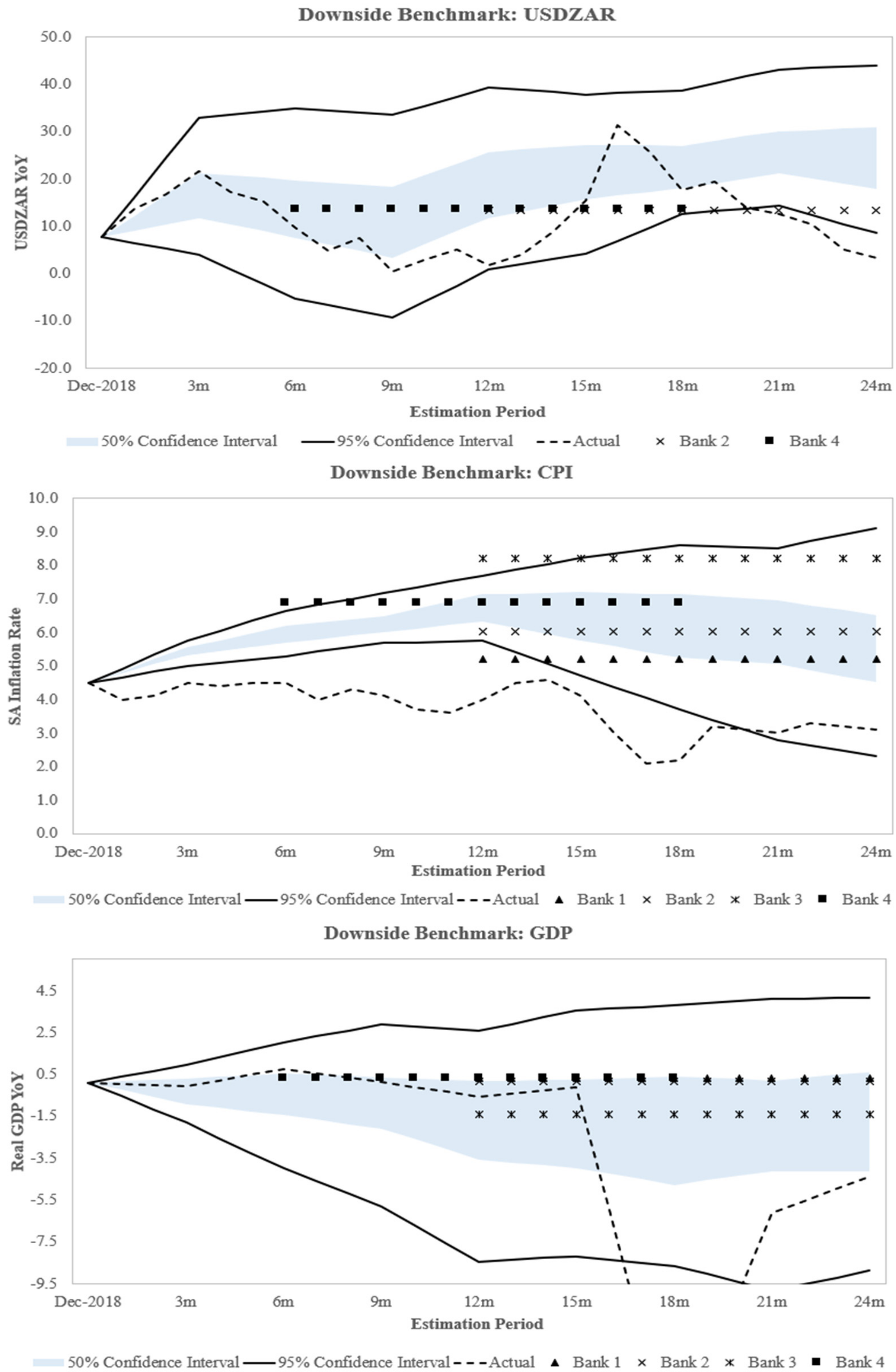


**Figure 8.** Illustrating the benchmark approach for the downside scenarios as published in the annual financial statements of the South African banks for FYE 2019.

The downside scenario captures more of the actual extreme currency depreciations observed in 2020. The economic growth scenarios are within the 50% confidence interval, and, except for the one extreme outlier, the benchmarks also captured the observed GDP growth very well. The CPI scenario values fall within the 50% confidence level; only one bank showed a significantly higher CPI, but it was still within the 95% confidence interval. Interestingly, this specific scenario story would eventually prove to be untrue because during the pandemic inflation decreased significantly.

### 6.6. Benchmarking the Scenario Probability

The IFRS 9 impairments are derived as a probability-weighted average of the expected credit loss calculated under a range of possible scenarios (usually three to five scenarios). The economic unit responsible for generating the IFRS 9 scenarios also assign the probability of the specific scenario being realised. The ARIMA–GARCH copula framework can be used to benchmark the economic scenario probability.

Table 5 shows an example of a fabricated downturn scenario out to two years for USDZAR, CPI, and GDP. The probability assigned to the downturn scenario is 5%. The year 1 scenario for USDZAR was set to the 95th percentile calculated from the quarterly historical data from 2000 to 2018; in year 2, the scenario indicates another small currency deterioration, leading on average to a 16.5% currency deterioration over the two years. CPI is just taken as the upper bound of the SARB inflation target levels as per the SARB monetary policy (SARB 2020b). The GDP scenario values for year 1 correspond to the 5th percentile calculated from the quarterly historical data from 2000 to 2018. The year 2 values are merely assumptions based on expert judgement.

**Table 5.** Example illustrating the benchmark of the probabilities assigned to the IFRS 9 scenarios.

| | **IFRS Scenario: Downturn 5%** | | | **Benchmark Probability** | | |
|---|---|---|---|---|---|---|
| | **Scenario Values $s_1$** | **Scenario Values $s_2$** | **Scenario Values $s_3$** | **Implied Probability P(Benchmark $\leq s_1$)** | **Implied Probability P(Benchmark $\leq s_2$)** | **Implied Probability P(Benchmark $\leq s_3$)** |
| **Economic Variable** | **Year 1** | **Year 2** | **Average** | **Year 1** | **Year 2** | **Average** |
| **USDZAR** | 28 | 5 | 16.5 | 98% | 63% | 89% |
| **CPI** | 6.0 | 6.0 | 6.0 | 94% | 94% | 94% |
| **GDP** | −0.72 | 0.0 | −0.36 | 46% | 58% | 52% |

The implied scenario probabilities are derived from the benchmark scenarios by calculating the number of benchmark scenario paths where the values fall below the downturn scenario value. The implied probabilities based on the average over the two years indicate that the scenario for CPI is in line with the downturn scenario probability assigned but that the USDZAR and GDP scenarios may not be severe enough. This assumes the 5% probability assigned to the downturn scenario is to be interpreted as with the probabilities relevant to the key variables.

### 6.7. Discussion of Findings

The study illustrated how multivariate copulas form a powerful tool for capturing various types of dependence structures, providing economic benchmarks that can enhance the governance around the IFRS 9 economic scenarios. The strength of the relationship is captured by the copula parameter, and the copula generator function captures aspects such as upper- and lower-tail dependence. Time-dependent correlation is handled by using the most recent available data to estimate the dependence structure; however, it is possible to extend the model formulation to incorporate the time-dependent copula parameters.

The copula vine algorithm is useful in determining the order in which to pair the variables to ensure that the highest correlations are captured at the appropriate lags. It is easy to automate the derivation of the benchmarks and to produce confidence intervals for the different economic variables.

The approach allows for the generation of economic scenarios, taking into account market events that have not been observed in the past. It is performed by setting the key variables based on new market information and then generating scenarios by conditioning on those key variables. Also illustrated is how to benchmark the economic scenario narrative and the probabilities assigned to each scenario. The methodologies presented can be applied to any set of economic variables, even though the ideas are illustrated specifically for South African variables.

The downside of using copula vines is that sophisticated algorithms are needed to select the best-fit copulas and to construct the d-vine. There is research underway to develop more functionality in this area, as shown by the Copulas Python library developed by the Data to AI Lab (2022).

## 7. IFRS Disclosure

IFRS impairment disclosures provide insight into the policies, methodologies, and assumptions used in determining impairments and to ensure comparability between the financial results of different banks. IFRS 7 specifically requires information on how forward-looking information is used in the calculations (International Accounting Standards Board 2010). Detailed qualitative disclosures around the macroeconomic scenarios are required to understand the background and sources of the economic scenarios, as well as the key drivers (Financial Reporting Council 2019). Qualitative disclosure is a useful way to identify and manage the forecast errors that may result from incorrect assumptions around exogenous variables (Fortin et al. 2020).

IFRS 9 requires economic scenarios to include a range of possible outcomes, including hypothetical events, but provides no clear guidance regarding the level of severity to incorporate. The IFRS 9 impairments are formulated to cover expected losses, in contrast to the Basel regulatory capital requirement for unexpected losses (Basel Committee on Banking Supervision 2017). The scenarios are expected to be used consistently across the different functions of a bank, which include capital planning and budgeting (Keller 2010; Kenny and Morgan 2011).

The non-linear relationship between the economic scenarios and the impairments refers to the fact that the impairments are more negatively impacted by a downturn economic scenario compared to the positive impact of a positive scenario. Significant bias can be introduced depending on the severity of the economic scenarios and the probabilities assigned to them (International Accounting Standards Board 2014; IFRS Foundation 2016). This emphasizes the need to include information on all scenarios in the financial disclosures.

Disclosure on the backtest results can be useful because it can clarify the observed impairment trends. Consider, for instance, a bank with four economic scenarios: upside, baseline, downside, and stress, with probabilities of 10%, 50%, 30%, and 10%, respectively. A comparison of the scenarios over time with the actual realised observations is expected to indicate that the scenarios form a kind of confidence interval around the observed values (similarly to the confidence intervals described in Section 6.4); deviations indicate possible misstated impairments.

Economic attribution is important in understanding which economic variables the different asset classes are sensitive to. Scannella and Polizzi (2021) propose disclosing a credit sensitivity analysis by shocking the credit risk drivers, similarly to what is done for the market risk.

Forest and Aguais (2019) highlight an interesting issue around the period out to which scenarios are generated. Economic scenarios are typically generated out to three or five years (Deloitte 2019) but then converge toward a long-run average. The convergence may lead to unrealistic volatility compression and a downward bias in the impairments. Detailed disclosure on the long-run behaviour of key economic variables is important.

The Financial Reporting Council (2019) points out that the disclosures should provide an indication of the shape of the macroeconomic forecasts, because disclosing only annual averages may not explain the observed behaviour in the impairments. This may occur when an economic scenario forecasts a deep trough followed by a strong recovery that, on average, indicates no significant impact.

The extent of the subjectivity in the economic forecasts should be disclosed as part of the significant judgements.

## 8. Concluding Remarks

The IFRS 9 impairment calculations are sensitive to the economic cycle, and events during the pandemic demonstrated the importance of strong governance processes to ensure unbiased impairment estimates. Benchmarking is a powerful tool in a model governance framework; however, obtaining the appropriate benchmarks in line with the economic scenario narrative of the bank is very difficult. To address this issue, this study illustrates how economic benchmarks can be derived with a copula vine algorithm that incorporates causality and lags when linking variable pairs into a d-vine structure. Unlike more established approaches such as VAR, copulas allow for asymmetric dependence structures where the marginal distributions can be specified separately from the dependence structure that links the variables into the multivariate distribution function. The d-vine enables the generation of events that have not occurred historically.

This study has illustrated how economic benchmarks can enrich a model governance framework and also provide the assurance to audit on material judgements. Subjective overrides are often used to compensate for flaws in the econometric models caused by structural correlation breaks or market uncertainty. A great risk is the impact of emotion, influenced by social networks and news, on those overrides. The d-vine structure can highlight instances where expert judgement applied to the IFRS 9 scenarios has led to broken economic relationships

This study explores greater governance and financial disclosure around economic scenarios given the impact on impairments. The copula vine is shown as a useful tool, not only to derive benchmarks for the IFRS scenarios, but also for the scenario narrative and the probabilities assigned to the scenarios. It is important that the scenario narrative is in line with the actual economic scenario values.

Ideas on how to enrich the IFRS 9 scenario review process were illustrated by comparing the generated benchmarks with the IFRS 9 scenarios published by six South African banks. When comparing the out-of-sample results to what happened during the pandemic, the benchmarks generally performed well.

The importance of financial disclosure was explored, and further disclosure on economic forecasts proposed. In the light of the nonlinear relationship between economic forecasts and impairments, it is vital to understand the level of severity and the dispersion of the economic forecasts. More detailed disclosure is needed to ensure that the shapes of the forecasts are understood. Sensitivity analyses may provide useful information on the key drivers of the impairments of the different asset classes. Backtest results may help to understand areas of over- or understated risk.

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## Appendix A. Historical Time Series

The Appendix shows a summary of the data sources for the economic variables included in the analyses.

**Table A1.** Description of the South African variables used in the study.

| Category | Variable | Variable Name and Description | Source | Data Frequency |
|---|---|---|---|---|
| Economic Activity | Real GDP | Gross domestic product at market prices. Constant 2010 prices. Seasonally adjusted. | South African Reserve Bank, Code: KBP6006D | Quarterly |
| Economic Activity | Real Gross Domestic Expenditure | Gross domestic expenditure. Constant 2010 prices. Seasonally adjusted. | South African Reserve Bank, Code: KBP6019D | Quarterly |
| Economic Activity | SA Unemployment Rate | Official unemployment rate. Seasonally adjusted. | South African Reserve Bank, Code: KBP7019L | Quarterly |
| Economic Activity | Household Debt to Disposable Income | Household debt to disposable income of households. Current prices. Seasonally adjusted. | South African Reserve Bank, Code: KBP6525L | Quarterly |
| Compensation | Personal Disposable Income | Disposable income of households. Current prices. Seasonally adjusted. | South African Reserve Bank, Code: KBP6246L | Quarterly |
| Credit Extension | Private Sector Credit Extension | All monetary institutions: total credit extended to the private sector. | South African Reserve Bank, Code: KBP1347M | Monthly |
| Consumption | Consumption Expenditure by Households | Constant 2010 prices. Seasonally adjusted. | South African Reserve Bank, Code: KBP6007D | Quarterly |
| Consumption | Consumption expenditure by households to GDP | Current prices. Seasonally adjusted. | South African Reserve Bank, Code: KBP6280L | Quarterly |
| Interest Rates | Long-term SA Bond Yield | Yield on loan stock traded on the stock exchange for government bonds 10 years and over. | South African Reserve Bank, Code: KBP2003M | Monthly |
| Inflation | Consumer Price Index | Headline CPI Year-on-Year Rates | Stats SA, Code: P0141 | Monthly |
| Inflation | Producer Price Index | PPI: Final manufactured goods. December 2016 = 100. | Stats SA, Code: P0142.1 | Monthly |
| Exchange Rate | USD/ZAR | Rand per US Dollar. Weighted average of the banks' daily rates at approximately 10:30 a.m. | South African Reserve Bank | Daily |
| Exchange Rate | GBP/ZAR | Rand per British Pound. Weighted average of the banks' daily rates at approximately 10:30 a.m. | South African Reserve Bank | Daily |
| Exchange Rate | EUR/ZAR | Rand per Euro. Weighted average of the banks' daily rates at approximately 10:30 a.m. | South African Reserve Bank | Daily |
| Real Estate | Residential Fixed Investment | National Accounts, Real Gross Fixed Capital Formation, Residential Buildings. Constant 2010 prices. Seasonally adjusted. | South African Reserve Bank, Code: KBP6110D | Quarterly |

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