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Factor structure of South African financial stocks

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Background: The financial sector within the locally listed equity market is an important component of the economy. Understanding the inherent risks of this sector is vital from a portfolio risk management perspective, as such insights can aid in protecting against capital loss in the event of exposure to risk factors in this sector.

Aim: The study aims to identify and explain the principal risk factors over time inherent to the financial stock sector of the locally listed equity market, accompanied by explaining the volatility of such principal risk factors.

Setting: The study looks at financial sector stocks within the South African listed equity space from June 2007 to March 2017.

Methods: The methods used to perform such an investigation were twofold, namely, factor analysis to statistically identify risk factors latent in a basket of financial sector firms and generalised autoregressive conditional heteroscedasticity (GARCH) analysis to examine the volatility of the principal risk factors.

Results: The findings suggest that the heterogeneity of risk factors within the financial sector has burgeoned in the past five years, explaining a large proportion of risk during this period. However, over the long-term, banks appeared to have been the main factor driving risk within the financial sector, explaining around 55% of risk. The volatility of banks was most noticeable during business cycle falls that were underpinned by known economic or political instability.

Conclusion: Banks have been the riskiest factor within financial sector firms over the past decade, explaining more than 50% of risk in recent years and notably susceptible to economic and political uncertainty.

Introduction

The financial sector represents an important part of the economy, as it facilitates the savings and investment process of economic agents. Understanding the risks inherent in such a sector is vital, particularly from a portfolio risk management perspective. Insight into the risks can aid in protecting against capital loss in the event of large exposure to such risk factors.

The past several years have borne witness to economic and political events that have caused a steady decline in the credit ratings of local banks and sovereign bonds. The most recent downgrade by S&P of foreign-denominated South African debt to junk status is an outcome of the challenging effects of local economic and political conditions (South African Reserve Bank [SARB] 2017). These uncertainties have the ability, *ceteris paribus*, to impact the profitability of firms within the financial sector, particularly banks (Appleton 2016). Amid a sluggish growth environment, this trend reinforces lower profitability.

A related aspect of deteriorating sentiment concerns the impact of capital flows on the stock prices of listed firms, such as those of banks, and the consequent volatility associated with these price movements. Portfolios may utilise listed equity markets such as the Johannesburg Stock Exchange (JSE) All Share Index in portfolio construction, which the financial sector is inherently a component of. From a portfolio risk management perspective, it is important to identify risk factors latent within a sector and explain the volatility over time. This may allow one to protect against capital loss, particularly portfolios that are substantially exposed to financial sector stocks.

Several studies in the literature have discussed the behaviour of listed stocks from international and local perspectives. From a local perspective, Moolman and du Toit (2005) examined the relationships between the South African stock market and macroeconomic variables from Q3 1987 to Q4 2000 using an error correction technique. This was intended to capture the short-term dynamics between the variables in question. Results revealed that in the short-term, volatilities or fluctuations in the local stock market were caused by macroeconomic variables, such as, inter alia, short term interest rates, the Rand/US$ exchange rate and the gold price.

Szczygielski and Chipeta (2015) utilised an asset-pricing model, namely, the arbitrage pricing theory (APT) to explain the risk factors of South African stocks from July 1995 to March 2011. Results revealed that various factors explained the behaviour of the South African stock market, namely, local inflation, changes in money supply, oil prices, real economic activity and the Rand/US$ exchange rate.

Van Rensburg (1995) utilised a multifactor model to examine the relationship between the local stock market and several macroeconomic factors, namely, term structure of the interest rate, returns of the New York Stock Exchange, the gold price and inflation expectations. Results revealed all four factors were significant drivers of local stock prices.

From an international perspective, Mouna and Anis (2016) investigated the sensitivity of returns in three financial sectors to macroeconomic variables, namely, the interest rate, stock market and the exchange rate using an adapted generalised autoregressive conditional heteroscedasticity (GARCH) model during the financial crisis. Eight countries were sampled and examined during this time period (2006–2009). Results revealed that overall across the eight countries, stock market returns, exchange rate volatility and interest rates had significant effects on the returns of the three financial sectors (banks, financials and insurance) during the financial crisis.

Zeng et al. (2014) examined whether the United States of America (US) banks played an important role in explaining the volatility of US stocks. The authors utilised a multifactor model based on monthly returns of US stock portfolios, size and value factors from January 1980 to December 2007. Results revealed that the banking risk factor significantly explained volatility in stock returns.

Schuermann and Stiroh (2006) examined the common factors that drove US bank stock returns from 1997 to 2005 using several multifactor models. Results revealed that the market factor noticeably drove the returns in bank stocks, with interest–related factors not being helpful in explaining such return behaviour of banks, particularly for the largest banks.

Berkowitz (2001) utilised the Fama and French (1993) model for determining common risk factor drivers of Canadian stock returns. The author used this type of multifactor model on monthly Canadian stock returns from January 1982 to December 1999. It was revealed that three factors explained the major part of the volatility in Canadian stocks over time.

The above studies in conjunction with a scan of available literature suggested no apparent presence of studies, at least locally, that have examined inherent risk factors within particular sectors of listed equities through time, such as the financial sector. Thus, a knowledge gap exists, which this study aims to fill by offering scientific value to the local literature. To investigate the problems of identifying and explaining the intertemporal principal financial sector risk factors and their related volatilities, two statistical models were employed. Firstly, factor analysis was used to extract risk factors latent within local financial sector stocks over three-year, five-year and 10-year periods. The aim was to identify the main risk factors and any changes in those factors. Secondly, because time-series variables tend to exhibit volatility clustering properties, a GARCH (1,1) model was used to explain the volatility of identified principal risk factors through time. This allowed us to clearly identify periods in which principal risk factors were volatile, and to attach economic rationale to those periods of volatility. The methodology and data section is followed by the Results section. The final section provides the concluding remarks.

Methodology and data

Data

Data for all financial sector stocks listed on the JSE main board between June 2007 and May 2017 were obtained from the data provider iNet **BFA**, denominated in South African Rands (ZAR). This was the method used to obtain the financial sector stocks. The financial sector comprises stocks from the industry membership groups of banks, insurance, real estate and financial services (FTSE Russell 2016). Weekly pricing history was utilised for all variables and was converted into monthly returns (Equation 1) and standardised (Equation 2) for factor extraction. Details on the variables appear in Appendix 1.

$$R_t = \left(\frac{p_t}{P_{t-1}}\right)-1 \quad \text{[Eqn 1]}$$

$$R_t = \frac{R_t-\mu}{\sigma} \quad \text{[Eqn 2]}$$

Factor analysis was conducted to extract risk factors latent within local financial sector stocks over three-year (short-term), five-year (medium term) and 10-year (long-term) time horizons. The respective monthly data points were 156, 260 and 520. Prior to standardisation, variables were checked for consistency regarding weekly returns. Those that did not have such on a frequent basis were excluded from the analysis. Thus, the sample size diminished as the time horizon increased, representing a limitation to this study.

All variables used in the study were standardised or normalised through the calculation of Z-scores, which has the effect of preserving the normality nature of the variables in question, particularly transforming variables into new scores with a mean of zero and a unit standard deviation (Abdi & Williams 2010). A Z-score for each observation of a variable is calculated by subtracting the mean of the variable from each observation's value, and then dividing the answer by the standard deviation of the variable in question (refer to Eqn 2). Mean centring and autoscaling are critical in factor analysis as they allow all variables to have equal importance in contributing to the analysis.

Factor analysis

Factor analysis extracts uncorrelated factors latent in a data set, with the approach aiming to explain most of the variance for the data, particularly the covariance between underlying variables. Factors constitute linear combinations of underlying variables, typically from a transformed matrix based on standardised variables such as a correlation coefficient matrix (Landau & Everitt 2004). Standardisation is critical as it centres the mean of each variable to allow for comparative analysis.

Factors are analogous to eigenvectors, with each eigenvector exhibiting an eigenvalue. An eigenvalue represents a measure of variance in all variables within a data set. Various factor extraction methods can be used, such as principal components analysis (PCA), principal factor analysis (PFA) and the maximum likelihood method (Iacobucci 2001). The PFA method was employed for this study as an appropriate method to extract the factors, as it takes into account uniqueness or measurement error of the underlying variables (Landau & Everitt 2004). In other words, PFA extracts factors based on the degree of variation between variables, whereas PCA extracts factors based on the level of variance within individual variables. The higher the level of common variance (known as communality) and the lower the level of uniqueness (non-common variation) of a variable, the more relevant the variable becomes in explaining the meaning of a factor.

Fundamentally, eigenvalues of a square matrix were computed using Equation 3:

$$Av = \lambda v \qquad \text{[Eqn 3]}$$

where:

- *$A = i*i$ matrix*
- *v = column vector of eigenvectors*
- *λ = eigenvalue or determinant*

Equation 3 above is analogous to an optimisation or maximisation problem solved by the Lagrange-Multiplier λ.

The PFA method uses spectral decomposition as suggested by Anderson–Rubin in 1956 (StataCorp 2013) to segment a correlation coefficient matrix into factors, assuming i variables and j factors:

$$C = \sum_{j=1}^{p} \lambda_j e_j e_j' + \varepsilon_i = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_j \end{bmatrix} \begin{bmatrix} \lambda_{1,1} & \lambda_{1,2} & \cdots & \lambda_{1,j} \\ \lambda_{2,1} & \lambda_{2,2} & \cdots & \lambda_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{i,1} & \lambda_{i,2} & \cdots & \lambda_{i,j} \end{bmatrix} \begin{bmatrix} \lambda_{1,1} & \lambda_{1,2} & \cdots & \lambda_{1,j} \\ \lambda_{2,1} & \lambda_{2,2} & \cdots & \lambda_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{i,1} & \lambda_{i,2} & \cdots & \lambda_{i,j} \end{bmatrix}^T + \begin{bmatrix} \psi_1 & 0 & \cdots & 0 \\ 0 & \psi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \psi_i \end{bmatrix} \qquad \text{[Eqn 4]}$$

where:

- *$C = i*i$ correlation coefficient matrix*
- *$\lambda_j = j*j$ diagonal eigenvalue matrix*
- *$e_j = i*j$ factor loading matrix orthogonal in nature*
- *e_j' = transpose of e_j*
- *$\varepsilon_i = i*i$ diagonal matrix of residuals/uniqueness*

After factor extraction is complete, rotation of the factors is required to clarify the interpretation of the factors (Yong & Pearce 2013). Traditionally, orthogonal varimax rotation is used as it preserves the lack of correlation among factors (Walker & Maddan 2013). This rotation approach geometrically rotates the extracted factors to form 'new' (adjusted) axes in a clockwise manner, causing the factors to remain perpendicular or orthogonal to each other. Mathematically, rotated loadings of underlying variables become correlated close to one in one eigenvector and close to 0 in other eigenvectors. Ideally, each factor should have a few large positive loadings and a large number of small or negative loadings.

After factor rotation, the last step is to describe the extracted factors, and to interpret their meaning in terms of economic theory. The factor analysis method is underpinned by variables that exhibit high loadings and low uniqueness levels clustering together (Yong & Pearce 2013); the researcher then attaches a description based on these clustered variables. Common descriptions refer to the fundamental characteristics of stocks, such as valuation metrics and industry memberships. Valuation metrics entail using valuation measures of stocks, such as price-to-book and earnings growth levels, to describe variables. Industry membership entails using the nature of the business based on revenue generation to describe the variables. The latter method was used in this study.

The generalised autoregressive conditional heteroscedasticity model

Generalised autoregressive conditional heteroscedasticity models are a type of conditional volatility model. The GARCH model explains and forecasts the volatility of time-series variables that exhibit autocorrelation and heteroscedasticity. A GARCH (1,1) model assumes that the best predictor of the current period's error variance is a function of a weighted long-run variance average, information obtained in the previous period (squared residual) and the previous period's variance (Poon & Granger 2005). Equation 5 is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \qquad \text{[Eqn 5]}$$

In essence, GARCH transforms each original variance at time *t* to be conditional upon the above three terms, thus taking into account heteroscedasticity and autocorrelation. This method provides a robust way to explain volatility through time (Engle, 2001). Although other models exist that are able to explain through time volatility of financial variables, such models were not investigated as this was not the sole focus of the paper. Thus, a robust, parsimonious and popular model was selected to show through time volatility of financial variables that exhibited heteroscedasticity and autocorrelation, namely, the GARCH (1,1) model. The statistical software Stata was used to run factor analysis and GARCH analysis in this study.

Results

Factor extraction

A prerequisite for factor extraction is that variables must show moderate to moderately high levels of correlation. This enables factors to be extracted and underlying variables to be assigned to the factors. The data conformed to this requirement, as confirmed by the high Kaiser–Meyer–Olkin (KMO) values of 0.865 for the short-term, 0.908 for the medium-term and 0.9336 for the long-term models, respectively (details provided in Appendix 2). The KMO statistic measures the proportion of variance among variables that might be shared. As a general rule, a KMO value of between 0.8 and 1 indicates sampling adequacy.

Table 1 shows the rotated factors that account for approximately 80% of the variance – hence volatility – in the financial sector. In this particular case, the variance can be labelled as risk in the financial sector. Over the short, medium and long terms, a single factor (Factor 1) stands out as explaining a large proportion of risk. The variance of this factor has diminished in recent years; it explained only 39% of variance (risk) over the most recent three-year period, compared with 55% over the longer 10-year period. However, Factor 1 still accounts for a large proportion of financial sector risk.

The sample size across the three time horizons was not consistent, owing to certain stocks not having a complete pricing history. This implies that the stock composition of the financial sector appears to have expanded during recent years. The sample was smallest for the 10-year time horizon and largest for the three-year time horizon (these details are provided in Appendix 1). This difference might explain the dilution in volatility contributed by Factor 1 for the shorter time horizons. The risk composition of the financial sector appears to have become more diverse, with a greater number of risk factors witnessed over the short-term that explain approximately 80% of the financial sector risk.

With the proliferation of short term risk factors latent in the financial sector and the dilution of risk emanating from Factor 1 over the short-term, the question arises: what does Factor 1 comprise? Answering this question would allow economic meaning to be attached to the factor. An inherent problem within factor analysis is the subjectivity in naming or describing factors. An approach to quantitatively naming the factors is to refer to the level of variance a variable contributes to the overall eigenvalue of the factor, in conjunction with the level of uniqueness of the variable in question. Highly unique variables imply a lesser relevance in explaining the factor in question. Table 2 shows the loadings for each model and the variance each variable contributed to Factor 1. As Factor 1 accounts for a large amount of volatility across the three time horizons, it is the focus of this paper.

TABLE 1: Factor eigenvalues (varimax rotation).

Three-year time horizon					Five-year time horizon					10-year time horizon				
Factor	Eigenvalue	Difference	Proportion (%)	Cumulative (%)	Factor	Eigenvalue	Difference	Proportion (%)	Cumulative (%)	Factor	Eigenvalue	Difference	Proportion (%)	Cumulative (%)
1	13.810	11.505	39.63	39.63	1	9.768	6.001	45.83	45.83	1	6.691	4.126	55.33	55.33
2	2.305	0.299	6.62	46.25	2	3.767	2.132	17.67	63.51	2	2.565	1.587	21.21	76.54
3	2.006	0.596	5.76	52.20	3	1.635	0.779	7.67	71.18	3	0.978	0.167	8.09	84.62
4	1.410	0.086	4.05	56.86	4	0.856	0.251	4.01	75.19	-	-	-	-	-
5	1.325	0.314	3.80	59.86	5	0.604	0.107	2.84	78.03	-	-	-	-	-
6	1.011	0.089	2.90	62.76	6	0.498	0.005	2.34	80.26	-	-	-	-	-
7	0.922	0.014	2.65	65.40	-	-	-	-	-	-	-	-	-	-
8	0.908	0.031	2.61	68.01	-	-	-	-	-	-	-	-	-	-
9	0.877	0.005	2.52	70.53	-	-	-	-	-	-	-	-	-	-
10	0.872	0.073	2.50	73.03	-	-	-	-	-	-	-	-	-	-
11	0.800	0.008	2.30	75.33	-	-	-	-	-	-	-	-	-	-
12	0.792	0.036	2.27	77.60	-	-	-	-	-	-	-	-	-	-
13	0.756	0.044	2.17	79.77	-	-	-	-	-	-	-	-	-	-

TABLE 2: Contribution to factor variance: Three-year time horizon.

Variables	Factor 1			
	Loading	Loading squared	Contribution (%)	Uniqueness
BGA†	0.834	0.695	5.12	0.106
CPI	0.676	0.457	3.37	0.182
FGL	0.127	0.016	0.12	0.516
FSR†	0.941	0.886	6.52	0.032
NED†	0.875	0.765	5.63	0.100
RMH†	0.947	0.898	6.61	0.034
SBK†	0.880	0.775	5.71	0.080
CML	0.635	0.404	2.97	0.360
EFG	-0.074	0.005	0.04	0.600
PGR	0.513	0.263	1.94	0.389
BAT	0.508	0.258	1.90	0.386
INL	0.683	0.466	3.43	0.214
JSE	0.494	0.244	1.80	0.359
PSG	0.621	0.385	2.84	0.223
PPE	0.117	0.014	0.10	0.559
SFN	0.237	0.056	0.41	0.526
AEE	0.172	0.029	0.22	0.497
GPL	0.381	0.145	1.07	0.464
TCP	0.160	0.026	0.19	0.432
TTO	0.155	0.024	0.18	0.515
ZED	0.409	0.167	1.23	0.488
CLI	0.078	0.006	0.04	0.460
DSY†	0.743	0.552	4.07	0.202
LBH	0.681	0.464	3.42	0.283
MMI†	0.868	0.754	5.55	0.122
OML	0.680	0.463	3.41	0.166
SLM†	0.843	0.710	5.23	0.122
CND	0.034	0.001	0.01	0.495
SNT	0.475	0.226	1.66	0.422
BRN	0.106	0.011	0.08	0.529
BRT	0.151	0.023	0.17	0.585
HCI	0.204	0.042	0.31	0.527
NIV	0.087	0.007	0.06	0.451
PGL	0.112	0.012	0.09	0.514
RMI†	0.812	0.660	4.86	0.119
REI	0.030	0.001	0.01	0.337
SCP	0.188	0.035	0.26	0.482
APF	0.323	0.104	0.77	0.393
CCO	-0.109	0.012	0.09	0.322
MSP	0.069	0.005	0.04	0.510
NEP	0.150	0.022	0.17	0.480
ROC	0.221	0.049	0.36	0.362
TDH	-0.012	0.000	0.00	0.604
EMI	0.535	0.286	2.11	0.604
FFA	0.460	0.212	1.56	0.274
FFB	0.375	0.141	1.04	0.327
GRT	0.695	0.483	3.56	0.140
IPF	0.459	0.211	1.55	0.401
REB	0.362	0.131	0.97	0.338
RPL	-0.094	0.009	0.07	0.287
RDF	0.622	0.387	2.85	0.175
SAC	0.487	0.237	1.75	0.166
TEX	0.192	0.037	0.27	0.415
TWR	0.244	0.060	0.44	0.374
AWA	0.446	0.199	1.47	0.252
DLT	0.215	0.046	0.34	0.410
IAP	0.010	0.000	0.00	0.510
Total	-	**13.576†**	-	-

Note: For the definitions of variables used in this table, see Table 1-A1.

†, Highlight the stocks that are deemed as important in explaining the risk factor. Table 2 shows the loadings for Factor 1, including each element's or variable's contribution to the overall variance of the factor. Loadings represent the level of correlation between a variable and its respective factor. To calculate the percentage amount that a variable contributes to the eigenvalue of the respective factor, loadings must be squared. A summation of the squared loadings amounts to the eigenvalue of the factor in question. Loadings above 0.70 paired with uniqueness levels below 0.30 were considered relevant in explaining the nature of Factor 1 in this study, with the following stocks meeting those criteria: **BGA**, FSR, NED, RMH, **SBK**, MMI, SLM, DSY and **RMI**. The last four in this list can be described as insurance stocks based on industry membership, namely, MMI Holdings, Sanlam, Discovery Holdings and Rand Merchant Insurance. Together they accounted for around 19.38% of the variance of Factor 1. The first five stocks were banks (BGA, FSR, NED, RMH and SBK) which accounted for 29.09% of the variance. Hence, the insurance stocks provide complexity to describing Factor 1 as 'banks', with the name 'banks and insurance' being more appropriate for Factor 1 over the short-term (three-year horizon).

Table 3 shows a similar level of loadings over the medium term, with most of the same stocks appearing to have the greatest relevance in explaining the variance of Factor 1. However, bank stocks appear to have greater relevance than insurance stocks, accounting for around 37.82% of the variance in Factor 1, compared with the 16.78% accounted for by MMI, SLM and RMI. (DSY accounted for less than 4.5% and was therefore dropped from explaining the factor.) None of the insurance stocks had loadings in excess of 0.8, unlike in the short term model. Thus, for the five-year time horizon, Factor 1 can best be described more clearly as 'banks'.

Table 4 shows loadings over the long-term, with bank stocks clearly appearing to account for most of the variance of Factor 1 at around 52.38%. None of the insurance stocks had

TABLE 3: Contribution to factor variance: Five -year time horizon.

Variables	Factor 1			
	Loading	Loading squared	Contribution (%)	Uniqueness
BGA†	0.752	0.565	5.78†	0.295
CPI	0.557	0.310	3.17	0.352
FGL	0.047	0.002	0.02	0.729
FSR†	0.929	0.863	8.83†	0.050
NED†	0.841	0.708	7.24†	0.182
RMH†	0.920	0.846	8.66†	0.076
SBK†	0.845	0.714	7.31†	0.147
CML	0.547	0.299	3.06	0.524
PGR	0.394	0.155	1.59	0.618
BAT	0.440	0.193	1.98	0.553
INL	0.593	0.351	3.60	0.327
JSE	0.423	0.179	1.83	0.614
PSG	0.500	0.250	2.56	0.409
PPE	0.085	0.007	0.07	0.727
SFN	0.150	0.022	0.23	0.721
AEE	0.120	0.014	0.15	0.668
GPL	0.298	0.089	0.91	0.681
TTO	0.124	0.015	0.16	0.730
ZED	0.331	0.109	1.12	0.586
CLI	0.059	0.003	0.04	0.708
DSY	0.652	0.425	4.35	0.329
LBH	0.581	0.337	3.45	0.393
MMI†	0.762	0.580	5.94†	0.232
OML	0.594	0.352	3.61	0.232
SLM†	0.753	0.566	5.80†	0.219
CND	0.063	0.004	0.04	0.746
SNT	0.352	0.124	1.27	0.558
BRN	0.120	0.014	0.15	0.720
BRT	0.118	0.014	0.14	0.777
HCI	0.173	0.030	0.30	0.662
PGL	0.084	0.007	0.07	0.701
RMI†	0.7015	0.492	5.04†	0.2664
REI	0.067	0.004	0.05	0.508
SCP	0.101	0.010	0.10	0.759
CCO	-0.087	0.007	0.08	0.480
NEP	0.086	0.007	0.08	0.663
TDH	0.005	0.000	0.00	0.766
EMI	0.399	0.159	1.63	0.360
FFA	0.304	0.093	0.95	0.405
FFB	0.211	0.044	0.46	0.643
GRT	0.487	0.237	2.43	0.209
IPF	0.283	0.080	0.82	0.523
REB	0.236	0.056	0.57	0.458
RPL	-0.045	0.002	0.02	0.559
RDF	0.437	0.191	1.95	0.293
SAC	0.309	0.095	0.98	0.374
TEX	0.144	0.021	0.21	0.670
AWA	0.345	0.119	1.22	0.404
Total	-	**9.768†**	**100.00**	-

Note: For the definitions of variables used in this table, see Table 1-A1.
†, Highlight the stocks that are deemed as important in explaining the risk factor.

TABLE 4: Contribution to factor variance: 10-year time horizon.

Variables	Factor 1			
	Loading	Loading squared	Contribution (%)	Uniqueness
BGA†	0.811	0.658	9.83†	0.281
CPI	0.350	0.123	1.83	0.599
FSR†	0.868	0.754	11.27†	0.156
NED†	0.814	0.662	9.90†	0.261
RMH†	0.840	0.706	10.55†	0.261
SBK†	0.851	0.725	10.83†	0.221
CML	0.496	0.246	3.67	0.567
PGR	0.289	0.084	1.25	0.720
BAT	0.254	0.064	0.96	0.729
INL	0.581	0.338	5.05	0.381
JSE	0.339	0.115	1.72	0.600
PSG	0.322	0.104	1.55	0.579
PPE	0.126	0.016	0.24	0.862
SFN	0.191	0.036	0.54	0.739
AEE	0.093	0.009	0.13	0.858
ZED	0.289	0.083	1.24	0.729
CLI	0.068	0.005	0.07	0.877
DSY	0.497	0.247	3.70	0.476
LBH	0.390	0.152	2.27	0.563
MMI	0.561	0.315	4.70	0.368
OML	0.525	0.276	4.12	0.370
SLM	0.613	0.376	5.62	0.338
CND	0.040	0.002	0.02	0.866
SNT	0.282	0.080	1.19	0.678
BRN	0.125	0.016	0.23	0.836
BRT	0.034	0.001	0.02	0.831
HCI	0.196	0.038	0.57	0.813
SCP	0.050	0.002	0.04	0.885
EMI	0.340	0.115	1.72	0.443
GRT	0.413	0.170	2.55	0.313
RDF	0.351	0.123	1.84	0.353
SAC	0.226	0.051	0.76	0.462
Total	**-**	**6.691†**	**100.00**	**-**

Note: For the definitions of variables used in this table, see Table 1-A1.
†, Bold entries highlight the stocks that are deemed as important in explaining the risk factor.

high enough loadings and low enough uniqueness levels to attach much importance to their role in describing Factor 1. Thus, for the 10-year horizon, banks contributed most to the risk in the financial sector and it is reasonable to describe Factor 1 as 'banks'. This finding provides impetus for examining the volatility of banks more in detail as it is the principal risk factor. The 'GARCH Analysis section' of this paper provides an explanation of the use of a GARCH (1,1) model to investigate the FTSE/JSE South African Banks Total Return Index. The GARCH (1,1) was selected as it represents a simple version of the GARCH model and provides parsimony to the analysis.

The generalised autoregressive conditional heteroscedasticity analysis

Figure 1 shows the weekly performance of South African banks over the past decade, proxied by the FTSE/JSE SA Banks Total Return Index. The data were obtained from iNet BFA. Graphically, there have been periods where volatility has clustered, highlighted by the red circles. This pattern renders the data appropriate for a GARCH model, which requires data to exhibit volatility clustering so that the model can appropriately explain volatility through time. A prerequisite for using GARCH is to determine whether an autoregressive conditional heteroscedasticity (ARCH) effect exists; the Lagrange-Multiplier (LM) test is used for this purpose (Abonongo, Oduro & Ackora-Prah 2016). The LM merely tests whether coefficients in a regression are jointly equal to zero, implying no ARCH effect. This null hypothesis must be rejected to statistically confirm that ARCH effects do exist. The output from the LM test on our data can be found in Table 5.

Table 5 shows a *p*-value less than 0.0001, which is highly significant. This means the null hypothesis ('there is no ARCH effect') can safely be rejected and the need for a GARCH model to explain the volatility is required. We, therefore, ran the GARCH (1,1) model on the data for weekly returns in the SA Bank Index. The start point was Week 22 of 2007 (03 June 2007) and the end point was Week 20 of 2017 (14 May 2017). The output of the GARCH (1,1) model transformed the original residuals as a function of Equation 5. A visual depiction of these transformed values is shown in Figure 2, which highlights various periods in which volatility has clustered.

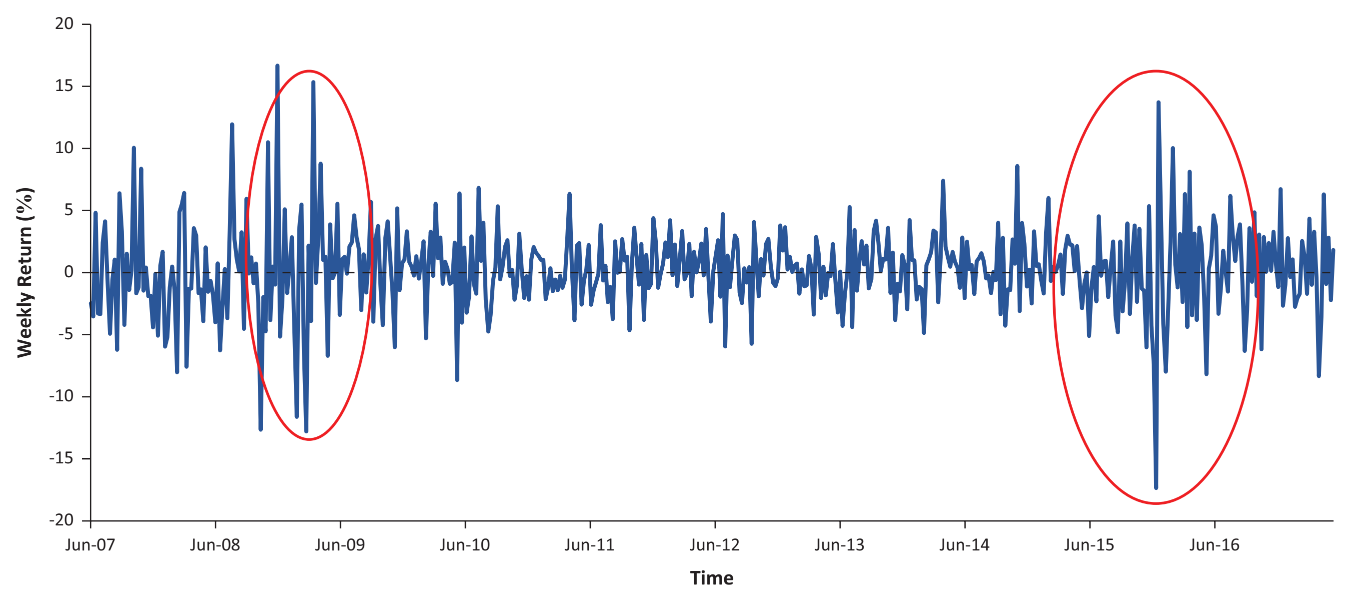

FIGURE 1: Weekly performance of South African banks.

TABLE 5: Lagrange-Multiplier test for autoregressive conditional heteroscedasticity effect.

Lags(*p*)	chi²	*df*	Prob>chi²
1	18.666	1	0.0000

Lags(*p*), the number of lags used in the model; Prob>chi², probability of obtaining the chi-square statistic given that the null hypothesis is true; Chi², chi-squared; *df*, degrees of freedom.

Of particular interest are the clusters highlighted in red circles in Figure 2. The first circle approximately represents the period October 2008 to March 2009, and the second circle approximately represents the period December 2015 to January 2016. The first period coincided with a fall in South Africa's business cycle, a period of volatility and uncertainty. This decline in the business cycle can be attributed to the global financial crisis (GFC). Figure 3 shows an estimation of the business cycle using the Hodrick–Prescott (HP) filter method to decompose seasonally adjusted real gross domestic product (GDP) into its trend component and cyclical component. The latter represents the business cycle (Hodrick & Prescott 1997). Seasonally adjusted real GDP data were obtained from the South African Reserve Bank (SARB). The HP filter minimises the following function to determine the trend within seasonally adjusted real GDP:

$$\min_{\{g_t\}_{t=-1}^{T}} \left\{ \sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=1}^{T} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2 \right\} \quad \text{[Eqn 6]}$$

The first term of Equation 6 above represents the sum of the squared deviations of output at time *t* from the trend. The second term represents the sum of squared second differences in the trend penalised by the Lagrange (λ) parameter (Hodrick & Prescott 1997). The λ parameter represents the extent to which the trend is required to be made smooth. Such a parameter is required to be specified, with a rule of thumb for calculating the estimation – that is, λ = 100*(number of periods in a year)^2. Quarterly data, for example, are given the parameter of 1600. Thus, the cyclical component is calculated by the difference between actual output and its trend.

The second period also coincided with a decline in the business cycle, witnessed from the start of 2015, a period rife with political instability. A case in point was the dismissal of Finance Minister Nene early in December 2015, which resulted in a sharp increase in the yield of the South African sovereign 10-year note by over 10%. This raised government borrowing costs and impacted bank stocks. Although no causality can be inferred from this apparent association, the pattern clearly shows that bank stocks are extremely volatile during periods of economic and political uncertainty, *ceteris paribus*.

Conclusion

The heterogeneity of risk factors inherent within the financial sector has burgeoned in recent times, explaining a large proportion of the risk within the sector. This trend appears to be because of the expansion of stocks within the financial sector. However, over the long-term (10-year horizon), a single risk factor evidently drove most of the risk (55%), and three risk factors collectively explained around 84% of the risk in the financial sector over the same period. Using industry membership as a basis to describe principal risk factors, it was clear that banks represented the principal risk factor over the long-term. Banks have been significantly volatile over two periods within this long-term time horizon, as shown by the GARCH analysis. The first period coincided with the fall in South Africa's business cycle, precipitated by the GFC. The second period was because of increased political risk (*ceteris paribus*) immediately after the dismissal of Finance Minister Nene, suggesting that economic and political risks have an intense effect on banks. The increased heterogeneity of risk factors within financial stocks in the short-term (three-year horizon) holds implications for portfolio risk management. Portfolios having wide exposure to the financial sector require one to be cognisant of the increased array of

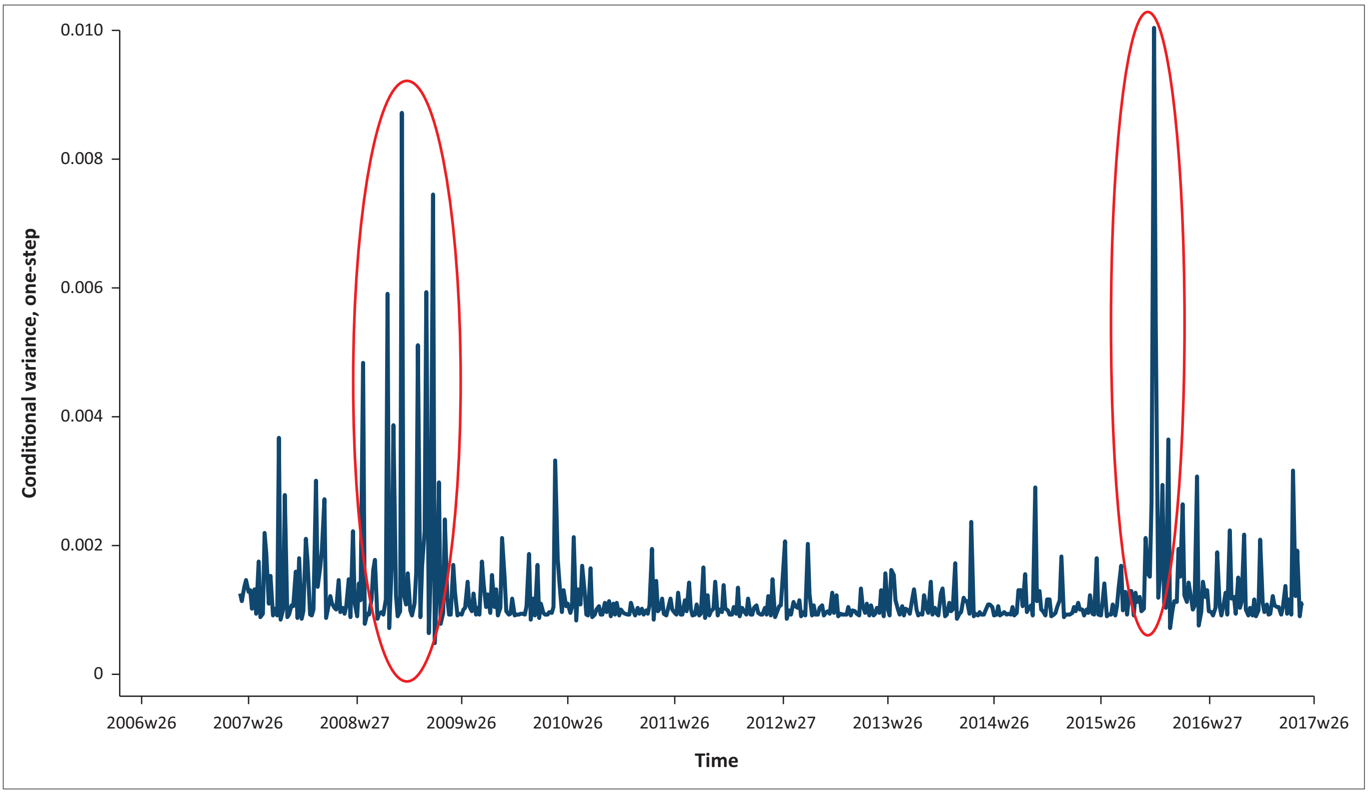

FIGURE 2: Conditional variance.

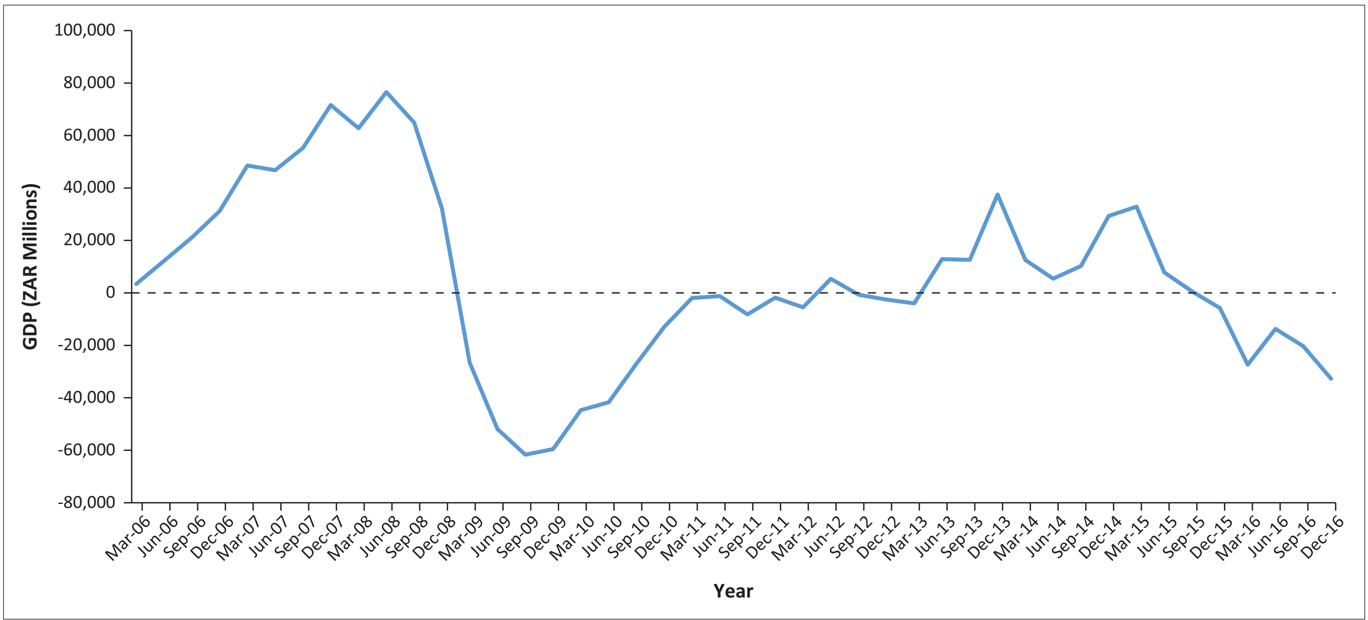

FIGURE 3: South African business cycle.

risk factors now present. Such awareness may aid in protecting against capital loss in the event of increased economic and political uncertainty. Given the current landscape in South Africa, such a scenario seems fairly probable at present.

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Competing interests

The author declares that he has no financial or personal relationships that may have inappropriately influenced him in writing this article.

Authors’ contributions

The author declares that he has no financial or personal relationships that may have inappropriately influenced him in writing this article.

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Appendices start on the next page →

Appendix 1

Names of variables

TABLE 1-A1: Variables used in factor analysis models.

Three-year time horizon model		Five-year time horizon model		10-year time horizon model	
iNet Code	**Name**	**iNet Code**	**Name**	**iNet Code**	**Name**
BGA	Barclays Africa Group Ltd	BGA	Barclays Africa Group Ltd	BGA	Barclays Africa Group Ltd
CPI	Capitec Bank Holdings Ltd	CPI	Capitec Bank Holdings Ltd	CPI	Capitec Bank Holdings Ltd
FGL	Finbond Group Ltd	FGL	Finbond Group Ltd	FSR	FirstRand Ltd
FSR	FirstRand Ltd	FSR	FirstRand Ltd	NED	Nedbank Group
NED	Nedbank Group	NED	Nedbank Group	RMH	RMB Holdings
RMH	RMB Holdings	RMH	RMB Holdings	SBK	Standard Bank Group
SBK	Standard Bank Group	SBK	Standard Bank Group	CML	Coronation Fund Managers
CML	Coronation Fund Managers	CML	Coronation Fund Managers	PGR	Peregrine Holdings Limited
EFG	Efficient Group Limited	PGR	Peregrine Holdings Limited	BAT	Brait SE
PGR	Peregrine Holdings Limited	BAT	Brait SE	INL	Investec Limited
BAT	Brait SE	INL	Investec Limited	JSE	JSE Limited
INL	Investec Limited	JSE	JSE Limited	PSG	PSG Group Limited
JSE	JSE Limited	PSG	PSG Group Limited	PPE	Purple Group Limited
PSG	PSG Group Limited	PPE	Purple Group Limited	SFN	Sasfin Holdings Limited
PPE	Purple Group Limited	SFN	Sasfin Holdings Limited	AEE	African Equity Empowerment (EMP) Investments
SFN	Sasfin Holdings Limited	AEE	African Equity Empowerment (EMP) Investments	ZED	Zeder Investment Ltd
AEE	African Equity Empowerment (EMP) Investments	GPL	Grand Parade Investments Ltd	CLI	Clientele Life Assurance Ltd
GPL	Grand Parade Investments Ltd	TTO	Trustco Group Holdings Ltd	DSY	Discovery Ltd
TCP	Transaction Capital Ltd	ZED	Zeder Investment Ltd	LBH	Liberty Holdings Ltd
TTO	Trustco Group Holdings Ltd	CLI	Clientele Life Assurance Ltd	MMI	MMI Holdings Ltd
ZED	Zeder Investment Ltd	DSY	Discovery Ltd	OML	Old Mutual Plc
CLI	Clientele Life Assurance Ltd	LBH	Liberty Holdings Ltd	SLM	Sanlam Ltd
DSY	Discovery Ltd	MMI	MMI Holdings Ltd	CND	Conduit Capital Ltd
LBH	Liberty Holdings Ltd	OML	Old Mutual Plc	SNT	Santam Ltd
MMI	MMI Holdings Ltd	SLM	Sanlam Ltd	BRN	Brimstone Investment Corp Class N
OML	Old Mutual Plc	CND	Conduit Capital Ltd	BRT	Brimstone Investment Corp
SLM	Sanlam Ltd	SNT	Santam Ltd	HCI	Hosken Consolidated Investments Ltd
CND	Conduit Capital Ltd	BRN	Brimstone Investment Corp Class N	SCP	Stellar Cap Partners Ltd
SNT	Santam Ltd	BRT	Brimstone Investment Corp	EMI	EMIRA Property Fund Ltd
BRN	Brimstone Investment Corp Class N	HCI	Hosken Consolidated Investments Ltd	GRT	Growthpoint Properties Ltd
BRT	Brimstone Investment Corp	PGL	Pallinghurst Resources Ltd	RDF	Redefine Properties Ltd
HCI	Hosken Consolidated Investments Ltd	RMI	Rand Merchant Investment Holdings Ltd	SAC	SA Corporate Estate Fund Ltd
NIV	Niveus Investments Ltd	REI	Reinet Investments SCA	-	-
PGL	Pallinghurst Resources Ltd	SCP	Stellar Cap Partners Ltd	-	-
RMI	Rand Merchant Investment Holdings Ltd	CCO	Capital and Counties Properties Plc	-	-
REI	Reinet Investments SCA	NEP	New Europe Property Investments Plc	-	-
SCP	Stellar Cap Partners Ltd	TDH	Tradehold Ltd	-	-
APF	Accelerate Property Fund Ltd	EMI	EMIRA Property Fund Ltd	-	-
ATT	Attacq Ltd	FFA	Fortress Fund Ltd A Class	-	-
CCO	Capital and Counties Properties Plc	FFB	Fortress Fund Ltd B Class	-	-
MSP	MAS Real Estate Inc	GRT	Growthpoint Properties Ltd	-	-
NEP	New Europe Property Investments Plc	IPF	Investec Property Fund Ltd	-	-
ROC	Rockcastle Global Real Estate	REB	Rebosis Property Fund	-	-
TDH	Tradehold Ltd	RPL	Redefine International Plc	-	-
EMI	EMIRA Property Fund Ltd	RDF	Redefine Properties Ltd	-	-
FFA	Fortress Fund Ltd A Class	SAC	SA Corporate Estate Fund Ltd	-	-
FFB	Fortress Fund Ltd B Class	TEX	Texton Property Fund Ltd	-	-
GRT	Growthpoint Properties Ltd	AWA	Arrowhead Properties Ltd	-	-
IPF	Investec Property Fund Ltd	-	-	-	-
REB	Rebosis Property Fund	-	-	-	-
RPL	Redefine International Plc	-	-	-	-
RDF	Redefine Properties Ltd	-	-	-	-
SAC	SA Corporate Estate Fund Ltd	-	-	-	-
TEX	Texton Property Fund Ltd	-	-	-	-
TWR	Tower Property Fund Ltd	-	-	-	-
AWA	Arrowhead Properties Ltd	-	-	-	-
DLT	Delta Property Fund Ltd	-	-	-	-
IAP	Investec Australia Property Fund	-	-	-	-

Appendix 2

Measure of sampling adequacy

TABLE 1-A2: Kaiser–Meyer–Olkin measure of sampling adequacy.

Variables	Three-year model	Five-year model	10-year model
BGA	0.895	0.951	0.958
CPI	0.895	0.912	0.917
FGL	0.458	0.382	-
FSR	0.926	0.891	0.926
NED	0.939	0.943	0.958
RMH	0.934	0.919	0.934
SBK	0.924	0.933	0.947
CML	0.935	0.950	0.967
EFG	0.380	-	-
PGR	0.888	0.941	0.955
BAT	0.883	0.946	0.942
INL	0.918	0.952	0.937
JSE	0.834	0.935	0.951
PSG	0.888	0.920	0.939
PPE	0.600	0.525	0.842
SFN	0.803	0.824	0.891
AEE	0.597	0.644	0.772
GPL	0.837	0.893	-
TCP	0.611	-	-
TTO	0.649	0.749	-
ZED	0.873	0.894	0.946
CLI	0.470	0.541	0.751
DSY	0.927	0.941	0.954
LBH	0.924	0.954	0.931
MMI	0.936	0.953	0.958
OML	0.926	0.937	0.928
SLM	0.934	0.948	0.958
CND	0.353	0.437	0.380
SNT	0.936	0.913	0.948
BRN	0.364	0.493	0.736
BRT	0.463	0.591	0.481
HCI	0.624	0.713	0.896
NIV	0.417	-	-
PGL	0.636	0.594	-
RMI	0.9266	0.937	-
REI	0.508	0.621	-
SCP	0.666	0.748	0.785
APF	0.850	-	-
ATT	0.850	-	-
CCO	0.860	0.658	-
MSP	0.477	-	-
NEP	0.664	0.729	-
ROC	0.742	-	-
TDH	0.463	0.466	-
EMI	0.896	0.934	0.933
FFA	0.895	0.933	-
FFB	0.834	0.846	-
GRT	0.935	0.923	0.928
IPF	0.892	0.898	-
REB	0.856	0.878	-
RPL	0.621	0.584	-
RDF	0.931	0.932	0.917
SAC	0.884	0.917	0.910
TEX	0.722	0.851	-
TWR	0.761	-	-
AWA	0.866	0.915	-
DLT	0.833	-	-
IAP	0.428	-	-

Note: For the definitions of variables used in this table, see Table 1-A1.