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IMPACT OF OPERATIONAL RISK EVENTS ON MARKET VALUE OF SOUTH AFRICAN BANKS

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Declaration

I, Jessica Tshepo Kutumela, declare that the research work reported in this dissertation is my own, except where otherwise indicated and acknowledged. It is submitted for the degree of Masters of Management in Finance and Investment at the University of Witwatersrand, Johannesburg, South Africa. This thesis has not, either in whole or in part, been submitted for a degree or diploma to any other universities.

Abstract

With the increase in operational risk related events that has seen some of the major international banks going under we investigate the South African market reaction to public announcement of operational risk related loss events by analysing the financial impacts and possible spillover effects of announcement on the market value of the four biggest banks in South Africa. The objective of this thesis is to expose the hidden costs to banks for not having adequate operational risk management practices.

The event study approached was used to estimate the cumulative abnormal returns and the following were observations from the analysis:

- Evidence of significant negative abnormal returns in the announcing bank, following an announcement of a large operational loss event were found, which implies that the market value of announcing banks in South Africa is particularly sensitive to the announcement of operational risk events of an announcing bank.
- Further evidence indicated that the market value decline or erosion of the announcing bank exceeded the actual operational risk event loss amount.
- While transmission of announcing bank's negative impacts to other non-announcing banks (negative intra-spillover effects - that the announcement of operational risk event losses in one bank causes contagion within the banking industry) were detected, the negative impacts were not necessarily applicable to all non-announcing banks.
- On the other hand, while evidence of announcing bank's negative impacts providing a competitive advantage to other non-announcing banks was detected, the positive reaction was found to not be the case in all banks analysed.

The variation of results in the spillover effects on non-announcing banks could be attributed to the markets sensitivity to perceived risk exposure of other non-announcing bank (in a case of negative spillover effect) and perceived robustness, resilient and sustainable control environment of non-announcing banks (in a case of a positive spillover effect), to announcing banks' operational risk loss event.

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1. INTRODUCTION

At the core of any bank's operations is operational risk management. Operational risk existed as far back as the banking industry itself however it is only recently that the industry defined what it is. In adapting to the evolution and the ever-changing business landscape that the banking industry operates in and the related emerging operational risks that this evolution brings Operational Risk practice also goes through a process of continual change. In recent years the significance of operational risk losses continues to grow in severity.

The magnitude of operational risk events varies from minor to large operational risk events. Minor events that can be isolated incidents or repetitive incidents that could serve as an indicator of the vulnerability, which if not mitigated can lead to a greater loss to the company. Large operational risk events are low frequency and high impact in nature. A proactive risk management approach is required to ensure that the operational risk related losses do not materialize or in a case where they do materialize that the impact thereof is minimized. Whist large losses are mostly infrequent when they occur they often lead to the collapse of financial institutions (e.g. rogue trading event that resulted in Barings Banks going under). There are over hundred operational risk losses reported greater than US$100 million globally.

The aim of this thesis is to examine the impact of operational risk related loss events and its resultant reputational losses on the market value of the announcing company to evaluate whether the principle that publicly announced operational risk events result in a decline in the

market value of the company. We further examine the impact of announcing banks operational losses on the market value of non-announcing banks.

Empirical studies done in the past on this topic revealed that publicly announced operational risk events can cause reputational losses which result in the significant decline market value of the financial institution. Previous literature on this topic focused only on US and European Banks. For instance, (Karpoff and John 1993) provided strong evidence that the publicly announced criminal fraud charges (fraud being an operational risk sub-category) that the company was confronted with resulted in statistically significant decline in the company's market value.

Subsequently, (Wei 2003) and (Cummins, Lewis and Wei 2006) performed an empirical study on announced operational risk events to assess their impact on announcing and non-announcing financial institutions in the United States. The results of both studies revealed that operational risk losses have a significant negative impact on the company's share price and that the loss in market value is greater than the related actual operation loss.

The studies have shown that where operational risk is not adequately managed by companies it could result in pure operational losses and consequential reputational losses. Reputational losses in financial companies are most incurred as a consequence of the underlying operational loss events (Cummins, Lewis and Wei 2006; Fiordelisi, Soana, and Schwizer 2014; Gillet, Hübner and Plunus 2010), which could be an indication that there is a general inter-relation between operational and reputational risk.

Due to data limitations, the impact operational risk events on the market values of South African banks analysis was performed based on four events over a period of 14 years by (Ferreira, Viljoen, and van Vuuren 2016). With the limited number of events that were analyzed the key objective of this study is to improve on the work that of (Ferreira, Viljoen and van Vuuren 2016) since we have a large sample of operational risk events that occurred over a period of ten years. The main contribution of this thesis to the existing literature arise from performance of further analysis of operational risk events data to assess whether the contagion and/or competitive effect principles occurs in the South African banking industry.

1.1. Problem Statement

Financial institutions have invested heavily in setting up governance structures and processes to manage operational risk within their organisations. While in the previous years the focus for implementing operational risk management processes had revolved mainly around meeting the regulatory requirements for measurement of regulatory operational risk capital, financial institutions are questioning the value add that operational risk practice brings to the table.

The intent of this study is to highlight the hidden costs of not having an effective and efficient operational risk governance structures and processes in a bank to protect and preserve shareholder's value. Having regulatory capital calculated and reserved for operational risk does not necessarily or adequately reduce the devastating impact of an operational risk event occurrence, specifically risk events that are publicly announced. By implementing an effective

and efficient operational risk governance structures and processes means implementing governance frameworks and policies that guides and drives a culture of risk identification, implementation of risk mitigating controls, key risk indicator monitoring and effective response strategies to minimize the impact of the risk event if and/ or when it occurs.

1.2. Research questions

To assess the sensitivity of the South African Market to public announcement of banking institutions operational loss events this study addresses the following questions:

1. Do operational risk related loss events impact the market value of a company negatively? If an operational loss event does have an impact which is negative, we further examine the following:
    1.1. Whether the decline in the market value of the announcing company exceed the actual operational loss amount.
    1.2. Whether operational risk events in one company cause contagion (i.e. intra-sector spillover effect) within the banking industry by transmitting the negative impacts to other non-announcing banks.
    1.3. Whether operational risk events of an announcing company give non-announcing companies a competitive advantage (competitive effect).

1.3. Significance of the study

While we found extensive of literature that examines the contagion effect and competitive effect of operational loss events on US and European banks, there seems to be lack or limited literature of this subject from a South African Banking industry context. This thus provides the motivation for our present thesis is to analyse the impact and possible spillovers effects of operational risk events related losses on the market value of banks in South African.

1.4. Outline of the study

The structure of the reminder of this thesis is as follows: In the reminder of Chapter 1 we provide background and describe definition of operational risk and the categories of event that are included in this definition. We the perform an extensive literature review of the contagion and the competitive effect principles in chapter 2. In Chapter 3 we describe the data, related data sources and the empirical methodology used to determine abnormal returns. In Chapter 4 we analyze the data by testing the hypothesis and discuss the results obtained. In chapter 4 we conclude on the study.

1.5. Background and definition of operational risk

Operational risk is defined by the Bank for International Settlements (BIS) Basel Committee as: “the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events” (Basel Committee on Banking Supervision 2001, p. 2). Included as part of this definition is legal risk, but excludes strategic and reputational risk.

Operational risk management integrates risk management practices into business processes, systems and organizational culture.

In the BIS Basel II accord operational risk events types categorizes as follows: damage to physical assets; Internal fraud; execution, delivery and process management; external fraud; employment practices and workplace safety; client, products and business practices; business disruption and system failures. For this research, we focused on the impact of the risk events on the market value of a company regardless of the event type.

Factors that increase operational risk include the following: The manner in which organisations and their staff conduct themselves towards to customers and the wider financial markets; Takeovers, mergers and acquisitions create risks of incompatible systems and Organizational integration problems; Digitalization of the financial industry makes it more susceptible to information technology risk, internal and external fraud including cybercrime; Innovation and implementation of new technologies in business introduces risks associated with change management; Outsourcing of critical business functions introduces third party (vendor) and fourth party risk which includes also includes breach of sensitive and confidential data by external third and/ or forth party vendor; and processes followed for managing other risk types (i.e. market, counterparty and/ or credit risk).

Operational risk management in its broader definition includes the following: model risk, legal risk, conduct risk, third-party risk, Anti money laundering, fraud cyber risk and IT risk.

Figure 1: Broader risk types included under the operational risk management

Obtaining a holistic understanding of the real impact of operational risk events is of high relevance to companies' decision-making process on the type and extent of investment required to implement preventative measures to mitigate operational risk events from occurring and/ or detective measures to reduce impact of operational events should they occur.

As per (Tattam 2011) the objectives of managing operational risk in an organisation financial institution includes: Decreasing preventable losses; Lessen insurance premiums; Protecting and/

or improving credit rating; Improving risk and control culture; Protecting and enhancing reputation; Improving objectivity and risk awareness; Promoting transparency and accountability for risk; Improving the efficiency and effectiveness of controls and processes; Identifying possible opportunities associated with the risk; Providing management with greater level of assurance; Facilitating and driving business in ensuring that external requirements are met. (Auer, van den Brink and Mormann 2015) highlights the following as the benefits of a strong operational risk management program: Improving the decision making process; Reducing cost of funds; Lowering operating costs; Lesser profit and loss volatility; a higher employee and client satisfaction index; Optimized insurance coverage and premiums; improved compliance to regulation; and Freeing up capital for income earning activities. In 2016 the BIS Basel committee introduced a Standardised Measurement Approach (SMA) for calculating operational risk capital as part of Basel III. With the SMA approach operational loss events will be included for a rolling period of 10 years in determination of the Internal Loss Multiplier. The implication of the rolling ten-year period means that large operational risk losses will remain a factor in the Operational Risk Capital amount for a period of ten years.

It is evident from the above-mentioned authors that there are several potential benefits that can be derived by a financial institution that have an integrated and proficiently managed operational risk management function. While is it is easy to define the potential benefits of an effective and efficient operational risk management is difficult to measure whether the objectives of operational risk management are met or not.

According to (Tattam 2011) challenges with measuring operational risk objectives could emanate from the following: Due to other contributing factors and time lag between the effort and the result it may be difficult to prove the causal effect between operational risk management and its objectives; The successes of operational risk management are often viewed from an angel of "what does not happen" as oppose to "what does"; and Operational risk objectives may be subjective and difficult to measure. An example of such would include measuring and objective such as protecting and enhancing reputation.

Operational risk events can result in severe financial impact being suffered especially by financial institutions (Cummins, Lewis and Wei 2006) and the magnitude of numerous large operational risk events that occurred in the past emphasizes the necessity for an adequate measurement and management of operational risks. The potential distressing power of operational risk has been displayed by many large operational losses.

Operational risk event could have an impact in three ways i.e.:

- Pure operational loss to the company on the incident date of the event.
- Reputational losses to the announcing company when public announcement of the loss event occurs.
- Reputational losses to non-announcing companies in the same industry when public announcement of the risk event occurs (intra-sector spillover).

The table below list some of the highest publicly report operational losses events that were made public through different media channels.

Table 1: The high value South African publicly announced operational risk events

Institution Name	Headline	Loss Amount	Date First in Media	Basel Event Type Level 1
FirstRand	First Rand loses ZAR 915 million after employees manipulate merchant transactions	R 915m	25-Feb-13	Internal Fraud
Standard Bank	Standard Bank ordered to surrender shares worth ZAR 528 million after court invalidates deal	R 528m	6-Dec-12	Clients, Products & Business Practices
Postbank (SA)	Postbank reportedly defrauded of ZAR 420 million in cyber breach	R 420m	26-Mar-12	External Fraud
Standard Bank	ZAR 300 million stolen from Standard Bank as part of credit card scam	R 300m	22-May-16	External Fraud
South African Reserve Bank	South African Reserve Bank returns ZAR 250 million after wrongfully charging exit levy on asset transfer	R 250m	2-Oct-14	Clients, Products & Business Practices
Citigroup	Citibank agrees to pay ZAR 69.5 million to settle claims in South African FX manipulation probe	R 69,5m	20-Feb-17	Clients, Products & Business Practices
Standard Bank	Standard Bank fined ZAR 60 million for anti-money laundering control failures	R 60m	16-Apr-14	Clients, Products & Business Practices
Old Mutual	Old Mutual defrauded of ZAR 48 million by investment client	R 48m	7-Sep-14	External Fraud
FirstRand	Man sentenced for defrauding First National Bank, Wesbank and Standard Bank of ZAR 39 million	R 39m	21-Dec-10	External Fraud
FirstRand	FirstRand fined ZAR 30 million for anti-money laundering control failures	R 30m	16-Apr-14	Clients, Products & Business Practices

Sources: ORX Database

Whilst the operational risk loss amount is highly insignificant when compared total revenue of the financial institutions, the reputational impact of the publicly known operational risk event

materializing due to lack or inadequately managed operational risk processes can be disastrous and might also have a negative impact by eroding the market value of a company. In extreme cases, the impact can spread across the industry, thus having an impact that is negative on the market value of other banks within the industry.

2. LITERATURE REVIEW

The broad objective of this study is to assess the impact of operational loss events on market value of South African banks individually and the broader banking industry. The emphasis is placed on whether the principles as discovered by other authors hold in the South African market context.

2.1. Prior Literature

2.1.1. Relationship between operation risk and reputational risk

(Cummins, Lewis and Wei 2006); (Gillet, Hübner and Plunus 2010); and (Fiordelisi, Soana and Schwizer 2014) provides evidence that reputational losses suffered by financial institutions are caused by operational loss events in most cases, especially where fraud is the root cause. Since the occurrence of an operational risk event is most certainly likely to result to reputational losses, this would require that an analysis of the impact of operational risks loss events on financial institutions should also include a comprehensive assessment of reputation loss suffered because of the operational loss event. In their results, most authors found that the stock market reacted significantly negative to operational losses and that the decline exceeded the announced operational loss amount, thus indicating substantial reputational losses. The consideration of reputational losses arising from operational risk events is thus of high relevance.

2.1.2. The Contagion effect theory

Transversal announcement of operational risk related loss in a company conveys bad news about the company's management of its operations. The announcement provides the investor with information that the control environment within the operating activities of a company is either designed inadequately and/ or operating ineffectively. (Stulz and Lang 1992) Describes the contagion effect as the change in the competitor's market value, which cannot be attributed to redistribution of wealth from the announcing company. Certain types of operational risk related losses can create doubts about the trustworthiness of the industry, thus resulting in a decrease in market value of other companies in the same industry. The decrease in value could be attributed to an industry reputational damage caused by the announcing company, which could in turn cause customer, supplier and investors to reassess their perception of all companies within the industry. (Kaufman 1994) Describes contagion as an expression often used to describe the spillover effects of the shock from one or more companies to others (i.e. negative externality effect). In the empirical study performed by (Kaufman 1994) on bank contagion, evidence is obtained to support firm specific contagion.

In the theoretical and empirical financial literature contagion has been studied widely by and (De Bandt and Hartmann 2000) and (Flannery 1998). In his study (Flannery 1998) concludes that banks share price generally behaves in the same way as the equity prices of non-financial companies and that bank liability investors also respond to changes in the conditions of banks.

Several studies have been performed ranging from currency crisis, systemic stock market crashes, multiple bank failures shocks, and information spillovers that resulted in stock prices being revalued and widely spread failures. In this thesis, we concentrate on the latter body of literature.

(Aharony and Itzhak 1983) Differentiate between pure (i.e. industry specific) and noisy (i.e. firm specific) contagion in their study. They defined pure contagion as the indiscriminate re-pricing of all stocks irrespective of the event cause and the non-announcing companies' risk characteristics. This is the case when negative news such as an occurrence of a fraud event in bank adversely affecting all other banks although those other banks have nothing in common with the first bank. As per (Stulz and Lang 1992) Noisy contagion refers to the informed stock re-pricing where investors can distinguish between companies with dissimilar risk characteristics such that only correlated banks (i.e. with common characteristics) experience spillover effects. Thus, if one bank fails, then other banks with similar balance sheet structure may, due to exposure to the same economic shocks may also be negatively affected. According to (Stulz and Lang 1992) information-based contagion highlights balanced revaluation which in most cases will not have social costs, whereas pure contagion imposes social costs.

In cases where investors detect that non-announcing companies are similarly affected regardless of differences in companies' characteristics and the cause of the events, pure spillover effects occur. This happens usually occurs when the market in unable to distinguish among companies. Where announced events affect only companies whose cash flows are highly correlated with those of the announcing company information-based spillover occurs. When information is

readily available and precise to enable investors to distinguish among the non-announcing companies' information-based spillovers are likely occur (Brewer and Jackson 2002). With the social media and internet, the speed at which news spread has increased tremendously and as such management of risks that could potentially result in reputation risk is vital for companies. With the current capacity for huge volumes of information to be transferred to the market in a timely and accurate manner it is high likelihood that operational risk related loss events can cause information based spillovers to non-announcing company's characteristics that shares similar characteristics with it. Where information based spillover, effects exist the operational loss event amount can provide a possible indicator of extent of the non-announcing company's operational risk exposure. High value operational risk events are more likely to convey new information to the market as compare to low value events due to their nature (i.e. unexpected and low frequency). It would thus be expected that the higher the operational risk loss events, the greater the magnitude of the non-announcing companies' loss of market value.

2.1.3. The competitive effect theory

(Stulz and Lang 1992) explained the competitive effect using an economic scenario that if the announcing company conveys information about the shift in demand and/ or a drop-in production efficiency, which becomes a good thing for the other companies within the industry as take advantage of the expected an increase in demand. A competitive effect can occur when, after announcing company is negatively impacted by the event, it become unresponsive to its competitors' predatory moves, which ultimately result in its customers moving their business to

rival companies. If investors have confidence in that non-announcing companies are more than likely to benefit from the announcing companies' operational risk loss event announcement, then the stock prices of non-announcing companies could be impacted positively by announcing companies' operational loss events. Where competitive effect exists, one would expect that the larger the operational risk loss event amount is for the announcing company, the greater the magnitude of the increase in market value for the competitor companies should be.

In some instance, it is possible for both the competitive effect and contagion effects to happen at the same time. Where this is the case, the two effects should offset each other as the competitive effect is positive and the contagion effect is negative.

2.1.4. Outcomes of event studies performed in the past

The following were the outcomes of the event study performed:

- (Karpoff and Lott 1993) investigated company's exposure to reputational losses emanating from criminal fraud charges (fraud being an operational risk sub-category) that they were confronted with. The results of their study revealed that fraud announcement resulted in statistically significant decline in the company's market value.
- (Docking, Hirschey and Jones 1997) found significant contagion effects in the stock prices of non-announcing regional banks after announcements of loan loss reserve by the announcing regional bank.

- (Akhigbe and Madura 2001) Found contagion effects on rival banks from the ninety-nine publicly announced bank failures examined. Where a bank collapsed a stronger level of contagion was observed in publicly held and multibank holding companies.
- (Wei 2003) performed an empirical study on operational risk to assessment the impact of operational risk loss announcements on the market value of announcing and non-announcing financial institutions in the United States. The outcomes of that study revealed that operational risk losses have an impact that is significantly negative on the company's share price and that decline in affected company's market value is larger than the related actual operation risk loss.
- (Kabir and Hassan 2005) Studied the near collapse of Long-Term Capital Management (LTCM) and the result of that study indicated that the banks that had exposure to LTCM lost significant market value around the event.
- (Cummins, Lewis and Wei 2006) examined of operational risk related loss events impact on market value of announcing United States financial institutions. The results of their study revealed that market values reacted negatively to operational risk related losses announced. Their results further revealed that value at which the market value decline far exceeds the actual operational risk related loss.
- In the study performed by (Ferreira, Viljoen and van Vuuren 2016) three out of the four event losses analyzed revealed that operational risk events negatively influence the reputation of banks.
- (Ferreira and Paul-Francois 2017) analyzed the impact of operational loss event announcement on return volatility and the related spill-over effects to other non-announcing

banks, the banking industry index and the overall stock market index. In the results of their study revealed that operational loss events did increase the return volatility of the announcing bank and that there was a volatility spillover effect to non-announcing banks. Only one of the four announcing bank's operational loss event had an impact on the banking index. With regards to the overall stock market index all four operational loss events analyzed did not result spillover effects to the stock market returns.

3. DATA AND METHODOLOGY

In this thesis an event study approach is adopted for analysis of the impact of operational risk events announced on market value of the big four banks in South Africa (i.e. Standard Bank (SBK), FirstRand (FSR), Absa (ABS) and Nedbank(NED)). The study includes performance of regression analysis to estimate expected stock returns and a variance analysis between estimated expected returns and actual returns is done to calculate abnormal returns, which are used to determine whether an event announcement resulted in a negative impact or not.

To achieve the above this chapter details the steps followed for an event study are as includes: event identification; selection criteria; model description; estimation procedures; and the determination of normal and abnormal return measurements.

3.1. Event Identification

Identification of the event involves identification of the operational risk event and the date on which the operational risk event was publicly announced. We downloaded operational risk events for South African banks for the period beginning 1 January 2010 to 31 December 2017 from the ORX News Database.

ORX News database has published over 5000 losses, covering events in over 130 countries. The service monitors news outlets worldwide and identifies operational risk stories in the financial

services industry as they happen. For operational risk events are reported on the database our focus will be on the categories:

- Event date
- Description of event/ Headline
- Basel event type and business line
- Loss amounts

In the ORX News database, operational losses are categorized according to the Basel Committee's event type's classification:

Table 2: Basel Committee's event type's classification

Risk Categories
1. Business Disruption and System
2. Business Disruption and System Failures;
3. Clients, Products and Business Practice;
4. Damage to Physical Assets;
5. Employment Practice and Workplace safety;
6. Execution Delivery and Process Management;
7. External Fraud;
8. Internal Fraud

3.2. Selection Criteria

From the data above operational risk event data parameters, 43 South African banks related events were obtained. Insurance companies were excluded from the scope of the study. We cleaned out the downloaded data and removed all operational risk events that had a "not identifiable"

value as a data entry point in loss amount column. The operational risk event data was filtered to exclude events pertaining to other banks (i.e. other than the big four banks). A further filter was applied to only include events that were greater that R10 million rand.

3.3. Model Description

The research methodology used in this research follows approaches as was performed by *(Gillet, Hübner and Plunus 2010)* in the investigation of the announcing bank stock market reaction to the announcement of operational losses and *(Cummins, Wei and Xie 2012)* for the investigation of announcing banks spillover effects to other non-announcing banks. While the impact on operational loss event study has been performed for South African banking by (Ferreira, Viljoen and van Vuuren 2016), they highlighted the scarcity of operational risk event announcement. In their study (Ferreira, Viljoen and van Vuuren 2016) examined the impact of operational risk events on volatility of the stocks of South African banks.

Assuming that the South African Equity market is efficient (i.e. the stock market reacts very quickly to new information, thus all know public and private information is factored into the market price of the stock within a short period of time.

The stock returns will be assessed to establish whether there is a significant decline in the market value of the company or not.

3.4. Estimation procedures

In defining the event a time-line can be depicted in the event time as follows:

Figure 2 Timeline for event study

- The interval between T_{-U} and T_{-1} is the estimation period. It is used to detect the normal behavior of the stock market features.
- The interval between T_{-1} and T_1 is the event window. For this analysis the event window is the time length beginning τ_{-10} days before to the event announcement day and ending τ_{10} days after the announcement event day. Thus, the event window for this study is represented as (τ_{-10}, τ_{10}). The data in event window is used together with the α and the β of the stock to determine whether the operational risk event was expected or leaked; and how long it takes the operational risk event information to be absorbed by the stock market post announcement.
- T_0 is the calendar date that the operational risk event was announced.
- The interval between T_1 and T_U is the post event window. This window is used to determine the performance of the company after the event window.

3.5. Determination of normal and abnormal return measurements

We downloaded the stock price data of the big four South African banks (i.e. FirstRand, Standard Bank, Asba and Nedbank), the JSE All Share Index (i.e. JSE ALSI), the South African Banking Index (i.e. J835) data and the South African 10 year yield bonds from Bloomberg for the period starting 1 January 2009 to December 2017. We plotted the time series of stock prices to analyse the trend and volatility of the stock prices.

Figure 3: Volatility of the stock prices

From the graphs in figure 3 above it is evident that there is a distinct upward trend over time and the volatility is also non-constant. This means that the series is non-stationary in both mean and variance. Since the stock prices can never be negative and because the series is non-stationary in variance we can apply a log transformation on the stock prices. This will make the series

stationary in variance and account for the stock price being always positive. The non-stationarity in mean will be accounted for in the time series with the differencing parameter. Since we have seven years data and we are mainly interested in the pre-intervention period and the post intervention period, we will need to partition the full data set into separate periods and model the pre-intervention period first. We will use the data to model the pre-intervention period and perform model diagnostics for this period. We will then use the same model type with the inclusion of the dummy variable and obtain parameter estimates based on the pre-intervention and post intervention period.

As per previous literature, event study methodology requires that we analyse the stock return of a company around the period that the operational risk event is publicly announced and separating the portion of the total stock returns that exist because of the reaction to the announcement of the event. The stock returns are separated to reflect the normal return movement in the overall stock market (i.e. predicted expected returns), and the unexpected event (i.e. abnormal returns). This is done by measuring the stock returns performance against a benchmark. The benchmark is usually the return that the security would have achieved had the operational risk event not occurred.

To compute the expected return, we will use statistical market model (i.e. model of the return-generation process for the big four banks stocks).

From prior literature section the market model is the most common model used to perform the event study analysis due to its simplistic and intuitive form. However, there are other factors that drive fluctuation in the log-returns of the stock, and therefore more advanced models based on arbitrage pricing theory (APT) models were developed. A three-factor model using the overall market index return, the banking index return and the risk-free interest rate (i.e. South African 10-year bond yields) were considered.

Table 3: Pearson correlation co-efficient

	ALS Ind_Ret	*Bank Ind_Ret*	*SA 10 YR YIELD*
ALS Ind_Ret	1		
Bank Ind_Ret	0.633053	1	
SA 10 YR YIELD	-0.12402	-0.3646	1

We performed a pearson correlation co-efficient analysis and as presented in table 3 above we found that the overall market index (ALS Ind) was highly correlated with the banking index (Bamk Ind). Using both the overall market index return and the baking index return as independent parameters in the model caused multi-collinearity. The parameters were analysed separately and the banking index return as an independent parameter in the model resulted in a higher r-squares as compared to the overall market index return and the risk-rate interest rate variable .

In the three-factor model both the overall market index and the risk-rate interest rate variables were insignificant contributors to the description of the dependent variable, and thus removed from the model. The lead to us adopting a single factor market model using the South African banking index as a benchmark parameter.

In this model we assume that the stock returns are linearly related to the banking index market returns. In the next step we then calculated the difference between the daily expected returns and the daily actual returns to arrive at the daily abnormal returns.

To predict the expectd stock return (*i*) at time (*t)* using the return on market at time (t) we apply the market model, which is expressed by the following linear equation:

$$E(R_{ilt}) = \alpha_{il} + \beta_{il}.E(R_{mt}) + \varepsilon_{ilt} \quad (1)$$

Equation 1: The market model

Where:

- R_{ilt} = the stock return (*i)* for operational risk loss event (*l)* on day (*t)*,
- R_{mt} = Return on South African banking industry index on day (*t),*
- α_{il} and β_{il} are parameters to be estimated via ordinary least squares regression
- ε_{il} is the regression error term

We applied the first differencing to make the series stationary in mean and applying model diagnostics on the associated error term to check if it satisfies the assumptions of the model (i.e. error term is assumed to be independent, uncorrelated and normally distributed).

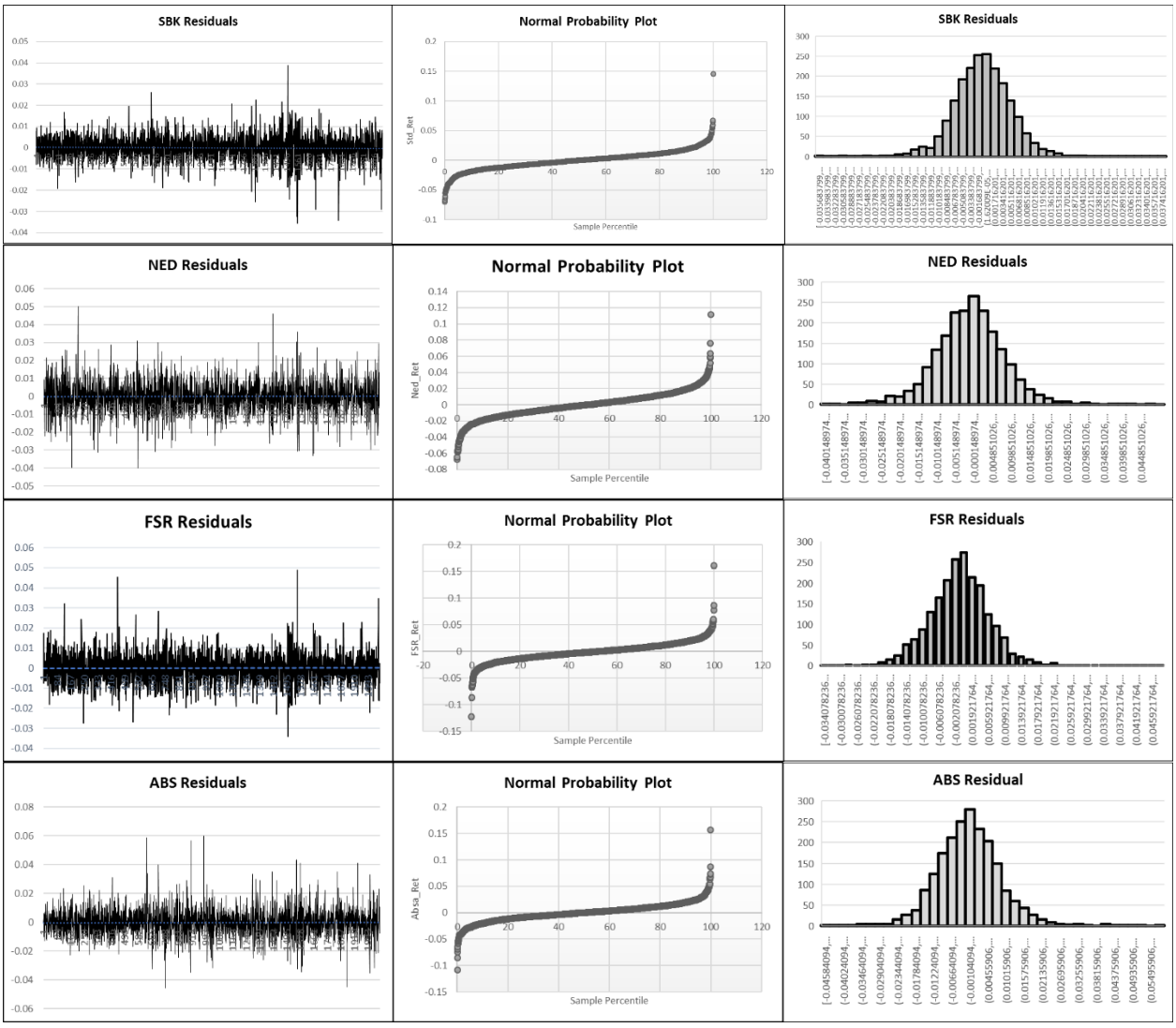

Figure 4: Regression normal probability plot and residuals

Based on the residual plot in the above figure it appears that the residuals/ errors are randomly scattered. Most of the auto-correlations of error terms lie within the 95% confidence limits, indicating that the auto-correlations are not statistically significant and the error terms are therefore not serially correlated. Examining the histogram in the above figure we find that the distribution of residuals appears to be normally distributed.

Table 3 below depicts the descriptive statistics of the data used to perform regression analysis in determining the expected stock returns for each bank.

Table 4: Regression descriptive statistics

	Std_Ret	***Predicted Std_Ret***	***FSR_Ret***	***Predicted FSR_Ret***	***Ned_Ret***	***Predicted Ned_Ret***	***Absa_Ret***	***Predicted Absa_Ret***
Mean	-0.00039	-0.00039	-0.00073	-0.00073	-0.00044	-0.00044	-0.00023	-0.00023
Variance	0.00026	0.00022	0.00030	0.00025	0.00026	0.00017	0.00030	0.00020
Observations	2067	2067	2067	2067	2067	2067	2067	2067
Pearson Correlation	0.92496		0.90782		0.81691		0.81263	
Hypothesized Mean Difference	0.00000		0.00000		0.00000		0.00000	
df	2066		2066		2066		2066	
t Stat	0.00000		0.00000		0.00000		0.00000	
P(T<=t) two-tail	1.00000		1.00000		1.00000		1.00000	
t Critical two-tail	1.96111		1.96111		1.96111		1.96111	

We performed a two tailed T-statistic test to determine whether the variables used in the regression model were statistically significant as a predictor variable. As per the results above, we found that t-statistics of all predictor variables were lower than the t-critical two-tail value. When testing for statistical significance of parameter estimates we are testing the null hypothesis (H_0) that the model parameters are greater than 0.05 vs. the alternative hypothesis (H_1) that the model parameters are not greater than 0.05 (i.e. they are statistically significant). If the p-value of the parameter estimates is less than 0.05 level of significance then we reject the H_0 in favor of the alternative and conclude that the corresponding parameter is statistically significant.

Table 5: Model parameter statistical analysis

		Coefficients	*Standard Error*	*t Stat*	*P-value*
FSR	Intercept	-0.00017	0.000161	-1.07114	0.284232
	Bank Ind_Ret	1.076054	0.010938	98.37491	0.000000
SBK	Intercept	0.000136	0.000136	1.002109	0.316408
	Bank Ind_Ret	1.018539	0.009225	110.4084	0.000000
NED	Intercept	1.93E-05	0.000204	0.094733	0.924536
	Bank Ind_Ret	0.891723	0.013855	64.36238	0.000000
ABS	Intercept	0.000262	0.000221	1.18705	0.235344
	Bank Ind_Ret	0.95064	0.015002	63.36551	0.000000

As indicated in the model parameter analysis results above, p-values of the South African banking index as an independent variable in model for all four banking stocks returns is less than 0.05. This implies that the South African banking index is significant as a benchmark variable in the model.

Since both P-values as stated in the table above are less than 0.05, we reject H_0 in favor of H_1 and conclude that the parameters are statistically significant.

We then performed model diagnostics on our fitted model to check if the model assumptions are satisfied. Adjusted R-squared – Determination of coefficient (it measures how efficient your model is). If it is greater than 50% the model is acceptable.

Table 6: Regression model statistical analysis

Regression Statistics	*FSR*	*SBK*	*NED*	*ABS*
Multiple R	0.907824	0.924737	0.816908	0.812633
R Square	0.824145	0.855139	0.667339	0.660372
Adjusted R Square	0.82406	0.855069	0.667178	0.660208
Standard Error	0.00731	0.006165	0.009259	0.010026
Observations	2067	2067	2067	2067

The South African banking index was used to perform a regression on all four banking stock returns. The R-square is bounded between 0 and 1, and results in the summary output below indicates that both R-squared and adjusted R-squared greater than 0.82, 0.85, 0.66 and 0.66 for FSR, SBK, NED and ABS respectively. Thus, this is an indication that the South African banking index is efficient as an independent variable in the model.

Under the assumptions of joint normality and (i) returns, the regression error is well–behaved, i.e., $E(\varepsilon_{ij}) = 0$ and $Var(\varepsilon_{ij}) = \sigma^2 \varepsilon_{ij}$. For each operational risk event announced, expected stock returns are estimated using OLS regression over the actual stock return data of the 250-days period ending the 10 days before the operational loss event window. The 250 days regression period is the standard length used in event study literature as the estimation period (Binder 1985). The estimation period and the event period should not overlap so that the parameters of normal/ expected return model are not influenced by the event (Mackinlay 1997). This is done to ensure that the expected return market model estimation does not overlap with the loss event window period and, to ensure that the actual returns that were earned 10 days before to the event announcement date are not influenced by the event announcement itself. Once we have estimated values for parameters α_{il} and β_{il} we determine predicted expected returns in the event window by inserting them in the market return. The market model will predict what the expected return of each bank stock should have been under normal conditions.

The daily abnormal returns are computed per operational risk event for window periods surrounding the event day (day 0 – the event announcement date) using the parameters

estimated from the market model. The abnormal return on day *(t)* that arise within the operational risk loss event window for stock *(i)* is articulated as the estimated market model disturbance term in the following equation:

$$AR_{ilt} = E(R_{ilt}) \quad (2)$$

Equation 2: Abnormal return equation

To provide for the possibility of information leakage prior to the public announcement of an operational risk event and to provide the market sufficient time to fully respond after the announcement, we calculate abnormal returns in a window beginning 10 trading days prior to each event and extending 10 trading days after for all events, thus, the event windows are (-10, +10). An extended event period can provide a heighted clarity on the effect of the operational loss events over time.

We express returns for window period of an overall ±10 days window to provide information on the stock reaction on an operational risk event announcement. We aggregate the abnormal returns for the bank stocks for each event day based on the assumption that they are independent and equally distributed. It is expected that market reaction to the impact of shock due to announcement of the event information should be larger at τ_1.

Prior literature such as (Bernard 1987) and (Collins and Dent 1984) has documented possible bias caused by cross-sectional dependence. When some of the stock returns in the sample are from a common period there is a likelihood that cross sectional dependence may arise. Consequently,

incorrect inferences could occur if bias caused by cross sectional dependence is not accounted for. In the normal return generating process if some underlying factors which are not adjusted for when the estimating parameters are determined, and the different banks stock returns responds to the same underlying factors in the same manner because of overlapping event windows, incorrect inferences become the case. As oppose to being independent this type of result in the error terms tend to be correlated across stocks. Thus, the existence of clustering will be addressed by aggregating abnormal returns into a portfolio dated using the event date (Mackinlay 1997) and (Bernard 1987).

The average abnormal return (AAR) across big four South African banking stocks for event (*l)* at day t in the event window. To determine the average abnormal return at each time (*t), the abnormal returns for (N)* stocks within the operational risk event window are aggregated, thus eliminating idiosyncrasies in the measurement due to stocks. The average abnormal return is expressed as follows:

$$\overline{AR}_{lt} = \frac{1}{N_l}\sum_{i=1}^{N_l} AR_{ilt} \quad (3)$$

Equation 3: Average abnormal return equation

Where: appropriate enhanced

- N_l is the number of stocks for event *(l).*

To help us get a sense of the aggregate effect of abnormal returns, we compute the cumulative average abnormal return (CAAR) or the mean cumulative abnormal returns. The CAAR is described as the sum of average abnormal returns over (T) days within the operational risk event

window. The cumulative average abnormal returns, across big four South African banking stocks and N events is expressed as follows:

$$CAR_{il}(\tau_1, \tau_2) = \sum_{t=T_1}^{T_2} AR_{ilt} \quad (4)$$

Equation 4: Cumulative abnormal return equation

4. RESEARCH ANALYSIS AND RESULTS

In this chapter we discuss the testing procedures, empirical results and interpretation of results.

In line with the prior literature the following four hypothesis are examined:

Hypothesis 1: *Public announcement of large (>R100 million) operational risk loss event result in a negative impact on the market value of the announcing bank.*

- *Null hypothesis H_0: CAAR ≤ 0*

- *Alternative Hypothesis H_1: CAAR > 0*

If the CAAR results are negative, then we reject the null hypothesis. To quantify the association between operational risk related losses and change in the market value CAARs of a company we will use a linear regression and correlation analysis. With the regression analysis, we will assess the relationship between a dependent variable (i.e. change in market value) and the independent variable (i.e. operational loss). We apply weighted least squares for this analysis to control for heteroskedasticity. The log of the operational loss amount is independent variable and the CAAR is a dependent variable. To analyse this hypothesis we use the FSR and the two SBK events since they were the only events greater than R100 million recorded on the ORX database for the big four South African Banks.

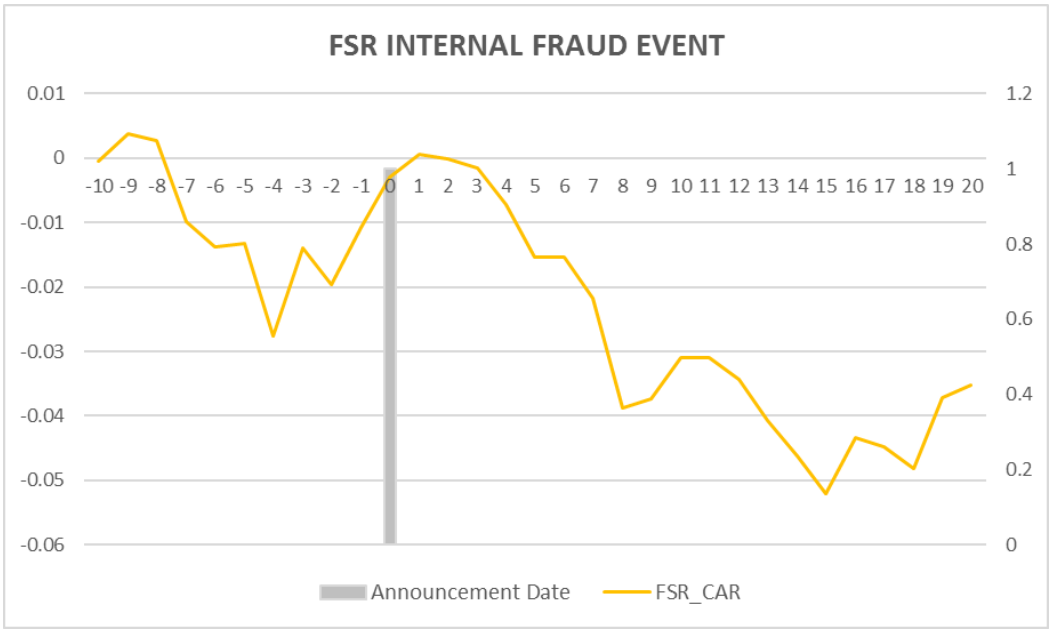

Figure 5: FSR cumulative abnormal returns plot based on the FSR Internal fraud event

In the linear graph depicted in figure 5 above, it is evident that the operational risk loss event had a negative impact on the FSR cumulative abnormal returns. The impacts points that had a statistical significant impact were in the window period (+4, +5) and (+16, +17). The cumulative average abnormal returns at (0, +10) window period are at negative -1%.

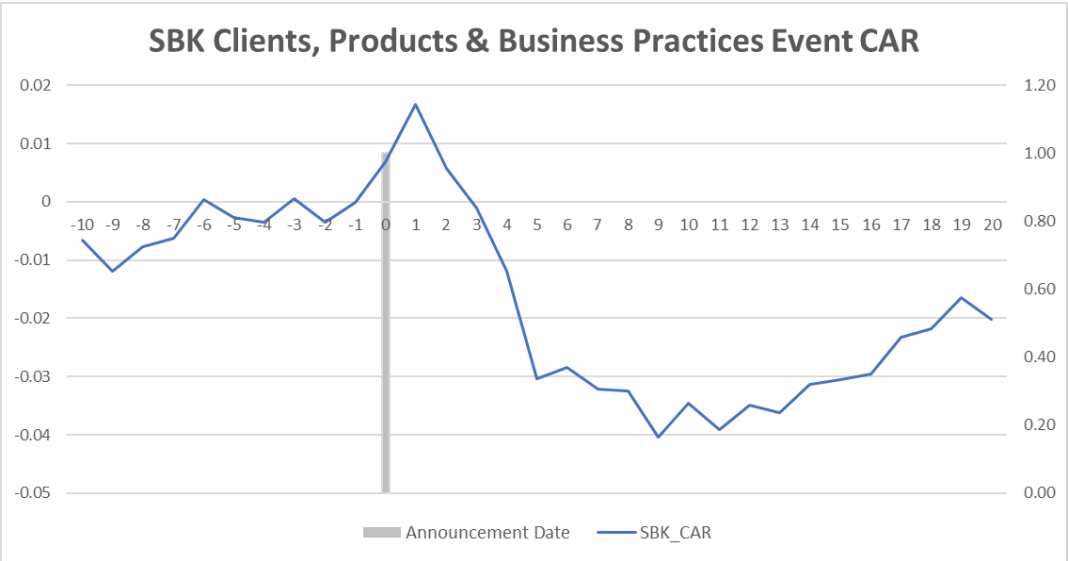

Figure 6: SBK cumulative abnormal returns plot based on the SBK client, product and business practices event

In the linear graph depicted in figure 6 above, it is evident that the SBK client, product and business practices (i.e. Conduct Risk) operational risk event had a negative impact on the SBK cumulative abnormal returns. The impacts points that had a statistical significant impact were in the window period (+3, +4). The cumulative average abnormal returns at (-10, +20) window period are at negative -2%.

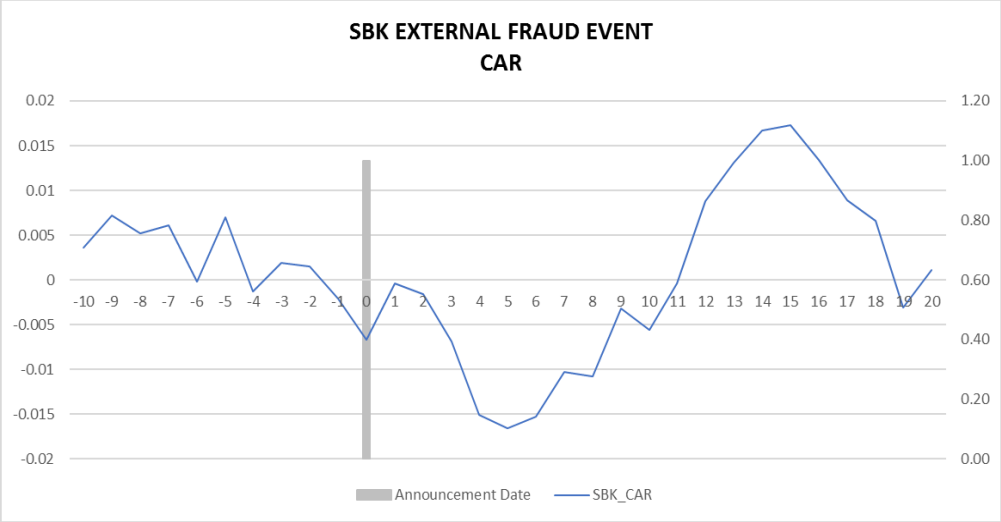

Figure 7: SBK cumulative abnormal returns plot based on the SBK External fraud event

In the linear graph depicted in figure 7 above, it is evident that the SBK external fraud operational risk event had a negative impact on the SBK cumulative abnormal returns. Multiple negative impacts were observed throughout the event window period but none of them were statistically significant. However, the cumulative average abnormal returns at (0, +11) window period are at negative -1%.

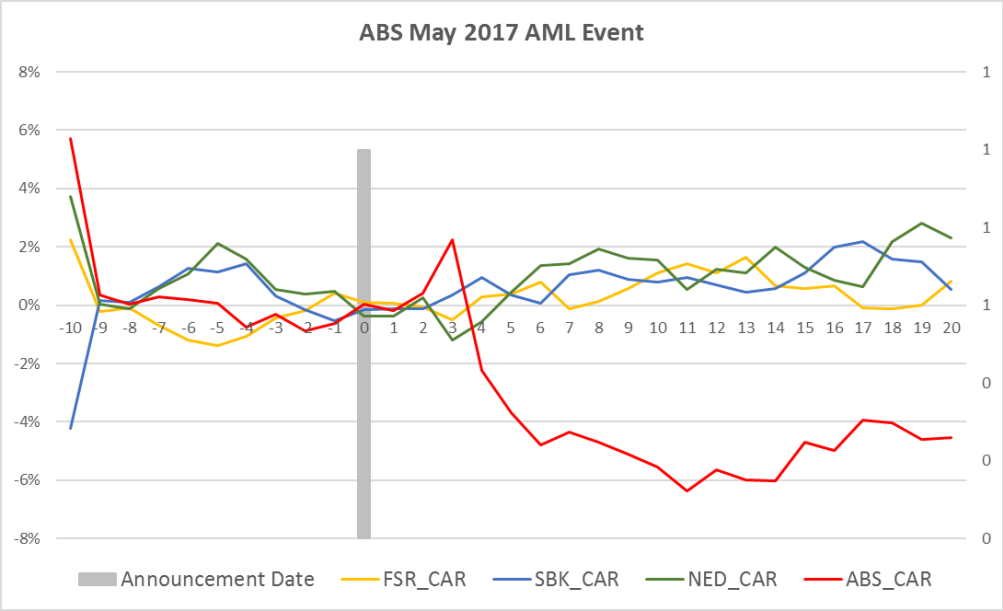

Figure 8: ABS May 2017 AML Event

In the linear graph depicted in figure 8 above, it is evident that the ABS AML (client, product and business practices) operational risk event had a negative impact on the ABS cumulative abnormal returns. Multiple negative impacts were observed throughout the event window period which were statistically significant. The decline in the returns were most severe between the window period point (0, +6). The cumulative average abnormal returns at (-10, +20) window period are at negative -2.41%.

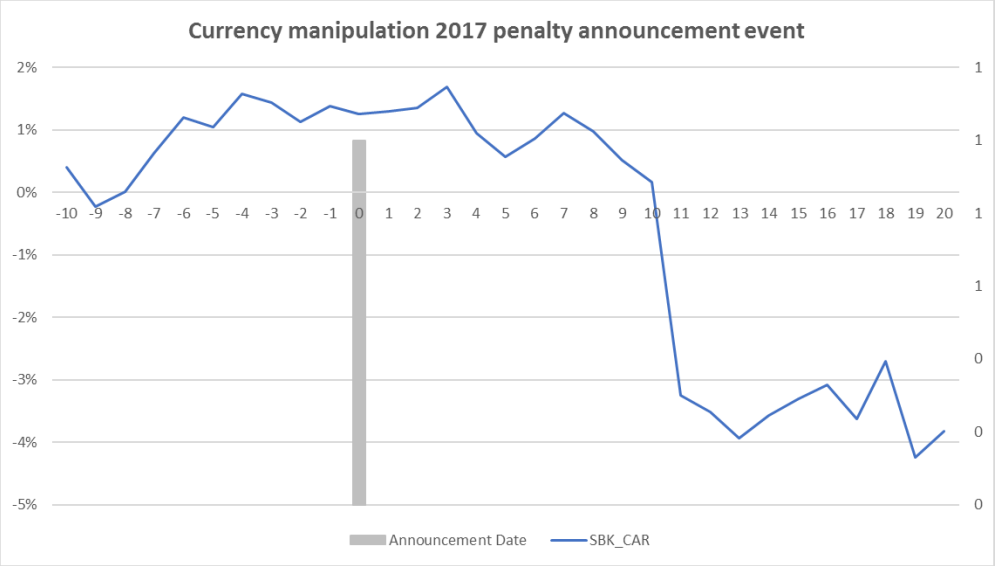

Figure 9: Currency manipulation 2017 penalty announcement event

In the linear graph depicted in figure 9 above, it is evident that the currency exchange manipulation penalty announcement event (client, product and business practices) operational risk event had a negative impact on the SBK cumulative abnormal returns. Multiple negative impacts were observed throughout the event window period which were statistically significant. The decline in the returns were most severe between the window period point (+9, +9). The cumulative average abnormal returns were negative at (-10, +20) window period are at -0.50% and at (+10, +20) window period are at -3%.

4.1.1. Hypothesis 1 – Negative impact conclusion

Based on the above results we reject the null hypothesis that the large (>R100 million) operational losses event does not have in a negative impact on the market value of the announcing bank.

In line with the empirical studies that was performed by (Wei 2003) and (Cummins, Lewis and Wei 2006) on financial institutions in the United States and (Karpoff and Lott 1993), this study revealed that operational risk losses do have an impact that is significantly negative on the company's share price.

Hypothesis 2: *The decline in the market value of the announcing company exceeds the actual operational loss event amount.*

Null hypothesis $H_{0:}$ The decline in the market value of the announcing company does not exceed the actual operational loss amount.

To test the above null hypothesis, we will measure the difference between the operational loss event amount and the CAAR multiplied by the average number of shares that were in issue during the event period (i.e. decline in the market value) of the announcing bank.

From the analysis that was performed on the following CAARs were attained:

Table 7: Cumulative average abnormal returns for banks

Event	FSR_CAAR	SBK_CAAR	NED_CAAR	ABS_CAAR
AML event CAAR	-3%	2%	1%	0%
FSR event CAAR	-1%	n/a	n/a	n/a
SBK event CAAR	n/a	-2%	n/a	n/a

From the table 7 above CAAR results it appears that the only events that resulted in negative impact on the market value of the company is the AML event on FSR market value, the FSR event on the FSR market value and the SBK event on the SBK market share. As a result, we will use the AML event to test the impact of the operational loss event on the FSR market value loss; and the SBK event to test the impact of the operational loss event on the SBK market value loss during

the event window period. If the decline in market value of the announcing firm is greater than the actual operational loss amount, then we will reject to accept the hypothesis.

Table 8: Comparative analysis of loss of market value vs. actual loss amount

Event	Weighted average number of shares*	Share price#	CAAR	Estimated loss of bank's market value	Actual loss event amount
AML event (FSR MV)	5,339,471,781	36.1	-3%	-R 5,782,647,939	R 30,000,000
SBK event (SBK MV)	1,580,163,333	106.82	-2%	-R 3,375,860,945	R 528,000,000

#The share price used is the last closing share price of the stock before the window period.
*The weighted average number of shares is based on the average number of shares that were in issue over a five-year period for a bank

4.1.2. Hypothesis 2 – Impact is greater than actual loss amount conclusion

Based on the in table 8 above results we reject the null hypothesis as the estimated loss of the market value during the event window does exceed the actual operational loss amount.

As with the empirical study that was performed by (Wei 2003) and (Cummins, Lewis and Wei 2006) on financial institutions in the United States, this study reveals and that decline in affected company's market value is larger than the related actual operation risk loss. The results of this study also support the results of (Ferreira, Viljoen and van Vuuren 2016) which found that three out of the four event losses analyzed revealed that operational risk events negatively influence the reputation of banks.

Hypothesis 3: *Operational loss event in one bank can cause a negative intra-sector spillover effect in the banking industry by causing contagion on other non-announcing banks.*

Null hypothesis $H_{0:}$ Operational loss event in one bank cannot cause negative intra-sector spillover effect (i.e. contagion) on other non-announcing banks.

If the operational loss amount (i.e. independent variable) is a statistically significant coefficient, this would suggest that operational losses events of an announcing bank sends information to the market regarding possible control weakness exposure to similar risk events in other banks. A significant negative coefficient would suggest that high value operational risk loss events encourage a revision of future expected losses for non-announcing firms. To test this hypothesis, we will use the ABIL (African Bank) event to assess whether the abnormal returns of the big four banks are statistical significance during the event window period.

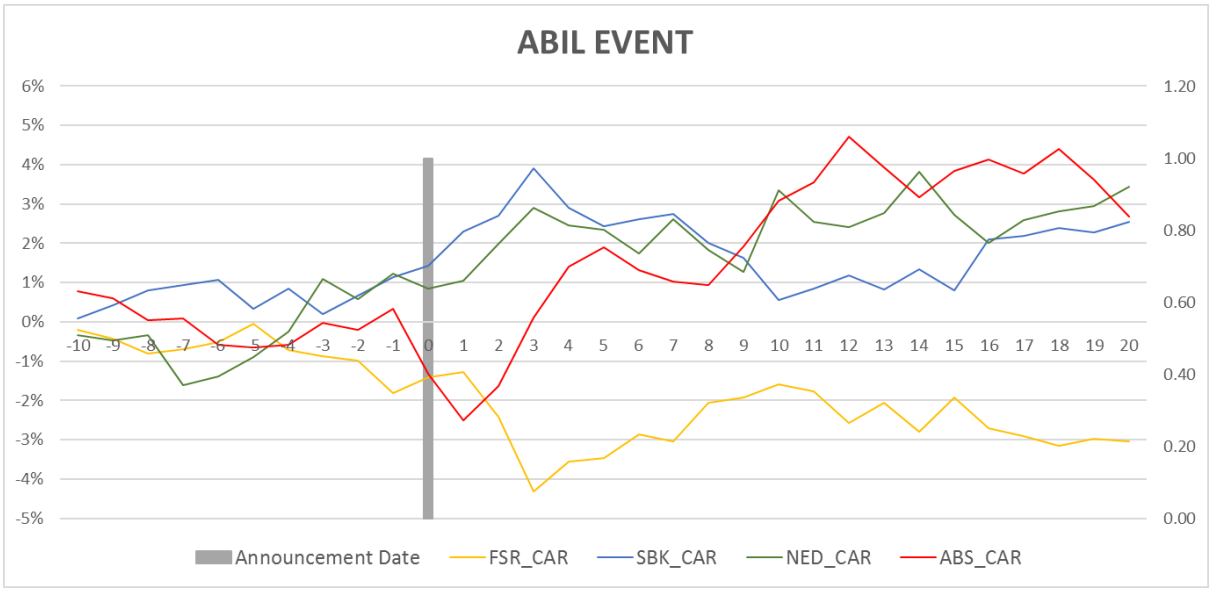

Figure 10: FSR, SBK, NED and ABS cumulative abnormal returns plot based on the ABIL event

From the line graph in figure 10 above we can observe that there was a negative impact in the CARs of non-announcing banks – FSR at (+1, +3), SBK at (+2.5, +5) and NED at (+2.5, +6) and (+10, +11). In all cases the decline was statistically significant.

4.1.3. Hypothesis 3 – Contagion effect conclusion

Based on above results we reject the null hypothesis that the operational loss event in one bank cannot cause negative intra-sector spillover effect (i.e. contagion) on other non-announcing banks.

As it was found in the analysis performed by (Docking, Hirschey and Jones 1997) that significant contagion effects in the stock prices of non-announcing regional banks, this study also finds contagion effect to non- announcing banks. The above results are also in line with the findings of (Akhigbe and Madura 2001) who found contagion effects on rival banks; and (Kabir and Hassan 2005) where the result of that study indicated that the banks that had exposure to the announcing bank lost significant market value around the event.

Hypothesis 4: *Operational risk events of an announcing company give non-announcing companies a competitive advantage (competitive effect).*

Null hypothesis $H_{0:}$ Operational loss event in one bank cannot cause competitive effect on other non-announcing banks. To test this hypothesis, we will use the ABIL and the ABS May 2017 operational risk event to observe whether evidence of a competitive effect exist. A significant positive coefficient would imply that there is a competitive effect.

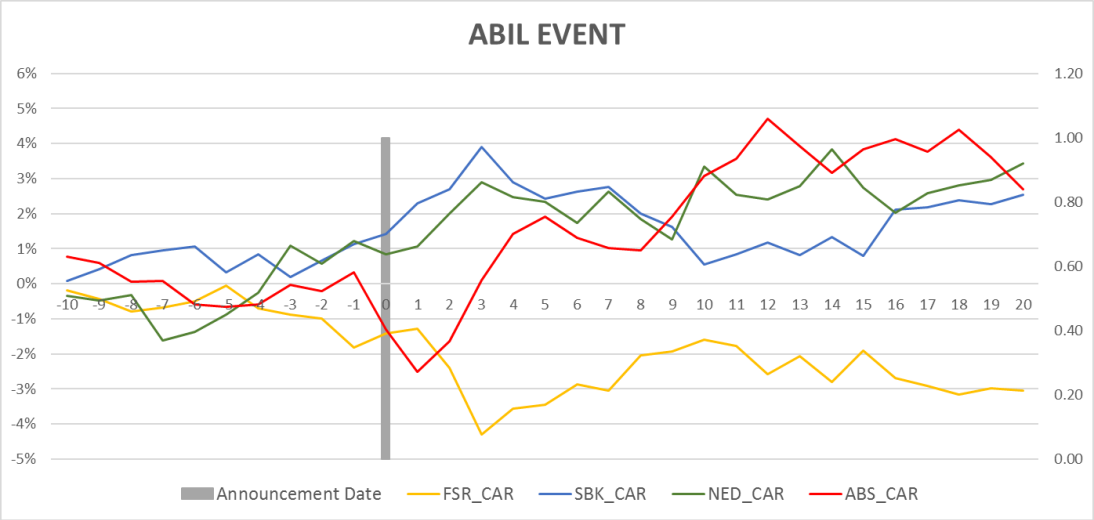

Figure 11: ABIL 2014 Event

From the line graph in figure 11 above we can observe that there was a positive impact in the CARs of non-announcing banks SBK at (+2.5, +5) and NED at (+2.5, +6) and FSR (+10, +11). In all cases the increase was statistically significant.

Table 9: FSR, SBK, NED and ABS cumulative average abnormal returns based on ABIL event

	FSR_CAAR	SBK_CAAR	NED_CAAR	ABS_CAAR
ALM Event	-0.01963	0.015552	0.01553	0.014158

From the cross-regression panel table above it is also evident that positive cumulative abnormal returns were gained by SBK, NED and ABS.

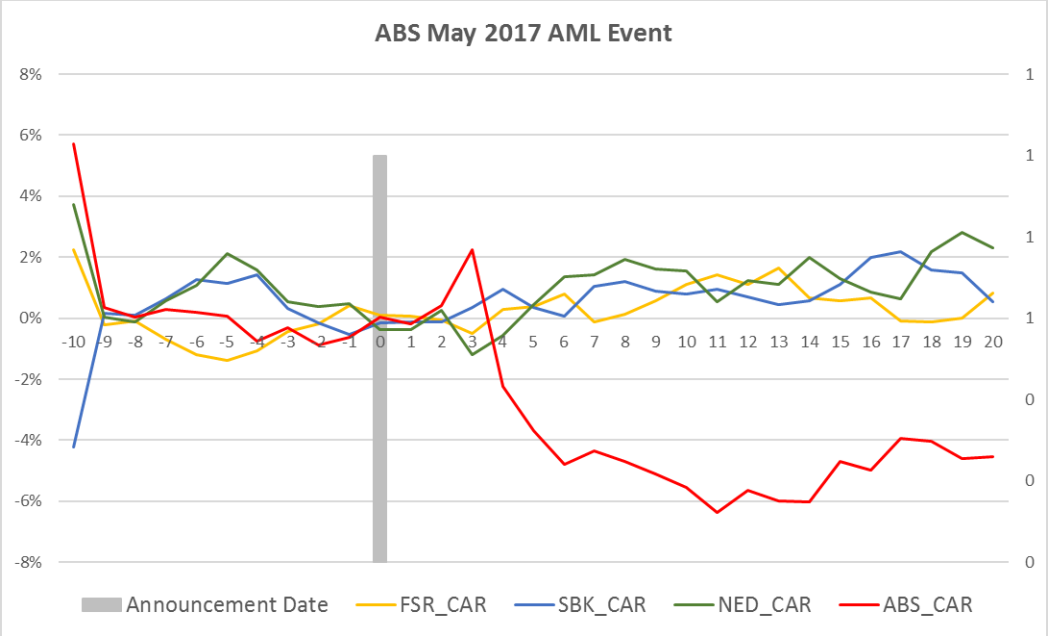

Figure 12: ABS May 2017 AML Event

From the line graph in figure 12 above ABS May 2017 ALM operational risk event graph above we can observe that there was a positive impact in the CARs of non-announcing banks SBK at (+1, +4) and NED at (+3, +6) and FSR (+3, +6).

Table 10: FSR, SBK, NED and ABS cumulative average abnormal returns based on ABS May 2017 event

	FSR_CAAR	SBK_CAAR	NED_CAAR	ABS_CAAR
ABSA May 2017ALM Event	0.22%	0.55%	1.02%	-2.41%

From the cross-regression panel table 10 above it is also evident that positive cumulative abnormal returns were gained by FSR, SBK and NED.

4.1.4. Hypothesis 4 – Competitive effect conclusion

Based on above results we reject the null hypothesis that the operational loss event in one bank cannot cause positive intra-sector spillover effect (i.e. competitive effect) on other non-announcing banks.

5. CONCLUSION

This thesis analysis the effect of operational loss events on both announcing and non-announcing banks in South Africa. This thesis is motivated by the increase in value of operational loss events either in the form of cybercrimes, data breaches, rouge trading or regulatory fines emanating conduct risk and/ or weak antimony laundering controls. Since the South African banks industry is integrated it is expected to have inter-banking spillover effects within the south African banking industry. To analyse the effects of the operational risk events on both the announcing banking and non-announcing banks an event study approach was used. Publicly announce operational risk data that were greater than R100 million rand obtained from ORX Database and used to perform the analysis.

The four principal hypothesis investigated in this study are the effects of publicly announced operational risk on the market value of the announcing firm (i.e. whether they result in a negative impact and whether the loss in the market value far exceeds the actual event loss amount); whether publicly announced operational risk events resulted in a negative spillover effect on the stock price, thus market value, of non-announcing banks (i.e. the negative information externality hypothesis); and whether the publicly announced operational risk events result in wealth being transferred from the announcing bank to other non-announcing banks.

The result of this study implies that large operational risk events experienced by South African banks does have a negative effect on the share price of the announcing banks. The results further suggest in some cases the announced operational risk loss events have a negative spillover effect in other non-announcing banks and in other cases a positive spillover effect is observed. The reaction of non-announcing to operational risk loss events in announcing banks implies that

announced operational risk events does convey new information about the risk that the bank is exposed, which result in the market revising downward estimates of future cashflows for announcing and some non-announcing banks perceived by the market to be exposed to similar risk event types. On the other hand, generation of net wealth transfer from announcing to some other non-announcing banks implies that the market to have sound, resilient and sustainable control environment.

In South Africa the investment banking and retail banking division falls within the bigger umbrella of the Banking Group structures, as such we were unable to perform an intra-sector competitive effect assessment at bank divisional level. As it was revealed in prior literature that operational risk loss events have a strong statistically significant negative spillover effects on announcing bank in South Africa, the present study also demonstrations that such events do have as strong significant negative inter-industry spillover on other non-announcing banks. This study supports the regulatory view that operational risk poses a significant threat to the market value of banks, thus, providing a decent rationale for to continue investing in resources aimed at pro-actively managing operational risk, although this risk type tends to be non-systematic. The spill-over effect hypothesis also provided us with a strong quantitative evidence of the extent to which the of the South African banking industry is integrated. The outcome of this study also demonstrated that indeed the investors in the South African stock market does takes cognizance of the weaknesses in the control environment (for which if not appropriately managed will result in high magnitude of operational risk related losses being experienced by a bank) and clearly penalizes banks for operational risk management failures.

6. ANNEXURES – Significance testing for operational risk events used in the event study analysis

Table 10: Abnormal returns statistical significant test results caused by the ABIL event

Event day	*FSR_AR*	*T-stats*	*FSR_CAR*	*SBK AR*	*T-stats*	*SBK_CAR*	*NED_AR*	*T-stats*	*NED_CAR*	*ABS_AR*	*T-stats*	*ABS_CAR*
-10	0%	-0.265	0%	0%	0.131	0%	0%	-0.368	0%	1%	0.773	1%
-9	0%	-0.330	0%	0%	0.543	0%	0%	-0.140	0%	0%	-0.183	1%
-8	0%	-0.496	-1%	0%	0.646	1%	0%	0.153	0%	-1%	-0.537	0%
-7	0%	0.150	-1%	0%	0.215	1%	-1%	-1.395	-2%	0%	0.035	0%
-6	0%	0.244	-1%	0%	0.203	1%	0%	0.263	-1%	-1%	-0.678	-1%
-5	0%	0.634	0%	-1%	-1.207	0%	0%	0.530	-1%	0%	-0.057	-1%
-4	-1%	-0.909	-1%	1%	0.834	1%	1%	0.685	0%	0%	0.055	-1%
-3	0%	-0.237	-1%	-1%	-1.047	0%	1%	1.447	1%	1%	0.563	0%
-2	0%	-0.134	-1%	0%	0.769	1%	-1%	-0.553	1%	0%	-0.169	0%
-1	-1%	-1.139	-2%	0%	0.764	1%	1%	0.700	1%	1%	0.535	0%
0	0%	0.547	-1%	0%	0.452	1%	0%	-0.412	1%	-2%	-1.647	-1%
1	0%	0.195	-1%	1%	1.425	2%	0%	0.233	1%	-1%	-1.198	-3%
2	-1%	-1.551	-2%	0%	0.642	3%	1%	1.010	2%	1%	0.872	-2%
3	-2%	-2.597*	-4%	1%	1.978*	4%	1%	0.977	3%	2%	1.744	0%
4	1%	1.011	-4%	-1%	-1.645	3%	0%	-0.466	2%	1%	1.301	1%
5	0%	0.142	-3%	0%	-0.754	2%	0%	-0.130	2%	0%	0.495	2%
6	1%	0.810	-3%	0%	0.307	3%	-1%	-0.656	2%	-1%	-0.586	1%
7	0%	-0.241	-3%	0%	0.220	3%	1%	0.953	3%	0%	-0.298	1%
8	1%	1.362	-2%	-1%	-1.224	2%	-1%	-0.842	2%	0%	-0.076	1%
9	0%	0.162	-2%	0%	-0.616	2%	-1%	-0.612	1%	1%	0.972	2%
10	0%	0.466	-2%	-1%	-1.727	1%	2%	2.235*	3%	1%	1.163	3%
11	0%	-0.251	-2%	0%	0.462	1%	-1%	-0.860	3%	0%	0.470	4%
12	-1%	-1.086	-3%	0%	0.553	1%	0%	-0.151	2%	1%	1.157	5%
13	1%	0.689	-2%	0%	-0.590	1%	0%	0.399	3%	-1%	-0.780	4%
14	-1%	-0.999	-3%	1%	0.843	1%	1%	1.137	4%	-1%	-0.764	3%
15	1%	1.202	-2%	-1%	-0.886	1%	-1%	-1.187	3%	1%	0.674	4%
16	-1%	-1.068	-3%	1%	2.128*	2%	-1%	-0.766	2%	0%	0.283	4%
17	0%	-0.297	-3%	0%	0.117	2%	1%	0.614	3%	0%	-0.357	4%
18	0%	-0.327	-3%	0%	0.339	2%	0%	0.243	3%	1%	0.620	4%
19	0%	0.238	-3%	0%	-0.196	2%	0%	0.154	3%	-1%	-0.773	4%
20	0%	-0.088	-3%	0%	0.441	3%	0%	0.516	3%	-1%	-0.930	3%

*Cumulative abnormal returns that are statistically significant within the event window period.

From the table 10, it is evident that announcement of the ABIL operational risk event did have a statistically significant negative impact on three of the four non-announcing banks (i.e. FSR, SBK and NED) after the event announcement date during the (0, +20) event window period.

Table 11: Abnormal returns statistical significant test results caused by the AML events

Event day	*FSR_AR*	*T-stats*	*FSR_CAR*	*SBK AR*	*T-stats*	*SBK_CAR*	*NED_AR*	*T-stats*	*NED_CAR*	*ABS_AR*	*T-stats*	*ABS_CAR*
-10	-1%	-1.184	-1%	0%	0.529	0%	2%	2.116	2%	0%	-0.289	0%
-9	-1%	-1.569	-2%	1%	1.024	1%	0%	0.501	2%	0%	-0.413	-1%
-8	-1%	-1.398	-3%	1%	0.889	2%	0%	-0.018	2%	0%	0.081	-1%
-7	0%	0.233	-3%	-1%	-1.080	1%	2%	1.673	4%	0%	0.147	0%
-6	0%	0.053	-3%	1%	1.737	2%	-1%	-1.480	3%	-1%	-1.272	-2%
-5	1%	1.381	-2%	-1%	-1.099	1%	-1%	-0.985	2%	1%	0.663	-1%
-4	1%	1.167	-1%	-1%	-1.106	1%	0%	-0.521	1%	0%	-0.057	-1%
-3	-1%	-1.975	-2%	1%	1.587	2%	0%	0.100	1%	1%	0.721	0%
-2	-1%	-1.510	-4%	1%	1.299	2%	0%	-0.296	1%	0%	-0.159	-1%
-1	0%	0.526	-3%	0%	-0.323	2%	1%	0.804	2%	0%	-0.302	-1%
0	0%	0.683	-3%	0%	0.440	2%	-1%	-0.995	1%	-1%	-0.921	-2%
1	-1%	-0.841	-3%	0%	-0.226	2%	1%	1.135	2%	1%	1.365	0%
2	0%	-0.482	-4%	0%	0.433	3%	1%	0.870	3%	0%	0.138	0%
3	-1%	-0.783	-4%	1%	0.953	3%	-1%	-1.071	2%	0%	0.193	0%
4	1%	0.824	-4%	0%	0.272	3%	-2%	-2.208	0%	0%	0.109	0%
5	0%	-0.402	-4%	0%	0.339	3%	0%	0.163	0%	0%	-0.451	0%
6	0%	0.293	-4%	0%	-0.020	3%	0%	0.358	0%	-1%	-0.632	-1%
7	0%	0.448	-3%	0%	-0.185	3%	-1%	-1.588	-1%	2%	1.667	1%
8	0%	-0.522	-4%	0%	-0.122	3%	1%	0.700	-1%	0%	0.052	1%
9	0%	-0.211	-4%	0%	-0.081	3%	0%	0.067	-1%	0%	0.281	1%
10	1%	0.921	-3%	-1%	-0.960	3%	-2%	-1.992	-2%	1%	0.789	2%
11	1%	1.577	-2%	-1%	-1.443	2%	0%	0.218	-2%	-1%	-0.685	1%
12	0%	0.065	-2%	0%	0.496	2%	0%	-0.528	-3%	-1%	-1.412	0%
13	0%	-0.479	-2%	0%	0.049	2%	2%	1.938	-1%	0%	0.467	0%
14	0%	-0.166	-2%	-1%	-1.097	1%	2%	2.339	1%	0%	0.095	0%
15	0%	-0.493	-3%	0%	0.637	2%	0%	0.166	1%	0%	-0.313	0%
16	0%	-0.439	-3%	0%	0.774	2%	0%	0.062	1%	-1%	-0.775	-1%
17	0%	-0.326	-3%	0%	0.203	2%	0%	-0.174	1%	1%	0.983	0%
18	0%	-0.315	-4%	0%	0.088	2%	0%	0.367	2%	0%	-0.133	0%
19	0%	0.477	-3%	0%	-0.016	2%	-1%	-0.640	1%	-1%	-0.790	-1%
20	0%	-0.001	-3%	0%	-0.632	2%	0%	0.416	1%	1%	0.523	0%

**Cumulative abnormal returns that are statistically significant within the event window period.*

From the table 11 above, it is evident that announcement of the AML operational risk event did have a statistically significant negative impact on two of the four banks (i.e. FSR and NED) within the event window period.

Table 12: Abnormal returns statistical significant test results caused by the FSR event

Event day	*FSR_AR*	*T-stats*	*FSR_CAR*	*SBK AR*	*T-stats*	*SBK_CAR*	*NED_AR*	*T-stats*	*NED_CAR*	*ABS_AR*	*T-stats*	*ABS_CAR*
-10	0%	-0.078	0%	0%	-0.344	0%	1%	1.230	1%	0%	-0.490	0%
-9	1%	0.837	1%	-1%	-1.242	-1%	1%	0.958	2%	0%	-0.335	-1%
-8	0%	0.442	1%	-1%	-1.054	-2%	1%	0.727	3%	0%	-0.052	-1%
-7	1%	0.900	2%	0%	0.093	-2%	-1%	-0.920	2%	-1%	-0.504	-1%
-6	0%	-0.007	2%	0%	-0.003	-2%	0%	0.010	2%	0%	0.001	-1%
-5	-1%	-0.712	1%	0%	-0.010	-2%	0%	-0.303	2%	2%	1.580	0%
-4	1%	0.913	2%	-1%	-0.961	-2%	0%	0.044	2%	0%	-0.427	0%
-3	0%	0.101	2%	-1%	-0.880	-3%	1%	1.199	3%	0%	0.277	0%
-2	0%	0.296	2%	0%	0.437	-2%	-1%	-1.189	2%	-1%	-0.689	-1%
-1	0%	-0.077	2%	0%	0.538	-2%	0%	-0.254	1%	-1%	-0.864	-2%
0	0%	0.598	2%	0%	-0.039	-2%	-1%	-1.144	0%	0%	-0.357	-2%
1	0%	-0.162	2%	0%	0.499	-2%	-1%	-1.548	-1%	0%	0.037	-2%
2	-1%	-1.705	1%	1%	1.002	-1%	0%	0.355	-1%	1%	0.942	-1%
3	0%	-0.550	1%	0%	-0.179	-1%	0%	0.167	-1%	1%	1.039	0%
4	0%	0.086	1%	0%	0.720	-1%	0%	0.049	-1%	-1%	-1.183	-1%
5	-1%	-1.961	-1%	0%	0.600	-1%	2%	1.951	1%	1%	1.346	0%
6	1%	1.851	1%	0%	0.035	0%	-3%	-2.718	-1%	-2%	-2.188	-2%
7	-1%	-0.763	0%	1%	0.823	0%	-1%	-0.825	-2%	0%	0.361	-2%
8	1%	1.218	1%	-1%	-1.142	-1%	0%	-0.292	-2%	0%	0.172	-1%
9	1%	1.063	2%	-1%	-1.176	-1%	-1%	-1.031	-3%	0%	0.455	-1%
10	0%	0.477	2%	0%	0.037	-1%	0%	0.259	-3%	-1%	-0.792	-2%
11	0%	-0.091	2%	1%	0.936	-1%	0%	0.389	-3%	-1%	-1.310	-3%
12	0%	-0.205	2%	-1%	-0.893	-1%	1%	1.538	-1%	2%	1.628	-1%
13	-1%	-0.769	1%	1%	0.847	-1%	-1%	-1.182	-2%	0%	0.008	-1%
14	-1%	-1.125	0%	0%	0.679	0%	-1%	-0.768	-3%	1%	1.275	0%
15	0%	0.000	0%	-1%	-1.392	-1%	1%	0.812	-2%	2%	1.554	1%
16	-1%	-0.862	0%	0%	-0.640	-2%	1%	1.237	-1%	1%	1.377	3%
17	-2%	-2.332	-2%	0%	0.640	-1%	1%	1.080	0%	3%	2.618	5%
18	0%	0.195	-2%	0%	-0.020	-1%	1%	0.637	0%	-1%	-1.330	4%
19	1%	0.866	-1%	0%	-0.171	-1%	0%	-0.357	0%	-1%	-1.384	3%
20	0%	0.011	-1%	0%	0.079	-1%	0%	0.533	1%	0%	0.269	3%

**Cumulative abnormal returns that are statistically significant within the event window period.*

Table 12 above provides evidence that announcement of the FSR internal fraud operational risk event did have a statistically significant negative impact on three of the four banks (i.e. FSR, NED and ABS) within the event window period.

Table 10: Abnormal returns statistical significant test results caused by the SBK event

Event day	*FSR_AR*	*T-stats*	*FSR_CAR*	*SBK AR*	*T-stats*	*SBK_CAR*	*NED_AR*	*T-stats*	*NED_CAR*	*ABS_AR*	*T-stats*	*ABS_CAR*
-10	0%	-0.40	0%	-1%	-1.07	-1%	1%	0.65	1%	1%	0.98	1%
-9	1%	0.86	0%	-1%	-0.85	-1%	0%	0.12	1%	0%	-0.06	1%
-8	0%	0.65	1%	0%	0.72	-1%	-2%	-2.01	-1%	-1%	-0.77	0%
-7	-1%	-1.30	0%	0%	0.20	-1%	1%	1.18	0%	1%	0.94	1%
-6	-1%	-1.13	-1%	1%	1.10	0%	0%	-0.09	0%	0%	0.07	1%
-5	1%	1.91	0%	0%	-0.51	0%	0%	0.25	0%	-3%	-2.65	-1%
-4	-1%	-0.99	0%	0%	-0.15	0%	0%	-0.08	0%	2%	1.67	0%
-3	-1%	-0.94	-1%	0%	0.66	0%	1%	1.13	1%	0%	-0.28	0%
-2	0%	-0.21	-1%	0%	-0.64	0%	1%	1.05	2%	1%	1.06	1%
-1	1%	1.71	0%	0%	0.61	0%	0%	0.29	2%	-5%	-4.57	-4%
0	0%	-0.01	0%	1%	1.15	1%	0%	0.49	3%	-3%	-2.55	-6%
1	-1%	-1.74	-1%	1%	1.61	2%	1%	1.06	4%	-1%	-1.15	-7%
2	1%	1.97	0%	-1%	-1.73	1%	2%	1.67	5%	-2%	-2.12	-9%
3	1%	0.84	1%	-1%	-1.13	0%	0%	-0.48	5%	1%	0.68	-9%
4	1%	1.94	2%	-1%	-1.72	-1%	-1%	-0.87	4%	0%	-0.42	-9%
5	2%	2.70	4%	-2%	-3.04	-3%	-2%	-1.76	2%	2%	1.67	-8%
6	0%	-0.02	4%	0%	0.32	-3%	1%	1.08	3%	-2%	-1.81	-9%
7	0%	0.56	5%	0%	-0.57	-3%	-1%	-1.14	2%	1%	1.12	-8%
8	-1%	-1.53	4%	0%	-0.02	-3%	2%	1.82	4%	1%	1.09	-7%
9	1%	2.01	5%	-1%	-1.27	-4%	-1%	-0.73	3%	-1%	-0.95	-8%
10	0%	-0.20	5%	1%	0.94	-3%	-1%	-1.62	2%	0%	0.04	-8%
11	0%	0.02	5%	0%	-0.77	-4%	1%	1.61	3%	1%	0.73	-7%
12	-1%	-0.69	4%	0%	0.69	-3%	0%	0.39	4%	0%	-0.45	-8%
13	0%	-0.52	4%	0%	-0.23	-4%	0%	-0.29	3%	0%	-0.12	-8%
14	0%	0.23	4%	0%	0.80	-3%	0%	-0.09	3%	0%	-0.03	-8%
15	0%	-0.09	4%	0%	0.06	-3%	0%	0.46	4%	0%	-0.04	-8%
16	0%	-0.38	4%	0%	0.11	-3%	1%	0.88	5%	1%	0.61	-7%
17	-1%	-1.72	3%	1%	1.07	-2%	-1%	-0.73	4%	2%	1.53	-6%
18	0%	0.17	3%	0%	0.29	-2%	0%	0.51	4%	-1%	-1.40	-7%
19	0%	0.48	3%	1%	0.95	-1%	0%	-0.47	4%	-1%	-1.09	-8%
20	1%	0.75	4%	0%	-0.62	-2%	-1%	-1.36	3%	0%	0.36	-8%

*Cumulative abnormal returns that are statistically significant within the event window period.

From the table 12 above, it is evident that announcement of the AML operational risk event did have a statistically significant negative impact on two of the four banks (i.e. FSR and NED) within the event window period.

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