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ANALYZING THE RELATIONSHIP BETWEEN DERIVATIVE USAGE AND SYSTEMIC RISK IN SOUTH AFRICA

Sheunesu Zhou
University of Zululand, South Africa
Email: zhous@unizulu.ac.za

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Abstract

This paper analyzes the relationship between derivative usage and systemic risk in South Africa. We employ expected shortfall as a measure of systemic risk for the banking sector. The more flexible Toda-Yamamoto Granger non-causality test is used to find the direction of causality between the variables, and the ARDL estimation technique is employed to estimate the specified model. We also test for the existence of a long-run relationship amongst the variables using the Bounds test approach. We find that credit derivatives and bank credit extensions increase systemic risk in the long run. Moreover, the systemic risk decreases in bank liquidity and usage of equity derivatives. However, in the short run, we find that increases in bank liquidity tend to increase systemic risk. We interpret this to imply that improvements in liquidity cause banks to undertake riskier transactions. Furthermore, the market can also perceive central bank interventions to increase liquidity as a sign of worsening financial conditions. On the backdrop of these results, we recommend continuous monitoring of derivatives markets to avoid risk excesses that could pose threat to the whole financial system.

Keywords: Systemic Risk, Derivative Usage, Bank Liquidity, Expected Shortfall, ARDL

JEL Classifications: G01, G21, G32

1. Introduction

There is considerable disagreement in finance literature over the impact of derivative usage on both systemic risk (or financial stability) and the performance of financial and non-financial firms. The extant literature on financial innovation categorizes derivatives as hedging instruments in risk management although other contributors have argued for the presence of monetary traits in these instruments (Bryan and Rafferty, 2007). In risk management, derivatives allow the holder to take a calculated risk under uncertainty by pricing the risk separately from the asset that drives the exposure, thereby enabling risk-sharing. As posited by Kim *et al*. (2017) and Prevost *et al*. (2000), increased use of derivatives in firms should impact firm value positively, as derivatives provide increased ability to undertake positive net present value projects through lowering contracting costs and increased efficiency of capital markets. However, both theoretical and empirical literature on derivative usage exhibits disagreements on whether derivatives result in increased welfare through increases in firm value. Theoretical arguments against the proposition of increased firm value arise from the notion of derivatives being speculative and opaque instruments, which can be used by financial corporations to undertake speculative positions to the detriment of financial market stability and societal welfare (LiPuma and Lee, 2004). Bae and Kwon (2020) also find that derivative hedging becomes difficult during times of crisis, hence increased derivative usage may result in decreased firm value and increased financial market fragility.

Furthermore, in support of the risk reduction proposition, Scholer-Iordanashvili (2020) finds that derivatives significantly reduce bank risk. In contrast, Mayordomo *et al*. (2014) demonstrate that regardless of the relatively small effect derivative use has on systemic risk compared to traditional risk sources, the impact of derivatives on systemic risk is non-negligible. The same finding is supported by Taskin and Sariyer (2020), who find a positive association between derivative use and bank risk. In addition, concerns about the use of derivatives and their impact on financial market stability have risen after their observed role in the 2008/9 Global Financial crisis. Credit derivatives were at the center of the crush and subsequent crisis. As a response, the initial G20 agreement of 2009 has provided increased surveillance on derivate markets by organizations such as The Financial Stability Board (FSB), Bank for International Settlements (BIS), and the International Organization of Securities Commissions (IOSCO). While these recent reforms have focused mostly on the over-the-counter markets (OTC), they point to increased recognition of the potential inherent in financial derivatives to trigger or exacerbate systemic risk.

Why discuss derivatives in South Africa? South Africa together with other emerging economies experiences huge movements of capital flows in both directions. Due to high levels of risk associated with emerging economies, investors in these countries tend to increase the usage of derivative financial instruments to hedge risk. Firms in emerging market economies also face highly volatile capital markets and tend to participate in derivative financial markets to counter inefficiencies associated with financial markets and economic instability characterizing such economies. Fluctuations in commodity prices and currencies of small open economies, for instance, are acknowledged in literature and these tend to raise the need for both commodity and currency derivatives in emerging markets such as South Africa. In line with its development thrust, South Africa has managed to develop the most sophisticated and largest derivatives market in Sub-Saharan Africa. Since 1987, several exchange-traded derivatives have been added to the Johannesburg Stock Exchange (JSE). Recently, in line with the G20 resolutions, South Africa has also begun licensing OTC derivative providers. The volume of trade in derivative instruments has significantly increased compared to the 1990s and early 2000s, although it has fluctuated widely. For instance, open interest for equity derivatives averaged 9,100 contracts in 1990 and leaped to an average of 45,525,768 contracts in 2008. For 2020, the average open interest for equities was at 6,927,504 contracts. Credit derivatives have also grown by about 13.4 percent between 2008 and 2020, signifying increased credit risk management through derivatives markets.

In the finance-growth literature, Demirguc-Kunt and Levine (2004) note that "policymakers should instead focus on strengthening the rights of outside investors and enhancing the efficiency of contract enforcement". Their argument shows that firms, industries, and economies are impacted by overall financial development, which is affected by regulation and activities that enhance market efficiency. Thus, increased market efficiency, price discovery mechanism, and hedging in derivative markets for hedging are expected to result in improved resource allocation and lead to economic growth (Sendeniz-Yuncu *et al*. 2007). These effects are captured more succinctly by Haiss and Sammer (2010), who suggest that there are three channels through which the use of derivative impact economic performance. These are the volume channel, the efficiency channel, and the risk channel. The volume channel expresses the increased pooling of funds into capital markets as a result of derivative use. The efficiency channel highlights the efficacy of derivatives as an instrument of risk management, whereby the derivatives are observed to be lowering capital costs, improving price discovery, and improve inter-temporal resource allocation. Hence, the first two channels emphasize the positive impact of derivative usage on both firm value and economic growth. Lastly, the risk channel relates to the connotation given to derivatives as being "weapons of mass destruction" (Tuckman, 2016, p.

62). This view looks at the market destabilizing effects of derivative usage and can be decomposed into two channels. Firstly, derivatives are sophisticated instruments and are largely opaque as most derivative transactions have historically been undertaken over the counter as opposed to other financial instruments that are traded on exchanges. This can result in misuse, leading to risk triggers such as excessive leverage. The second subchannel is the building-up of vulnerabilities as a result of over-confidence caused by excessive over-dependence on derivative instruments. Financial market participants could end up taking high risks compared to their risk appetite, resulting in increased financial market fragility, which is detrimental to financial stability and economic performance.

We find a dearth of literature focusing on the impact of derivative usage on systemic risk in emerging economies, and in particular, no study has been undertaken to analyze the impact of the growth of South Africa’s derivatives market on both systemic risk and firm performance or value. Therefore, this study seeks to provide empirical evidence on the impact of derivative usage in South Africa on systemic risk. Unlike previous studies, we consider expected shortfall as a measure of systemic risk following Acharya et al. (2012). Our results show that equity derivatives tend to reduce systemic risk, whereas credit derivatives increase systemic risk. We also show that bank liquidity is important in lowering systemic risk, which underscores the theoretical proposition that financial crises emanate from increased illiquidity in financial markets (Bruno and Shin, 2013, Diamond and Dybvig, 1983).

This section is of an introductory nature. The rest of the study is organized as follows: Section 2 reviews both the theoretical and empirical literature on derivative usage covering global markets, emerging markets, and the South African market specifically. In section 3, the methodology used in the paper is explained, whereas section 4 presents the results from the analysis. Section 5 concludes the paper and provides some policy recommendations.

2. Literature review

2.1. Systemic risk and derivative usage

Diamond and Dybvig's (1983) model on bank runs provides a useful departure in analyzing theoretical research on systemic risk and contagion. The underlying element of their model is the liquidity transformation function of banks, which exposes banks to runs in the event that depositors withdraw their deposits en masse. The theory defines a consumer who faces uncertainty with regards to liquidity in the short term and a bank that is capable of providing liquidity insurance to the consumer (depositor). However, the bank insurance scheme only promises to pay a fixed amount in the event of early withdrawal. Withdrawal from a large number of depositors at the same time can only be financed through the liquidation of some assets. Therefore, rational depositors would be inclined to withdraw their deposits if they believe a large number of depositors are withdrawing, making a bank run a self-fulfilling prophecy.

Recently, other studies have suggested several versions of systemic risk models, which relax or add to the assumptions in the Diamond and Dybvig (1983) model and some studies provide new lenses to the analysis of systemic risk (Allen and Gale, 2002, Kinateder and Kiss, 2014, Berger and Bouwman, 2017, Diamond, 2007). Another dimension provided by the literature is that financial crises emanate from business cycles (Jorda *et al*. 2016). This approach argues that systemic risk could be a result of macroeconomic shocks. In this dimension, macroeconomic variables such as economic growth, unemployment, and inflation are used in modelling systemic risk. Another important contribution to the study of systemic risk is the discovery that liquidity mismatches are at the center of financial crises (Brunnermeier *et al*. 2014, Diamond, 2007). This liquidity risk in turn leads banks and their depositors to participate in derivative markets, which provides a hedge for their assets such as forward contracts. Thus derivatives are useful in providing liquidity support in financial markets. Furthermore, the theory on hedging argues for the utilization of derivative instruments to reduce the impact of negative price movements in markets (Ammon, 1998). Derivative usage is argued to improve price discovery, increase the liquidity of financial instruments, and improve market efficiency. In turn, these lead to a decrease in financial frictions, resulting in increased efficiency in the allocation of capital, which has a positive impact on economic activity.

However, Brunnermeier *et al*. (2014) show that derivatives have potentially negative effects on bank liquidity. They demonstrate that credit derivatives and exchange-traded derivatives have the potential to drain liquid resources from the firm's balance sheet. Increasing illiquidity due to derivative usage exposes the financial sector to external shocks and can result in increased contagion, hence systemic risk. This proposition supports the role played by credit derivatives during the Global Financial Crisis in 2008. The idea is grounded in derivatives becoming instruments of speculation in contrast to their hedging role (Bohmann *et al*. 2019). Apart from liquidity changes emanating from movements in asset prices, derivatives have been accused of being complex and opaque to the extent that their use could trigger or propagate risk (Junior, 2013, Bohmann *et al*. 2019). Next, we focus below on empirical studies that have analyzed the influence of derivative usage on systemic risk and other determinants of systemic risk in general.

2.2. Empirical literature

Scholer-Iordanashvili (2020) examines the influence of derivative usage on financial stability in Argentina. The study employs the ordinary least squares approach and finds that derivatives negatively influence financial stability. Taskin and Sariyer (2020) carry out a similar study using bank-level data for Turkey. They use the Z-statistic as a measure of bank risk and estimate fixed-effects regression models. Bank-specific variables such as liquidity, size, and credit exposures are controlled for. They conclude that derivatives increase bank profitability but also increase bank risk. Their results are supported by Kurun and Yilmaz (2007), who investigate derivative usage by non-financial firms in Turkey. According to Kurun and Yilmaz (2007), potential financial instability could be triggered due to a lack of understanding of financial derivatives by users.

On the other hand, Mayordomo *et al*. (2014) investigate the impact of derivatives holding on a bank's contribution to systemic risk for 95 US banks. They employ the Net Shapley Value as a measure of systemic risk and find that banks' holdings of credit derivatives and currency derivatives increase systemic risk, whereas equity derivatives and interest rate derivatives decrease risk. Keffala (2016) undertakes a comparative study, in which the author compares the impact of derivative usage on financial stability in emerging economies and recently developed economies such as Singapore and Poland. Unsurprisingly, their findings show that derivative usage is more detrimental to financial markets of emerging economies compared to recently developed economies. Thus, the impact of derivative usage on systemic risk is heterogeneous, depending on both the types of derivatives used and the underlying economic and financial conditions.

Works by Bliss and Kaufman (2006) and Sinha and Sharma (2016) argue that derivative usage does not pose any threat to financial stability under certain conditions. Bliss and Kaufman (2006) investigate the proposition that netting, collateral, and closeout of derivatives position help reduce systemic risk. Increased collateral through central clearinghouses is discussed in Singh (2010) and is expected to increase market liquidity, hence reducing the probability of contagion risk. Their findings show that netting and collateral tend to reduce systemic risk, but on the contrary, closing out positions can be a source of systemic risk. Their argument demonstrates that the relationship between derivative market activities and systemic risk is a complex one, requiring further inquiry. Sinha and Sharma (2016) also investigate the determinants of derivative usage and the impact of derivative usage on systemic risk in India. Their study employs cross-sectional data and the Tobit model. They find derivative users to be large, liquid, and well-capitalized banks. In their study, derivative usage significantly decreases currency risk and lowers long-term interest rates for banks participating in derivative markets. They do not find any negative effect of derivative use on systemic risk.

Cont and Minca (2015) analyze the impact of central clearing of OTC credit default swaps on financial stability. Their study employs a network model and finds that allowing central clearing in the OTC markets reduces systemic risk through its impact on systemic liquidity. Their findings are supported in a similar study by Ali *et al*. (2016) in which the authors use network modeling to analyze the systemic importance of derivative participants. Their findings show that derivative participants could be interconnected beyond their immediate counterparts, which promotes contagion. In both Cont and Minca (2015) and Ali *et al*. (2016), derivatives impact financial stability through their impact on market liquidity. Thus, whereas derivative instruments are acknowledged for lowering market inefficiencies, the transaction that results in liquidity strains could increase systemic risk.

In other empirical studies, the direct impact of derivatives on economic performance has been explored, both at the firm and country levels (Jankensgard and Moursli, 2020, Bae and Kwon, 2020, Kim *et al*. 2017, Vo *et al*. 2020, Lazovy and Sipko, 2014). Bae and Kwon (2020) and Kim *et al*. (2017) investigate the impact of derivative usage on firm value in Korea and a group of East Asian economies respectively. Bae and Kwon (2020) show that firms experiencing significant changes in exchange rate exposures use more derivatives and have lower firm value. On the other hand, Kim *et al*. (2017) find derivative use as a value-enhancing activity for domestic firms and domestic multinational corporations (MNCs). This positive influence of derivatives on firm value is supported by Jankensgard and Moursli (2020) who establish that derivative usage has a positive and significant impact on investment. Vo *et al*. (2020) and Lazovy and Sipko (2014) demonstrate that derivative usage increases economic growth by mainly improving market efficiency. This finding is further corroborated by Prabha *et al*. (2014), who find that derivatives played a major role in increasing the GDP of the US.

3. Data and methodology
3.1. Data and variables

This study uses monthly time series data collected from the South African Reserve Bank (SARB) and Statistics South Africa for the period between January 1994 to December 2019 to compute the systemic risk measure. The estimated model covers the years between 2008 to 2020 due to a lack of data on credit derivatives for previous periods. Derivative usage is measured using both open interests on equity derivatives and the total value of credit derivatives that are traded. The study constructs a systemic risk measure by using expected shortage utilizing returns data for the five largest banks in South Africa. The VaR and ES are computed on a 100-day rolling basis. All variables to be used in the study are given in Table 1.

Table 1. Variable Definitions and Data Sources

Variable	Description	Source
ES	Expected shortage. Measure of systemic risk.	Author Computation
Der_e	Total open interest for equity derivatives. Percentage of total assets.	SARB
Der_c	Bank credit derivatives. Percentage of total bank assets.	SARB
$Size$	Total bank assets. Expressed as a percentage of total manufacturing production.	SARB
$Liquid$	Total liquid assets/total assets.	SARB
$Credit$	Private credit to GDP.	SARB
$lprod$	The logarithm of total manufacturing production.	SARB

3.2. Measuring systemic risk

The study adopts a measure of systemic risk suggested by Acharya *et al*. (2012) in the Marginal Expected Shortfall (MES). The MES is a measure based on the value at risk (VaR), which describes the expected loss of a firm conditional on the loss being greater than the VaR. In other words, this is the expected loss on the tail or expected loss during the periods when the loss exceeds the VaR. It can be interpreted as a bank's propensity to be fragile when the whole financial system is fragile. The expected shortfall can be expressed as in Equation 1.

$$ES_\alpha = -E(r_i | R \leq -VaR_\alpha) \tag{1}$$

, where r_i denotes the bank's returns, and $1-\alpha$ is the level of confidence. The argument for the expected shortfall (ES) measure is that it is coherent, contrary to VaR, which is non-coherent. In addition, ES is also capable of picking up tail losses, which cannot be identified by VaR.

Given a group of banks and financial institutions, which may include insurance companies and other systematically important financial institutions, an aggregated ES can be derived to which each firm's ES contributes. Thus, if y is a weight representing firm i, it is possible to state the ES of a financial system as in Equation 2.

$$ES_{\alpha} = -\sum_i y_i \, E[r_i | R \leq -VaR_{\alpha}] \tag{2}$$

The marginal expected shortfall (MES) for each firm can therefore be derived by taking the partial derivative of ES with respect to y_i as shown in Equation 3.

$$MES_{\alpha}^{i} = \frac{\partial ES_{\alpha}}{\partial y_i} = -E[r_i | R \leq -VaR_{\alpha}] \tag{3}$$

The MES for a certain bank can be taken as the bank's contribution to systemic risk. It measures the impact of bank i's risk-taking on the overall market-wide risk. We use daily data to construct the ES measure for each bank and convert these to monthly data before aggregating the contributions for each of the five banks into a single measure based on the size of the bank by the end of March 2020. Figure 1 shows the calculated marginal expected shortfalls for the five largest banks in South Africa.

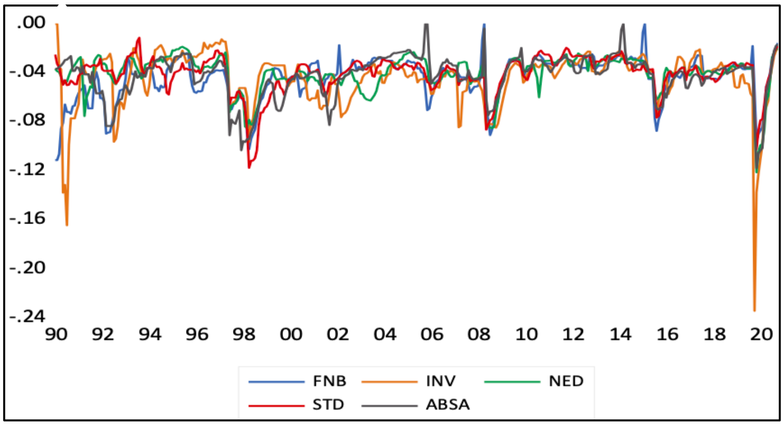

Figure 1. Individual banks' contribution to the systemic risk

As expected, the measure of systemic risk is able to capture major periods of financial stress, mainly the Asian currency crisis, 2002/2003 corporate crisis, and the 2008/2009 Global financial crisis. It also depicts the slump of 2015/2016 brought about by a drought, a fall in commodity prices, and low business confidence. The last shock in 2020 represents the Covid-19 financial shock. Figure 2 shows the aggregated expected shortfall, which depicts systemic risk. Again, we can clearly identify the periods of financial stress in the banking sector.

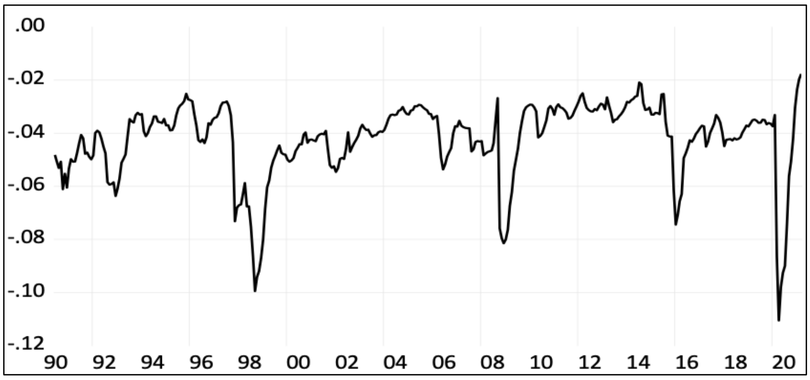

Figure 2. System risk in South Africa (expected shortfall)

The study employs the aggregated ES measure of risk in the South African context in a time series model as it promises to provide a theoretically sound and internally consistent measure as opposed to the VaR and other measures. Independent variables are as provided in Table 1.

3.3. Model specification

Following other studies (Taskin and Sariyer, 2020), we estimate a time series model in which expected shortage (ES_t) is determined by derivative activity, other bank-specific variables, and macroeconomic factors. However, consideration of data availability and statistical validity of the estimated models had an impact on the particular variables used in the estimated model. The model is specified in Equation 4.

$$ES_t = \beta_0 + \beta_1 Der_{c_t} + \beta_2 Der_{e_t} + \beta_3 size_t + \beta_4 liq_t + \beta_5 credit_t + \beta_8 prod_t + \varepsilon_t \quad (4)$$

, where ES_t is the industry's expected shortfall, which is the weighted sum of the expected shortfall for the representative financial institutions (MES). In our case, we construct this variable using returns of the five largest banks[1] in South Africa at the time of writing. We use manufacturing production ($prod_t$) to proxy general economic activity as there is no GDP data at higher frequencies. All other variables are as defined in Table 1, and ε_t is the error term, assumed to be independent and identically distributed (*i.i.d*).

3.4. Toda-Yamamoto test for causality

Toda and Yamamoto (1995) suggest a causality test based on an augmented vector autoregressive (VAR) model. Their approach is more appealing for three reasons. Firstly, unlike the conventional Granger causality tests, their procedure does not require variables to be integrated of the same order (Ghosh and Kanjilal, 2014, Toda and Yamamoto, 1995). Secondly, causality can be established even when series are cointegrated. Thirdly, Toda and Yamamoto causality procedure is relatively less cumbersome compared to alternative approaches such as the error correction model (Dritsaki, 2017). However, the highest level of integration that is labeled d_{max} is used to augment the maximum number of lags as selected by the VAR lag selection criterion. The $VAR_{k+d_{max}}$ estimated in our paper can be presented as in Equation 5.

$$\begin{bmatrix} ES_t \\ Der_{e_t} \\ Der_{c_t} \\ liquid_t \\ credit_t \\ lprod_t \\ size_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \end{bmatrix} + \begin{bmatrix} \beta_{11,k} & \beta_{12,k} \cdots & \beta_{17,k} \\ \beta_{21,k} & \beta_{22,k} \cdots & \beta_{27,k} \\ \beta_{31,k} & \beta_{32,k} \cdots & \beta_{37,k} \\ \beta_{41,k} & \beta_{42,k} \cdots & \beta_{47,k} \\ \beta_{51,k} & \beta_{52,k} \cdots & \beta_{57,k} \\ \beta_{61,k} & \beta_{62,k} \cdots & \beta_{67,k} \\ \beta_{71,k} & \beta_{72,k} \cdots & \beta_{77,k} \end{bmatrix} \begin{bmatrix} ES_{t-k} \\ Der_{e_{t-k}} \\ Der_{c_{t-k}} \\ liquid_{t-k} \\ credit_{t-k} \\ lprod_{t-k} \\ size_{t-k} \end{bmatrix} + \begin{bmatrix} \beta_{11,\gamma} & \beta_{12,\gamma} \cdots & \beta_{17,\gamma} \\ \beta_{21,\gamma} & \beta_{22,\gamma} \cdots & \beta_{27,\gamma} \\ \beta_{31,\gamma} & \beta_{32,\gamma} \cdots & \beta_{37,\gamma} \\ \beta_{41,\gamma} & \beta_{42,\gamma} \cdots & \beta_{47,\gamma} \\ \beta_{51,\gamma} & \beta_{52,\gamma} \cdots & \beta_{57,\gamma} \\ \beta_{61,\gamma} & \beta_{62,\gamma} \cdots & \beta_{67,\gamma} \\ \beta_{71,\gamma} & \beta_{72,\gamma} \cdots & \beta_{77,\gamma} \end{bmatrix} \begin{bmatrix} ES_{t-\gamma} \\ Der_{e_{t-\gamma}} \\ Der_{c_{t-\gamma}} \\ liquid_{t-\gamma} \\ credit_{t-\gamma} \\ lprod_{t-\gamma} \\ size_{t-\gamma} \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \end{bmatrix} \quad (5)$$

, where $\gamma = k + d_{max}$ and k is the maximum lag length as selected using the conventional VAR lag length selection criteria. The error vector is assumed to be white noise and identically and independently distributed. The test applies standard Wald tests, which follow a chi-square asymptotic distribution to the first "k" coefficients.

3.5. Estimation method

This study uses single equation time series regression to identify the determinants of systemic risk in South Africa. Specifically, it captures the dynamic effects of financial and economic

[1] These include Standard Bank, First National Bank, ABSA, Nedbank, and Investec Ltd.

variables on systemic risk by using the auto-regressive distributed lag model (ARDL) of Pesaran and Shin (1998). The ARDL framework allows for a mixture of I(0) and I(1) variables and is able to capture both the short-term and long-term relationships between the dependent variable and independent variables.

3.6. ARDL technique and Bound test for long-run relationship

This study employs the bound test approach to test for a long-run relationship (Pesaran, 2001). Pesaran's (2001) bound test for long-run relationships has advantages over the other measures of cointegration in that it does not impose the restriction that all variables should be integrated of the same order. The second advantage is that the estimator provides efficient estimates in small samples. Pesaran and Shin (1998) compare the ARDL technique to Phillips and Hansen's (1990) fully modified ordinary least squares (FMOLS) using Monte Carlo experiments and find ARDL to be more efficient in small samples. The third advantage of the ARDL estimator is that it provides unbiased estimators in the presence of endogenous regressors (Odhiambo, 2009, Harris and Sollis, 2003). The bounds test procedure is an F-test and t-test based statistic for long-run relationships among I(0) and I(1) variables. The null hypothesis is that there is no long-run relationship among the variables. The test provides two sets of critical values, one at I(0) (lower bound) and another at I(1) (upper bound), creating a band that captures all I(0) and I(1) variables. If the test statistic is greater than the upper bound, we reject the null hypothesis and conclude that there is a long-run relationship between the variables. However, a test statistic below the lower bound suggests that we cannot reject the null hypothesis, and this leads us to conclude that there is no long-run relationship amongst the variables in the model. A test statistic that falls in between the two bounds makes the analysis inconclusive. Equation 6 is a representation of the specified model in the ARDL framework.

$$\Delta ES_t = \alpha_1 + \sum_{i=1}^{q} \beta_1 \Delta ES_{t-i} + \sum_{i=0}^{q} \beta_2 \Delta DER\_E_{t-i} + \sum_{i=0}^{q} \beta_3 \Delta PROD_{t-i} + \sum_{i=0}^{q} \beta_4 \Delta DER_{C_{t-i}} + \sum_{i=0}^{q} \beta_5 \Delta SIZE_{t-i} + \sum_{i=0}^{q} \beta_6 \Delta CREDIT_{t-i} + \sum_{i=0}^{q} \beta_7 \Delta LIQUID_{t-i} + \beta_8 ES_{t-i} + \beta_9 DER_{E_{t-i}} + \beta_{10} DER\_C_{t-i} + \beta_{11} PROD_{t-i} + +\beta_{12} SIZE_{t-1} + \beta_{13} CREDIT_{t-1} + \beta_{14} LIQUID_{t-1} + \varepsilon_t, \quad (6)$$

,where β_1 till β_7 represent short-run coefficients, and β_8 till β_{14} are the long-run coefficients in the restricted model. The error term ε_t is assumed to be white noise and Δ is the first difference operator. The variables in the model are as defined in Table 1.

4. Results and discussion

In this section, we present the results from the Toda-Yamamoto causality tests and the ARDL estimations. First, we analyze the univariate characteristics of our series and present the results and the descriptive statistics in Table 1. The second step involves testing for the stationarity of all variables to define the maximum order of integration to be used in the Toda-Yamamoto causality test. It also involves ensuring that we meet the requirement of the ARDL method as there should be no variables integrated of second order and above. We use both the Philips-Peron and KPSS tests as discussed in the previous section. In the third step, we employ the Toda-Yamamoto procedure to examine the direction of causality among the variables of interest. The fourth step involves reporting on the estimated elasticities and in our case the variables that resembled the mixed order of integration, leading us to the conclusion that we should use the ARDL technique for our estimations. We, therefore, present the results from the estimated ARDL models in this section.

4.1. Descriptive statistics

The data shown in Table 2 is analyzed after initial transformations to make it suitable for analysis. Variables which needed logarithmic transformation were transformed into logarithms before descriptive statistics could be analyzed. We also converted our ES measure into positive numbers by multiplying them by -1 to make it less difficult to interpret the coefficients. Table 2 shows the univariate characteristics of the variables used in the study.

Table 2. Descriptive Statistics

	DER_C	ES	LCREDIT	LIQUIDITY	SIZE	LPROD	DER_E
Mean	1.5231	0.0405	14.8521	0.1413	0.0167	18.8205	16.6786
Median	1.4459	0.0356	14.8372	0.1404	0.0167	18.8555	12.6677
Maximum	3.2699	0.1106	15.3030	0.2433	0.0348	19.1388	41.6771
Minimum	0.2537	0.0209	14.3924	0.0731	0.0134	18.4424	3.9311
Std. Dev.	0.8191	0.0158	0.2674	0.0355	0.0020	0.1986	10.6180
Skewness	0.1947	2.0921	0.1014	0.2071	5.7119	-0.1529	0.9178
Kurtosis	1.8211	7.37366	1.6301	3.4548	51.8060	1.7883	2.7468
Jarque-Bera	9.8264	233.5522	12.2260	2.4125	16017.39	9.9558	21.8894
Probability	0.0073	0.0000	0.0022	0.2993	0.0000	0.0069	0.0000
Sum Sq. Dev.	101.9814	0.0381	10.8721	0.1914	0.0006	5.9941	17136.63
Observations	153	153	153	153	153	153	153

The descriptive statistics from Table 2 show that all transformed variables do not contain any outliers and the observations used are the same for all series, confirming that there are no missing observations. The JB statistic shows that only 1 out of 7 of the variables used is normally distributed. However, normal distribution of individual series is not a requirement for application of regression methods. We therefore continue to estimate the models explained in Section 3 using the data presented.

4.2. Stationarity tests

This study tests for the stationarity of all the variables used in the model. Most financial and macroeconomic variables resemble non-stationarity at levels and regressing non-stationary variables could result in spurious regressions (Agung, 2011). The study, therefore, employs two tests for stationarity, the Philips-Peron test (PP) and Kwiatkowski *et al*. (1992) (KPSS). The test suggested by Philips and Peron (1988) uses a non-parametric approach to correct for serial correlation in the unit root regression. The null hypothesis for the PP test is that series are non-stationary. However, De Jong *et al*. (1992) show that the PP test can suffer from size distortions, and Charemza and Syczewska (1998) opine that a mixture of tests that have a null hypothesis of non-stationarity and those with a null hypothesis of stationarity could result in robust conclusions. Therefore, for robustness purposes, we confirm the PP test results with the KPSS test. The KPSS test assumes a deterministic trend and trend stationarity under the null hypothesis. We note that while testing for unit root is not a requirement in using the ARDL technique, stationarity tests are conducted to ensure that variables are integrated at levels I(0) or order one I(1), and there are no I(2) variables in the model. As reported in Table 3, the dependent variable ES is stationary as expected since it is based on stock returns. However, five of the six independent variables used in the study are integrated of order 1. The logarithm of manufacturing production is stationary at levels when we use the PP test but it turns out to be I(1) under the KPSS test. Since no variable is integrated of order 2 or higher, we proceed to estimate our model using the ARDL technique.

Table 3. Unit Root Tests

Variable	PP		KPSS		Conclusion
	Level	1st Difference	Level	1st Difference	
ES	-4.5868***		0.0774		I(0)
$Credit^t$	0.3424	-21.4564***	0.4713***	0.1162	I(1)
Der_c^t	-2.6359	-13.0096***	0.1225*	0.0468	I(1)
$Liquid$	-0.8227	-16.2514***	0.4808***	0.0598	I(1)
Der_e^t	-1.8501	-15.6955***	0.1739**	0.0561	I(1)
$Size^t$	0.4598	-18.1883***	0.4485***	0.1390	I(1)
$lprod^t$	-3.5159**		0.3376***	0.0297	Inconclusive

Notes: ***, **, * represent 1% level of significance, 5% level of significance and 10% level of significance respectively. ^{t} depicts the test including trend and intercept. The H_0 for the PP test is that the series are non-stationary. The H_0 for the KPSS test is that the series are stationary.

4.3. Causality test results

The results from the Toda-Yamamoto causality test are shown in Table 4. We provide only results for the main variables of interest. First, we estimate a VAR in levels and check the lag length using both the Bayesian information criterion (BIC) and Akaike information criterion (AIC), which we find to be 17 lags. This implies the $k + d_{max} = 18$. We, therefore, re-estimate the model by using 17 lags and augmenting the VAR with $k + d_{max}$. The null hypothesis of the Granger non-causality test used in the Toda-Yamamoto approach is that the excluded variable does not Granger-cause the specific dependent variable. For instance, in part (a) of Table 4, the chi-square statistic is significant for Der_c. Thus, we reject the null hypothesis of no causality and conclude that the Der_c Granger-causes ES. Essentially we find only one-way causality between derivative usage and systemic risk. According to our results, both credit derivative and equity derivatives cause systemic risk. Using the chi-square statistic, we reject the null hypothesis of non-causality at a 5% level for Der_c. We also reject the null hypothesis for non-causality between systemic risk and equity derivatives. The causality is unidirectional from equity derivatives to systemic risk. All other control variables are found to cause systemic risk. We find bidirectional causality between systemic risk and bank credit, production, and total bank assets.

However, parts (b) and (c) of Table 4 shows that systemic risk does not cause either credit derivatives or equity derivatives. Instead, we find that both bank credit to private sector and bank liquidity cause credit derivatives. In addition, we find a unidirectional causality between bank liquidity and systemic risk as expected from the theory. Bank liquidity causes systemic risk, but the latter does not Granger-cause bank liquidity. These results support existing literature on the determinants of systemic risk, which identify both economic and financial variables as contributing to instability in financial markets (Ali *et al*. 2016, Bliss and Kaufman, 2006, Andersen *et al*. 2005).

Table 4. Toda-Yamamoto Non-Causality tests

(a) Dependent variable: ES		(b) Dependent variable: Der_c		(c) Dependent variable: Der_e	
Excluded	Chi-sq	Excluded	Chi-sq	Excluded	Chi-sq
Der_c	29.318** (0.0317)	ES	20.930 (0.2294)	ES	8.0040 (0.9236)
$Credit$	45.057*** (0.0002)	$Credit$	31.798** (0.0159)	Der_c	15.479 (0.4175)
$Liquid$	42.147*** (0.0006)	$Liquid$	31.229** (0.0187)	$Liquid$	7.9547 (0.9675)
Der_e	34.356*** (0.0075)				
$lprod$	32.456** (0.0132)				
$Size$	32.218** (0.0141)				

Notes: ***, **, * represent 1% level of significance, 5% level of significance and 10% level of significance respectively. Numbers in parenthesis are p-values.

4.4. Estimated results

Tables 6 and 7 present short-run and long-run coefficients for the estimated models respectively. We use automatic lag selection in Eviews and since the data frequency is monthly, we set the highest lag order at 12 lags for both the dependent and independent variables. The estimated model selected using the AIC is ARDL (12, 12, 11, 11, 7, 12, 12). Table 5 presents the results for the bounds test of a long-run relationship. The long-run relationship is confirmed by the rejection of the null hypothesis of no levels relationship at a 1% significance level. The critical value is greater than the upper bound test statistics. This implies that the variables in the model have a long-run/equilibrium relationship. The error correction term is negative and significant at a 1% level with a value of -0.96, indicating that 96% of the deviation from the equilibrium is restored in the next month. Therefore, we proceed to interpret our long-run and short-run coefficients.

Table 5. Bound Test for the Long-Run Relationship

F-Bounds Test		**Null Hypothesis: No levels relationship**		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	5.532	10%	2.53	3.59
		5%	2.87	4
		1%	3.6	4.9

As reported in Table 6, our results show that in the long run, the systemic risk is impacted by all independent variables in the model. According to the results, a percentage point increase in credit derivative usage in the South African banking system results in a 164 basis points increase in systemic risk. In the same vein, credit extension to the private sector also increases systemic risk. Specifically, a 1 percentage point increase in credit results in a 33 basis points increase in systemic risk. These findings confirm previous research of Mayordomo *et al*. (2014), who find that credit derivatives and currency derivatives increase the susceptibility of banks to systemic risk. Increasing credit derivatives could signal rising risk perceptions of market agents. The expectation of a worsening risk environment could lead to increased use of credit derivatives, which in turn could become a self-fulling prophecy as the use of these instruments dries up liquidity in the market. Secondly, misuse and underuse of credit derivatives due to their complexity and opacity could also trigger systemic risk. In this case, underuse describes the inability of the user to use the instrument efficiently to the level where gain can be achieved. Nijskens and Wagner (2011) show that bank use of credit derivatives could reduce their idiosyncratic risk for the bank but at the same time increase systemic risk.

Table 6. Long-Run Coefficients

Variable	**Coefficient**	**Std. Error**
Der_e	-0.000490*** (0.0003)	0.0001
$lprod$	-0.352825** (0.0201)	0.1451
$Size$	-0.272912*** (0.0034)	0.0869
$Liquid$	-0.420908*** (0.0091)	0.1526
Der_c	1.649158*** (0.0005)	0.4327
$Credit$	0.329943** (0.0270)	0.14308

Note: ES is the dependent variable, whereas numbers in parenthesis are p-values. ***, **, * represent 1% level of significance, 5% level of significance, and 10% level of significance respectively.

Conversely, we find that increases in bank liquidity, total assets, and participation in equity derivative markets lower systemic risk. Usage of equity derivatives decreases systemic risk, implying the ability of equity derivatives to hedge risk and reduce transmission of risk. Economic growth, as measured by $lprod$, reduces systemic risk by 35 basis points for every 1 percentage point increase in $lprod$. We interpret this to imply that a growing economy contributes to bank liquidity through increased bank deposits as economic units increase their earnings. We also relate high economic growth to the ability of firms to attract more liquidity even through credit markets. High economic growth implies improved strength of credit records for economic agents, hence financial resources can be easily pooled together for investment without posing a high risk to the lender.

A 1 percentage point increase in bank liquidity results in a 42 basis point decrease in systemic risk. This result particularly supports theoretical propositions surveyed in this paper (Diamond, 2007, Diamond and Dybvig, 1983) and empirical findings in a number of previous studies(Júnior, 2013, Mayordomo *et al*. 2014). Liquidity is at the center of the theory of bank runs and its various modifications, in which crises are treated as sudden drying up of liquidity from the banking or financial system as a whole. Therefore, we find that an increase in liquidity has the potential to stabilize the banking system. Accordingly, on the policymaking front, we support the several liquidity backing systems that central banks use to inject liquidity into the banking system. These include the recent actions by the South African Reserve Bank[2] and other central banks that are taken to increase liquidity in the face of the Covid-19 shock (Shikwane J, 2020; Adam *et al*. 2020).

Our results also show that the size of the banking system relative to the economy as a whole significantly and negatively impacts systemic risk. Specifically, a 1 percentage point increase in the size of the banking system results in 27 basis points decrease in systemic risk. Previous studies have shown that an increase in the size of the financial sector increases liquidity available (Lee and Chou, 2018), which in turn enhances the financial systems' ability to absorb liquidity shocks more easily. Thus, it is imperative to develop and grow the financial sector. However, this might seem contrary to the general notion raised by Mayordomo *et al*. (2014) and Nijskens and Wagner (2011), who attribute the probability of propagating systemic risk to the systematic importance of a banking institution. We argue in this paper that at the aggregate level the size of the financial sector acts as a shock absorber to any systemic risk shocks. A larger financial system should be able to absorb financial shocks quicker than smaller financial systems. Equity derivatives also show a negative and significant impact on systemic risk. This confirms the literature on exchange-traded derivatives, where settlement procedures such as marking to market improve liquidity in equity markets and are able to improve market efficiency.

The results of the ARDL error correction model in Table 7 show that the error correction term (ECT) is negative and significant at -0.96, showing that 96% of the deviation from the equilibrium is corrected in the next month. This also confirms the findings from the bounds test procedure that there exists a long-run relationship among the variables in the model. However, except for its own lag and liquidity, most of the variables do not have a statistically significant effect on the ES on impact. This might be due to the fact that our data is of high frequency, and that the effect of the independent variables could be felt with a lag. However, we find that an increase in bank liquidity impacts ES positively, in other words it increases systemic risk. We interpret this to show the negative market sentiments that grip financial agents when liquidity support programs are initiated. Improvements in liquidity can also cause banks to undertake riskier transactions, and the market can also perceive central bank interventions to increase liquidity as a sign of worsening financial conditions.

[2] In response to the Covid-19 shock, the SARB supported bank and market liquidity through several interventions, including lowering the repo rate by accumulative 275 basis points by May 2020, purchasing government securities, and lowering the liquidity coverage ratio for banks.

Table 7. Short-Run Coefficients / ARDL Error Correction Regression

Variable	Coefficient	Std. Error
Constant	2.2237*** (0.000)	0.331269
@Trend	-0.0001*** (0.000)	1.97E-05
$D(ES(-1))$	0.7829*** (0.000)	0.127973
$D(Der\_e)$	-9.56E-05 (0.428)	0.000120
$D(lprod)$	0.1433 (0.123)	0.090782
$D(Size)$	0.0912 (0.109)	0.055603
$D(Liquid)$	0.2725** (0.025)	0.116601
$D(Der\_c)$	-0.0224 (0.896)	0.171391
$D(Credit)$	-0.0035 (0.943)	0.050633
ECT(-1)*	-0.9690*** (0.000)	0.144175
Diagnostics		
Jarque-Bera	4.96 (0.0836)	
Breusch-Godfrey LM	0.90 (0.555)	
Breusch-Pagan and Godfrey	0.89 (0.6620)	

Notes: ***, **, * represent 1% level of significance, 5% level of significance and 10% level of significance respectively. Numbers in parenthesis are p-values.

Finally, the model is tested for normality, serial correlation, and heteroscedasticity. The results are reported also in Table 7. The Jarque-Bera test statistic is 4.96 and is not statistically significant at the 5% level, showing that we cannot reject the null hypothesis that the residuals follow a normal distribution. The F-statistic for the Breusch-Godfrey serial correlation LM test is 0.90 and is not statistically significant at the 5% level. Therefore, we cannot reject the null hypothesis of no serial correlation in the residuals. We also test for heteroscedasticity and find that the model does not suffer from heteroscedasticity as shown by Breusch-Pagan and Godfrey F-statistic, which is not statistically significant at the 5% level. Furthermore, the CUSUM test and CUSUM of squares tests show that the model coefficients are stable as shown in Figure 3 and Figure 4.

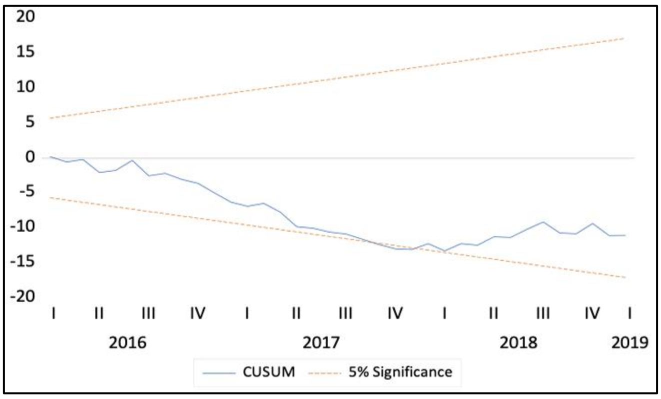

Figure 3. CUSUM test

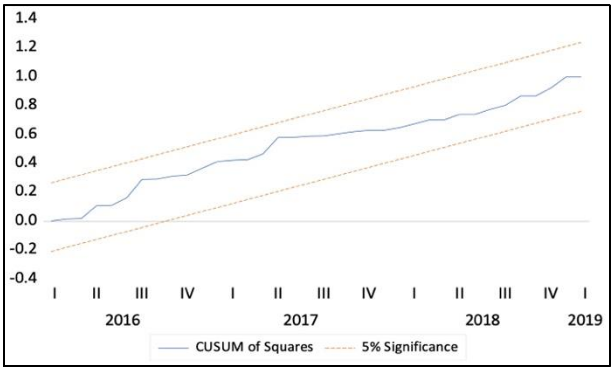

Figure 4. CUSUM of squares

While our results could raise important implications for both theory and financial policy, we do not claim to have exhausted the determinants of systemic risk for South Africa in the estimated model. We also note some weaknesses of the approach used. Due to the high frequency of other variables, we could not use GDP as a measure of the size of the economy. Instead, we proxy it using manufacturing production. The high frequency of the data may have affected the efficiency of the estimated VAR from which the non-causality results are extracted. Conclusions from the study and recommendations are discussed in the following section.

5. Conclusion and recommendations

This paper investigates the impact of derivative usage on systemic risk in South Africa. We use expected shortfall as a measure of systemic risk and employ the Toda and Yamamoto (1995) causality test and the ARDL technique to analyze the relationship between systemic risk and derivative usage in South Africa. Our measure of systemic risk is capable of capturing all periods of crises between 1994 and 2021, signaling increased systemic risk during each crisis.

The Granger non-causality tests conducted using the Toda-Yamamoto approach show that all variables considered in the study Granger-cause systemic risk. In particular, both credit derivatives and equity derivatives Granger-cause systemic risk. However, we only find unidirectional causality and we do not find evidence that systemic risk Granger-causes derivative usage. Furthermore, we find bank liquidity, the size of the financial system, and the size of the economy to Granger-cause systemic risk. These findings underscore the need for further analysis, which we provide using the ARDL technique.

Our results from the ARDL estimated model show that the long-run usage of credit derivatives is detrimental to financial stability in South Africa as it worsens systemic risk. Furthermore, we also find growth in credit to the private sector to impact financial stability negatively. However, we find participation in equity derivatives to be reinforcing financial stability. Specifically increasing equity exchange-traded derivative usage reduces systemic risk in the long run.

We also find that the size of the banking sector, level of economic activity, and bank liquidity reduce systemic risk. We measure the size of the banking sector by taking the total bank assets ratio to total manufacturing production and find that an increase in the size of the banking sector reduces systemic risk. We interpret this to imply increased liquidity supply to meet liquidity requirements of the different economic units. In addition, the growth of the economy also has a negative and significant effect on systemic risk. We note that increased economic activity reduces borrowers' risk and increases savings deposits.

A finding in tandem with the basic theory of bank runs and other financial crises is that bank liquidity reduces systemic risk. Diamond (2007) shows that bank crises are at their core due to the drying up of liquidity from financial markets. This proposition is supported in other studies (Berger and Bouwman, 2017) and our results clearly show that liquidity is an important determinant of systemic risk. On the backdrop of these findings, we recommend continued monitoring of derivatives markets to ensure stopping excessive risk early. Secondly, measures to support market liquidity during period of crises are justified.

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