

## **SPILL OVER EFFECTS OF OPERATIONAL LOSS EVENTS WITHIN THE SOUTH AFRICAN BANKING SECTOR**

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### **-Abstract-**

This study analysed return volatility after operational loss announcements concerning major South African banks during 2000-2014. The sample of banks that experienced losses over the sample period was compared with a sample of unaffected banks, the banking index and the stock market index, to identify whether the operational loss announcements had spill over effects on the whole South African banking sector. Daily share returns were analysed using event study methodology and the weighted moving average (EWMA) model. On one hand, the results showed that the operational loss events for two of the affected banks exerted no effect on the number of unaffected banks. On the other hand, the operational loss events for the two remaining banks were found to have spill over effects. The returns of the unaffected banks as well as the whole banking sector were effected, which led to systemic risk. However, results revealed that operational losses in the South African banks did not spill over to the stock market. Overall, the findings indicate that the effect of operational losses may depend on the level of integration between individual banks.

**Keywords:** Volatility, EWMA, operational losses, banks, South Africa

**JEL classification:** G21

## 1. INTRODUCTION

Operational risk can be regarded as the most prominent risk faced by the South African banking sector (Ferreira, Viljoen & Van Vuuren, 2016). However, the difficulty in capturing the significance of an operational risk lies in the unsuccessful attempts by many researchers to define operational risk accurately (Soprano, Crielaard, Piacenza & Ruspantini, 2009). Therefore, the global regulatory authority, the Basel Committee for Banking Supervision (BCBS), took on this responsibility and defined operational risk as “the risk of direct and indirect losses arising from inadequate or failed internal processes, people and systems or from external events” (BCBS, 2001). From this definition, it is clear that an operational risk will inevitably lead to a loss, whether direct or indirect and, therefore, may be classified as a pure risk (Micocci, Masala, Cannas & Flore, 2009). Due to the difficulty in anticipating an operational risk, its abrupt appearance can have tremendous financial consequences (Lewis, 2004). Among these consequences are severe fluctuations (volatility) in the share price of a bank (Daly, 2011). Volatility can be regarded as the magnitude in which the current share price deviates from its historical movement (Ekta & Rajkumar, 2013).

Volatility clustering which can be defined as severe phases of low and high volatility, has become the most overbearing characteristic of financial data (Ferulano, 2009). The study of volatility is imperative since a severe fluctuation in a bank’s share price and returns can erode the confidence and trust of investors (when they become more risk adverse) (Daly, 2011). Extended periods of severe volatility may also result in greater probability of defaulting of a bank. Hence, there is a close relationship between volatility and risk. Extensive periods of high volatility constitutes a higher degree of uncertainty and ultimately a higher level of risk (Daly, 2011).

Previous studies (Fiordelisi, Soana & Schwizer, 2014; Gillet, Hubner & Plunus, 2009) have emphasised the effect of operational loss events and its monetary impact on financial institutions. Gillet et al. (2009) focused on the various consequences financial institutions suffered after the announcement of an operational loss. This study included 152 financial institutions (banks and insurance companies), within the United States (US) and United Kingdom (UK), from 1990-2004. The results found by Gillet et al., (2009) proved negative returns at the announcement of operational loss events. Fiordelisi et al. (2014) followed a comparable approach by focusing on both investment banks and commercial banks located within the UK and US from 1994 to 2008. Cummins, Wei and Xie (2007) followed a similar approach by analysing the market value impact of

operational loss events of US banks and insurance companies on other non-announcing banks and insurance companies. Cummins et al. (2007) found some level of integration between the banking sector and the insurance sector. However, the main shortcoming with these studies was that share volatility was omitted from the context. Therefore, there is much room for the analysis of volatility after the announcement of operational loss events within a South African context.

Operational risk has the potential to influence a bank's or a chain of banks' value negatively (Daly, 2011). The unsuccessful management of operational risk can inherently lead to larger firm-wide risks, which can have severe spill over effects for the rest of the financial industry and market (Sweeting, 2011). Hence, contagion within a banking sector would affect not only individual banks but can extend towards a downward spiral for other market related asset prices (Visser & Van Vuuren, 2014). For investors, the share price of a bank is equal to the current discounted expected cash flows. Whenever a bank is perceived to have weak internal control due to operational risks, stakeholders might perceive cash flow losses as imminent (Daly, 2011). The more a share return fluctuates, the more volatile that return is said to be. Therefore, a large magnitude of share return volatility is expected to have adverse effects on bank customers, as most of these customers view volatility as a proxy for financial risk (Fakhfekh, Hachicha, Jawadi, Selmi, & Cheffou, 2016).

Evaluating the dynamics of volatility within the South African financial markets presents a significant role in the pricing of shares, bank valuation, risk management as well as investment decisions (Fakhfekh et al., 2016). The recent turmoil over the past decade (2007-2017) within the South African banking sector had led to a series operational risk events. Determining the effect on these loss events can shed more light on volatility modelling within the banking sector after operational risk events. Thus, this paper aims to make the following contributions. First, it intends to determine the share price volatility after the announcement of operational loss events within a sample of South African banks, where previous studies only focused on the US and UK. Secondly, it compares the results of the sample of affected banks with the sample of unaffected banks to identify further spill over effects in the South African banking sector. Thirdly, this study aims to provide empirical evidence on the volatility transmission between the affected banks, the banking sector and the whole market.

## **2. METHODOLOGY**

### **2.1 Sample and data description**

For this study, the relevant sample frame comprised of the entire banking sector in South Africa. Yet, the sample consisted of four banks within the South African banking sector that publically announced operational losses. The motivation for the inclusion of these banks relies on the fact that these four banks experienced unanticipated operational losses between 2000-2014. The resilient banking sector of South Africa, over the past two decades (1994-2014), contributed towards the reduced number of recorded operational loss events (Mlambo & Ncube, 2011). Further events of operational losses were omitted as a result of incomplete information (event date or monetary loss amount). All operational loss information was publically recorded within the public domain (including newspapers and bank websites).

The four banks that had operational loss events were compared against three unaffected South African banks registered during the same time period. To maintain confidentiality the names of the banks were not mentioned; thus, the affected banks are referred to as BANK 1, BANK 2, BANK 3 and BANK 4. Banks that had no operational events during the event window are referred to as unaffected. Additionally, the affected banks were compared to the Bank Index (benchmark) and the Johannesburg Stock Exchange All Share Index (JSE ALSI). This was done to identify any spill over effects from the operational loss events to the entire banking sector and the market as a whole. Daily stock price data were retrieved from both the JSE and INET BFA. Daily returns were estimated from the stock prices (for the individual banks) and stock price indices (Banking Index and JSE ALSI).

### **2.2 Models specification**

This study adopted an event methodology, which examined the behaviour of return volatility after specific operational loss events within the South African banking sector. An appropriate event window of 41 days was selected, where the event 20 days before and 20 days after the events were taken into account. This time period allowed for stock prices to reflect the new information. A shorter event window would not have captured the aggregate effects, while a longer event window would have captured fluctuations not relevant to the event (Woon, 2004).

In order to compare the return volatility of the sample of banks after operational loss events, the exponential weighted moving average model (EWMA) was utilised. The EWMA has proven its superiority compared to a simple historical

return and, therefore, was deemed more acceptable for this study (Brooks, 2002). Thus, the weight of the volatility attributed by a single operational loss event decreases, while the relevant weight to the most recent events increase. The overriding feature of the EWMA, which contributed towards the use of it, is that the model works well with a smaller sample size (Hull, 2011). Contrary to the standard deviation, the EWMA is not affected by normality and utilises individual stocks (Ferreira, 2015). Furthermore, the EWMA incorporates external shocks more effectively, offering a more accurate measure of volatility (J.P. Morgan, 1996).

EWMA was calculated as follow:

$$\sigma = (1 - \lambda) \cdot \sqrt{\sum_{t=1}^T \lambda^{t-1} \cdot (r_t - \mu)^2} \quad (1)$$

The standard deviation is denoted as  $\sigma$ , where  $\lambda$  represented the decay factor,  $r_t$  is the relative share return of a bank and  $\mu$  is the mean share return. A relative return of zero was assumed (Brooks, 2002). The EWMA is fully reliant on the parameter  $\lambda$  based on the condition that the decay factor is greater than zero and less than one (J.P. Morgan, 1996). The  $\lambda$  value measures the responsiveness of the daily volatility compared to the change in the current percentage. A  $\lambda$  value of 1 shows that the majority of weight is being allocated to the most recent data (Hull, 2011). A  $\lambda$  value far from one and closer to zero suggests that the majority of weight is being allocated towards past data (Alexander, 1998).

The calculation of the decay factor contributed toward the EWMA ability to react faster to price changes and, therefore, contributes to the overriding motive to make use of this variance model. A standard value for  $\lambda$  of 0.94 was recommended by J.P. Morgan (1996) to forecast the variance rate closest to the realised variance rate (Hull, 2011). A common requirement for the quantification of the optimal  $\lambda$  value is to minimise the average squared errors. The following equation indicates the daily root mean squared error (RMSE):

$$RMSE_v = \frac{1}{T} \sum_{t=1}^T (r_{t+1}^2 - \hat{\sigma}_{t+1}^2(\lambda))^2 \quad (2)$$

Where RMSE is the root mean squared errors,  $r_t$  is the relative return for time period  $t + 1$ ,  $\hat{\sigma}_{t+1}^2$  is the variance for time period  $t + 1$ ,  $\lambda$  is the decay factor.

The period  $t + 1$  determines the forecast of the return variance  $r_{t+1}$  made one period prior (J.P. Morgan, 1996:98). The calculation of the RMSE points to the estimated variance as a function of  $\lambda$ . The optimal functions to produce the most realistic forecast are found by generating the lowest values of RMSE over diverse values of  $\lambda$ . The sum of all  $N$  minimal RMSE  $\tau_i$ s values are then found by generating  $\Pi$ :

$$\prod = \sum_{i=1}^N \tau_i. \quad (3)$$

Equation 4 indicates how the relative error measure was calculated:

$$\theta_i = \frac{\tau_i}{(\sum_{i=1}^N \tau_i)} \quad (4)$$

Equation 5 indicates the weight,  $\phi_i$ , for the average decay factors:

$$\phi_i = \frac{\theta^{-1}}{\sum_{i=1}^N \theta_i^{-1}} \quad (5)$$

As a final point, the optimal decay factor represented by  $\lambda$ , was calculated by means of Equation 6. The  $\lambda$  signifies the weighted average of the singular  $\lambda$ , where these weights represent a measure of discrete accuracy (J.P. Morgan, 1996). Applying this approach to the daily returns of the sample of South African banks, an optimal decay factor for the South African market,  $\lambda = 0.94$ , was simulated to generate the most accurate forecast by using data for the ten years of  $r$ , the sample period.

$$\lambda = \sum_{i=1}^N \phi_i \lambda_i \quad (6)$$

To test for the spill over of operational risks across the banking sector and the whole stock market, the following hypotheses were formulated with the intention to determine whether the variance of the affected banks is different from that of other banks:

Null hypothesis ( $H_0$ ): Variance affected banks ( $\sigma_1^2$ ) = variance affected banks ( $\sigma_2^2$ )

Alternative ( $H_1$ ): Variance affected banks ( $\sigma_1^2$ ) variance affected banks ( $\sigma_2^2$ )

In order to test whether the variances of the affected banks varied from the variances of the unaffected banks, an F-test was utilised. Where the value of the estimated F-statistic was greater than the F-critical value, the null hypothesis was rejected and it was concluded that the variances of the two samples differ. This would indicate that the announced operational loss in the affected banks did not spill over to the unaffected banks. Where the F- statistic value was less than the F-critical value, the null hypothesis was not rejected. This would indicate that the announced operational loss in the affected banks did indeed spill over to the unaffected banks. This method was also used to test the affected bank’s variance against the JSE ALSI and Banking Index.

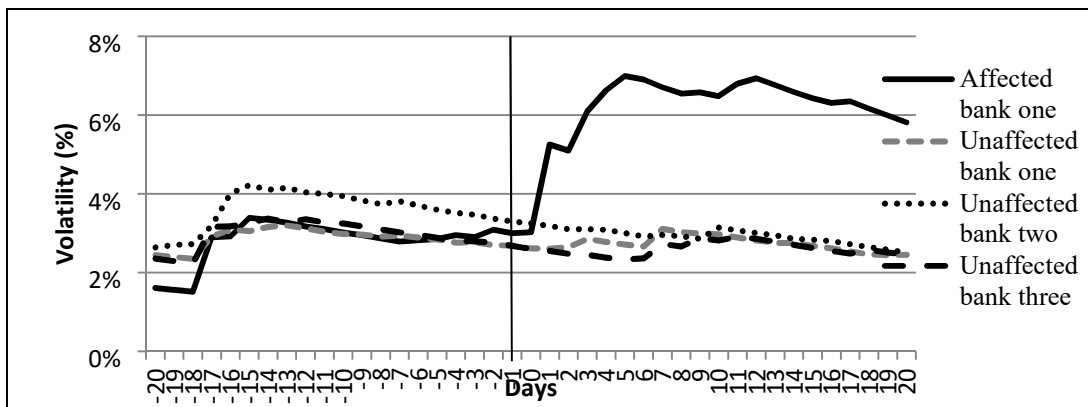
### 3. RESULTS

The following section describes and illustrates the results found concerning the volatility of the sample of affected banks compared to the sample of unaffected banks, the JSE ALSI and the Bank Index.

#### 3.1 Analysis of volatility between affected and unaffected banks

Graphical analysis of the volatility between each of affected banks and the three unaffected banks, during the event window, are indicated in figures 1 to 4. Announcement day of operational losses is [0], while [-20] and [+20] indicate 20 days before and after the announcement, respectively.

**Figure 1: Volatility of affected BANK 1 vs. unaffected banks**

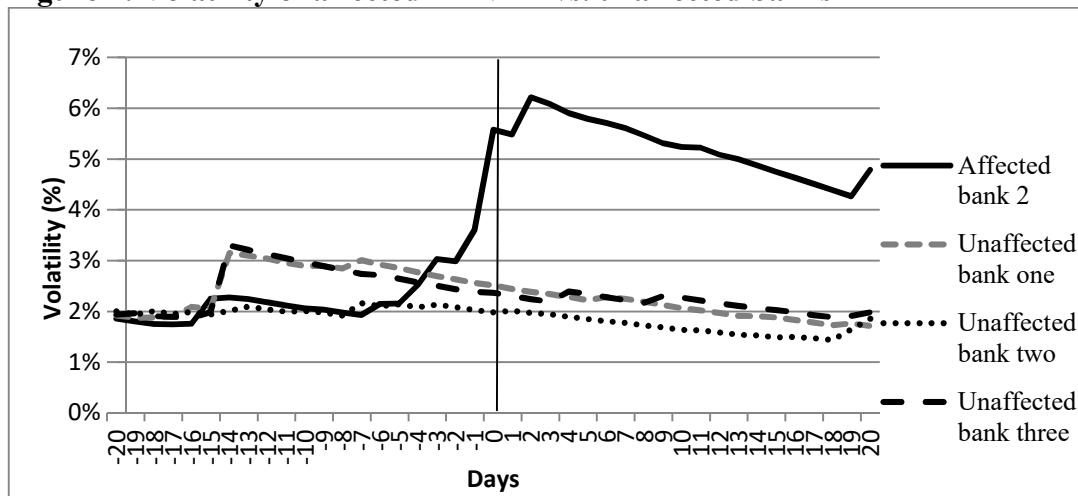


Source: Author compilation

Figure 1 demonstrates the daily EWMA for affected BANK 1 and three unaffected banks. Affected BANK 1 experienced relatively minor levels of volatility prior to the operational loss announcement [-20;-1]. After the

announcement day, BANK 1 appears to experience a high magnitude of return volatility relative to unaffected banks. A minor increase in volatility was experienced by the three unaffected banks on day [0] but deteriorated during the last 20 days of the event window. Affected BANK 1 experienced a higher level of fluctuations since the banks volatility increased from 1.61 percent on day [-20] to 5.82 percent on day [+20]. After the announcement day, the affected BANK 1 experienced higher volatility than unaffected banks. From Figure 2, affected BANK 2 indicates weakened levels of volatility prior to the announcement day. However, five days before the operational loss announcement day [-5] volatility amplified reaching a peak of 6.21 percent on day [+2]. Affected BANK 2 indicated greater levels of volatility after the announcement day. Unaffected banks showed minor increases in volatility and declined afterwards.

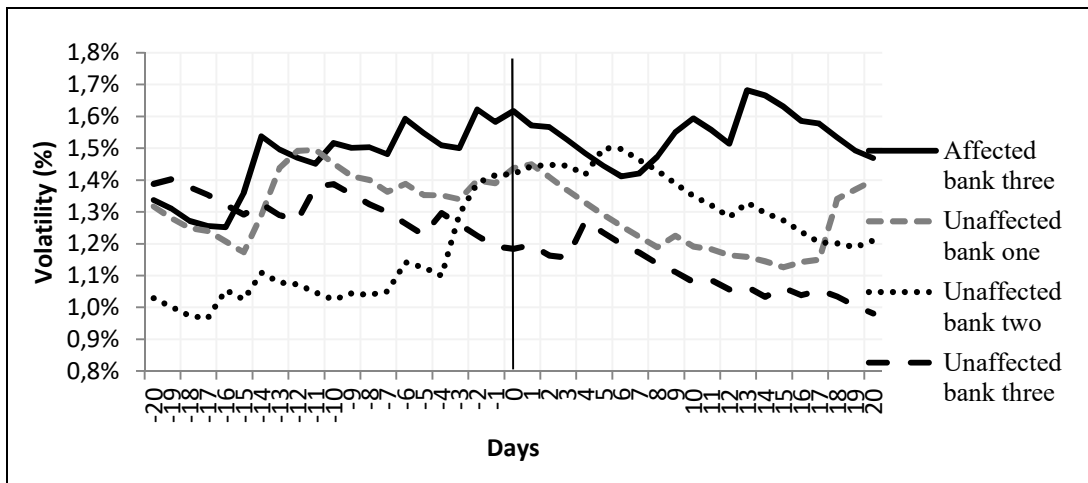
**Figure 2: Volatility of affected BANK 2 vs. unaffected banks**



Source: Author compilation



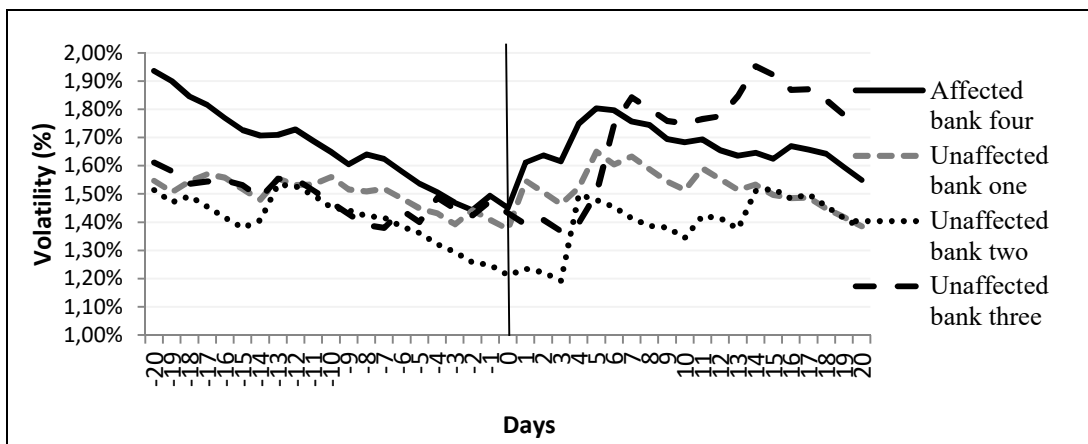
**Figure 3: Volatility of affected BANK 3 vs. unaffected banks**



Source: Author compilation

The daily EWMA for affected BANK 3 and the three unaffected banks is in Figure 3. Affected BANK 3 experienced severe volatility prior to the operational loss announcement [-20:-1]. A high magnitude of volatility for affected BANK 3 and all unaffected banks is observed prior and after the announcement day. Two of the three unaffected banks seem to move in the same direction as affected BANK 3, prior and on the announcement date [-20:0]. However, all four banks showed a general decline in volatility after the announcement.

**Figure 4: Volatility of affected BANK 4 vs. unaffected banks**



Source: Author compilation

As seen in Figure 4, affected BANK 4 experienced little volatility, with a downward trend, before day [-20 to 0]. After the announcement day [0], high levels of volatility can be observed for affected BANK 4 and all unaffected banks. There was no indication of a spike in volatility concerning the unaffected banks on day [0]. These results may indicate that market inefficiencies exist whereby prices react in random waves and that it takes time for investors to adapt to changes in price. A volatility peak can be seen on day [+5] for affected BANK 4 as well as for the unaffected banks. These values were higher than the observed values on day [0]. Therefore, there seems to be no difference between the volatility of the affected BANK 4 and the three unaffected banks. In addition to the graphical analysis, the F-test was used to test whether the variance of the affected banks is the same as the variance of the unaffected banks. Table 1 provides a summary of the F-statistic.

**Table 1: F-statistics of affected banks vs. unaffected banks**

Sample of affected banks	Unaffected bank 1	Unaffected bank 2	Unaffected bank 3
Affected BANK 1	5.62***	5.36***	5.53***
Affected BANK 2	7.79***	6.62***	5.83***
Affected BANK 3	1.01	1.47	2.24**
Affected BANK 4	1.25	1.26	0.79
<b>F-critical values are 3.03; 2.17 and 1.82 at the 1%, 5% and 10% level of significance, respectively</b>			

\*\*\*, \*\*, \* indicate the rejection of  $H_0$  at the 1%, 5%, and 10% level of significance, respectively

Results in Table 1 show that the  $H_0$  of similar variance between affected BANK 1 and all 3 unaffected banks is rejected, implying that affected BANK 1 experienced a different volatility during the event window. This means that the operational losses experienced by affected BANK 1 did not spill over to the unaffected banks. Table 1 shows that the variances of affected BANK 2 were different to that of unaffected banks, as the F-test values 7.79, 6.62 and 5.83 were larger than the F-critical value (3.03) at the 1 percent level of significance. The  $H_0$  of similar variances between affected BANK 2 and the three unaffected banks is rejected. Therefore, the operational losses experienced by affected BANK 2 did not spill over to the unaffected banks. The  $H_0$  for similar variance between affected BANK 3 and each of the unaffected banks is rejected only for unaffected bank three, at the 1 percent level of significance. This means that the operational losses from affected BANK 3 did not spill over to unaffected bank three. However, there is evidence of volatility spill over between affected BANK 3 and unaffected bank

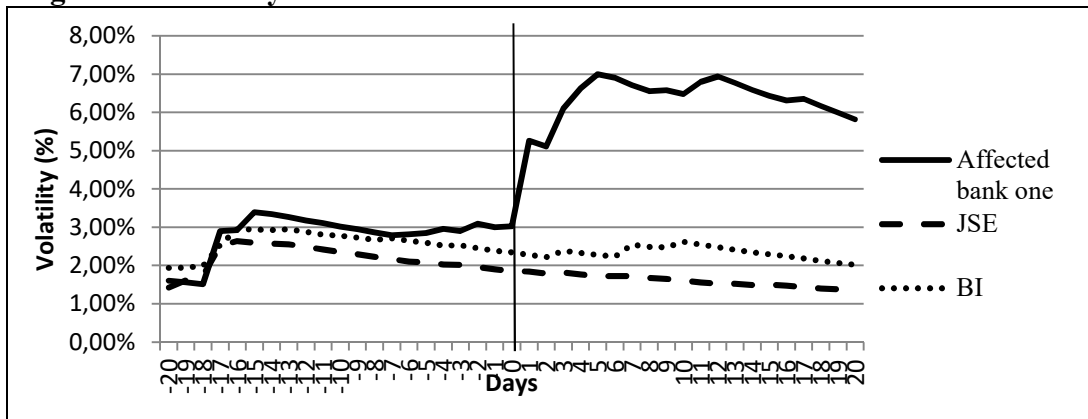
one and two. The volatility spill over of the operational risks may suggest that affected BANK 3 and unaffected bank one and two seemed to have some level of integration (Levine, Stephan & Szabat, 2014).

The F-values in Table 1 show that the  $H_0$  for similar volatility between affected BANK 4 and each of the three unaffected banks cannot be rejected, even at the 10 percent level of significance (the F-statistics are smaller than critical values). Therefore, it can be concluded that the variance of affected BANK 4 was similar to that of the three unaffected banks during the event window. There is therefore empirical evidence that the operational losses in affected BANK 4 led to return volatility in unaffected banks. This may suggest affected BANK 4 may be highly integrated with other banks. Overall, the F-test revealed that there was a volatility spill over between two of the affected banks (BANK 3 and BANK 4) and the unaffected banks. This implies that the announcement of operational losses in these two affected banks may have affected the other banks, which did not experience operational losses.

### 3.2 Analysis of volatility of affected banks, Bank Index and JSE ALSI

Figures 5 to 8 present a graphical analysis of the volatility of the affected banks, Bank Index and the overall stock market (JSE ALSI). High levels of volatility can be seen in Figure 5 concerning affected BANK 1 in comparison with the JSE ALSI and the Bank Index after the announcement day [0]. A slight increase can be observed by the JSE ALSI of 1.86 percent as well as the Bank Index 2.35 percent on the day of the operational loss announcement but deteriorated afterwards. Hence, as a result of weakened volatility, it can be argued that the JSE ALSI as well as the Bank Index were not affected by the volatility in the returns of affected BANK 1.

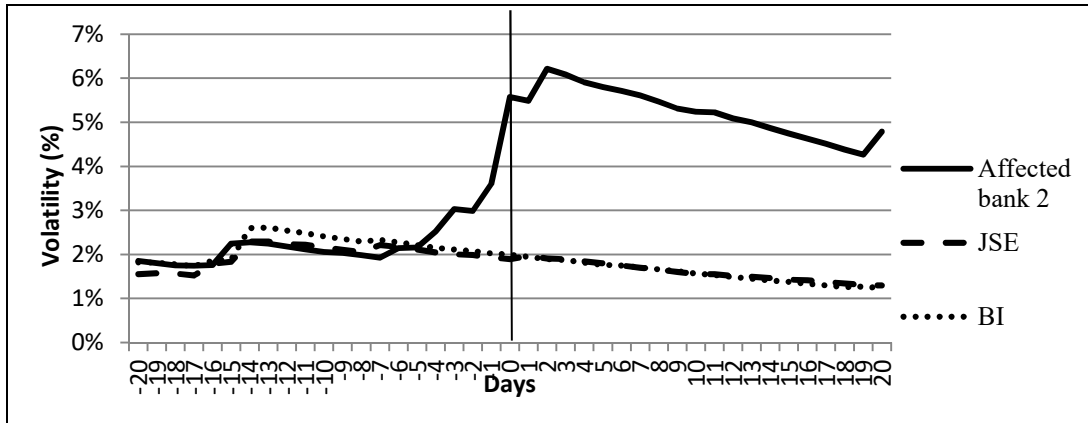
**Figure 5: Volatility of affected BANK 1 vs. Bank Index and JSE ALSI**



Source: Author compilation

Figure 6 illustrates high volatility for affected BANK 2 relative to the JSE ALSI and the Bank Index. A minor increase of 1.90 percent can be noted by the returns of the Bank Index and a 2.00 percent on the JSE ALSI, compared to day [-20] 1.56 percent and 1.82 percent but deteriorated after the announcement day to 1.30 percent and 21.24 percent on day [+20]. Based on graphical analysis, there appears to be no link between the volatility of the affected Bank 4 and the overall stock market.

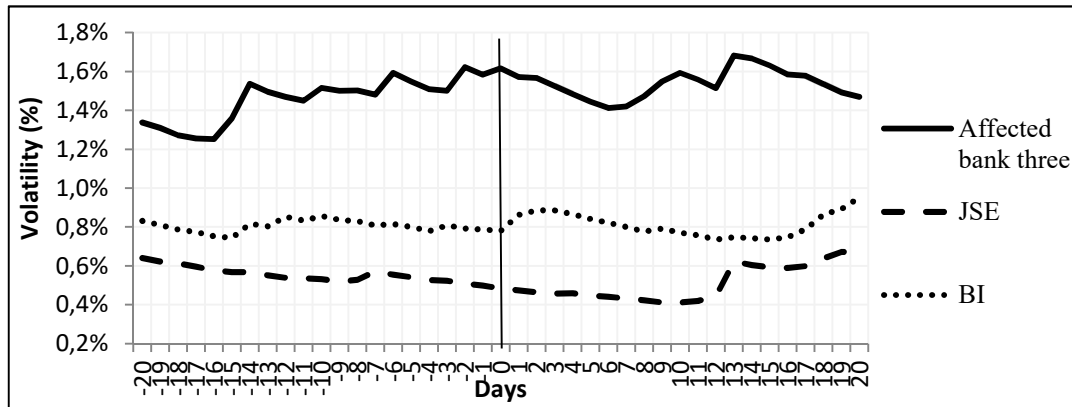
**Figure 6: Volatility of affected BANK 2 vs. Bank Index and JSE ALSI**



Source: Author compilation

Figure 7 illustrated high levels of volatility concerning affected BANK 3 in relation to the JSE ALSI and Bank Index, post the operational loss announcement day. The return volatility of both the JSE ALSI and the Bank Index slightly declined, 0.48 percent and 0.78 percent respectively, on the announcement day [0]. Over the event window, the return volatility of affected BANK 3 seems to be higher than that of the Bank Index and the stock market. Hence, the JSE ALSI as well as the Bank Index were not affected by the volatility in the share returns of affected BANK 3.

**Figure 7: Volatility of affected BANK 3 vs. Bank Index and JSE ALSI**



Source: Author compilation

Figure 8 demonstrates a high levels of volatility concerning affected BANK 4 compared to the JSE ALSI, post the event day. On the other hand, the Bank Index's movement looked similar to EWMA of affected BANK 4, suggesting that the Bank Index had high volatility during this period. Hence, the movements in the share returns of affected BANK 4 affected the Bank Index.

**Figure 8: Volatility of affected BANK 4 vs. Bank Index and JSE ALSI**

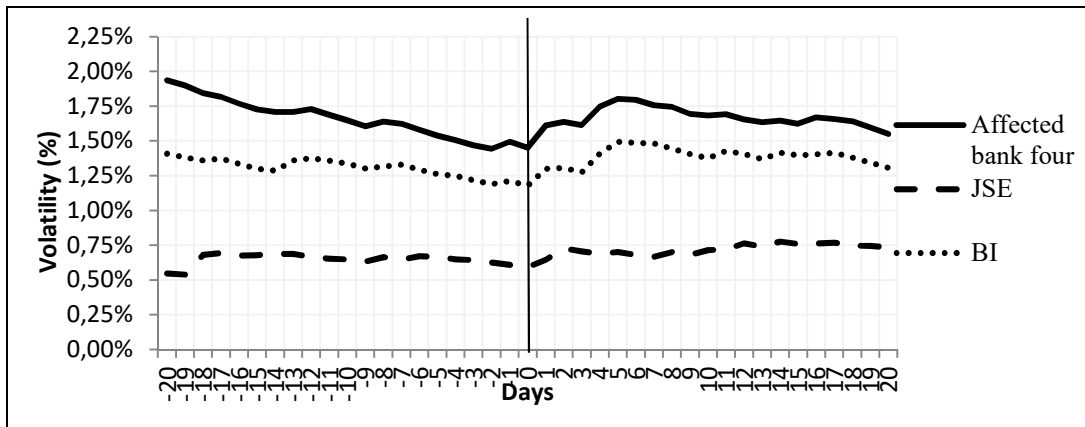


Table 2 provides a summary of the F-statistics performed on the volatility of each of affected banks, the Bank Index and the JSE ALSI.

**Table 2: F-statistics of affected banks vs. Banking Index and the stock market**

Sample of affected banks	Bank Index (BI)	Market (JSE)
Affected BANK 1	5.36 <sup>***</sup>	5.62 <sup>***</sup>
Affected BANK 2	14.91 <sup>***</sup>	13.60 <sup>***</sup>
Affected BANK 3	2.38 <sup>**</sup>	4.74 <sup>***</sup>
Affected BANK 4	1.40	4.41 <sup>***</sup>

F-critical values are 3.03; 2.17 and 1.82 at the 1%, 5%, and 10% level of significance, respectively

\*\*\*, \*\*, \* indicate the rejection  $H_0$  at the 1%, 5%, and 10% level of significance, respectively

The F-statics for a similar volatility between affected BANK 1, the stock market (5.62) and the Bank Index (5.36) were greater than the F-critical value (3.03), at the 1 percent level of significance, leading to the rejection of the null-hypothesis. This implies that the variances of affected BANK 1 were different from that of the stock market and the Bank Index during the event window. The fluctuations of share returns of affected BANK 1, due the announcement of operational losses, did not spill over to the Banking Index and the JSE ALSI. For affected BANK 2, the  $H_0$  is rejected for the Bank Index and the stock market at the 1 percent level of significance. This suggests that the volatility of the affected BANK2, due the announcement of operational losses, did not spill over to the Bank Index and the overall stock market. Similarly, the  $H_0$  is rejected at the 5 percent and 10 percent levels of significance at for Bank Index and the stock market, respectively. Thus, there is no evidence supporting the link between the volatility of the affected BANK 3 and that of the Bank Index and the overall stock market, during the event window. For affected BANK 4, the  $H_0$  for the equal variances between of affected BANK 4 and Bank Index cannot be rejected, even at the 10 percent level of significance. This suggests that the fluctuations in share returns, due to the announcement of operational losses, did spill over to the banking index. However, there is no significant link between the stock market volatility and that of affected BANK 4 during the event period.

Overall, results showed that operational losses increased the return volatility of the affected banks, which also seemed to spill over to the unaffected banks. These results agree with the analysis of Cummins et al. (2007) conducted in the US. The study of Cummins et al. (2007) also found operational events of announcing banks and firms to have strong spill over effects, influencing the stock prices of unaffected banks and firms. Contrary to the study of Gillet et al. (2009), the

returns of the affected banks did not severely react on the announced day [0] but rather on days [+1] and [+2]. The unaffected banks only indicated volatility at day [+5]. However, for our study the volatility from the affected banks did not spill over to the banking sector and the overall stock market index. This means that the operational losses did indeed affect the returns of the affected but not the overall market.

#### **4. CONCLUSION AND RECOMMENDATIONS**

For the period 2000–2014, a number of South African banks experienced operational losses. The announcement of such operational losses can have devastating effects on the banking and the stock market as whole. Previous studies have focused on operational loss events and the effects on stock returns. However, the main shortcoming with these studies was that share volatility was omitted from the context. This study used the exponential weighted moving average model with the event study methodology to analyse the effect of the announcement of the operational losses on share returns of the specific South African banks, banking sector and the overall market. A sample of four banks that experienced operational losses, over the sample period, was selected. The share returns of the affected banks were compared to three other banks that did not experience operational losses over the sample period, Bank Index and the overall stock market index. Findings of this study showed that operational losses did increase the return volatility of the affected banks and there was evidence of the spill over to the other banks that did not experience operational losses. These results were comparable with previous operational risk studies performed by Gillet et al., (2009) and Fiordelisi et al. (2014). Although the operational losses in one of the four affected banks did affect the banking sector, there was no evidence of volatility spill over between the other three affected banks and the banking sector. Similarly, our results revealed that operational losses in the South African banks did not spill over to the stock market returns.

Based on the literature and the previous studies from Gillet et al., (2009) and Fiordelisi et al. (2014), the effect of operational losses from one bank to another may depend on the level of integration between the banks. For example, the operational losses from a retail bank can be spread easily to other retail bank as opposed to investment banks. This was the case in our findings. Thus, if all the banks in the banking industry are fully integrated, the operational risk can easily spill over the whole banking sector, leading to systemic risk in the banking sector.

Although, the risk from operation losses did not spread over the whole banking sector, the evidence of spill over between individual banks suggests that

operational risks can eventually affect the reputation of the whole banking sector negatively. Thus the following recommendations can be made. Firstly, bank regulatory bodies should develop strong frameworks to guard against operational losses. Furthermore, a proper management of operational risks should also be established. A mitigation model for managing reputational risk within the banking sector could be means for further research. The results in this study suggests that the sample of banks underestimated the operational loss events and did not have sufficient capital to withstand these losses or their spill-over effects.

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