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On bank stock return spillovers in South Africa: Implications for portfolio hedging

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ABSTRACT

The purpose of this study is to investigate the return spillovers among the five systemically important banks in South Africa. The study employs a time-varying parameter vector autoregression (TVP-VAR) framework utilising daily data between 2000 and 2024. A minimum return connectedness portfolio is constructed from the spillover indexes and compared with traditional portfolio optimisation methods in terms of risk reduction and reward-to-risk ratios. The research findings reveal that Capitec, the smallest bank in terms of assets, has weaker return connectedness with other banks while ABSA, FirstRand, Nedbank and Standard Bank are moderately connected. Moreover, the two largest banks in terms of assets, Standard and FirstRand, are more connected than any other pairwise connection in the network. During significant events such as national elections, the global financial crisis and the COVID-19 pandemic, system-wide connectedness increases.

Introduction

The banking sector is a crucial component of any economy, and stock markets constitute one of the primary sources of financing for banks. The performance of banks' stock prices is therefore important, and the interdependence of stock prices between banks can lead to spillover effects. This phenomenon, known as stock return spillovers, has been extensively studied in the literature (e.g. [1,2]). However, few studies have examined the spillover effects among South African banks, despite their importance to the African economy[1]. This paper aims to fill this gap in the literature by investigating bank stock return spillovers in South Africa (we use five listed bank stocks – FirstRand, ABSA, Capitec, Nedbank and Standard) and the associated implications for hedging strategies.

According to Demirer et al. [3], an understanding of connectedness/spillovers is essential for managing and measuring financial risk. The concept plays a significant role in several important aspects of market risk (return connectedness and portfolio concentration), credit risk (default connectedness), counter-party and gridlock risk (bilateral and multilateral contractual connectedness), and systemic risk (system-wide connectedness) [3]. According to Apostolakis, Floros and Giannellis [4], a knowledge of the connectedness of financial institutions is important to regulators as it makes it easy to determine the extent of risk contagion during crisis periods.

South Africa is the largest economy in Africa[2], and its banks have a significant presence in the continent's financial sector. South African banks are a crucial player in African economies due to their well-established financial sector and regional presence. Statistics

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[1] South African banks operate actively in most sub-Saharan countries (https://gfmag.com/emerging-frontier-markets/unfazed-south-african-banks-expand/)

[2] https://www.bloomberg.com/news/articles/2024-04-18/nigeria-s-economy-once-africa-s-biggest-slips-to-fourth-place

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show that South African-owned banks account for the largest number of cross-border linkages [5]. Also, current statistics show that, of the five largest banks in Africa, four are South African major players – FirstRand, Standard, ABSA and Nedbank[3]. These banks provide financial services and support economic growth in other African countries, making it a regional financial hub. Given their importance to the African economy, the spillover effects among South African banks can have far-reaching impacts that can go beyond the South African borders. Thus, studying the spillover effects among South African banks is crucial for understanding the interconnectedness of the African banking sector.

Our findings show that South African banks are moderately connected (average total connectedness is 51.9 %). Also, in terms of bivariate connectedness, Capitec Bank is weakly correlated with other banks. Using the TVP-VAR framework, Capitec Bank remains the weakly connected bank with the other banks as the pairwise total connectedness measures show that the bank has the lowest pairwise total connectedness measures across all possible pairwise relationships. We construct portfolios based on minimum variance, minimum connectedness and equally weighted methods and find that for the first 2 methods, Capitec Bank receives the most weights in both static and dynamic models. Our minimum connectedness portfolio outperforms the other portfolios in terms of cumulative portfolio returns as well as the return-to-volatility ratios.

The study proceeds as follows; Section 2 reviews the literature, Section 3 describes the data and methods, Section 4 presents the findings, Section 5 discusses the results and Section 6 concludes.

Literature review

Theoretical framework

The theoretical framework for this paper is based on the literature on financial contagion and systemic risk. Systemic risk refers to the risk of the collapse of the entire financial system due to the interconnectedness of financial institutions and markets [6] whereas financial contagion refers to the transmission of shocks and risks between financial institutions and markets [1]. Both financial contagion and systemic risk are closely related to the spillover effects of bank stock returns, as shocks in one bank or market can quickly spread to other banks and markets. The transmission of spillover shocks between banks can occur through various channels, such as interbank lending, common exposures to market risk, and contagion effects from negative sentiment and loss of confidence [7]. The degree of spillover effects can vary depending on the level of interconnectedness between banks, the structure of the banking system, and the regulatory environment [8].

Empirical literature review

Some studies have attempted to explore bank return connectedness within single countries. For example, Baruník and Křehlík [9] examine return and volatility spillovers in a time-frequency domain using US financial institutions. They conclude that economically, when connectedness is produced at high frequencies, stock markets appear to receive information quickly and calmly, and a shock to one asset in the system will mostly have an immediate impact. Lower frequency connectedness suggests that shocks are enduring and are being propagated for longer periods.

Several studies examining bank return connectedness have been done in the context of the USA, with findings showing that bank connectedness amplified around the global financial crisis of 2008 (e.g. [1]). Anand and Cotter [10] examined and evaluated the level of connectedness in a group of 357 banks in the United States for a period of 25 years (1993 to 2017). The authors define the degree of integration of a bank within the U.S. banking sector by evaluating how well its stock returns can be explained through regression analysis using principal components derived from the stock return matrix of all U.S. banks. The findings revealed that the size of the bank is the most influential and statistically significant factor in explaining the levels of integration, both from an economic and statistical perspective. In Morocco, using six banks as well as the Moroccan banking sector index (between 2012 and 2021) Beraich and El Main [11] found that return and volatility connectedness spiked during the COVID-19 period. We extend this line of literature by constructing hypothetical portfolios to assess the effect of return connectedness on hedging effectiveness.

There also exist several studies that have examined the return connectedness of banking institutions from an international and cross-border point of view. Singh, Gómez-Puig and Sosvilla-Rivero [12] use 199 banks in the European Economic and Monetary Union (EMU) to understand the banking sector and financial regulation at the country level. The study sought to understand banking risk connectedness using a suite of methods that include correlations, Diebold-Yilmaz connectedness measures as well as Granger causality. The results from the study show low connectedness among country-level banking risk indices. In contrast, a more recent study by Niţoi and Pochea [2] report that banks in developed European countries form a large network, alongside the U.S. banks, while banks in European catch-up countries are gathered in their own clusters. Using weekly returns of 377 publicly traded banks from 2014 to 2019, Wang et al. [13] examine the connectedness and systemic risk of the banking industry along the Belt and Road. According to the authors, the dynamic total connectedness peaked during the 2015–2016 outbreak of the abnormal swings in the Chinese stock market and reached its trough during the Brexit vote. Also, the study reports that intra-regional risk spillovers are stronger than inter-regional risk spillovers.

Lastly, rather than merely looking at inter-bank connectedness, another strand of literature has used a sectoral approach to

[3] https://money-gate.com/largest-african-banks-in-the-world/

understand how the banking sector is connected with other sectors. Using the Indian stock market, Chatziantoniou, Gabauer and Marfatia [14] show that the financial sector is a net receiver of return spillovers. Chirilă [15] uses the Polish market and divides the sample period into the pre-COVID and the COVID to establish sectoral connectedness in the market. The results show that in both subsamples, the banking sector is the most influential emitter of volatility spillover shocks in the system.

Data and methods

Data

The study uses 5 banks listed in the JSE/FTSE banks index (JS3011) namely, ABSA, Capitec Bank, FirstRand, Nedbank and Standard Bank. These banks are the largest in South Africa as they are also incidentally listed in the FTSE/JSE Top 40 index (J200). The banks have also been designated as systemically important financial institutions (SIFIs) by the South African Reserve Bank[4]. Our data are sampled at daily granularity and span a period between 19 February 2002 to 21 May 2024. We get the closing prices of the bank stocks from IRESS and these are used to compute log returns to ensure the stationarity of the variables. We visualise the trajectories of the closing prices of the sample stocks (Panel A, Fig. 1) and their corresponding log returns (Panel B, Fig. 1).

From Panel B of Fig. 1, episodes of volatility clustering across all the bank returns can be observed and this amplifies in 2008, 2016 and 2020; periods that coincide with the global financial crisis, municipal elections in South Africa and the declaration of the COVID-19 as a global pandemic respectively.

Time-varying connectedness

In determining the return spillover within the five South African banks used in this study, we depend on the time-varying parameter vector autoregression (TVP-VAR). We implement this by first instituting a multivariate Kalman filter TVP-VAR algorithm as described in Antonakakis et al. [16]. The method not only allows the parameters of the VAR model to change over time, but it also incorporates multivariate exponentially weighted moving average models to allow the parameter variance matrix and error variance to change over time as well. The model may thus capture dynamics with a great deal of flexibility. The TVP-VAR model can be represented as follows:

$$y_t = \Phi_t y_{t-1} + e_t, e_t|F_{t-1} \sim N(0, H_t) \tag{1}$$

$$vec(\Phi_t) = vec(\Phi_{t-1}) + \xi_t, \xi_t|F_{t-1} \sim N(0, \Xi_t) \tag{2}$$

Where F_{t-1} represents all information available up to $t-1$, y_t and e_t represent $m \times m$ dimensional matrices. In addition, ξ_t and $vec(\Phi_t)$ are $m^2 \times 1$ dimensional vectors and Ξ_t is an $m^2 \times m^2$ dimensional matric. As such the time-varying parameter transition equation assumes a random walk nature and has been demonstrated as effective in succinctly capturing time-varying parameters. Since financial time series are widely known for possessing time-conditional heteroscedasticity, the matrices H_t and Ξ_t handle this by permitting time-varying variance terms in the model. The seminal connectedness frameworks of Diebold and Yilmaz [1,17,] are based on the generalised forecast error variance decompositions (GFEVD) of Koop, Pesaran and Potter [18] and Pesaran and Shin [19]. To get the generalized impulse response functions (GIRF) and the GFEVD, we first convert the TVP-VAR into its TVP-VMA representation by applying the World representation theorem which states that:

$$\varkappa_t = \sum_{i=1}^{p} \Phi_{it} \varkappa_{t-i} + e_t = \sum_{j=1}^{\infty} \Lambda_{jt} e_{t-j} + e_t \tag{3}$$

GIRFs $\left(\Psi_{ij,t}(K)\right)$, where K is the forecast horizon, do not assume or depend on the structure/order of the errors and therefore provide a more robust approach to interpreting VAR models than standard IRFs which are sensitive to the order of variables entering into the econometric model. The GIRF approach captures the difference in the dynamics among and between all variables j. This is formalised as:

$$GIRF\left(K, \sqrt{H_{jj,t}}, F_{t-1}\right) = E\left(y_t + K|\epsilon_{j,t} = \sqrt{H_{jj,t}}, F_{t-1}\right) - E(y_t + J|F_{t-1}) \tag{4}$$

$$\Psi_{j,t}(K) = H_{jj,t}^{-\frac{1}{2}} \Lambda_{K,t} H_t \epsilon_{j,t} \tag{5}$$

Subsequently, the GFEVD $\left(\psi_{ij,t}(K)\right)$ demonstrates the specific contribution of each variable to the forecast error variance of variable i interpreted as how much, in percentage terms, one variable influences another in the system. This can be expressed as:

$$\psi_{ij,t}(K) = \frac{\sum_{t=1}^{K-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{K-1} \psi_{ij,t}^2}, \sum_{j=1}^{m} \psi_{ij,t}(K) = 1, \sum_{i,j=1}^{m} \psi_{ij,t}(K) = m \tag{6}$$

Given the measures of GIRF and GFEVD presented above, it is possible to describe how much each variable i is influenced by others

[4] https://www.businesslive.co.za/bd/economy/2019-11-28-reserve-bank-labels-six-sa-banks-as-systemically-important/

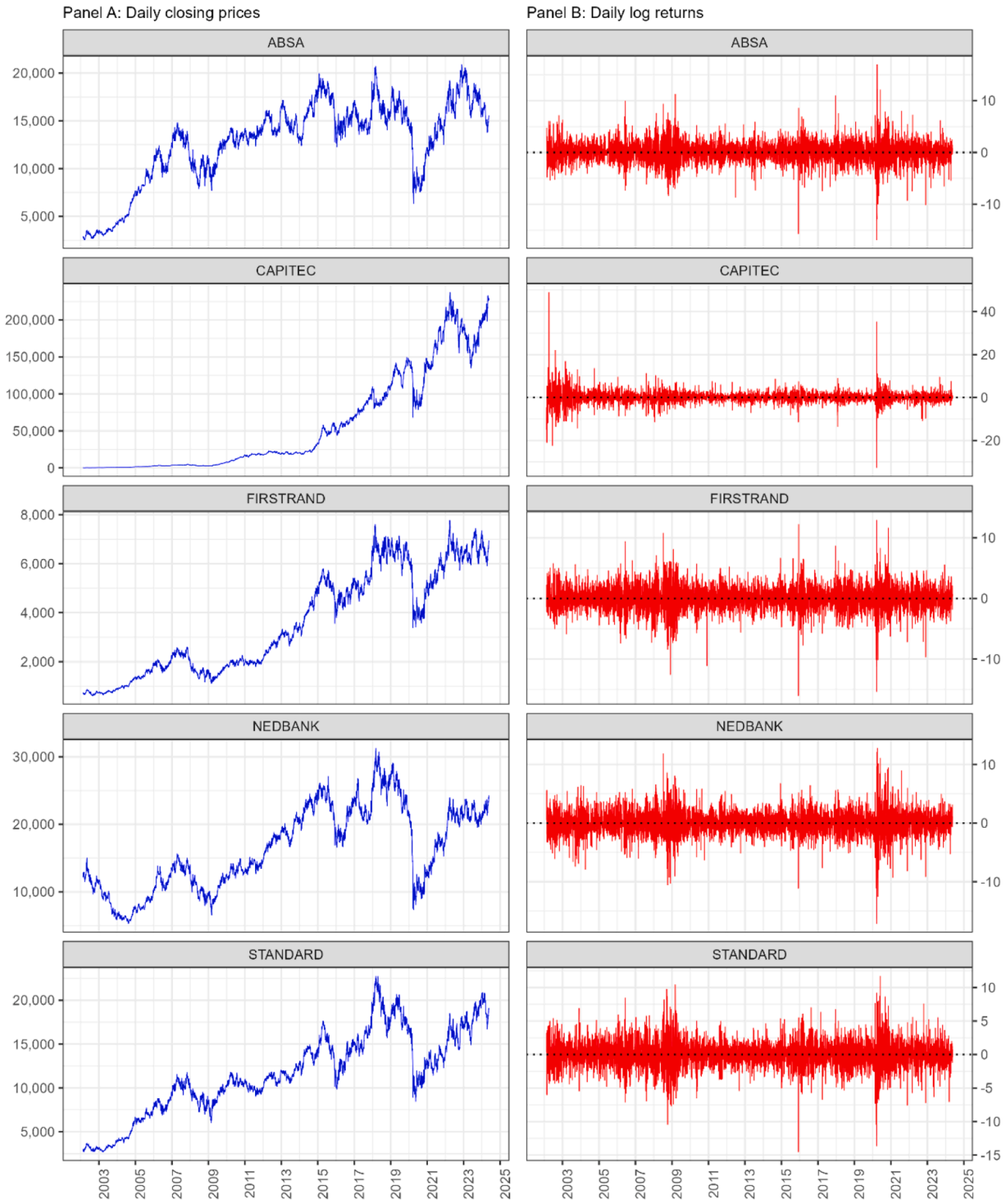


Fig. 1. Trajectories of the closing prices and stock returns.

and how much variable i influences all others. This also allows establishing whether variable i is influencing others more than it is being influenced by them in the system. Following the literature on variable connectedness (e.g [17]), we use the following metrics:

- Total directional connectedness **FROM** all others: Used to establish how much all other variables in the system influence variable i. This is attained by getting the sum of the shares of the error variance for variable i due to all other variables j. This metric is estimated as follows:

$$\Gamma_{i\leftarrow j,t}(K) = \frac{\sum_{j=1,i\neq j}^{m}\psi_{ij,t}(K)}{\sum_{i=1}^{m}\psi_{ij,t}(K)} \times 100 \tag{7}$$

The influence of all the others on variable i must strictly be below 100 % since the influence of i to itself has been excluded.

- Total directional connectedness **TO** all others: It is the reverse of the first metric above and seeks to quantify the influence of variable i on all other variables j in the system. The measure is estimated by accumulating the effects (error variance) that variable i has on each other variables' forecast error variance:

$$\Gamma_{i\rightarrow j,t}(K) = \frac{\sum_{j=1,i\neq j}^{m}\psi_{ji,t}(K)}{\sum_{i=1}^{m}\psi_{ji,t}(K)} \times 100 \tag{8}$$

The measure can take values up to a maximum of 100 %.

- **NET** total directional connectedness: This measures whether the influence of variable i on others is greater than the influence of others on variable i. It is obtained as the difference between Eqs. (8) and Eq (7).

$$\Gamma_{i,t}(K) = \Gamma_{i\rightarrow j,t}(K) - \Gamma_{i\leftarrow j,t}(K) \tag{9}$$

A positive (negative) value shows that variable i is driving the others more (less) than it is being driven by them.

- The total connectedness index (TCI): Shows the average amount of network comovements as a percentage. It is computed as follows:

$$TCI_t^g(K) = \frac{\sum_{i,j=1,\ i\neq j}^{m}\widetilde{\psi}_{ij,t}^{g}(K)}{k-1} \quad 0 \leq TCI_t^g(K) \leq 1 \tag{10}$$

- Pairwise connectedness index PCI: is a modification of the TCI that seeks to obtain pairwise connectedness between variables i and j as follows:

$$PCI_{ijt}(K) = 2\left(\frac{\widetilde{\psi}_{ij,t}^{g}(K)+\widetilde{\psi}_{ji,t}^{g}(K)}{\widetilde{\psi}_{ii,t}^{g}(K)+\widetilde{\psi}_{ij,t}^{g}(K)+\widetilde{\psi}_{jj,t}^{g}(K)}\right),\ 0 \leq PCI_{ijt}(K) \leq 1 \tag{11}$$

To check the robustness of our results, we re-estimate the return connectedness of the banks using a recently introduced model-free connectedness approach "which can be used as the baseline model for the broader connectedness literature" [20]. Assuming a null hypothesis that there is no connectedness among the banks (lagged variables do not influence contemporaneous variables), this means that the VAR coefficients are equal to zero. This leads to the following collapsed model as well as the associated GFEVD:

$$\mathscr{Z}_t = \boldsymbol{u}_t\ \mathscr{Z}_t,\ \boldsymbol{u}_t\ \sim \boldsymbol{N}\left(0, \sum\right) \tag{12}$$

$$\boldsymbol{A}_0 = \boldsymbol{I}_k\ \boldsymbol{A}_i = 0,\ i = 1,\ldots,p \tag{13}$$

$$\phi_{i\leftarrow j}^{gen} = \frac{\sum_{ij}^{2} ij}{\sum_{jj}\sum_{ii} jj} = \left(\frac{\sum_{ij} ij}{\sqrt{\sum_{jj}\sum_{ii} ii}}\right)^{2} = \rho_{ij}^{2} = R_{ij}^{2} \tag{14}$$

The measure shown in Eq. 14, is invariant of the forecast horizon, H, and is equivalent to the squared Pearson correlation coefficient

(defined as the R^2 the goodness-of-fit measure of a bivariate linear regression between *i and j*). The following identities emanate from the above relationships:

$$R_{ii}^2 = 1 \text{ and } R_{ij}^2 = R_{ji}^2 \tag{15}$$

By using the Diebold and Yilmaz [21] framework, the scaled GFEVD can be written as follows:

$$gSOT_{i \leftarrow j} = \frac{R_{ij}^2}{\sum_{l=1}^{k} R_{il}^2} \tag{16}$$

The TCI of Diebold and Yilmaz [21] can therefore be interpreted as the average sum of the weighted bivariate R_{ij}^2 values where $i \neq j$ and formulated as below:

$$TCI = 1 - \frac{1}{k} \sum_{i=1}^{k} gSOT_{i \leftarrow i} \tag{17}$$

$$TCI = 1 - \frac{1}{k} \sum_{i=1}^{k} \frac{R_{il}^2}{\sum_{i=l}^{k} R_{il}^2} \tag{18}$$

Portfolio back-testing

Portfolio construction

Having examined the time-varying connectedness of bank returns, we investigate historical investment performance by back-testing hypothetical portfolios constructed using the concept of connectedness as well as other traditional methods of portfolio construction. This allows us to assess the financial significance of our findings. We do not consider the implication of trading costs and other portfolio construction factors as the purpose is not to build profitable portfolios but to assess the risks inherent in connectedness portfolios. We consider a few portfolio design strategies, including traditional strategies and modern connectedness-based portfolios. The techniques we employ for portfolio construction are summarised here:

- **Minimum variance portfolio**

The minimum variance portfolio (MVP) strategy, which seeks to create the portfolio with the lowest volatility based on a variety of assets, is one of the most popular methods used in portfolio construction [22]. The following formula can be used to determine this portfolio's weights:

$$\omega_{Ht} = \frac{H_t^{-1} I}{I H_t^{-1} I}$$

Where ω_{Ht} is an $m \times 1$ dimensional portfolio weight vector, I is an $m-$ dimensional vector of ones and H_t is the $m \times m$ dimensional conditional variance-covariance matrix in period t.

- **Equally weighted portfolio**

The equal-weighted portfolio (EWP) is a portfolio strategy that evenly allocates investments across all assets or securities within a portfolio.

- **Minimum connectedness portfolio**

Instead of using the variance or correlation matrix, we use all pairwise connectedness indices to generate a minimum connectedness portfolio (MCoP). A portfolio that is more resilient to network shocks is possible by minimising the interconnectedness between variables and, consequently, their spillovers. As a result, the portfolio will assign a higher weight to variables (investment instruments) that do not influence or are not influenced by others. This is created as follows:

$$\omega_{Rt} = \frac{PCI_t^{-1} I}{I PCI_t^{-1} I}$$

Where PCI_t is the pairwise connectedness index matrix and I is the identity matrix.

- **Market weighted Portfolio**

Constructing a market-weighted portfolio involves allocating investment capital based on the market capitalisation of each asset, ensuring that larger companies with higher market values have proportionally greater representation within the portfolio.

Portfolio performance

Lastly, we utilise various portfolio evaluation metrics to compare the performance of the different portfolios constructed.

Treynor/modified Treynor ratio - The Treynor ratio is a performance metric that evaluates the returns of an investment relative to its systematic risk, as measured by beta. It is calculated by subtracting the risk-free rate from the portfolio's return and then dividing the result by the portfolio's beta. This ratio helps investors understand how well a portfolio has compensated for its exposure to market risk, with a higher Treynor ratio indicating a more favourable risk-adjusted performance. The standard Treynor ratio divides the excess return by the beta, whereas the modified Treynor ratio divides it by the standard deviation. This essentially replaces the measure of systematic risk (beta) with standard deviation in the calculation.

Information ratio - The information ratio (IR) is a performance metric used to evaluate the efficiency of an investment portfolio or fund relative to a benchmark. It measures the excess return of the portfolio over the benchmark, adjusted for the volatility of those excess returns, providing insight into the manager's ability to generate consistent, above-benchmark performance.

Sharpe ratio - The Sharpe ratio [23] shows the reward to volatility and can be expressed as follows:

$$SR = \frac{\bar{r}_p}{\sqrt{Var(r_p)}}$$

Where r_p denotes the returns on the portfolio[5]. Higher values of SR denote a higher level of return relative to the level of risk.

Hedge ratios - Following Ederington [24] we also compute the hedge effectiveness (HE) ratio. The HE represents the percentage reduction in the unhedged position's variance. The risk reduction increases with more HE and *vice versa*. The HE is computed as follows:

$$HE = 1 - \frac{Var\left(y_p\right)}{Var\left(y_{unhedged}\right)}$$

Where $Var\left(y_p\right)$ represents the variance of the portfolio returns and $Var\left(y_{unhedged}\right)$ the variance of the unhedged asset. The statistical significance of the HE ratios is tested using the Fligner-Killeen test, following Antonakakis et al. [16] whose Monte Carlo simulations show that volatility reduction follows an F-distribution such that an F-test can be used to test whether the volatility reduction of creating a portfolio is significant or not.

Results

Properties of the time-series variables

Before presenting findings from the econometric models used in the study, we, first of all, show the summary statistics of the variables including tests for normality, stationarity and ARCH/GARCH effects.

Table 1 shows the summary statistics of the time series used in the study. Capitec has the highest daily mean return while Nedbank has the lowest. All the variables are significantly negatively skewed except for Capitec which is the only bank with returns which are significantly positively skewed. There is also evidence that all series do not follow a Gaussian distribution [25], are stationary [26] and exhibit autocorrelation and ARCH/GARCH errors [27]. The summary statistics motivate modelling the interdependence of the variables using a TVP-VAR with heteroscedastic variance-covariances adopted in the study. In Fig. 2 we visualise the pairwise correlations between the variables using a correlogram.

The scatter plots in Fig. 2 demonstrate the presence of outliers in pairwise relations between the variables which call for robust econometric models that capture these outliers. In terms of the pairwise correlations, all the coefficients are statistically significantly different from zero which gives evidence of comovements between bank returns in South Africa. The largest correlation (0.741) is between Standard Bank and FirstRand which are coincidentally the largest South African banks by assets[6]. Capitec is weakly correlated with the other banks (all correlations are less than 0.31) while pairwise correlations among the remaining 4 banks are all strong (all correlations are more than 0.65). The high correlations among the biggest banks are in line with existing literature (e.g. [30]).

Static connectedness measures

We begin by presenting a collection of findings related to averaged connectedness. Table 2 presents these outcomes. It is important to note that all other elements of Table 2 pertain to the interactions between the various banks, but the elements of the major diagonal correspond to own-variable shocks (i.e. idiosyncratic).

According to the diagonal elements, the highest own shocks can be attributed to Capitec, of which 70.44 % of return evolution is driven by within return shocks, with only 29.56 % of the return movement being due to network connections. The average TCI value for the whole system is 53 % showing that on average 53 % of the forecast error variance in one bank can be associated with return

[5] Following Broadstock, Chatziantoniou and Gabauer [32] we assume the risk-free rate is equal to zero for simplicity

[6] https://www.statista.com/statistics/1346961/leading-banks-in-south-africa-by-assets/

Table 1
Summary statistics

	STANDARD	FIRSTRAND	ABSA	NEDBANK	CAPITEC
Mean	0.034	0.041	0.032	0.013	0.128
Variance	3.723***	4.012***	4.014***	4.097***	6.436***
Skewness	-0.086***	-0.205***	-0.107***	-0.172***	1.126***
Ex.Kurtosis	3.594***	4.018***	5.561***	5.494***	43.521***
JB	2999.104***	3780.547***	7176.271***	7020.434***	440054.232***
ERS	-33.783***	-17.038***	-5.850***	-29.963***	-2.034**
Q(20)	45.324***	45.422***	35.861***	26.014***	61.922***
$Q^2(20)$	1671.100***	1738.632***	2400.002***	3357.723***	303.892***

Notes: Skewness: D'Agostino [28] test; Kurtosis: Anscombe and Glynn [29] test; JB: Jarque and Bera [25] normality test; ERS: Elliott, Rothenberg & Stock [26] unit-root test; (20) and $Q^2(20)$: Fisher and Gallagher [27] weighted portmanteau tests.

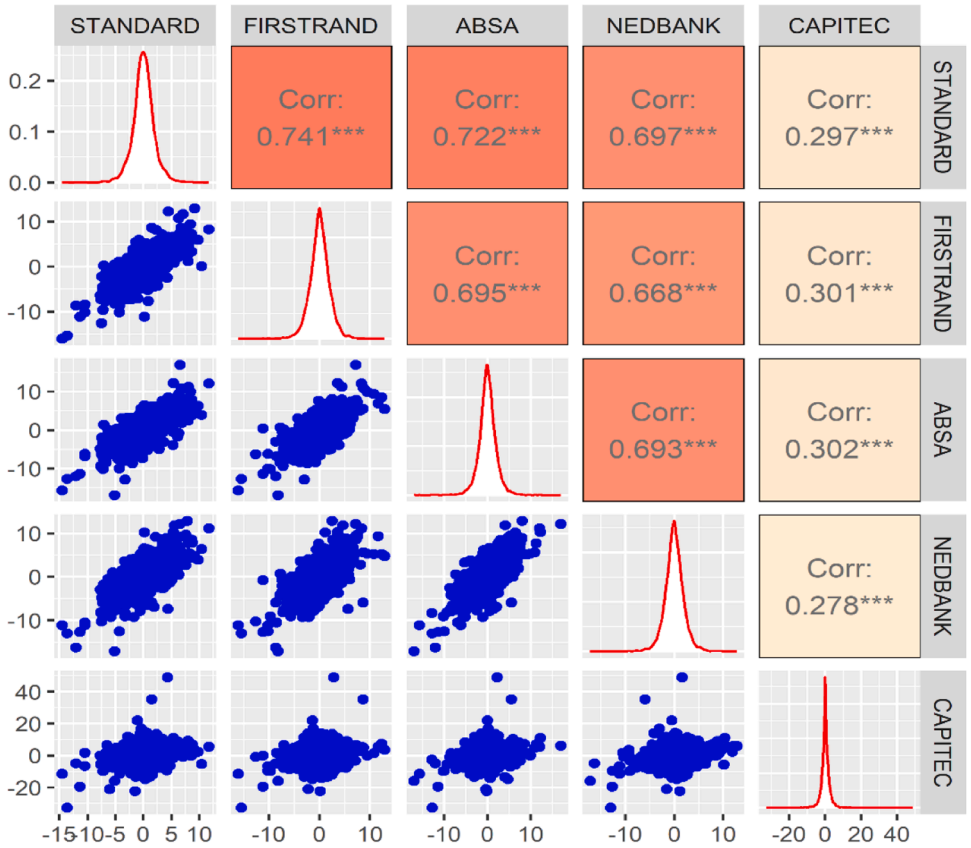


Fig. 2. Pairwise correlations.
Notes: The upper triangle shows the Pearson pairwise correlations with levels of significance represented by asterisks where *** means statistical significance at the 1 % level. Also in the upper triangle, the darker (lighter) the colour the stronger (weaker) the strength of the correlation between variables. The lower triangle shows scatter plots between the different combinations of bank returns while the diagonal shows the frequency density.

innovations from other banks included in the network. Like the results shown by the Pearson correlation coefficients reported in Fig. 2, the off-diagonal elements show that Capitec bank is weakly connected with the remaining banks. By the same virtue, the pairwise connectedness measures show that Standard Bank is the most connected with the other banks.

The **NET** spillover measures show that all the banks are net transmitters of return spillovers except for Capitec Bank which is a net receiver. In terms of the magnitudes of net return spillovers, Standard and FirstRand are respectively the largest emitters of return spillovers in the bank system. According to Broadstock, Chatziantoniou and Gabauer [32], averaged connectedness measures sometimes fail to reveal the effects of specific events, shadowing the linkages existing in financial markets and may therefore result in the loss of important information. These events can include significant political, economic, sector-specific or globally significant events like the recent COVID-19 pandemic. These influences can best be demonstrated by a dynamic model that captures time-varying

Table 2
Average connectedness results

	STANDARD	FIRSTRAND	ABSA	NEDBANK	CAPITEC	FROM
STANDARD	39.34	20.19	18.34	17.26	4.87	60.66
FIRSTRAND	20.77	40.14	17.2	16.6	5.29	59.86
ABSA	19.37	17.56	41.79	16.45	4.83	58.21
NEDBANK	18.28	17.1	16.57	43.31	4.74	56.69
CAPITEC	7.42	8.06	7.14	6.93	70.44	29.56
TO	65.85	62.91	59.26	57.24	19.72	264.98
Inc.Own	105.19	103.05	101.05	100.54	90.16	cTCI/TCI
NET	5.19	3.05	1.05	0.54	-9.84	66.24/53.00

Notes: The "Inc.Own" row indicates how much each variable contributes to the total connectedness within the network. cTCI represents the corrected TCI of Chatziantoniou and Gabauer [31].

dynamics of connectedness. In the next section, we, therefore, report findings of the time-varying connectedness of banks.

Time-varying connectedness

We report findings of the evolution of time-varying total connectedness in Fig. 3. It can be observed that return connectedness is not static across time but varies in response to specific local and global events. The TCI ranges from a minimum of 29.61 % (17 Jan 2005) to a maximum of 92.43 % (18 March 2020). Coincidentally, the spike in return connectedness in March 2020 can be attributed to uncertainty surrounding the early stages of the COVID-19 pandemic. Specifically, 18 March 2020, the day with the highest TCI value had some significant events in South Africa that amplified uncertainty on how the disease would progress. These events include the deliberations of the COVID-19 command council on the possibility of a national lockdown, and the imposition of travel restrictions, coupled with the closure of ports of entry and the closure of schools- all of these events took place on the 18th of March 2020[7].

Another spike in TCI appears in 2016, a year coinciding with municipal elections in South Africa. We can therefore conclude that return connectedness in the banking system is dynamic and responds to local and global events. Generally, we observe an increase in connectedness over time. This could be due to advances in information technology and data sharing that may lead to faster transmission of market-relevant information among banks, causing their returns to become more synchronised. Fig. 4 shows the dynamic net total connectedness of the banks.

Fig. 4 shows that Capitec is mostly a net receiver of return spillovers across the sample period. The largest banks (Standard Bank and FirstRand) are mostly net transmitters of return spillovers in the system. Nedbank and ABSA show a role-changing behaviour, being net transmitters of return spillovers during some periods while being net receivers at other times. Interestingly, though Capitec is an overall net receiver of return spillovers across the sample period, it momentarily becomes a net transmitter of return spillovers on 20 March 2020 with net spillover reaching a maximum of 9.61 % on that day. Intuitively, there seem to be diversification opportunities by constructing portfolios of bank stocks that incorporate both receivers and transmitters of return spillovers.

Even though results for net total connectedness are quite helpful in identifying net transmitters and net receivers within our network of banks, these results fall short of capturing pairwise dynamics, which might reveal additional insights and a clearer picture of what is the precise role that each bank adopts within our network with respect to the others, as well as over time. We, therefore, present the results of the total dynamic pairwise connectedness in Fig. 5.

In Fig. 5, it can be observed that total dynamic pairwise connectedness is time-varying, with intermittent episodes of high connectedness and low connectedness across time. Also, total pairwise connectedness seems to spike in the presence of significant events like the COVID-19 pandemic. Pairwise total connectedness is higher between the largest banks (Standard and FirstRand). Capitec has the weakest pairwise connectedness with the rest of the banks respectively and for all the pairwise connectedness, the effect seems to be weaker between 2000 and 2015 (connectedness is mostly less than 20 %) and from there reached moderate values mostly above 40 %.

The total dynamic pairwise connectedness fluctuates over time, indicating that the level of interconnectedness between banks is not constant. There are periods of high connectedness, where banks influence each other more significantly, and periods of low connectedness, where the influence is weaker. Notably, during major events like the COVID-19 pandemic, there is a spike in total pairwise connectedness. This suggests that such events can lead to higher systemic risk, where disturbances in one bank's activities have a more pronounced effect on others in the system. The largest banks, Standard and FirstRand, show higher pairwise connectedness with each other compared to other banks in the system. This indicates that these large banks have stronger interactions and potentially pose a higher systemic risk due to their size and significance in the financial system. Capitec, on the other hand, shows the weakest pairwise connectedness with the rest of the banks. This implies that Capitec's activities have a relatively smaller impact on other banks and the overall system.

[7] https://www.bpesa.org.za/coronavirus-news/240-government-gazette,-18-march-2020-no-43107-regulations-issued-in-terms-of-disaster-management-act-covid-19.html

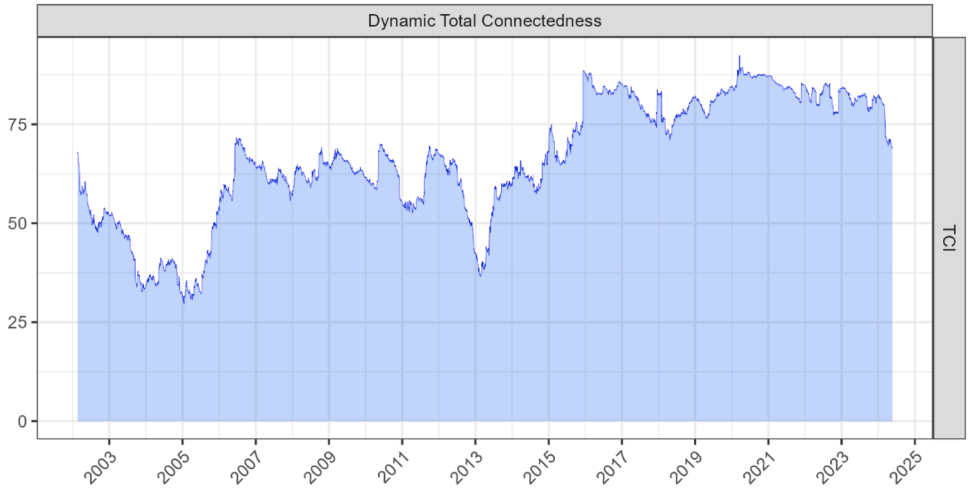


Fig. 3. Time-varying total connectedness.
Notes: The graph plots the estimated total connectedness index of bank returns based on the TVP-VAR(1) model.

Dynamic portfolios

In this section, we describe the weights and performance of the various investment portfolios constructed namely, Minimum Variance Portfolio (MVP), Equally Weighted Portfolio (EWP), Market weighted Portfolio (MwP) and Minimum Connectedness Portfolios (MCoP). In Fig. 6[8], we visualise the dynamic multivariate portfolio weights of the different portfolios.

Fig. 6 shows that the individual weights using the McoP methods are quite stable while the MVP shows wide fluctuations in the portfolio contributions across time. Using the MCoP method, Capitec contributes the highest weights than the remaining banks across the sample period. This can be explained by the fact that the method gives more weight to the stocks that have the weakest pairwise connectedness with other stocks within a network. In this instance, Capitec Bank receives and emits the lowest return spillovers to and from other banks within the network, and hence the sustainably higher weights compared to the other banks. After identifying the evolution of portfolio weights for MCoP, EWP, MwP and MVP, we further explore the implications for portfolio and risk management. By comparing the hedging effectiveness scores and sharp ratios for each method, we can compare and contrast the MCoP approach with traditional portfolio optimisation methods like MVP and EWP. It is crucial to remember that, in contrast to the competing portfolio construction strategies, the MVP strategy, by definition, reduces portfolio volatility, whilst the MCoP technique seeks to reduce pairwise connectedness and, as a result, the bilateral spillovers across assets. In Table 3 we present the averaged portfolio weights and the associated hedge effectiveness ratios for the competing portfolios.

Concerning the HE ratios reported in Table 3, the results of the MVP technique show that, if on average we invested 18 % in Standard, 13 % in FirstRand, 15 % in ABSA, 21 % in Nedbank and 33 % in Capitec, then the volatility of each asset in this portfolio would be statistically significantly lowered by 40 %, 45 %, 45 %, 46 % and 65 % respectively. These volatility reductions are all statistically significant at the 0.1 % level of significance. Notably, Capitec contributes the largest average portfolio weights for the MVP (33 %) and the MCoP (39 %) portfolios as well as the associated HE ratios. In Fig. 7 we show the time-varying cumulative portfolio returns using the competing portfolio construction techniques used in the study.

Fig. 7 shows that the competing portfolios perform with a visible level of equivalence as they share the same underlying dynamics including sharp drops in cumulative portfolio returns in 2008, 2016 and 2020 - periods corresponding to the global financial crisis, local general elections as well as the COVID-19 pandemic respectively. However, in general, the minimum connectedness portfolio outperforms the other two portfolios consistently across time. The margin of outperformance is narrow between 2000 and 2008 and starts widening henceforth. Fig. 7 also includes the cumulative returns for the individual stocks (in grey) and they show that besides Capitec and FirstRand, the other banks all underperform the competing portfolios. It can also be observed that the largest banks (ABSA, FirstRand and Standard) are clustered together while Nedbank and Capitec are visibly detached from either the hypothetical portfolios or the largest banks. In our final analysis, we evaluate the historical performance of the portfolios. The results are presented in Table 4.

Table 4 shows that the MCoP-based portfolio outperforms the other portfolios in terms of average daily returns. Though MCoP has the highest risk (as measured by standard deviation), it produces the highest average returns and Sharpe ratio. MVP has the lowest risk but the return per 1 standard deviation unit of risk is lower than a portfolio constructed with minimum return connectedness. The performance metrics for the portfolios reveal distinct differences in how each one handles risk and returns. Starting with the Treynor ratio, which measures how well a portfolio compensates for its market risk, MCoP emerges as the top performer with a Treynor ratio of 17.9363. This suggests that MCoP provides the best returns relative to its systematic risk. The information ratio, which evaluates the

[8] We do not show the portfolio weights of the EWP because they do not change at 0.2

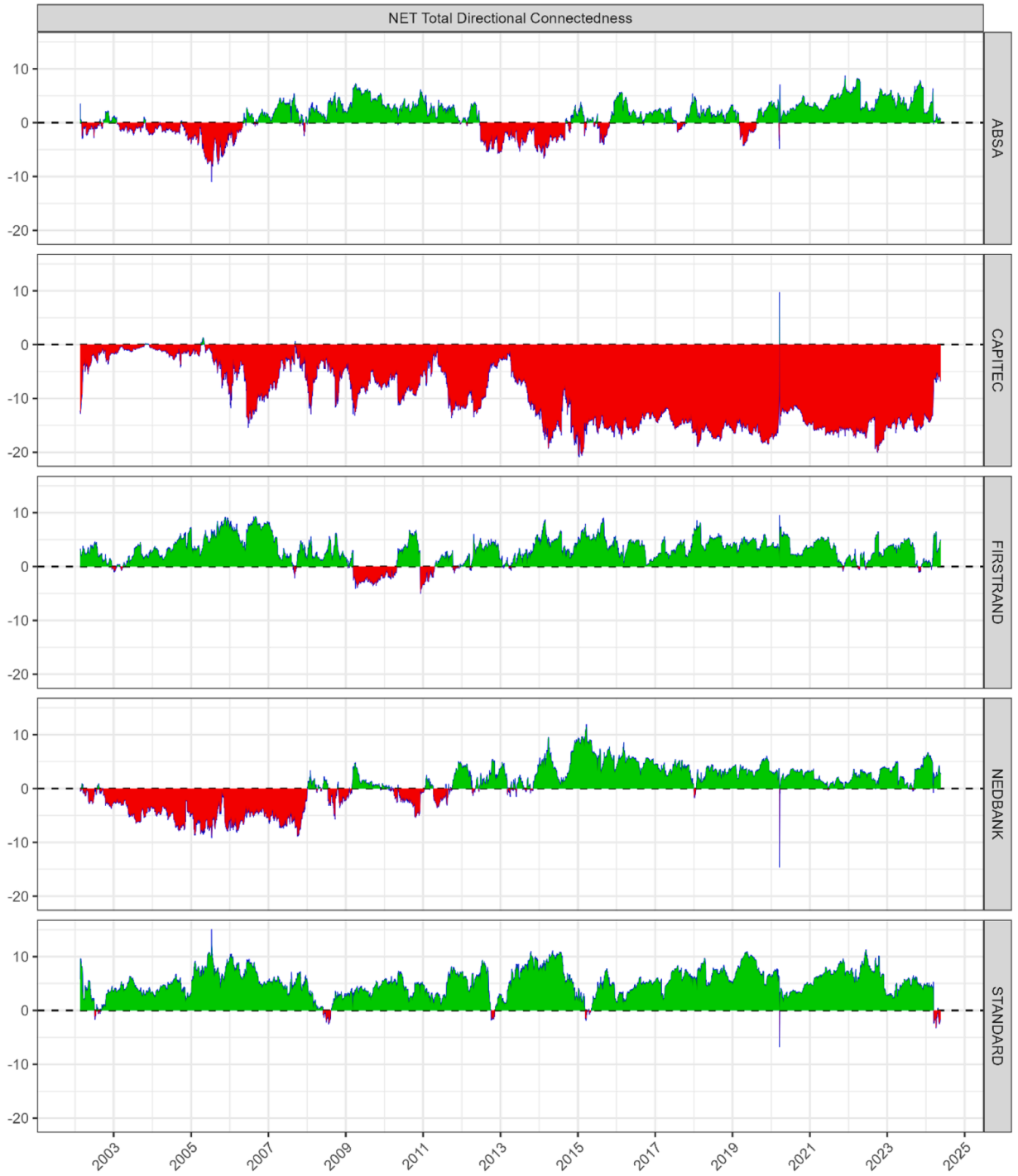


Fig. 4. Dynamic NET total connectedness.
Notes: Results are based on a TVP-VAR(0.99,0.99) with one lag. Periods in which a bank is a net transmitter (receiver) of return spillovers are shown in green (red).

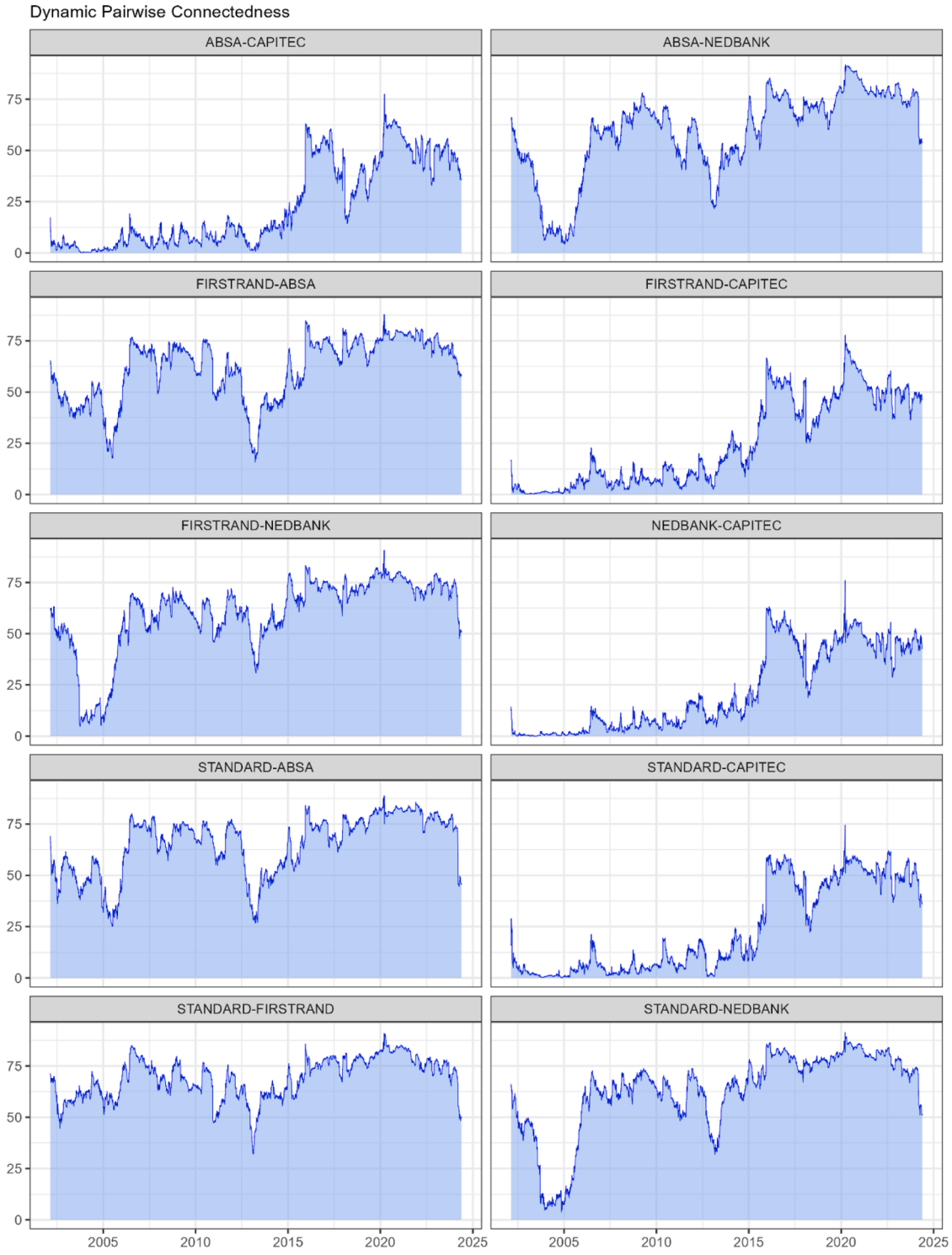


Fig. 5. Dynamic pairwise connectedness.
Notes: Results are based on a TVP-VAR (0.99,0.99) with one lag.

consistency of excess returns relative to a benchmark, further underscores MCoP's superior performance with the highest ratio of 0.0606.

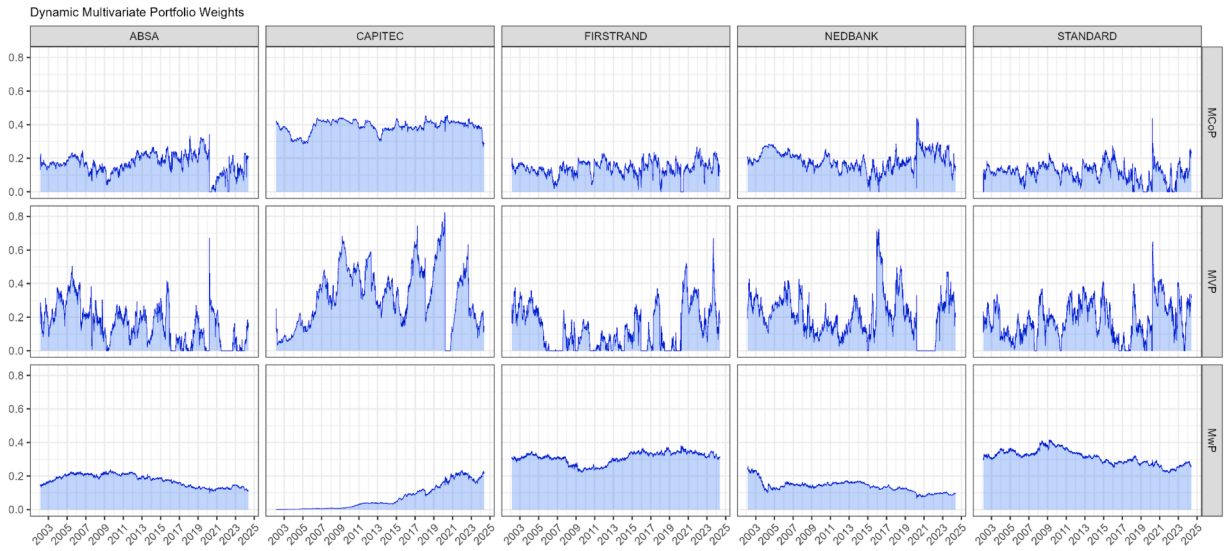


Fig. 6. Dynamic multivariate portfolio weights.
Notes: Results are based on the time-varying variance-covariance matrices retrieved from the TVP-VAR (0.99,0.99) with one lag.

Table 3
Hedge effectiveness ratios

Minimum Variance Portfolio						
	Mean	Std.Dev.	5 %	95 %	HE	p-value
STANDARD	0.18	0.11	0	0.37	0.4	0
FIRSTRAND	0.13	0.12	0	0.35	0.45	0
ABSA	0.15	0.11	0	0.36	0.45	0
NEDBANK	0.21	0.13	0	0.43	0.46	0
CAPITEC	0.33	0.18	0.06	0.63	0.65	0
Equally Weighted Portfolio						
STANDARD	0.2	0	0.2	0.2	0.27	0
FIRSTRAND	0.2	0	0.2	0.2	0.33	0
ABSA	0.2	0	0.2	0.2	0.33	0
NEDBANK	0.2	0	0.2	0.2	0.34	0
CAPITEC	0.2	0	0.2	0.2	0.58	0
Minimum Connectedness Portfolio						
STANDARD	0.12	0.05	0.01	0.2	0.25	0
FIRSTRAND	0.14	0.04	0.06	0.21	0.3	0
ABSA	0.17	0.06	0.06	0.25	0.3	0
NEDBANK	0.19	0.06	0.1	0.28	0.31	0
CAPITEC	0.39	0.04	0.3	0.43	0.56	0
Market weighted Portfolio						
STANDARD	0.31	0.04	0.24	0.39	0.2	0
FIRSTRAND	0.31	0.03	0.24	0.35	0.26	0
ABSA	0.17	0.04	0.12	0.22	0.26	0
NEDBANK	0.14	0.03	0.09	0.21	0.28	0
CAPITEC	0.07	0.07	0	0.21	0.54	0

Discussion

Contributions to literature

The findings show that the McoP portfolio outperforms the other conventional portfolio construction techniques. This is in line with most recent literature which has reported the same using international oil and commodity futures markets [33], commodity and financial indices [34] as well as oil, stocks and exchange rates [16]. In a contemporary world where technology has amplified the within-country and cross-country connectedness of stocks, it is essential to tap into portfolio construction tools that utilise connectedness measures to mitigate the propagation of risk. Furthermore, the study finds that systemwide connectedness increases during significant events such as national elections, the global financial crisis and the COVID-19 pandemic. This result is consistent with previous studies that have shown increased connectedness during periods of economic stress and uncertainty [35]. Diversification



Fig. 7. Dynamic Multivariate cumulative portfolio returns.
Notes: Results are based on the time-varying variance-covariance matrices retrieved from the TVP-VAR(0.99,0.99) with one lag. MVP refers to the minimum variance portfolio, EWP refers to the equally weighted portfolio, and MCoP refers to the minimum connectedness Portfolio. The grey lines depict cumulative returns on individual bank returns.

Table 4
Portfolio performance

	MCoP	EWP	MVP	MwP
Mean	0.0655 %	0.04946 %	0.0575 %	0.04132 %
SD	0.0168	0.0164	0.01661	0.0149
Sharpe	0.03897	0.03009	0.03851	0.02401
Treynor	17.9363	11.19606	17.1404	7.51785
Modified Treynor	0.94755	0.59146	0.90550	0.39715
Information ratio (J203)	0.0606	0.0584	0.0599	0.0571

benefits may therefore fail during times when they are most needed. The moderately high connectedness of ABSA, FirstRand, Nedbank, and Standard Bank suggests that these institutions have significant systemic importance in the South African financial system.

The minimum connectedness return portfolio is constructed in a way that considers the interconnections and correlations between assets, aiming to reduce systemic risk and the potential impact of shocks propagating through the portfolio. By diversifying investments based on their connectedness, this portfolio achieves a more efficient risk-reward trade-off compared to the minimum variance portfolio, which focuses solely on risk minimisation. The minimum connectedness return portfolio takes into account tail risks and the potential for extreme events. It strategically allocates assets to minimise exposure to highly connected and systemic-risk-prone assets, thus enhancing the portfolio's resilience during turbulent market conditions. In contrast, the minimum variance and equally weighted portfolios might not adequately address tail risk concerns.

Implications of the findings

The findings of this study have several implications for financial institutions and investors in South Africa. First, the study

highlights the importance of understanding the dynamic connectedness of financial institutions and their impact on market risk management. Investors and regulators can use the results of the TVP-VAR model to identify the most connected banks and adjust their portfolios accordingly to minimise the impact of potential shocks or crises. Second, the results of the portfolio optimisation exercise suggest that portfolios constructed using minimum return connectedness outperform those constructed using other optimisation methods. This finding implies that investors can potentially improve portfolio performance by considering dynamic connectedness and using portfolio optimisation techniques that incorporate this information. Lastly, the moderately high connectedness of ABSA, FirstRand, Nedbank and Standard Bank suggests that these institutions have significant systemic importance in the South African financial system. This finding has implications for regulators and policymakers, who may need to consider measures to mitigate systemic risks posed by these institutions. Overall, the findings of this study provide important insights into the interconnectedness of financial institutions in South Africa and can aid in better risk management and investment decision-making.

Conclusion

This study investigates return spillover patterns among the largest and most systemically important financial institutions in South Africa, given their critical role in the continent's economic development. Using a TVP-VAR model on daily data from 2002 to 2024, we find that while Capitec, the smallest bank, is weakly connected, the larger banks—ABSA, FirstRand, Nedbank, and Standard—show moderate to strong connections, with FirstRand and Standard exhibiting the highest pairwise connectedness. Systemwide connectedness peaks during significant local and global events, such as elections, the global financial crisis, and the COVID-19 pandemic.

Our portfolio construction exercise, based on empirical results, reveals that a portfolio with minimum return connectedness outperforms those with minimum variance and equal weights in terms of cumulative returns and Sharpe ratios. This highlights the value of quantifying dynamic return linkages in portfolio optimization and risk management. Future research could expand to include non-bank financial institutions as well as explore the connectedness of South Africa's banking sector with the global financial system.

Author statement

Kingstone Nyakurukwa: Conceptualisation, Writing, methodology, analysis; **Yudhvir Seetharam:** Conceptualisation, Writing, methodology, analysis, review, supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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