

THE IMPACT OF NEWS ON THE SOUTH AFRICAN SOVEREIGN BOND MARKET

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I, Elizabeth-Ann van der Westhuizen, declare that the research work reported in this thesis is my own except where otherwise indicated and acknowledged. It is submitted for a PhD (Financial Management Sciences) at the University of Pretoria, Gauteng. This thesis has not, either in whole or in part, been submitted for a degree or diploma to any other university. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references.

Mesthulizen.

Elizabeth-Ann van der Westhuizen

Signed at Pretoria, South Africa

On this 21th day of October 2022



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ABSTRACT

This study investigates how South African government bond yields react to news announcements and what types of news drive the South African bond market. A reverse event study approach is used to measure the impact of headline news on the South African government bond yield curve. Abnormal return dates are determined using three GARCH models that are applied to the zero-coupon yields derived from coupon bonds to identify dates of abnormal volatilities. Machine-learning algorithms are used to analyse and classify news items into seven categories and to identify the news types that affect asset prices. Various econometric models and statistical processes are applied to link abnormal returns to specific news categories. The results show that there is a link between abnormal price changes and the effects of different news categories. Economic news has the greatest impact on bond prices, followed by political news and emerging market news for both increase and decrease event dates. In terms of the semi-strong form of the efficient market hypothesis (EMH), the reaction of the sovereign spread to new information within one business day shows that the South African bond market is efficient.



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LIST OF ABBREVIATIONS

Abbreviation	Meaning
ALBI	All Bond Index
ANOVA	Analysis of Variance test
APT	Arbitrage Pricing Theory
BDT model	Black-Derman-Toy model
BESA	Bond Exchange of South Africa
BIS	Bank for International Settlements.
BRICS	Brazil, Russia, India, China, South Africa
САРМ	Capital Asset Pricing Model
CIR model	Cox, Ingersoll and Ross model
EHT	Expectations Hypotheses Theory
ЕМН	Efficient Market Hypotheses
Eq	Equation
FX	Foreign Exchange
GCH formula	Gilt Clearing House formula
GDP	Gross Domestic Product
GOVI Bond	South African Government Bond
GOVI Index	South African Government Bond Index
GRMA	Global Master Repurchase Agreement
IMF	International Monetary Fund
IPO	Initial Public Offering
JIBAR	Johannesburg Interbank Average Rate
JSE Limited	Johannesburg Stock Exchange Limited
LBO	Leveraged buyout
LPH	Liquidity Preference Hypothesis
LSEG	London Stock Exchange Group



MSH	Market Segmentation Hypothesis
MTBPS	Medium Term Budget Policy Statement
OLS	Ordinary Least Squares
PHT	Preferred Habitat Theory
RFR	Risk-Free Rate
SABOR	South African Benchmark Overnight Rate
SARB	South African Reserve Bank
SME	Small and mid-size enterprises
SOE	State-owned Enterprise
USA	United States of America
WGBI	World Government Bond Index
YTM	Yield to Maturity
ZAR	South African Rand



LIST OF DEFINITIONS

Term	Definition
Bootstrapping	As used in this study is the process of deriving spot
	rates from the par yields.
BRICS countries	A group of emerging economies consisting of Brazil,
	Russia, India, China, South Africa, the main objective
	being to foster cooperation between the member
	nations for development, financial assistance, and to
	support various projects, such as infrastructure
	initiatives (Gammeltoft, 2008).
	Electronic Broking Services (EBS): a wholesale
EBS	electronic trading platform used to trade on the foreign
	exchange market with market-making banks.
Economic risk	Risk that relates to changes in the macroeconomic
	conditions of a country.
Efficient Market Hypothesis	EMH in its simplest form states that security prices fully
(EMH)	reflect all available information (Fama, 1991).
Eurobond	An international bond denominated in a currency not
	native to the country where it is issued. Eurobonds
	include EuroDollar bonds (denominated in US Dollars
	and sold outside the USA, Euroyen bonds
	(denominated in Euro and sold outside the European
	Union), Euro sterling bonds (denominated in Pound
	sterling and sold outside the United Kingdom (Reilly &
	Brown, 2011).
Event or news announcement	New information that is unexpected and unanticipated.
Fixed coupon bond	A fixed income instrument that pays periodic interest
	payments, called coupons, with a face value at maturity
	to the bondholder or owner.

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Foreign bond	A bond denominated in the currency of the domestic
	country and issued in the domestic country's markets.
	For example, a Yankee bond issued in US Dollars and
	sold in the USA by foreign governments or corporations
	(Fabozzi, 2021).
FTSE World Government Bond	A total return index created in 1987 by Citi Bank Group
Index (WGBI)	and acquired by LSEG in 2017. The index measures
	the performance of investment-grade sovereign bonds
	from developed and emerging markets. The WGBI is a
	widely used benchmark that currently includes
	sovereign debt from over 20 countries, denominated in
	a variety of currencies, and has more than 30 years of
	history available. The WGBI provides a broad
	benchmark for the global sovereign fixed income
	market (FTSE, 2018).
Inflation compensation	The difference between nominal and indexed bonds'
	interest rates (Gürkaynak, Sack, et al., 2010).
JIBAR	The Johannesburg interbank average rate. Calculated
	as the average mid of the n -month NCD rates quoted
	by a number of local and foreign banks. The average
	is calculated after excluding the two highest and the
	two lowest mid rates. JIBAR is published for n = 1,3,6,9
	and 12 months.
Long-horizon event study	Using a long sampling interval or event window, one
	year or longer (Kothari & Warner, 2007).
Long-term interest rate	Interest rates of government bond securities traded in
	the capital markets with maturities longer than 1 year
	(Van Wyk et al., 2015).
Macroeconomic variables	Economic factors that affect the economy as a whole.
	The main variables included are balance of payments,
	inflation; economic growth and unemployment.

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Markov process	The future movement of a value is only dependent on
	the current value but not on any other past values
	(Klebaner, 2012).
Nominal interest rate	Interest rate before taking inflation into account
	(Fabozzi, 2021).
Political news	Political news events that include statements or press
	releases of a political nature and politically driven
	decision-making by the law makers of the country, like
	government officials (Bilson et al., 2002).
Political risk	Risk that relates to political changes and or political
	instability in a country (Bilson et al., 2002).
Risk Free Rate	Closest riskless rate for a given maturity within the
	financial markets of a specific jurisdiction.
Risk premium	The spread above the base interest rate that reflects
	additional risks, caused by various factors, that the
	investor faces (Cochrane & Piazzesi, 2005; Haddad &
	Sraer, 2020).
SABOR	A benchmark for rates paid on overnight interbank
	funding (SARB, 2020).
Securities	A security is a fungible, negotiable financial instrument
	that holds monetary value and can be broadly
	categorised into to two distinct types, equities and
	bonds.
Short-horizon event study	Using a short sampling interval or event window,
	usually shorter than one year. It can be shorter than a
	day when intra-day data is available (Kothari & Warner,
	2007).
Short-term interest rate	Interest rates of securities traded in the money markets
	with maturities that range from one day to twelve
	months (Van Wyk et al., 2015).



South African government	Includes all bonds issued by the South African
bond index (GOVI)	government that fall into the top 10 ranking of the ALBI
	composite index (JSE, 2020).
Sovereign bond spread	Spread between the US government bond and the
	South African government yield curve.
Sovereign bonde	Bonds issued by a national government denominated
Sovereign bonds	, ,
	in either local currency or denominated in foreign
	currency (Arellano & Ramanarayanan, 2012).
Spot rate	Zero-coupon rate calculated using bootstrapping
	methodology (Fama & Bliss, 1987).
Stochastic process	A process that describes how a value changes over
	time in an uncertain way. Thus one can only know the
	distribution of the possible values of the process at any
	one point in time (Klebaner, 2012).
Tenor	The length of time remaining before a financial contract
	expires.
Term risk premium	Difference between the short end and the long end of
	the yield curve.
Term structure of interest rates	The calculation of the relation between the yields on
	zero-coupon bonds (also referred to as spot rates) of
	default-free or risk-free securities, normally sovereign
	bonds of the same credit quality that only differ in their
	term to maturity (Du Preez, 2012).
Yield curve	The graphical depiction of the relationship between the
	spot rates for a continuum of maturities in the same
	time interval for bonds of the same credit quality (Du
	Preez, 2012).
Yield spread	The difference between interest rates on long-term and
	short-term bonds (Gebka & Wohar, 2018).
Zero-coupon rate	The rate on an instrument that pays interest only on the
	redemption date.

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CHAPTER 1 INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Investors and issuers in government bond markets are exposed to vast amounts of information on a daily basis and face challenges in understanding how, when, and to what extent the release of new information affects bond yields. The South African sovereign debt market is influenced by various domestic and external factors, including but not limited to inflation, GDP growth, fiscal deficit, and political risks. Government bonds are a major source of funding for the governments of emerging markets and represent an important asset class for both domestic and international investors (World Bank, 2001).

Similar to the shock waves of an earthquake, news announcements can send waves of disruptions reverberating through the financial markets. Surprises and shocks occur in the financial markets with regularity (Balduzzi et al., 2001a). Over the last several decades investors have experienced turmoil and uncertainty. News of unforeseen events has triggered severe reactions in the financial markets. Merton (1976) found that underlying stock returns are caused by a mixture of both continuous and jump processes. These jumps are reflected in the price behaviour as abnormal price changes in the financial markets. Merton (1976) found that these abnormal changes in prices were due to the arrival of new key information at discreet time periods, in accordance with the expected market efficiency.

Market efficiency, as promulgated by the Efficient Market Hypothesis (EMH), assumes that a large number of rational investors act in ways that seek to maximise their profits, thereby ensuring that current asset prices fully reflect all information available and that new information is incorporated into asset prices quickly and efficiently. Malkiel (2003) found that key new information causes financial markets to overreact or underreact to positive or negative news. The Uncertain Information Hypothesis (UIH) was developed given the occurrence that asset prices can differ from their fundamental values due to a level of uncertainty in the information available to investors (Brown et al., 1988, 1993; Mehdian et al., 2008) and the Overreaction Hypothesis (OH) points to the idea that prices tend to overreact and correct themselves over time as investors adjust their perceptions of the company asset (De Bondt & Thaler, 1985, 1987).



Several event study analyses have been conducted on how bond yields across the maturity spectrum show pronounced price movements around the release times of news related to macroeconomic variables (Altavilla et al., 2014; Fleming & Remolona, 1999a; Swanson, 2011; Urbschat & Watzka, 2020). The strength of the bond yield's reactions depends on the types of announcements and the surprise element contained in the announcement (Hördahl et al., 2018). In addition to economic news, news relating to political variables can also have a significant impact on bond yield spreads. In particular, sentiment associated with the political statement can be highly significant in explaining bond market spreads (Gade et al., 2013). The change in the quoted yield of a government bond can be directly observed on any of the trading platforms. In most cases the majority of government bonds are quoted in the market on an on-going basis. Financial markets respond to news that may impact the country's fiscal and monetary policy. Investors closely monitor these events and revise their expectations in line with the new information (Pantzalis et al., 2000). Political risk was found to be an important variable in explaining return variations in emerging markets and in developed markets, but not to the same extent in developed markets (Bilson et al., 2002).

Classified under the research philosophy of positivism, the broad framework of the event study methodology is a simplistic and straightforward identification process of events using high-frequency financial market data. The event study methodology enables the researcher to conduct a controlled experiment by focusing on a specific market and related price behaviours and subsequently to identify relevant news events (Gürkaynak & Wright, 2013). The event study methodology is a systematic approach that monitors the news and then the effect of specific news on a specific asset price. The methodology is based on the premise that the news content is not known to market participants prior to the release thereof. After the news has been released, efficient markets discount the information content and the impact is then quickly reflected in asset prices (French & Roll, 1986). The change in asset prices in a small time window around the announcement date reflects the causal impact of the release of the new information and likely little else. Hence, the way in which news is released to the public is a source of identification of the event date, as discussed by Faust et al. (2007). The process of identifying the abnormal price changes for the identified event date is applied in event study methodology.



The reverse event study methodology uses a different approach: it first determines the abnormal price behaviour, and then uses the identified dates as a source for finding news items released around an event window to explain the abnormal price behaviour.

The main objective of this study was to identify and quantify the impact of different types of news announcements (headline news) on the South African sovereign bond markets. The news types were classified into specified categories. The impact of the headline news announcements on the South African zero-coupon yield curve was analysed by using the reverse event study methodology.

For this study there was a substantial volume of headline news to analyse across many different sources. The process of hand-labelling or manually coding and sorting each article or headline news item into different categories according to topics or themes can be a time-consuming task. To address this challenge the researcher used supervised machine-learning algorithms for text classification. This method helps researchers to systematically classify and examine texts in a way that humans cannot do (Jurka et al., 2013; Takahashi et al., 2007).

The reverse event study methodology identifies abnormal price change dates, or dates of interest, prior to assigning the news to the event (Bech & Lengwiler, 2012). In this study the researcher used three econometric models to isolate specific and identifiable news events, namely, the Generalised Autoregressive Conditional Heteroskedasticity model (GARCH) as introduced by Engle (1982), the Exponential GARCH model (EGARCH) by Nelson and Cao (1992) and the Glosten, Jagannathan and Runkle model (GJR) model (Glosten et al. (1993), to estimate extreme moves in volatility, which is equated to abnormal price changes. Volatility is defined as a measure of dispersion of returns for a financial instrument or index (Tsay, 2005). Econometric models are used to determine the extreme volatilities, which are reflected as event dates. Models that implicitly account for the heteroskedasticity observed in the data provide a better unbiased estimate of the abnormal event dates. The autoregressive conditional heteroskedasticity (ARCH) model and its subsequent variants can model time-dependent changes in volatility (Schwert, 1989). Higher volatility will generally be caused by an event in the financial markets.



The identified event dates can be described as the abnormal return event dates. After linking news to relevant dates within a specified event window the research results can provide insight as to what kind of news types drive changes in the South African bond market yield curve. The study used a sorting algorithm to pre-classify headline news data, after which the data was classified into seven broad categories using three supervised machine-learning algorithms. A step-by-step process was followed to analyse the headline news using text analysis.

Further to the analysis of the impact of different news categories on the zero-coupon yield curve, a question relevant to international investors is: 'What was the impact on the sovereign bond spread on these identified dates?' The sovereign bond spread is defined as the difference between the yield of an emerging market curve and the yield of the US government bond curve for similar tenors. The purpose of analysing the spread differential on these news event dates is to quantify the impact of such events on the sovereign spread over the entire maturity spectrum of the zero-coupon yield curve. Political risk, economic risk and financial risk are indicators of an emerging market's country-specific risk. These risks can be used to explain sovereign bond spreads over time (Comelli, 2012). The researcher aimed to isolate the changes (ascribed to abnormal news event dates) in sovereign bond spreads between the South African zero-coupon yield curve and US government bond yield curve by using different maturity dates over a period of ten years.

As discussed above, economic (Altavilla et al., 2014; Fleming & Remolona, 1999a; Swanson, 2011; Urbschat & Watzka, 2020) and political variables (Gade et al., 2013) can also have a significant impact on bond yield spreads. To be able to understand the significance of these variables some background information is provided below in sections 1.2 and 1.3.

1.2 RESEARCH PROBLEM

The relationship between short-term interest rates and long-term interest rates in an economy is a dynamic relationship which changes with the flow of information. In financial markets, the flow of information provides a critical catalyst for price changes, the extent of the price change and the longevity of the change. The resultant impact on asset returns is



not a constant. The sovereign yield curve is a collection of all the current information available to the market, as well as the sum of all the risks relating to the sovereign yield curve, such as political risk, fiscal policy risk, economic risk and debt (Ferrucci, 2003). Changes in the yield curve can be linked to specific news events at a local or global level.

Using a reverse event study methodology the bond market reaction to specific news can be established and quantified. News items, in the form of news headlines, are released in substantial numbers that need to be sorted and classified into categories, so that news types can be identified and then linked back to the event windows of price movements. An increase in the price volatility can be linked to increased perceived risk. Consequently increased price volatility generally indicates changes in the risk environment. Establishing links between headline news, increased price volatility and risk changes can provide a deeper understanding of the financial market's risk perception of sovereign debt.

1.3 BACKGROUND TO SOUTH AFRICAN ECONOMIC CONDITIONS

The South African society is considered to be one of the most unequal societies in the world, according to the International Monetary Fund (2020) regional Sub-Saharan African economic outlook report. The country's fiscal policy on reducing the inequalities relating to poverty and exclusion is hampered by low economic growth. The study further emphasises that growth by the private sector should be the favoured mechanism for alleviating inequality and that such growth should be complemented and supported by efficient public policies. According to the study, the projected increase in unemployment figures, if job creation remains at the average levels seen during 2010-2016, could be as much as 10 million by 2030 (Clements et al., 2015). This will fuel social tensions and place a substantial (and possibly unsustainable) burden on the fiscus in terms of fiscal transfers. When inequalities are high (in terms of unmet needs in education, health and infrastructure) and where there is lack of transparency in the conduct of public affairs, this can lead to frustration as well as perceptions of corruption (OECD, 2017).

The economic survey of South Africa published by the Organisation for Economic Cooperation and Development (OECD, 2017) identified some of the foundations for future inclusive growth in South Africa: increased access to higher education, a more integrated



labour market, expansion of regional markets, and efforts to promote entrepreneurship and SMEs. According to the economic forecast published by the OECD (2021) growth projections for the South African economy were 5.2% for 2021, slowing to 1.9% in 2022 and 1.6% in 2023.

The South African economy has weathered several challenges. Both internal and external shocks have plagued the economy in the past two decades. Economic growth is weak, public-sector debt is rising, and its world class financial sector, although well capitalised, is exposed to weak state-owned enterprises (SOEs). SOEs in South Africa play a key role in providing service inputs to businesses, SOEs for the most part provide the only viable solution for most businesses for utilities, transportation and communication. SOEs receive support from the government in the form of transfers and guarantees, borrowing from the private sector through the issuance of corporate debt (Mothibi & Mncayi, 2019). The contingent liabilities created through the guarantees offered to the SOEs is a source of fiscal risk. Fiscal risks from SOEs need to be contained to reduce the burden on taxpayers from recurrent and large bailouts. In their report on the South African economy, the International Monetary Fund (2020) lists the following domestic vulnerabilities:

- Rising public sector debt as a result of low growth and continual fiscal deficits
- Rising fiscal risk
- Policy uncertainty and political infighting resulting in sovereign credit rating downgrades

Public sector debt (approximately 53% of GDP in 2019) has nearly doubled since 2007, largely as a result of central government debt. Since 2014 the economy has not grown by more than 2% per annum and the fiscal deficit has not been lower than 4% during the last decade. The debt of SOEs has risen from 7% of GDP in 2004 to around 14% in 2016. This excludes the government's contingent liabilities to SOEs. In March 2018 the state-owned entities of Eskom and South African Airways had combined outstanding government guarantees of 7.2% of GDP. Public sector debt is sensitive to weak growth. If economic growth should fall below 1% over the projection period, public sector debt will continue to increase and could surpass 70% of GDP in 2023.



In April 2017 Fitch downgraded South Africa's local currency rating to below investment grade, noting that the early 2017 cabinet reshuffle would likely result in a policy change, and that SOE debt could then be migrated onto the government's balance sheet. In November 2017, after the Medium-Term Budget Policy Statement (MTBPS), Standard and Poor (S&P) reduced South Africa's currency sovereign credit rating to sub-investment grade.

The initial market reaction to policy uncertainty is cause for concern in the real economy. After the release of the MTBPS in October 2017, during a period of eight business days, approximately 1 billion Dollars of net portfolio outflows from South Africa occurred. This caused a 3.5% depreciation in the currency and an increased volatility in the exchange rate. A subsequent downgrade by S&P led to the exclusion of SA bonds from the Barclays Global Aggregate index, prompting a further (almost) 1 billion Dollar outflow in a three-week period. It took the financial market five months to recover from the outflows.

The general view is that the South African economy is resilient even though the economy is vulnerable to domestic and external shocks. The financial sector provides a stable base for government bonds, but this relationship is subject to shocks, especially given the government's rising risk of financial exposure to the debt of SOEs. South Africa's foreign investment needs remain large. Current account deficits are financed by flows that are subject to sudden reversals. When the financial market is exposed to domestic or external shocks it increases the risk of large capital outflows from non-resident investors.

The consensus from the OECD and IMF reports on the South African economy is that of an economy constrained by inequality, low levels of education, increasing inflation, high unemployment, slow economic growth as well as the poor state of its infrastructure and health services. Policies aimed at supporting inclusive growth and fiscal consolidation could help to reduce South Africa's economic vulnerabilities.

1.4 BACKGROUND TO SOUTH AFRICAN POLITICAL CONDITIONS

According to a report by Fitch (2017) political risk in South Africa is high and there is substantial uncertainty regarding various elements of economic policy. The political profile of South Africa is as follows:



- South Africa is a federal republic with a parliamentary democracy.
- The executive power resides with the president, who is the chief of state, the head of the government, and the commander-in-chief of the armed forces and he appoints the cabinet. The president is elected by parliament to serve a five-year term.
- The ruling party is the ANC (African National Congress) which is allied with two leftwing groups, the Congress of South African Trade Unions (COSATU) and the South African Communist Party (SACP). The other main political parties are: the official opposition party, the Democratic Alliance (DA), which supports a liberal democracy and free market principles; the Economic Freedom Fighters (EFF), a left-wing party; and the Inkatha Freedom Party (IFP), which is dominated by rural Zulu-speaking members mostly concentrated in KwaZulu-Natal.

According to the 2018 *Doing business* report by the World Bank, South Africa's ranking dropped from 32 in 2008 to 82 in 2017 (World Bank, 2018). The report lists the period under President Jacob Zuma as an era marked by slowing activity, rising unemployment, poverty and inequality.

Political instability is a key driver in the sovereign risk assessment by external agencies. Ratings agencies frequently referred to South Africa's surprise cabinet reshuffles and the inability of parliament and the judiciary to hold the president to account, as cause for concern. The irresponsible fiscal behaviour of state-owned enterprises (SOEs) and the government's lack of decisive action to kerb fruitless and wasteful expenditure is driven by the policies of the governing party.

As a result of the challenges facing the political system in South Africa, and due to the struggle to provide a stable environment conducive to economic growth and investment, the economy has stagnated. Due to several sovereign credit risk downgrades, South Africa's general socio-economic environment is one of tension, especially in the lower income brackets.



1.5 PURPOSE STATEMENT

This study aims to link the association between specific abnormal return changes in the sovereign bond yield curve to specific identifiable categories of news events. The study further investigates the resultant effect on the sovereign bond spread.

1.6 RESEARCH QUESTIONS

The primary research questions are:

- 1. Does increased volatility in government bond prices foreshadow abnormal returns?
- 2. Which news events are associated with abnormal returns in the South African sovereign bond zero-coupon yield curve?
- 3. What are the primary categories of news events that lead to abnormal price changes in the South African sovereign bond zero-coupon yield curve?
- 4. What is the impact of specific news categories on the South African sovereign bond spread?

1.7 RESEARCH OBJECTIVES

The specific objectives of this study are to:

- 1. Analyse the volatility of the South African sovereign bond zero-coupon yield curve returns.
- 2. Categorise specific news items during the window of abnormal volatility event dates in the South African sovereign bond zero-coupon yield curve returns.
- 3. Link abnormal event returns to specified news categories to determine what news types affect South African sovereign bond zero-coupon yield curve returns.
- Analyse the impact of specific identified news events on the sovereign bond spread between the South African government bond zero-coupon yield curve and US government bonds for specific tenors.



1.8 SIGNIFICANCE OF THE STUDY

The findings of this study will broaden the understanding of the interaction between emerging market sovereign bonds and the impact of categorised headline news on sovereign debt. The findings will expand the knowledge base of the relationship between the impact of categorised news on different bond maturities, thereby expanding the knowledge base of the risk premia in the interest rate markets as further discussed in 3.5.

The importance of the research is shown in three ways. First, the body of research literature providing empirical evidence that links public information with asset market behaviour is still growing, the main focus being on developed countries and with limited evidence being available on emerging market economies (Andritzky et al., 2007). There are various studies relating to stock market price reactions following the release of news events (Brown & Warner, 1985; Hanousek et al., 2009; Ryan & Taffler, 2004). In addition, studies on the corporate bond markets have been conducted (Bessembinder et al., 2009; Janner & Schmidt, 2015; Kolari & Pynnönen, 2010), but there are few studies on government bond markets and none that specifically relate to the South African government bond yield curve. Second, to the best of the researcher's knowledge, there are no studies that consider several news categories of headline news in a government bond reverse event study. Third, given the limited number of studies (Ederington et al., 2015b) on the reverse event methodology either in the stock market or the bond market, this study will add to the current body of reverse event methodology literature.

1.9 DELIMITATIONS OF THE STUDY

As the purpose of the research was to establish the impact of news on the South African sovereign bond yield curve, only South African government bonds were included in the study, namely government bonds listed and actively traded from 2010 to 2020. Other bonds listed on the JSE, namely corporate bonds, green bonds and asset-backed securities, were excluded from the study. In the sovereign bond sample used only benchmark fixed-coupon bonds were considered. The research conclusions were drawn from a 10-year sample period of 4 January 2010 to 31 December 2019. This was done to exclude the outbreak of the Covid 19 pandemic in early 2020 and its influence on the financial markets.



According to Gürkaynak and Wright (2013) the best way to measure the impact of news on an asset price is to use high frequency data. In this study, the researcher used a daily sample of bonds and a short event window for news. Such data is considered to be high frequency and is consistent with other event studies. The reason for using this method is that the effect of the event that took place is best captured in a small window around the event's announcement or news release. In this way the researcher can assess the impact of the news event on asset prices in a controlled experiment.

The news analysed in this study covered the period from the first trading date in January 2010 to the last trading date in December 2019, which is the same time period reflected in the asset price changes in the yield curve. The daily headline news was collected and surveyed to include all South African related news events but filtered to exclude company news events. This enabled the researcher to exclude company-specific news, but ensured that all news relevant to the South African financial markets was collected for analysis.

The analytical process was limited to the use of the reverse event study methodology.

1.10 ASSUMPTIONS OF THE STUDY

First assumption: South African bond markets comply with the semi-strong Efficient Market Hypothesis (EMH). Efficiency in the financial markets, as described by Malkiel (2003), entails the dissemination of information into the price of an asset. Furthermore, Malkiel (2003) defines efficiency in the context of financial markets as markets that do not allow investors to earn above-average returns without accepting above-average risk. This study did not seek to either affirm or disprove the efficiency of the South African bond market, but it rather sought to confirm that external (international) and internal (domestic) factors provide the catalyst for price changes in the bond market (Ferrucci, 2003).

Second assumption: The effect of the change in rates on the zero-coupon yield curve is representative of changes in the yields of the instruments used in the construction of the zero-coupon yield curve. Although the zero-coupon yield curve is a derived curve (from the observed market yields of benchmark instruments) changes in daily bond yields (prices) can be accurately reproduced by tracking the changes in the derived zero-coupon yield curve.



Third assumption: The date when the news was published was the first time that the news was available to market participants and that there was no prior leakage of the new information. News identification took place as soon as the news was announced or published in different sources.

Fourth assumption: Identified events could be uniquely linked to news released during the event window.

1.11 THESIS OUTLINE

Chapter		Chapter Objective
Chapter 1	Introduction	The introduction and overview highlights the core research problems as well as the main objectives, significance and major contributions of the study.
Chapter 2	Impact of news on the financial markets	The chapter provides a background on the EMH and market anomalies, with a review of the UIH, OH and UH. Further, it provides a review of available literature relating to different news events and yield curve studies. The aim of this chapter is to give the reader an understanding of the effect of different types of news events on bond markets, specifically economic and political news.
Chapter 3	Interest rates, interest rate theories and interest rate models	This chapter explains interest rate markets (specifically South African markets) and how securities were used as inputs in the model to construct a daily zero-coupon rate yield curve, The importance of the zero-coupon rate yield curve is highlighted. In addition, different interest rate theories are discussed and an overview is provided on the most used interest rate models, with an emphasis on static interest rate models.



Chapter 4	Event studies	The literature survey pertaining to event studies
		identified research that used bond instruments and
		the yield curve to measure the impact of news on
		the yield curve.
Chapter 5	Research methodology	The research method used to analyse the data is
		explained. Various aspects of the data, including
		the source, sampling and collection are discussed
		and outlined. The method for determining the
		abnormal event dates and the news categorisation
		process is described. A quantitative analysis, as
		well as manual reliability and relevance checks
		were used to determine the news frequencies for
		each category's event date. Lastly, the chapter
		describes the statistical methods used to link the
		association between the abnormal event yield
		returns and the news.
Chapter 6	Research data analysis	The data analysis covered the following: (1) the
		exploratory data analysis of yield returns (2) the
		identification of specific abnormal volatilities using
		GARCH models (3) the quantitative news analysis
		using machine-learning algorithms and a manual
		relevance check, and (4) statistical analyses were
		used to link news events to the abnormal returns.
Chapter 7	Research results	The final research results are presented and linked
		to the research objectives and research problem.
Chapter 8	Research conclusion	The final chapter presents the findings and insights
	and recommendations	gained from the research. It also provides
		recommendations for future research.



1.12 SUMMARY

The sovereign debt markets provide a liquid market for both domestic and foreign investors to gain exposure to fixed income instruments in their portfolios. During the last several decades investors have experienced instability and uncertainty. The turmoil in the financial markets can be associated with specific unforeseen news events that have severe reactions in the debt markets.

The main objective of this study was to analyse the association between specific abnormal return changes in the sovereign bond zero-coupon yield curve and to link such changes to specific identifiable categories of news released during the event window.

The study is limited to the South African sovereign debt market and focussed on the benchmark bonds listed on the JSE during the sample period. The assumptions underlying the study were based on the market efficiency, the translation of price changes from the zero-coupon yields to bond YTM and the exact determination of the news date.

The findings of this study will broaden the understanding of the interaction between the South African sovereign bond market and the impact of categorised headline news on the sovereign debt. The study made use of the reverse event study methodology and will contribute to the body of literature that analyses the effect of news on emerging market sovereign debt.



CHAPTER 2 THE IMPACT OF NEWS ON THE FINANCIAL MARKETS

2.1 INTRODUCTION

News announcements can be described as noteworthy newly released information made public by a news provider or source. Information has always been a vital driver of investment decisions. Different types of news affect financial variables and asset prices in different and in wide-ranging ways. The Efficient Market Hypothesis (EMH) states that the aggregate market comprised of rational investors with the same homogenous expectations will ensure that securities fully reflect all available information, to such an extent that all new information will in a very short time be reflected in a new price for the security. As such, the new price is an 'unbiased' indicator of the future price of the security (Fama, 1991).

There exists a large number of studies (as reflected in 2.4) that analysed the impact of different types of news on various financial variables. This chapter discusses the literature that investigated the effect of news on financial markets. The main aim of this chapter was to provide an overview of news-related studies in general and to pay particular attention to studies that include the influence of news on long-term interest rates or the yield curve.

2.2 EFFICIENCY OF THE FINANCIAL MARKET

New information in the form of news provides a catalyst for asset price changes. The investigation of the different strands of literature relating to bond pricing mechanisms starts with the theories of the efficient market hypothesis of financial markets. Market efficiency is important for markets to function well.

2.2.1 The efficient market hypothesis

The premise that a well-functioning capital market is dependent on market efficiency has been widely accepted by market participants and is rooted in academic work. The Efficient Market Hypothesis (EMH) originated in the works of, Fama (1965) and Samuelson (1973). Subsequently many studies have been based on the subject of EMH. Some studies have contradicted the EMH and as a result various alternative hypotheses to the Efficient Market Hypothesis have been developed (and tested in the event study framework), namely the



Uncertain Information Hypothesis (UIH), the Overreaction Hypothesis (OH) and the Underreaction Hypothesis (UH). Each of these theories is addressed in this study.

Fama (1991) stated that the reflection of new information in asset prices indicates that markets are efficient in discounting the new information as it becomes available. He tested three different hypotheses, namely the weak form, the semi-strong form and the strong form of the hypothesis. We can differentiate between these different forms by understanding the concept of what is meant by the term 'all available information' with respect to each form (Salameh & AlBahsh, 2011).

- i. The weak form asserts that asset prices already reflect all information that can be derived by examining market trading data such as the history of prices, trading volume or short interest, therefore any subsequent price changes are independent. This implies that any previous analysis of the series of data is of no value in predicting future prices, which suggests that an investor cannot expect future higher returns by looking at historical asset prices. The weak form is also based on successive price changes that are identically distributed.
- ii. The semi-strong form states that all past and currently available information regarding the asset is already reflected in the prices. The information, which includes past prices and fundamental data that has been incorporated into the asset price, efficiently supports the EMH. The seminal EMH event studies that examined the semi-strong form using event study methodology were conducted on stock returns and the impact of new information on the financial markets (Ball, 1968; Fama, 1991; Fama et al., 1969).
- iii. The strong form hypothesis specifies that asset prices reflect all information relevant to the asset, that is, all past, public and private information. Investors do not have access to inside information that could be relevant to asset prices. The strong form studies attempted to confirm that no individual or group can generate abnormal returns from having non-public or private information, as it is illegal to trade on such classified information.

From the above forms of the EMH, it should be stressed that the market cannot be both efficient and predictable. This dichotomy lies at the heart of the various studies performed



to dispute the foundations of the EMH (Stiglitz, 1981), which has resulted in new study fields in behavioural finance.

2.2.2 Variations of EMH as explained by the behaviour of the investor

According to traditional finance, the EMH relies on rational homogenous investors making rational investment decisions. Markets are assumed to be efficient and asset prices reflect all available information supporting the EMH. Contrary to the EMH, behavioural finance research has observed market anomalies that contradict traditional finance and cannot be explained by the EMH. This has led to the development of new relevant hypotheses, such as the UIH (Brown et al., 1988, 1993), OH and UH (De Bondt & Thaler, 1985, 1987).

2.2.2.1 The uncertain information hypothesis (UIH)

The UIH developed by Brown et al. (1988) provides a framework for the response of rational risk-averse investors to unanticipated information. The UIH states that unanticipated new information will increase risk and uncertainty in the financial markets. The UIH was developed to provide a more realistic variation of the EMH as it accounts for investors' reactions to unexpected new information. In their study the authors concluded that the market reacts to uncertain information in an efficient, although not necessarily instantaneous manner. In such circumstances asset prices can be set below the fundamental values in reaction to favourable or unfavourable information so that subsequent price corrections have an upward trend, whether the unexpected information was good news or bad news (Ajayi et al., 2006). The impact of the new information cannot be instantaneously incorporated in the price of the assets, as there is increased uncertainty and risk following the release of the unexpected information. Thus the UIH states that there will always be a positive market correction following both favourable and unfavourable events (Akkoç & Özkan, 2013; Mehdian et al., 2008).

A growing amount of research on equity markets has examined the reactions of investors to the arrival of unexpected information. Shachmurove (2002) examined investor reactions in small European stock markets and concluded that investors active in these markets reacted to uncertain information in an efficient and rational way. Research on the Turkish stock



market includes a study by Mehdian et al. (2008). The authors could not find statistical support for significant price reversals after the release of unexpected news. A study by Erzurumlu (2011) found that the OH holds true for the BIST 100 index following unfavourable events, while the EMH is true for the more liquid and informational efficient stocks of the BIST 30 index. A Chinese stock market study by Rezvanian et al. (2011) concluded that investors set equity prices below their fundamental values following the release of unexpected information, which supports the UIH.

As discussed, many studies have been conducted on stock markets and investors' reactions to unexpected news, but only one study on bond markets was found. Pantou (2015) examined South European bond markets with a specific focus on UIH. He found that investors reacted efficiently but differently to different types of news depending on the economic cycle. For instance, in the period before the 2007/2008 global financial market crisis participants reacted effectively to positive extreme returns. In the same study, after the financial crisis, there was a tendency of shorter dated bonds to overreact to negative news.

2.2.2.2 Overreaction hypothesis (OH)

The OH states that the reactions of stock prices are too sensitive to new information. A study by De Bondt and Thaler (1985), which received much attention, argued that investors overreact to unexpected or unanticipated news. In certain cases stock prices moved up too far on good news and down too far on bad news. The OH states that the extent of the overreaction (the extremeness of the reaction) must be moderated by considerations of the predictability of information. Stated in a manner that reflects the phenomenon in the equity markets, the hypothesis states that stocks that have underperformed in the market over a period of time will outperform the market over a subsequent and similar period (Clare & Thomas, 1995). Mun et al. (2000) tested the hypothesis on the US and Canadian stock markets and found that the hypothesis holds true.

The OH hypothesis is sometimes referred to as the contrarian hypothesis (or winner-loser anomaly). This hypothesis (although it is not applicable to all stocks) provides a framework for stocks where there is a level of predictability based on past performance, thus refuting



the EMH. Empirical work has proved the validity of the OH hypothesis in various emerging and developed markets (Kashif et al., 2018).

A similarity exists between the OH and UIH for investor's reaction to unfavourable price movements. However, there is a difference in the predictability of their responses to unexpected favourable information. After the arrival of positive news the OH predicts a declining price trend, while the UIH expects a rising price adjustment.

2.2.2.3 Underreaction hypothesis (UH)

The UH, in contrast with the OH, states that stock prices incorporate new information slowly. This can be described as the stock price not moving up far enough in reaction to good news, nor does it move down far enough in reaction to bad news (Bloomfield et al., 2000). The underreaction by investors is due to conservative behaviour and the slow dissemination of information.

2.2.3 Efficiency of the South African bond market

As seen above, the efficiency of a specific financial market, or even a single instrument, is not a quantifiable variable, although the concept itself is central to the effective performance of the market. The manner in which new information is assimilated in the price of an asset reflects the efficiency of the market. In any economy and financial system a well-functioning bond market is important. Since the granting of an exchange licence to the Bond Exchange of South Africa (BESA) in 1996 the South African bond market quickly developed to become one of the leading emerging bond markets due to its efficiency and stability, thereby attracting domestic and foreign investors.

2.3 THE CLASSIFICATIONS OF NEWS

Information comes in different forms and can (broadly) be classified as being either qualitative or quantitative (Costantino et al., 1997). The financial information extraction system used by Costantino et al. (1997) produced a set of relevant templates which represented the most important information in the article. It should be noted that the



classification of information can be subjective and the concept of a specific category is not necessarily universal, and can be uniquely tailored to suit the analysis (Lillo et al., 2014).

In a study that analysed the impact of several types of news on interest rate expectations Connolly and Kohler (2004) investigated the following four types of news: macroeconomic, international, monetary policy and central bank communications. In their taxonomy for classifying financial headline news, Mellouli et al. (2010) proposed the following four news categories: financial, economic, social and environmental.

Some studies classified news based on the geographical area of origination. Kaminsky and Schmukler (1999) analysed the types of news that triggered movements in the Asian markets during the Asian financial crisis in 1997 and concluded that local and neighbouring countries' news, as well as news about agreements with international organisations and credit ratings, had the biggest impact on the financial markets.

Some studies classified news based on the impact created by the sentiment embedded in the news. An investigation by Hayo and Kutan (2005) found evidence that financial markets distinguish between news items with different sentiments. The study considered IMF-related news and the impact it had on the market returns of stocks, foreign exchange and bonds. The news events were categorized into three different sentiment types; good, neutral and bad. The study concluded that bad news decreased the return of the stock markets by about one percentage point and that bad news had no significant effect on foreign exchange markets. There was no effect on the interest rate spreads by either good or bad news.

A further news type classification is the binary classification methodology followed by both Ederington and Lee (1996) and Fornari et al. (2002) for scheduled versus unscheduled news. This classification has become an accepted classification methodology, which differentiates scheduled and unscheduled news as follows:

- i) Unscheduled can be defined as news of which the time of release is uncertain; and
- ii) Scheduled news can be defined as news that has a planned or predetermined release date and time.



Several studies on financial disclosures and earnings announcements used the scheduled and unscheduled binary news classification method (Bamber et al., 2010; Beaver, 1968; Karpoff, 1987; Vickrey et al., 2007).

The first part of the literature review deals with macroeconomic news releases, which can be classified either as scheduled or unscheduled and it include studies that discussed the effect of economic news on financial variables. Macroeconomic news announcements (such as news pertaining to GDP, CPI, PPI or unemployment) are generally scheduled to be released on a predetermined date and at a certain time and they are therefore anticipated by market participants. Examples of unscheduled economic news are articles or news releases that involve statements or discussions by prominent governmental, economic or bank officials or other economy-related articles (Ben Omrane & Hafner, 2014). Their study found that the information content of news relating to the general economic environment can have a significant impact on the price behaviour of financial assets.

The second part of the literature survey includes studies that relate to political news and political risk and the impact thereof on financial assets. These announcements can be classified as mostly unscheduled news announcements that are not necessarily anticipated by market participants. In the South African context an example would be an unexpected announcement by the president, finance minister or governor of the Reserve Bank.

The ability of the financial markets, as well as specific asset classes and investors within the markets, to assimilate the information received from news announcements timeously, has become an essential characteristic in financial markets. Chapman et al. (2018) found that firms with investor relations officers have lower stock volatility, lower analyst forecast dispersion and quicker price discovery. Since the advent of electronic news vendors and data providers, the opportunity to analyse news scientifically has been available to market participants. Effective analytical tools that incorporate news data are in high demand (Hajizadeh et al., 2010).



2.4 THE INFLUENCE OF NEWS

News travels fast and the influence of news has no limits. In their study Büttner and Hayo (2012) analysed the impact of news originating from the European Economic and Monetary Union (EMU) on the financial markets of the Czech Republic, Hungary and Poland. They found that macroeconomic shocks in the EMU significantly affected short-term rates in the Eastern European markets studied. Their study concluded that the macroeconomic shocks had the strongest impact on Hungary's financial market, while political news had the largest impact in both Hungary and Poland, thereby demonstrating that the influence of the EMU news is wider than just the EMU area. In a similar study, Önder and Şimga-Mugan (2014) investigated the impact of economic and political news items published in the *Wall Street Journal* and *New York Times* on the stock markets of Argentina and Turkey. The study found that both types of news affected the emerging markets to varying degrees, which again illustrated the potential of news to have far-reaching effects.

2.4.1 The influence of macroeconomic news

The impact of macroeconomic news is discussed with the emphasis on three different asset classes, namely stock markets, foreign exchange markets and interest rate markets.

2.4.1.1 The effect of macroeconomic news on the stock markets

Multifactor asset pricing theory and models suggest that news about macroeconomic factors should influence financial markets, as it carries public information about the aggregate investment opportunities in an economy (Merton, 1973). The empirical evidence that supports the effects of macroeconomic news on financial markets reflects a wide spectrum of macroeconomic news variables. Securities affected by macroeconomic (and other market external factors) should earn risk premia in a risk-averse economy, in terms of the Arbitrage Pricing Theory (APT) postulated by Ross (2013). Accordingly, changes in these factors should result in security price changes. Iqbal and Haider (2005) investigated the validity of the APT as applied to a subset of 24 actively traded stocks on the Karachi Stock Exchange, using monthly data and two pre-specified macroeconomic factors, as well as anticipated and unanticipated inflation. They found that the empirical data supported the premise for the period January 1997 to December 2003. In a similar but earlier study using South African



market data, Page (1986) concluded that there are at least two factors that influence security returns, rather than just the return on the market, as predicted by the Capital Asset Pricing Model (CAPM).

Hardouvelis (1987) analysed the reaction of stock prices to announcements of 15 representative US macroeconomic variables and concluded that stocks of US financial companies are most sensitive to monetary news announcements. Pearce and Roley (1983) investigated the short run response of stock prices to anticipated and unanticipated changes in weekly money announcements. The study found that stock prices responded only to unexpected money supply changes and that an unexpected increase in money depressed stock prices. They concluded that the market discounts the announcement effect after taking prior expectations into account.

Another study by Pearce and Roley (1985) examined the daily response of stock prices to announcements of a series of macroeconomic news variables that included money supply, CPI, PPI, the unemployment rate, industrial production and the Federal Reserve discount rate. In this study the new information component of an announcement was measured in terms of the market's expectations as expressed in analyst forecasts of the announcement. The study found that news related directly to unexpected monetary policy announcements had a significantly negative effect on stock prices. They found limited evidence to support the view that unexpected news regarding either inflation or real economic activity affected stock prices.

Extending the work of Pearce and Roley (1985) Jain (1988) used hourly stock prices and hourly trading volumes to investigate the response of market participants to announcements about macroeconomic news variables relating to money supply, the consumer price index (CPI), producer price index (PPI), industrial production and unemployment rate. The results of this study indicated that surprises in money supply and CPI are significantly associated with volatility in stock returns, whereas the other three types of announcements did not have a significant impact. Trading volumes were found to be unaffected by any of the five economic variables under investigation. The intra-day data analysis found that the speed by



which the market information was reflected in the stock prices was a short period of time, namely one hour.

Ghent (2010) investigated the effect on stock returns of macroeconomic news after controlling for changes in the market's expectations of future Federal Reserve policy. The study examined the effect of seven major economic news announcements on stock returns. The study found no evidence to explain the weak response of stock markets to good news about the economy. Such news implies tighter future monetary policy. The negative response of stock markets to unanticipated inflation was unchanged.

Equity markets respond differently to macroeconomic news during different business cycles (Wei, 2009). The impact of market news becomes more apparent when the different stages of business cycles and economic conditions are taken into account. It has been suggested that good macroeconomic news tends to have a negative impact on stock returns during expansions while markets respond favourably to positive surprises during recessions (Engle et al., 2013). Mcgueen and Roley (1993) found evidence to support the importance of taking the business cycle into account. They found that news with a higher-than-expected influence on real activity during a strong economy leads to lower stock prices, whereas the same surprise in a weak economy results in higher stock prices. Sun and Tong (2000) used the same approach as Mcqueen and Roley (1993) but found weak evidence of the differential impact of news under the two economic conditions. Boyd et al. (2005) found that news regarding rising unemployment rates signalled information about future interest rates, as well as future corporate earnings and dividends. They stated that a rise in unemployment signals a decline in interest rates (which is good news for stock markets) and a decline in future corporate earnings and dividends, which is bad news for the stock market. These phenomena change with economic business cycles. The authors concluded that rising unemployment is good news for stocks during economic expansions and bad news during economic contractions.

Birz and Lott (2011) used a different method to measure the effect of macroeconomic news on stock prices. They argued that the way in which news is interpreted by the public should be taken into account, not only the statistical facts of economic news announcements. Their



study used newspaper stories sourced from the LexisNexis database, which were classified using the Lott Jr and Hassett (2008) methodology relating to GDP growth, unemployment, retail sales and durable goods. They found that GDP growth and unemployment news items significantly affect stock returns.

French and Roll (1986) showed that volatility in the stock markets is higher when public information is released during normal business hours. Flannery and Protopapadakis (2002) reviewed macroeconomic risk factors by simultaneously examining the impact of macroeconomic announcements on the level and conditional volatility of daily stock returns. The dataset of the study included 17 macro series announcements over the period of 1980 to 1996. The study found that only six of the 17 macro variables were strong risk factors. News regarding CPI and PPI affected only the level of the returns, whereas portfolio returns and balance of trade, employment/unemployment and housing starts affected only the returns' conditional volatility and did not have a significant impact on stock prices. Monetary aggregate (M1) affected both returns and conditional volatility. Two of the popular measures of aggregate economic activity, real GNP and industrial production did not form part of the risk factors and were therefore associated with lower return volatility.

Brenner et al. (2009) provided an analysis of the impact of unexpected components of important US macroeconomic news releases on the prices of US equity, government bond and corporate bond markets. The macroeconomic news used in this study included target rate decisions by the Federal Reserve, CPI, unemployment and non-farm payroll data. The study found that the arrival of surprise macroeconomic news had a statistically and economically significant impact on the US financial markets.

The discussion of the literature thus far has focused on the effects of macroeconomic news announcements on stock returns in a domestic economy. With increased globalisation and economic integration among different countries (Christie-David et al., 2002) investors now analyse domestic as well as international information when valuing stocks. The next discussion of the literature focuses on different cross-country studies of the stock markets.



2.4.1.2 The effect of macroeconomic news on stock markets across different countries Kim and In (2002) examined the impact of the major stock markets (US, UK and Japan) and of the domestic and US macroeconomic news announcements on Australia's financial markets. US and Australian scheduled macroeconomic variables (CPI, GDP and employment announcements) were used to analyse the impact on daily returns and the volatility of the Australian futures and stock markets. The number of announcement days were 186 (Australian) and 335 (US). The authors found that the futures market leads the stock market and that the US announcements had a significant influence on the Australian financial markets.

Nikkinen et al. (2006) investigated how global stock markets are integrated regarding their response to US macroeconomic news announcements. The study confirmed earlier findings that the CPI, employment cost index, employment situation and NAPM reports are the most influential US macroeconomic news items and that the importance thereof varies across different regions in the world. They found that the G7 countries, European countries other than G7 countries, developed Asian countries and emerging Asian countries are closely integrated with respect to the impact of US macroeconomic news. However, the emerging economies (Latin America and transition economies) were not affected by US macroeconomic news announcements, thereby showing that they are not integrated with world stock markets. Market integration is higher among developed stock markets, whereas some emerging markets are segmented (Bekaert & Harvey, 1995; Rockinger & Urga, 2001).

Andersen et al. (2007) studied the response of US, German and UK stock markets to US macroeconomic news announcements and found that the stock markets reacted differently to the news depending on the state of the US economy. Harju and Hussain (2011) investigated the effect of US macroeconomic news announcements on the return and volatility of major European stock markets (France, Germany, Switzerland and the UK) using high frequency intra-day data. Their study found evidence that US macroeconomic news had cross-border impact on both European stock returns and volatilities. The potential market risk factors for European stocks included US inflation measures (CPI and PPI), three real macroeconomic variables (retail sales, advanced durable goods and unemployment rate) and a US broad output measure (industrial production).



2.4.1.3 The effect of macroeconomic news on stock markets in emerging market economies

Studies on emerging market economies include a study by Hanousek et al. (2009) on emerging European Union financial markets (Czech Republic, Hungary and Poland). The authors investigated the effect of US and EU macroeconomic news announcements on stock returns. The results showed found that EU news affected the stock markets of all three countries, while US announcements only had an impact on the Czech Republic and Hungarian markets. The study also found that the markets with higher trading volumes could be ascribed to a high percentage of foreign investors.

Another study by Hanousek and Kočenda (2011) analysed the impact of foreign news in the emerging EU stock markets (the Czech Republic, Hungary and Poland). The authors classified macroeconomic news into four general categories (based on the 15 different categories of macroeconomic news announcements used in their 2009 study), namely:

- category 1 prices: measured by CPI and PPI;
- category 2 real economy: measured by industrial production, GDP, factory orders, retail sales, trade balance, current account and unemployment;
- category 3 monetary-type indicators: represented by money aggregate and central bank key interest rates; and
- category 4 business climate and consumer confidence: contains business climate and consumer confidence indicators and the purchasing managers index (PMI).

The study found that all three countries were significantly affected by EU macroeconomic news but not by US macroeconomic news.

The study of Hanousek and Kočenda (2011) was challenged by Buettner et al. (2010). In their research on the Czech Republic, Hungary and Poland markets the authors used a longer dataset (1999-2006 compared to 2004-2007). They investigated the impact before and after the Copenhagen Summit in December 2002. The study used integration of these countries into the European Union as the breaking point for analysis. The authors found that both US and European macroeconomic news had a significant impact on these three financial markets. The process of European integration was reflected in the increased



importance of Euro area news compared to US news. Examples of country-specific differences were that the Czech stock market was more affected by foreign news after the Copenhagen Summit compared to the period prior to the Summit and that Euro area news had more impact than US news across all Czech Republic markets for both periods. The Hungarian and Polish markets were more affected by macroeconomic shocks before the Copenhagen Summit than after it.

Fedorova et al. (2014) investigated the impact of Euro area macroeconomic news announcements in various countries: Colombia, Indonesia, Vietnam, Egypt, Turkey and the South African stock markets, the so-called CIVETS. The study found that Euro area macroeconomic announcements affected the returns and volatility of Colombia, Vietnam, Egypt and Turkey with the announcements regarding GDP, retail sales and unemployment having a significant impact on stock returns. Hussainey and Khanh Ngoc (2009) studied the impact of US macroeconomic news on the Vietnamese stock prices and found that there was a significant impact on stock prices from US real sector announcements, which was stronger than the impact of domestic Vietnamese money market news announcements.

On the African continent a study by Kyereboah-Coleman and Agyire-Tettey (2008) found that macroeconomic indicators, such as lending rates and the inflation rate, had an impact on the Ghana Stock Exchange stock returns.

South African studies relating to the impact of macroeconomic variables and stock returns include a study by Gupta and Reid (2013). The study started by using an event study approach to isolate the macroeconomic news events and then used a Bayesian Vector Autoregressive (BVAR) analysis, which provided insight regarding the surprise element in the news. The study concluded that monetary surprise news is the only variable that consistently affects stock returns negatively. The BVAR model results indicated that, in addition to monetary surprises, CPI and PPI surprises also have a significant impact on stock returns. Adding to the literature on the impact of international macroeconomic news on emerging market economies, a study by Esin and Gupta (2017) used the GJR-GARCH model to analyse the impact of both positive and negative surprises relating to US inflation news and US unemployment figures on the FTSE/JSE All Share Index (FTSE/JSE ALSI),



which is representative of the South African stock markets. The authors concluded that positive news regarding the US economy (such as unemployment decreases) resulted in a decrease in volatility of the South African stock market, which is indicative of a stable market. With respect to US inflation the study found that South African stock volatility increased on receipt of positive US inflation news.

2.4.1.4 The impact of macroeconomic news on the foreign exchange markets

Dominguez and Panthaki (2006) examined the influence of a broad set of news announcements on the FX markets to determine to what extent different types of news are able to predict exchange rate behaviour. The authors discerned several types of news in addition to the standard 'fundamental' scheduled macroeconomic news types that were used in previous studies to explain exchange rate behaviour. They included unscheduled non-fundamental news, macroeconomic news surprises, and order-flow information in their study, and concluded that unscheduled non-fundamental news has a statistically significant influence on continuous exchange rate returns and volatility. The authors used the median response of surveys from Money Market Services International to determine the surprise component of scheduled news announcements (expressed as the difference between the expected median value and the actual value) and found that, although these announcements did influence the return and volatility of the market, they occurred too infrequently to explain the majority of the exchange rate movements.

A study by Engel and Frankel (1984) examined money supply announcements and the reaction of the Deutsche Mark/Dollar exchange rate and found that a positive money supply announcement resulted in an appreciation of the Dollar. Hakkio and Pearce (1985) found that money supply announcements had a significant impact on exchange rates. Hardouvelis (1988) concluded that money supply news affected the exchange rate significantly, and that an unanticipated increase in the US money supply gave rise to an appreciation of the Dollar, irrespective of the currency against which the Dollar was measured. Ito and Roley (1987) studied the Yen/Dollar exchange rate and found that US money announcements had the greatest effect of money supply, industrial production and producer prices in both the US and Japanese markets. In a study by Kim et al. (2004) the impact of six macroeconomic



variables on the FX market was analysed and they found that the surprise element of balance of trade news had the greatest impact on the FX market.

Andersen et al. (2007) studied the effect of US macroeconomic news on stocks, FX and bonds and found that the equity and financial markets appear to be equally responsive to news announcements. The authors qualified their earlier work that suggested bond markets reacted most strongly to macroeconomic news. Almeida et al. (1998) studied the reaction to publicly announced German and US macroeconomic news announcements of the Deutsche Mark/Dollar exchange rate using high frequency exchange rate data. Their study found significant impacts on the exchange rate within 15 minutes of most news announcements. Galati and Ho (2003) studied the US and the EMU and found evidence of asymmetric responses to different extents at different times. Their study also found that the US market remained fixated on bad news from the Euro area, but only for some time.

Ben Omrane and Hafner (2014) investigated the spillover effect of macroeconomic news announcements in the FX markets. The premise being that the impact of news has a direct effect in the domestic market which is well documented, but the news also has a spillover effect on other currencies (the indirect effect). Their study used scheduled and unscheduled, as well as domestic and foreign news allocated to a set of eight categories of announcements related to the US, UK, European and Japanese economies. They found that the volatility spillover from EUR and USD accounted for more than 50% of the total accumulated volatility effect on GBP and JPY.

2.4.1.5 The impact of macroeconomic news on the interest rate markets

A number of research studies focused on the role of macroeconomic news and the impact of scheduled announcements on Treasury bond prices in the US (Balduzzi et al., 2001a; Balduzzi et al., 2001b; Brenner et al., 2009; Gürkaynak et al., 2005; Jones et al., 1998).

The news relating to the US domestic economy was found to be important for interest rates and specifically the bond market (Kim et al., 2004). The short end of the yield curve was considered less sensitive to economic news announcements compared to the longer end of the yield curve. This was confirmed by Balduzzi et al. (2001a), who found that the US three-



month Treasury bill was only affected by three out of 27 announcements, while the price of the two-year note reacted to 17 out of 27 of the announcements and the ten-year note reacted to 16 of the 27 news announcements. Smirlock (1986) studied inflation and the response of long-term interest rates to unanticipated inflation. They found a significant response to unanticipated inflation in long-term interest rates.

Several studies conducted on the US Treasury markets found that macroeconomic news announcements have a significant impact on bond markets. The focus on specific macroeconomic news announcements was conducted during a time period when the money supply variable was deemed to be very important (Fleming Michael J., 1997). Money supply studies that investigated the response of interest rates to money announcements were mainly conducted in the 1980s and found a significant impact in short-term and long-term interest rates (Roley, 1982b; Urich & Wachtel, 1981). Urich and Wachtel (1984) found a significant impact in short-term interest rates to money supply announcements. A study by Roley and Troll (1983) found that nine percent of daily interest rate volatility could be ascribed to weekly money supply announcements. Grossman (1981) studied the federal funds rate and the surprise component in money supply announcements and found that the larger the surprise (where the surprise measure was expected versus actual) the greater the chances of a change in policy and also a change in interest rates. Cornell (1982) and Cornell (1983) found that the announcement of an increase in money supply led to an increase in the expected rate of inflation and an increase in the real rate, because of expected future tightening of monetary policy. However, there was no evidence that monetary shocks affect the real rate. Dwyer and Hafer (1989) found a significant relationship between money supply announcements and both the short-term 3-month Treasury bills and long-term 30-year interest rates. However, other macroeconomic variables included in their study (CPI, PPI, unemployment rate and industrial production) were found to not have a significant impact on interest rates. Hardouvelis (1988) found a positive reaction in interest rates to the announcements of unanticipated increases in money supply. Strongin and Tarhan (1990) found that interest rates responded to unanticipated money supply announcements and that the magnitude declined with the maturity of the instrument.



Unexpected news of macroeconomic variables (such as industrial production, retail sales, unemployment rates and non-farm payroll) did not have a significant impact on interest rates when using daily data (Dwyer & Hafer, 1989; Hardouvelis, 1988; Roley & Troll, 1983). Hardouvelis (1988) suggested that one should measure the interest rate impact from just before to just after the news announcement (as short as intra-day). A study by Prag (1994) suggested that the effect of jobless rate announcements on interest rates is conditional on the existing level of unemployment. Cook and Korn (1991) found that interest rates reacted significantly to the US unemployment report and that the significance increased over longer periods of time.

Inflation reactions are measured by announcements of the Consumer Price Index (CPI) and the Producer Price Index (PPI). If the announced inflation news is higher than expected, the expectation of future inflation increases. The resultant effect of the higher inflation causes nominal interest rates to increase. A second outcome that is caused by unexpected inflation surprises relates to the expected reaction of monetary authorities to the news shocks. Their consequent tighter monetary policy implementations result in higher interest rates. Several studies investigated the impact of PPI on interest rates (Dwyer & Hafer, 1989; Hardouvelis, 1988; Mcqueen & Roley, 1993; Urich & Wachtel, 1984). The studies on CPI (Edison, 1997; Hardouvelis, 1988; Mcqueen & Roley, 1993; Smirlock, 1986) examined only select points on the yield curve. While these studies used daily data, the more recent studies used high frequency intra-day data to measure the reaction to news surprises closer to the event to achieve more precise results (Balduzzi et al., 2001b; Fleming Michael J., 1997; Fleming & Remolona, 1999b). Balduzzi et al. (1998) studied the effect of news in an intra-day and daily data set. They found that the same five out of ten news announcements found to be significant in the intra-day data set were also significant in the daily data set.

As discussed in section 2.4.1.2 Andersen et al. (2007) studied the effect of US macroeconomic news on stocks, bonds and foreign exchange markets and found that bond markets almost uniformly react the strongest to macroeconomic news.

Becker et al. (1995), examined the impact of scheduled US and UK macroeconomic news announcements on futures prices of US, UK, German and Japanese government bonds.



They found that US macroeconomic news announcements had a significant influence on German, Japanese and British interest rates, while UK macroeconomic news announcements had almost no effect on foreign rates. The impact of factory productivity and investment-specific technology news on the US economy and the US bond yield term structure was investigated by Badarinza and Margaritov (2011). They found that investment-specific technology news and anticipated monetary policy shocks had a statistically significant influence on the bond yield term structure.

A study by Andritzky et al. (2007) on the effects of macroeconomic and policy announcements in emerging markets, found definite differences between emerging markets and developed bond markets. The authors highlighted that they could not find evidence that domestic macroeconomic data and policy announcements had systemic effects on the level of international bond spreads for emerging market countries.

However, a working paper by Pistora and Hausenblas (2015) with a focus on Polish and Czech government bond markets found that scheduled domestic macroeconomic indicators had an impact on the Polish bond prices and that news was incorporated in the first hour after being released. For the Czech government bond market they found less evidence that prices responded to news timeously.

Vasishtha et al. (2006) used high-frequency data from Brazil, Turkey and Poland and found that during periods of uncertainty budget news had the most significant impact on country spreads and interest rates.

2.4.2 The influence of political news on financial markets

This literature review includes the impact of political news on three different asset classes, namely stock markets, foreign exchange markets and interest rate markets with emphasis on the interest rate markets.

2.4.2.1 The impact of political news on the stock market

Harms (2002) concluded that political risk is an important determinant of total foreign direct investment and portfolio equity investment per capita in an economy. Andrianaivo and



Yartey (2010) investigated the determinants of financial market development in Africa, specifically the stock markets and banking sectors. They found that, as a result of the powerful impact of political risk on the development of these two sectors, the resolution of political risk is important for the development of African financial markets. Diamonte et al. (2019) also found that political risk is a more important determinant of stock returns in emerging markets than in developed markets. Their study further highlighted that there seems to be a global convergence of political risk, whereby the risk in emerging economies is decreasing, but the political risk in developed economies is increasing. Against this background, the impact of news on emerging economy stock markets determines not only the aggregate investment value, but political risk is also an important determinant of the level of the returns.

In his study on the reaction of stock markets to political news, Suleman (2012) split political news into two categories, namely good and bad news. The author studied the effects that good news had on the Karachi Stock Exchange Top 100 Index. He found an asymmetrical response, in that bad political news had a negative influence on returns and it increased the volatility of the index to almost twice that of the dampening effect that good news had on the index volatility. Pástor and Veronesi (2013) developed a general equilibrium model in which they allowed stock prices to respond to political news. The results of the model indicated that greater political uncertainty induced a political risk premium that increased in weaker economic conditions. In a follow-up study, Kelly et al. (2016) investigated the price of political uncertainty by studying option premiums for equity options. They found that options with life cycles that spanned several political events tend to be more expensive, as the implied volatilities for these option contracts would be higher than for other expiry dates. Kaminsky and Schmukler (1999) investigated what types of news caused the extreme stock market moves experienced in the East Asian markets in 1997-1998. They concluded that news items from local and neighbour-country sources regarding agreements with international organisations and credit rating companies were the most influential. The authors found that nearly a fifth of the largest stock price movements during this period could be associated with political news.



Chan et al. (2001) concluded that the impact of political news was greater than the impact of economic news on the Hang Seng Index during the same period. Khan et al. (2017) used the event study methodology to investigate the influence of political and budget events on the stock market. They found that the Pakistan market exhibited a weak form of the EMH, where the results showed that investors overreacted to good political news and underreacted to bad political news. In a similar study on the Pakistan market, Murtaza and Ali (2015) found that the Karachi Stock Exchange readjusted to previous levels within two days of a political event occurring.

The impact of scheduled news versus unscheduled news was studied by Fornari et al. (2002). They found that unscheduled news resulted in higher volatility in the Italian financial markets than the release of scheduled news in the period 1994-1996. The classification and categorisation of news enhanced the results of their analysis. The effect of political news on equity markets can be summarized as follows: unscheduled news increases volatility, bad news increases volatility and decreases returns.

2.4.2.2 The impact of political news on the interest rate markets

Several studies examined the relationship between short-term stock returns and short-term interest rates (Breen et al., 1989; Fama & Schwert, 1977; Ferson, 1989). Both of these asset classes are influenced by new information, and although the effect of such information on the asset classes might not be the same, the catalyst for the change is new information (news) (Brenner et al., 2009). The following sections review the literature that relates to the influence that new information has on the interest rate markets and, by extension, on the term structure of interest rates in different economies.

Political risk is broadly defined as government activities and political events that change over time. In addition, Root (1972) describes political risk as an event (decisions or activities) by government that causes loss. Political risk is linked to a country's willingness to pay its debt, which is an executive political decision (Eaton & Gersovitz, 1981). The main factors that influence the fixed income markets in emerging markets are economic and political conditions (Önder & Şimga-Mugan, 2014). The South African markets are no exception and



they are affected daily by both economic and political conditions in the country (Kapingura, 2015).

Political knowledge, defined as interest and participation, is one of the most important values for an individual from a democratic perspective (Strömbäck & Shehata, 2010). The origin of political knowledge lies in access to information and it has been well established that the media is the most important source of political information. Due to the various forms of media through which news has become available (traditional sources being television, radio and printed media, and also more modern sources - such as streaming news services, social media, Facebook, Twitter and WhatsApp) the general public can now receive political information almost instantaneously (Bode, 2015). Groß-Klußmann and Hautsch (2011) investigated the effect of high frequency firm-specific news and found that there is a distinct advantage in being able to receive and react to news faster.

Harvey (2004) defined political risk by separating the total political risk into categories, in line with a previous study that compared different political risk measures performed by Erb et al. (1996). He also examined the components of the International Country Risk Guide's political risk metrics. Harvey (2004) separated total political risk into the following categories: government stability, socioeconomic conditions, internal conflict, corruption, law and order, ethnic tensions, democratic accountability and bureaucracy quality. From this multifaceted approach to understanding political risk, it became apparent that, although a news announcement might not be classified as political news, it could still have an impact on the political risk of a country.

Although there are few studies that analysed the impact of political news on the interest rate markets directly, several studies investigated the impact of political risk on the returns of emerging and developed markets. Duyvesteyn et al. (2016) noted that emerging countries have a slower absorption rate of information compared to developed government bond markets. They confirmed that poor political risk ratings are associated with worse credit ratings and higher bond yields. Bekaert et al. (2014) introduced a new concept which they referred to as the political risk spread. This was first used to extract the political risk component from the sovereign spread. Thereafter, the political risk spread was used as a



forward-looking measure. An important observation made by the authors was that, on average, a third of the sovereign spread reflects political risk. Cuadra and Sapriza (2008) confirmed this finding. In their study increased levels of political uncertainty raised the default frequency, which resulted in an increase in the levels and volatility of sovereign spreads. Several studies showed the asymmetrical impact that a change in credit rating has on the bond market of an emerging market country, as well as on other emerging economies in the same region (Bales & Malikane, 2020; Böninghausen & Zabel, 2015; Gande & Parsley, 2005; Nhlapho & Muzindutsi, 2020). The negative effects of a downgrade are more pronounced than the positive effects from upgrades.

Moser (2007) examined the impact of political risk on sovereign bond spreads (with a specific focus on the impact of cabinet reshuffles affecting the ministry of finance or economics) and concluded that such news immediately increases the sovereign bond spreads. In addition to the specific risk examined by Moser (2007), Gande and Parsley (2005) also determined that there is an asymmetrical spillover effect of news on a credit rating change in one country, which affects the sovereign credit spreads of other countries.

In an extreme case of market volatility, Ganapolsky and Schmukler (1998) analysed the impact of policy decision announcements in Argentina made during the Latin American market crisis in 1995. During this period interest rates increased over a short horizon period, but the volatility of interest rates decreased in response to several of the measures taken by the government to stem the spillover effect from the Mexican peso devaluation in December 1994. This shows that the effects of news announcement are important for emerging market debt. Few studies have been conducted on the impact that news announcements have in emerging markets (Andritzky et al., 2007; Eichengreen & Mody, 1998; Moser, 2007)

2.4.2.3 Influence of political news on foreign exchange markets

The 2008 financial crisis was the turning point for the analysis of the impact of news on foreign exchange markets and price movements, as the micro-structure of the market fundamentally changed after the crisis (Li et al., 2015). Since the 2008 crisis until 2015 the daily trading volumes in FX markets increased from 1.9 trillion USD to 5.3 trillion USD. The composition of the trading strategies employed show that the traditional discretionary trading



strategies are being phased out (Hendershott et al., 2011). Thus the speed at which news is disseminated and incorporated in trading decisions has increased and the demand for ever faster delivery and decision making has increased in line with this requirement (Chaboud et al., 2014).

2.4.3 Influence of news on the yield curve

In this section the impact of news on interest rates, and more specifically the yield curve, is discussed. Some studies investigated the yield curve as a whole, whereas other studies tended to focus on specific maturity points on the yield curve. The following section provides an overview of how wide-ranging and significant the research has become regarding news and the impact of news on the yield curve.

Studies that focused specifically on the yield curve and how the yield curve reacts to macroeconomic news announcements have been well documented in the academic literature. Fleming Michael J. (1997) found that the biggest price increases and decreases in US bond yields occurred after the release of macroeconomic news. In theory, news affects the prices of assets before market participants can trade the assets (French & Roll, 1986). Their study found that certain announcements are consistently considered important namely, unemployment, PPI and CPI. The authors concluded that a high degree of uncertainty in interest rate markets can explain the magnitude of the markets' responses. Fleming and Remolona (1999a) studied the trading volume and bid-offer spreads of the yield curve after major macroeconomic news announcements. They found that market prices reacted instantly and significantly to major announcements, whilst trading volumes showed a reduction and market spreads widened. In a subsequent study Fleming and Remolona (1999b) examined the effects of macroeconomic news announcements on the entire yield curve and found that the yield curve in the intermediate maturities (1 to 5 years) showed strong reactions to macroeconomic news announcements, which resulted in a humped shape of the yield curve. Other studies which also found that significant yield changes tended to be at the intermediate maturities of the yield curve include Balduzzi et al. (2001b) and Faust et al. (2007). Green (2004) found an increase in order flow in the half-hour after economic announcements were released, which suggested an increase in information



asymmetry in the US government bond market, which is similar to the findings of Pasquariello and Vega (2007).

Hördahl et al. (2018) studied macroeconomic fundamentals as risk factors. News announcements were sorted into five categories with 20-minute event windows to capture the surprise element of the announcement along the yield curve by using six maturity yields. They found that the yield curve reacted to announcement surprises due to risk premia responses and that the effect was stronger for long-term maturities than short-term maturities. The effect was reflected in a hump-shaped pattern of the yield curve.

Altavilla et al. (2017) studied macroeconomic news and its effect on bond yields using different frequencies. Their study used data from Bloomberg's economic calendars for news-related data and zero-coupon bond yields with 1-year to 10-year horizons, as constructed by Gürkaynak et al. (2007). The results showed that macroeconomic fundamentals have a sizable impact on bond yields, where low frequency (quarterly), as opposed to high frequency (daily), movements showed that macroeconomic news had a persistent effect on bond yields.

Benamar et al. (2019) used a different approach to investigate the impact of news on information demand and interest rates. They found that when, during the sample period, the number of non-farm payroll announcement web-based queries increased by one standard deviation in the two hours preceding the announcement, this news type affected the US Treasury yields significantly, ranging from four to six basis points (bps), depending on the maturity.

Lombardi et al. (2019) used data samples that preceded and followed the US subprime mortgage financial crisis of 2007-2009 and the Eurozone or European sovereign debt crisis of 2010-2012. The study investigated how responsive market participants were to news in economies that are at, or very close to, the effective lower bound (ELB) for interest rates. The authors examined the reaction of sovereign bond yields to news events and central bank communications by implementing a methodology where the news metrics included press releases and meeting minutes published by central banks that had a broad range of



content. Their study found that the longer-end yield curve is more sensitive to shocks contained in the content of central bank communications at the ELB.

Hansen et al. (2019) used an event study approach to investigate why long-run interest rates respond to central bank communications using the Bank of England's inflation report from 1998 to 2015. The inflation report provides information but not guidance on future policy. The authors measured a set of high-dimensional signals from the central bank's report to determine exactly what drives market responses. They found that the signals that drive long-run interest rates do not affect short-run rates and that the signals operate primarily through the term premium. This suggests that central bank communications play a crucial part in shaping perceptions of long-run uncertainty.

De Santis (2020) employed an event study to examine the impact on long term yields using news data from Bloomberg containing keywords relating to the Asset Purchase Programme (APP). The APP for the Euro area was introduced by the European Central Bank (ECB) on 15 January 2015. On news conference days it was found that all sovereign yields declined, which suggested that the news announcements to a large extent represented a positive surprise to the markets. Even though the APP programme was introduced during a time of low financial distress, the impact on the Euro area's long-term sovereign yields was significant.

2.5 SUMMARY

New information is released to global financial markets continuously and some of this information has an impact on the current market prices of instruments in different asset classes. Research has shown that the type of news, the extent of the impact, and the permanence of the impact are all variables that differ from asset class to asset class, economy to economy, and from cycle to cycle across the financial markets. The emerging debt markets differ from those of industrialised countries. Emerging market countries have a relatively short modern history of access to international capital markets and their economies continue to undergo significant structural changes. In emerging market by difficulties experienced in gathering and interpreting information about such economies.



Also, the effect that volatile political environments often have on the domestic policies of emerging market economies can significantly impact the creditworthiness of these countries.

CHAPTER 3 discusses the interest rate environment in general and the yield curve in particular.



CHAPTER 3 INTEREST RATES: DEFINITIONS, MODELS AND PROPERTIES

3.1 INTRODUCTION

This chapter provides an overview of interest rates and interest rate models. It outlines the different types of interest rates, as well as long-term interest rates and the yield curve. Term structure models explain the difference between dynamic and static models.

3.2 CATEGORISATION OF INTEREST RATES

Interest rates can be categorised into short-term and long-term interest rates. Interest rate instruments of different maturities are necessary as inputs to construct a yield curve. Central to the risk-free yield curve are the long-term interest rates, namely government bonds that are used as the constituents to derive the yield curve.

Government bonds react daily to news events and not necessarily in exactly the same way as they did previously to the same or similar news. On the release of new information there is an impact on bond yields and volatility in response to market expectations (Emir et al., 2007).

3.2.1 Short-term interest rates

Short-term interest rates are important benchmark rates for financial stability (Carlson et al., 2014). Short-term interest rates are quoted in the money markets and consist of interestbearing instruments with a maturity of less than one year (Dube & Zhou, 2013). A special type of short-term interest rate (that is set and controlled by the central bank of a country) is called the official accommodation/borrowing rate. It represents the overnight (secured) borrowing cost of banks from the central bank in a jurisdiction. Short-term interest rates are exogenously determined by a central bank, which affects all general short-term money market interest rates (Dube & Zhou, 2014; Nomsobo & Van Wyk, 2018). One of the central bank's main objectives is to achieve monetary stability. In South Africa, the South African Reserve Bank (SARB) sets the official repurchase or repo rate to achieve and maintain price stability. SARB strives to keep inflation within an acceptable range (in accordance with the inflation-targeting framework) as measured by the annual increase in the consumer price index (CPI) (Van Wyk et al., 2015). SARB operates in the domestic money markets to



achieve this goal (Plenderleith, 2003). SARB, through its Financial Markets Division, uses open market operations to control the supply of funds in the money markets. Banks borrow at the repo rate to fund any short-term liquidity requirements. When the repo rate changes, the banks also adjust their prime lending rates to reflect the monetary authority's direction with respect to interest rates (Matemilola et al., 2015). Accordingly, all other money market interest rates will change and the prices, or yields, of financial interest rate instruments will also be affected (Nomsobo & Van Wyk, 2018).

Short-term interest rates are important inputs when constructing a yield curve model. Interest rates ranging from overnight to one year are considered short-term. A short discussion on the different types of short-term rates follows in sections 3.2.1.1 to 3.2.1.6.

3.2.1.1 Repo rate

In South Africa, the official repo rate (in some jurisdictions this is referred to as the vertical repo rate) is the rate at which commercial banks can borrow money from the central bank, provided that they can deliver securities as collateral for the borrowing (Dube & Zhou, 2014). The repo, or accommodation rate is one of the most significant rates in financial markets and it is the main instrument used by the South African Reserve Bank for inflation targeting.

SARB creates a 'shortage' of cash in the money markets by making sure that commercial banks are in debt at all times and that they are dependent on SARB for funding purposes. Banks that have a shortage of funds sell assets to SARB in exchange for the cash they borrow and they pay the repo rate for this accommodation. The funding or refinancing to banks takes place as part of the refinancing operations of SARB under its system of accommodation (Faure, 2015). The interbank market plays an important role regarding the changes that occur in other money market interest rates. An efficient interbank market will ensure that changes in the repo rate will be quickly and immediately reflected in money market rates, thereby ensuring the effective pricing of the money market as a whole. When constructing the zero-coupon rate yield curve, the market rate closest to the repo rate, the South African Benchmark Overnight Rate (SABOR), is used as an input for the short-term Risk-Free Rate (RFR). This rate serves as a benchmark rate and it is a reliable indicator of overnight liquidity in the interbank market (SARB, 2020).



The other types of repo transactions performed in the financial markets are executed between commercial banks, but the mechanics of the transactions are the same, whereby collateral (generally in the form of government debt) is provided against a cash loan. A distinction is made between the official repo and a sell/buy back transaction, which is commonly referred to as carry transactions in South African financial markets. A carry (repo or sell-buyback or buy-sell back) transaction is a form of short-term (overnight) lending using (generally, but not exclusively) government bonds as collateral. These carry transactions can also be conducted for longer time periods (Van Wyk et al., 2015).

The official reportate is generally referred to as the monetary policy rate. It is used by the South African Reserve Bank to increase or decrease liquidity in the money markets to keep inflation within its targeted range (De Angelis et al., 2005).

Other money market interest rates that are affected directly by changes made to the reportate are briefly discussed below to provide a comprehensive overview of all short-term interest rates in the money markets.

3.2.1.2 Interbank call rate

According to Mitchell-innes et al. (2007), the repo rate has an almost direct influence on bank lending rates, as discussed in 3.2.1.1. Even banks that do not directly participate in the repo accommodation process change their interest rates when the repo rate is increased or decreased. With this direct correlation between the SARB repo rate and the interbank call rate, SARB has substantial control over the cost of credit to the private sector (Van der Merwe, 1999).

A call rate is an overnight rate that is paid on a deposit received from one bank to another bank. This is also referred to as the interbank market and the interest rate that is paid is called the interbank call rate. There are also call transactions that take place between a bank and its customers. The rate that is paid to large depositors by the bank is referred to as the wholesale call rate. The call rates that are charged to customers who wish to borrow funds overnight will depend on the type of customer and the credit quality of the customer (Van der Merwe, 1999).



3.2.1.3 Prime rate

A study by De Angelis et al. (2005) investigated the econometric link between the repo rate and three other money market rates, namely the prime lending rate, the interbank call rate and the 3-month Negotiable Certificate of Deposit (NCD) rate. They found that all three rates respond on an almost one-to-one basis to changes in the repo rate, with the prime lending rate being in perfect correlation with the repo rate.

The prime rate is a reference rate that is used by banks for lending purposes. The prime rate convention originated in 1934 when US banks started to set and administer a loan price as the minimum price consistent with profitable loan operations (Goldberg, 1982).

In South Africa, the prime rate is announced by commercial banks when SARB changes its repo rate. The prime rate is a commercial lending rate to some of the banks' good credit quality clients. There is a distinction made between the prime mortgage rate and the prime overdraft rate. The prime mortgage rate is used as the lending rate for home loans, whereas the prime overdraft rate is used for other credit transactions, such as credit cards. The prime rate is quoted as a notional monthly compounded rate. Interest accrues in an account and it is only paid on the last day of the month (Van Wyk et al., 2015).

3.2.1.4 Overnight foreign exchange rate swap

Overnight foreign exchange rate swaps entail a simultaneous purchase and sale of identical amounts of one currency for another with two different value dates, a spot date and a forward date. The transactions are conducted on an overnight basis, but they can also be conducted for specified longer-term periods. For example, a bank sells US Dollars (USD) against South African Rand (ZAR) to a counterparty on a spot basis while simultaneously buying USD back and selling ZAR on a forward basis. The domestic currency (ZAR) interest rate is a rate implied (using no-arbitrage principles) from selling USD spot and buying USD forward (Van Wyk et al., 2015).

The overnight foreign exchange swap rate is a significant rate, as banks within the financial markets can use foreign currency funding and swap this by using an overnight foreign exchange rate swap to fund a Rand (ZAR) shortage, instead of using normal interbank



transactions or the repo accommodation process through SARB. The transactions are taken into account when SARB determines the liquidity shortage on any given day, as changes in net foreign assets will have an impact on the balance sheet of the banks (SARB, 2016).

3.2.1.5 Johannesburg Interbank Average Rate

The Johannesburg Interbank Average Rate (JIBAR) rate is calculated and published by the Johannesburg Stock Exchange (JSE). It represents the interest rate on longer-term money market instruments (up to 12 months). Four different maturities of JIBAR rates are published, namely 1-month, 3-months, 6-months and 12-months. South African banks, and also foreign international banks based in South Africa, are asked on a daily basis to provide or quote the mid-point between the bid and offer rate of their Negotiable Certificates of Deposit (NCD) and submit the quote as a yield rate. It is important to note at this stage that the different maturities are all quoted as term to maturity rates (or simple interest rates), which makes them incomparable without performing some conversions first. After all of the guotes have been received, the rates are arranged in order and the top two quotes and bottom two quotes are discarded, with the remaining number of quotes averaged and then rounded to three decimal places and published by the JSE (Gumbo, 2012). The JIBAR rate is considered to be similar to the London Interbank Offered Rates (LIBOR), as this rate is also used as a reference rate for derivative instruments and it is also a benchmark money market rate. However, it is important to note that JIBAR is a middle rate while LIBOR is an offered rate, while the London Interbank Bid Rate (LIBID) is the bid rate quoted by banks on a daily basis in the London money markets.

JIBAR is also used as a key input in the Short Term Fixed Interest Index (STEFI), which is a non-tradable index that is used for benchmarking money market portfolios. According to Van der Merwe (1999) there is low transparency with respect to price discovery, given the small number (nine as at 2018) of banks that quote JIBAR rates. STEFI is not considered to be representative of actual trades taking place in the South African financial markets.

The JIBAR rates are, however, used as reference rates for all Forward Rate Agreements (FRAs), Interest Rate Swaps (IRS), and Interest Rate Guarantees (IRGs) in the over-thecounter (OTC) domestic derivatives markets. JIBAR is also used for a range of products



offered on the interest rate markets of the South African Futures Exchange (Yield-X). As such, JIBAR rates are the most suitable rates to use for determining market-related shorter-term interest rates.

3.2.1.6 Negotiable Certificates of Deposit

Negotiable Certificates of Deposit (NCDs) were first introduced into the global financial markets in the 1960s when US banks, specifically major New York banks, launched these instruments to attract funding from corporations and other large depositors (Murdeshwar, 1970). According to Faure (2012), South Africa was the second country to issue NCD. A joint press statement by the four large banks was released on 21 July 1964 regarding the introduction of NCDs into the South African financial markets. The first banks to issue NCDs in the South African financial markets included Barclays Bank (now known as First National Bank) and the Netherlands Bank (now known as Nedbank).

A NCD can be defined as a financial instrument issued by a bank that is negotiable in the secondary market for financial assets. The issuing bank guarantees the certificate holder (if issued in bearer form) to pay the amount of the deposit after a specified period of time (the maturity date) plus interest at a specified interest rate. These instruments are similar to fixed deposits, with the difference that NCDs are tradable and can be sold prior to maturity (Matanda, 2020). The fact that they are negotiable makes NCDs attractive instruments for investors, as the investors are not locked into the deposit and they can sell the instrument in the secondary market.

NCDs are only available in large denominations, for example R1 million and above, which makes them 'wholesale' financial instruments. Thus, the primary (and secondary) market is limited to the large institutional and corporate investors (Aziakpono et al., 2007; Patel, 2004).

From a legal and regulatory perspective, NCDs are common law instruments. This means that there is no specific law that provides for and regulates NCDs. However, regulations of the Banks Act 1990 (Act no. 94 of 1990) limit the term of the instrument and the amount which banks may issue (Patel, 2004).



NCDs are used as a source of interbank funding and can be issued for any maturity up to 12 months. Generally, banks issue 3-month, 6-month, 9-month and 12-month NCDs. Banks may also issue longer than one-year NCDs, should their funding needs require longer-term funding (Van Wyk et al., 2015). As discussed in 3.2.1.3, there is a strong correlation between the repo rate and NCD rates. NCD rates are adjusted over the entire maturity spectrum according to the changes made to the repo rate by SARB (De Angelis et al., 2005).

3.2.2 Long-term interest rates

Hiroyuki and Phuong (2019) stated that, if a country's financial markets are susceptible to international factors, monetary policy management could be a challenge. While short-term rates are under the direct control of policy makers, long-term interest rates reflect many factors, including global factors. Long-term rates that affect financial and economic activities directly may not reflect the policy makers' intentions. Policy makers are vulnerable to shocks emanating from major global economies when managing the short-term interest rates and they are consequently less capable of controlling long-term interest rates.

Long-term benchmark interest rates consist of various long-term interest-bearing instruments with a maturity of longer than one year, issued by the government of a jurisdiction (Reilly & Brown, 2006). In South Africa government bonds are issued by the National Treasury to raise capital for the fiscus. The South African government issues different kinds of bonds, which include fixed-rate bonds, inflation-linked bonds, foreign currency bonds, zero-coupon bonds and variable rate bonds (Van Wyk et al., 2015).

Long-term government bonds of different maturities are important inputs when constructing a yield curve. A short review of the various kinds of bonds follows in sections 3.2.2.1 to 3.2.2.5.

3.2.2.1 Fixed coupon bonds

A fixed rate bond is classified as a fixed-income instrument because it imposes fixed financial obligations on issuers, where the issuer agrees to pay a fixed amount of interest periodically to the bond holder. The regular interest payments are known as coupons. At the



date of maturity the issuer repays the initial principal amount, also referred to as the par value of the bond (JSE, 2018a). Generally, the fixed interest on these types of bonds is paid every six months (semi-annually), although there are exceptions where some bond issuers may also pay interest in intervals as short as a month or as long as a year.

3.2.2.2 Inflation-linked bonds

Inflation is considered a key risk to investment performance. Investment returns must consider the rate of inflation at all times to protect investors from the erosion of purchasing power. Inflation-linked bonds, or inflation-indexed bonds as they are referred to in the US markets, were introduced to financial markets to offset inflation threats to stable investment returns (Fabozzi & Mann, 2021).

In South African financial markets inflation-linked bonds are issued by the South African government. These bonds offer protection against inflation by compensating investors for adverse changes in inflation, with the bond being linked, or indexed, to headline inflation and the coupon interest being paid on a nominal amount adjusted for inflation with a three month lag (Van Wyk et al., 2015).

3.2.2.3 Foreign bonds

Foreign bonds are identified by their country of origin and are classified in various ways: the country of the issuer, the location of the primary trading market, the home country of the major buyers and the currency in which the securities are denominated (Reilly & Brown, 2006). Some of these classifications include Eurobonds and foreign bonds (Fabozzi & Mann, 2021).

Table 3-1 shows that the South African government's foreign debt has stayed relatively constant with respect to the domestic issuance of debt.



Table 3-1

Composition of debt of the South African National Government 2010 – 2019

Year	Total outstanding domestic debt of SA	Total outstanding foreign debt of SA	Foreign debt as percentage of total
	government (ZAR Mio)	government (ZAR Mio)	debt
2010	804,929	99,454	12.4%
2011	990,572	97,851	9.9%
2012	1,187,790	116,851	9.8%
2013	1,365,689	124,555	9.1%
2014	1,584,758	143,659	9.1%
2015	1,798,915	166,830	9.3%
2016	2,018,971	199,607	9.9%
2017	2,232,889	212,754	9.5%
2018	2,489,718	217,811	8.7%
2019	2,814,349	320,223	11.4%

Source: (National Treasury, 2019)

Note. The foreign debt as percentage of total debt for the South African government have been constant at 9%-10% for the period 2011-2018, with higher exposures in 2010 and 2019.

The South African government issues foreign bonds on a regular basis by means of private placement or by listing the foreign bond on a foreign bond exchange. A lead manager, acting as the primary dealer and market maker, is appointed and an auction process is followed as part of the listing process (Van Wyk et al., 2015).

3.2.2.4 Zero-coupon bonds

A zero-coupon bond is a market instrument that does not pay a coupon during the tenor of the instrument. The yield of the zero-coupon bond can be observed in the market (Gushee, 2018). When we consider a zero-coupon bond of n-years maturity, the n-year interest rate observed in the markets is the zero-coupon rate or the spot rate (Choudhry, 2019). Due to the higher settlement risk, and consequently higher credit risk of a zero-coupon bond, the preference of investors is to purchase coupon bonds, therefore there are not a lot of zero-coupon bonds in issue (Caks, 1977).



3.2.2.5 Variable rate bonds

Although the South African government has issued debt securities linked to JIBAR, these issues have tapered off, and the primary variable rate instrument of choice has become inflation-linked bonds (National Treasury, 2017).

3.3 SOUTH AFRICAN SOVEREIGN BOND MARKET AND YIELD CURVE

The South African bond market was established in 1989 by an act of parliament. Trading was formalised in 1996 and took place through the Bond Exchange of South Africa (BESA). In 2009 BESA was acquired by the JSE(JSE, 2018b).

The South African sovereign debt market is one of the most liquid emerging fixed-income markets in the world. Eighty-two percent of South Africa's total fixed income market (R1.76 trillion or \$140 billion) is comprised of sovereign debt, of which 51% is held by foreign investors (Brand, 2018).

Primary auctions of government debt are held by the South African Reserve Bank on behalf of National Treasury, with direct participation limited to authorized primary dealers for the fixed coupon bonds. Primary dealers are appointed by National Treasury to make South African government bond prices for investors by quoting bid and offer prices (National Treasury, 2017).

South Africa introduced a primary dealer system in 1998 as a mechanism through which government can access the primary capital markets. There are currently nine primary dealers (JSE, 2018b). The criteria to be considered a primary dealer are as follows:

- 1. Only banks registered in South Africa are eligible
- 2. Applicants must have at least R1 billion or Tier 1 capital as defined by the Registrar of Banks
- 3. Applicants must be members of the JSE

The primary dealers significantly add liquidity to the bonds market and account for the majority of all flow reported through the JSE (SARB, 2018).



Table 3-2 Primary Dealers Primary Dealers Absa Bank Limited Citibank Deutsche Bank Investec Bank Limited JP Morgan Chase Bank Nedbank Limited FirstRand Bank Limited Standard Bank HSBC Bank Source: (National Treasury, 2017)

Primary dealers are obliged to participate actively in the weekly auctions by submitting minimum competitive bids equal to 14.5% of the amount offered on each bond. In addition, primary dealers are required to quote a two-way price from 8h30 to 16h30 local time. However, they are not obliged to quote prices within 10 minutes of the auction closing time and until the results of the auction are announced (National Treasury, 2017).

The National Treasury (2017) provides primary dealers with an incentive through a noncompetitive bid auction, where they can exercise an option of taking up to 50% of the allocated amount at the same clearing yield of the fixed-rate competitive bid auction. This option remains open for 48 hours after the auction closes with settlement taking place on the following Wednesday (T+3). The National Treasury conducts weekly bond auctions according to a calendar published at the beginning of the financial year on the websites of both the National Treasury and the South African Reserve Bank. The nominal amount to be issued on a weekly basis is determined at the beginning of each year and remains unchanged, unless there is a compelling need to adjust it (National Treasury, 2017).

Sovereign bonds are listed on the JSE Debt Board. Inter-dealer brokers and agency brokers act as intermediaries between the banks and investors respectively. The listed debt market is predominately a wholesale market, with large investors taking positions in bonds to satisfy portfolio needs (SARB, 2018).



3.3.1 Liquidity in the bond markets

A report on fixed income market liquidity, published by a study group of the Bank for International Settlements (BIS) established by the Committee on the Global Financial System in September 2013, provides for a number of market-based liquidity metrics that provide an approximation of the liquidity conditions prevalent in the markets (Beau, 2014). The report defines market liquidity broadly as the ability to rapidly execute large financial transactions at low cost with limited price impact. The metrics measure the immediacy, tightness, depth, resilience and indicators of market breadth when comparing similar instruments across different jurisdictions. A price-based metric used in the study relates to the bid-ask spread for specific benchmark issues. Quantity-based metrics investigate the market depth and transaction sizes of the instruments and are indicative of the breadth of the market. The willingness and capacity of dealers, specifically the market makers in the issue, to warehouse securities (their security inventories) is used as an indication of the willingness to provide risk capital for the securities. The demand for immediacy can be gauged from the changes in the bond holdings of mutual funds and exchange-traded funds. A study by Chordia et al. (2005) states that on average government bonds have higher liquidity compared to stocks and corporate bonds. The South African bond market is considered a well-established market with high liquidity and competitive pricing.

3.3.2 South African sovereign bond pricing

In the absence of arbitrage, the price of a coupon paying bond must be the sum of the present value of all the bond's future cash flows (Du Preez, 2012), as illustrated by equation Eq 3-1.

$$Price = \left[\frac{Face \ value}{\left[1 + \frac{Yield}{Frequency}\right]^{\left[N-1 + \frac{DSC}{E}\right]}}\right] + \left[\sum_{k=1}^{N} \frac{Coupon}{\left[1 + \frac{Yield}{Frequency}\right]^{\left[k-1 + \frac{DSC}{E}\right]}}\right]$$
Eq 3-1

For N > 1 (N is the number of coupons payable between the settlement date and redemption date).



Where:

- DSC = number of days from settlement to next coupon date
- *E* = number of days in coupon period in which the settlement date falls

In South Africa, bonds are quoted in the market for trade on a Yield to Maturity basis (YTM), which is expressed as an annualized rate, compounded semi-annually, but settled on the rounded dirty price (T+3) (JSE, 2018b). The standard convention for converting between a yield and price on a given settlement date in South Africa is the bond pricing formula of the JSE's Gilt Clearing House (GCH formula) introduced in 1984 (JSE, 2005).

The GCH formula only applies to what are considered 'conventional' bonds. These are bonds with a fixed maturity that pay fixed (including zero) coupons, with two coupon payment dates per year, one of which coincides with an anniversary of the bond's maturity date, on which date the whole capital of the bond is redeemed. South African sovereign bonds that meet the criteria are valued using the GCH formula. The GCH formula is described for bonds with more than 6 months to maturity (Eq 3-2) and for bonds with less than 6 months to maturity (Eq 3-3).

Bonds with more than 6 months to maturity:

Unrounded All-in-Price=
$$V_i^{\frac{d_1}{d_2}} \left(100 \times \frac{1}{2}g(a_n^i + e) + 100V_i^n\right)$$
 Eq 3-2

Where:

- d_1 = number of days from settlement to next coupon date
- d_2 = number of days from last coupon date to next coupon date
- i = YTM of the bond as a percentage

$$V_i = 1/(1+i/2)$$

- = present value of 1 payable in 6 months' time
- g = coupon as a percentage
- n = Number of full coupon periods from next coupon date to redemption

$$a_n^i = (1 - V_i^n)/(i/2)$$



= PV of annuity of 1 every 6 months payable in arrears

e = 1 if bond is cum or 0 if ex

Accrued interest = $\frac{d_2e - d_1}{365} \times g \times \frac{1}{2} \times 100$ Clean Price = All-in-Price – Accrued interest

Bonds with less than 6 months to redemption:

Unrounded All-in-price =
$$\frac{100 + e \times 100 \times \frac{g}{2}}{1 + \frac{d_1}{365} \times i}$$
 Eq 3-3

3.3.3 Bond market efficiency

One of the stated assumptions in section 1.10 of this study is that the South African sovereign bond market is efficient.

In their study of the US, UK, South African and Indian government bond markets, Charfeddine et al. (2018) analyzed long spans of historical data and concluded that the efficiency of the markets varies over time. It would therefore be more accurate to speak of a time-varying efficiency, as opposed to a single time-frame measure of efficiency. Their study shows that efficiency is dependent on the prevailing economic, political and market conditions in the economy. Chordia et al. (2008) investigated the impact of market liquidity, specifically the bid-ask spread and tick size, on the efficiency of the market. They concluded that liquidity stimulates arbitrage opportunities, which in turn improves efficiency.

In their study on the efficiency of the South African debt and equity markets, Guduza and Phiri (2017) split the data into two sub-samples corresponding to periods prior to and after the global financial crisis of 2007-2009. From these samples the authors concluded that South African debt markets conform to the weak-form EMH.



3.4 INTEREST RATES AND THE YIELD CURVE

The review of short- and long-term interest rates connects the different interest rates to the yield curve. The government securities that are used to construct the yield curve typically consist of a variety of short-term and long-term instruments. The short-term instruments comprise instruments with a maturity of less than one year and long-term instruments include various maturities of zero-coupon and coupon-bearing government bonds. The definition of a yield curve is that it is a graphical depiction which describes the relationship between a particular redemption yield and a bond's term to maturity (Chib & Ergashev, 2009). The slope of the yield curve, measured as the difference between short-term and long-term interest rates, is regarded as a leading indicator of economic activity (Benzoni et al., 2018; Christensen, 2018). As discussed by Choudhry (2019), different types of yield curves exist, namely: the yield to maturity yield curve, the par yield curve, zero-coupon rate (spot) yield curve and the forward yield curve, which is derived from the zero-coupon (spot) yield curve (or vice versa). Each of the different curves has a specific function and application in financial markets. Investors use a yield curve for analysis and valuation purposes to determine if a bond is overvalued or undervalued and then to decide whether to buy or sell the bond (Zaloom, 2009). The yield curve is imperative for investors' decision making process and for understanding the relationship between short-term and long-term interest rates. In the absence of zero-coupon bonds, the prices of hypothetical zero-coupon bonds can be estimated using the observed yields or prices of coupon-bearing bonds. These yields can be summarized as a series of zero-rates plotted against different maturity dates on a given date and it is referred to as the zero-rate curve. It is also referred to as the theoretical spot rate curve (Campbell, 1995).

It is important to distinguish between the most commonly used yield curve, the yield to maturity yield curve, and the concept of term structure of interest rates, as well as the zero-coupon (spot) yield curve used in this study.

3.4.1 Yield to maturity yield curve

As per the definition of a yield curve, the yield to maturity yield curve is a plot of the yield to maturity (YTM) of individual bonds against the term to maturity of the bond, using the available government bonds (Finnerty, 1985). This approach is inadequate for the purpose



of accurately valuing financial contracts. As a result of the inconsistencies in the couponbond yields, these curves are not especially smooth, in terms of reflecting specific supply and demand factors amongst other factors (Cairns, 2018). Consider a scenario where two coupon paying bonds with similar maturity dates, but with different coupon rates, trade at the same or a similar yield to maturity in the market, implying different structures to the shorter-term rates in the specific jurisdiction. An implicit assumption of the term yield to maturity is the assumption that all future coupons can be reinvested at the yield to maturity rate, which is problematic when the curve has any shape other than flat (Cooper, 2004).

The South African market uses a specific function to calculate the market price of the bond from the market traded yield (see section 3.3.2).

3.4.2 Term structure of interest rates

The concept of a term structure of interest rates, as defined by Cox et al. (1985) measures the relationship between yields on default-free securities that differ only in their term to maturity. This definition would then exclude bonds that have the same maturity date but different coupon rates. As defined by the authors, the term structure then assumes a theoretical probability distribution, which can or cannot relate back to observed market yields. Thus, the concept of term structure, as applied throughout their study, took the form of a theoretical mathematical function developed to fit the observed market to a certain extent for a specific period of time and used for a very specific purpose. Several different approaches have been used to describe the function that relates to the term structure of interest rates. These approaches and concepts are discussed in more detail in section 3.7.

3.4.3 The zero-coupon rate yield curve

The zero-coupon rate yield curve (spot rate curve, or spot curve), needs to be derived from the observed prices of coupon paying bonds. The zero-coupon yields or spot yields can then plotted against the term to maturity. This form of the yield curve produces pure discount rates that can be used to value financial contracts accurately (Gzyl & Mayoral, 2016). The spot curve has the advantage of not having to rely on any assumptions of the distribution of interest rates. It has no requirement to take mean-reversion into account, nor does the



determination of the spot curve require that a universe of bonds exists with continuous maturities to enable the accurate reflection of observed market prices (Heath et al., 1990).

The zero-coupon (spot) yield curve is regarded as the true term structure of interest rates because there is no reinvestment risk involved. It is an important information source for central banks and investors (Collin, 2007). The true price of a bond is given as the present value of all future cash flows. Using no-arbitrage pricing principles, the price of the bond traded in the market should be equal to the true price of the bond, regardless of the structure used to determine the present value of the future cash flows (Moraleda & Pelsser, 2000).

3.4.4 Variables affecting the yield curve

In recent years the bond markets of developed countries as well as emerging market countries have experienced turmoil and uncertainty (Ahmad et al., 2018). Communications by government officials and politicians have an impact on the financial markets, and even more so in turbulent times (Gade et al., 2013). In general, the yield curve is affected by macroeconomic announcements (Balduzzi et al., 1996), fiscal news (Falagiarda & Gregori, 2015), ratings changes (Andritzky et al., 2007) and liquidity constraints. A study by Mohl and Sondermann (2013) further suggests that political communication is a variable that impacts bond spreads. Piazzesi (2001) in her research on an econometric model for the yield curve, distinguished between expected and unexpected announcements. Furthermore, Piazzesi (2001)considered macroeconomic variables and related those variables to the impact that the information contained therein had on the yield curve.

3.5 THE YIELD CURVE AND RISK PREMIUM

Implicit in the various term structure models that have been developed (see section 3.7) is that there are certain specific risk premia that can explain the difference between short-term rates and longer-term rates in the market. Campbell and Shiller (1991) stated that the spread between short-term and long-term interest rates can be explained by time-varying risk premia. The risk premia that the authors refer to include (but are not limited to) the term risk premium (Bauer, 2011; Duffee, 2002), the inflation risk premium, the liquidity risk premium and others (Brooks & Moskowitz, 2017).



Risk premia refers to the amount by which the return of a risky asset is expected to outperform the known return on a risk-free asset. Where risk premia are a positive function of the term (for example in the case of government bonds, where the issuer is of good quality so that the associated risk premium depends essentially only on the term and is known as term premia (Collin, 2007). Bond investors expect to be compensated for holding a bond through a period when shock news announcements could be made and which could cause a change in the price of the bond. This type of risk premium and the value of the compensation is extremely difficult to quantify *ex ante*, but the phenomenon exists nonetheless. Various studies sought to quantify the premia by means of a predictive model (Cochrane & Piazzesi, 2005; Cochrane & Piazzesi, 2009). The importance of the premia, by connecting them across maturity and understanding how the level, slope and curvature of the yield curve can predict future risk premia (Cochrane & Piazzesi, 2005; Cochrane & Piazzesi, 2005; Cochrane

3.5.1 Yield curve and macroeconomic risk

In their study of US markets Balfoussia and Wickens (2007) applied a stochastic discount factor model of asset pricing using observable macroeconomic factors. They found that term premia tend to increase with maturity. Hördahl et al. (2018) considered the changes in the US yield curve after the release of key macroeconomic news announcements by using an arbitrage-free dynamic term structure model with macroeconomic fundamentals. The results showed that bond yields react to announcement surprises in terms of observed risk premium responses.

3.5.2 Yield curve and political risk

According to a study by Gade et al. (2013) political risk (in the context of debt markets) relates to both the ability of a government and its willingness to repay debts. van der Merwe and Smit (2015) found that South African political news did not display a day of the week pattern and was entirely random or unexpected. This observation is contrary to other studies that analysed economic news. Numerous studies of stock markets found that political news



events have a significant impact on stock market returns and volatility (Frisbie, 2018; Sajid Nazir et al., 2014). A study by Stephanou and du Toit (2003) found that during periods of intense political change, political events drive stock market returns. Huang et al. (2015) found a positive and significant relationship between political risk and government bond yields. There are a limited number of studies that analysed the yield curve and political risk in emerging markets. A study on political risk and government bond returns by Duyvesteyn et al. (2016) included emerging market countries and specifically South Africa. The authors analysed the relationship between political risk and bond returns. They concluded that political risk is an important factor regarding bond risk premium changes and that political risk is directly related to the creditworthiness of a country.

Interest rates change as a country's economic and political outlook change. The relationships between the different tenor interest rates play an important role in a central banks' conduct of monetary policy. Hiroyuki and Phuong (2019) stated that long-term rates might not reflect the intention of policy makers to manipulate the short-term interest rates, whereas the short-term rates are under the direct control of policy makers. Long-term rates reflect many factors, including global factors. Central banks implement monetary policy to guide market-determined short-term interest rates, whilst long-term interest rates are used by central banks as informal indicators of expected future inflation rates (Gerlach, 1996). The relationship between short-term and long-term rates in the commercial banking domain is the area where banks facilitate maturity transformation, which is critical to the supply of long-term credit to the private sector (Drechsler et al., 2018).

Gotthelf and Uhl (2018) proposed using news sentiment as an additional factor in modelling yield curves, as a result of the perceived dependency of decision makers on news and news sentiment. Ben Omrane et al. (2019) studied the effect of macroeconomic news on Euro-Dollar returns and found that the impact of news was not stable over time, and that higher market risk dampened the news effects on the returns. Research on US financial markets suggests that markets do not react in any meaningful way to the act of releasing information by the government, but it is rather the news content of these announcements that causes the market reaction (Kim et al., 2004).



3.5.3 The yield curve and sovereign bond risk spread

Sovereign bond spread is the differential between the yield curve of an emerging market country and a benchmark country. For example, the sovereign bond spread can theoretically be calculated using the US yield curve and the South African yield curve (Patel et al., 2018). The difference between the yields is referred to as the sovereign bond spread. Andrade (2009) argued that the country risk of emerging markets is implicitly included in the sovereign yield spread.

Ferrucci (2003), in researching the determinants of emerging market sovereign bond spreads, derived a model that assessed whether the sovereign risk for a specific country is over-priced or under-priced. Andritzky et al. (2007) showed that emerging market bond spreads respond to credit rating actions and changes in US interest rates, rather than domestic macroeconomic news and fiscal policy announcements, but that all announcements have an effect on market volatility. Jin and Gerard (2011) found that international political events have more influence on bond yield spreads than domestic news events. The authors used Malaysian-issued US Dollar denominated bonds and US Treasury securities, as well as a series of domestic and international events in their study.

3.6 EMERGING MARKET BOND OR YIELD CURVE STUDIES

In investigating emerging market bond spreads and the effect of, or reaction to, macroeconomic news and policy announcements thereon, Ferrucci (2003) found no evidence that news announcements have systematic effects on the level of the international bond spreads for emerging market countries. However, the results showed that all of the analysed news announcements affected the volatility of bond prices. There was a lesser impact for countries with more transparent policies and higher credit ratings. Ferrucci (2003) used the country sub-indices of the Emerging Market Bond Index, which is calculated and provided by JP Morgan. The sub-index spreads were measured relative to US treasury bonds of similar duration. The main independent variables of this study included dummy variables for various types of macroeconomic or policy announcements taken from Bloomberg's calendar events (Andritzky et al., 2007).



South Africa is one of a handful of emerging economies that is able to borrow in local currency for long maturities at fixed or floating rates, both in the domestic market and in international markets (Eichengreen et al., 2003).

3.7 TERM STRUCTURE MODELS

Apparent from the consideration given to interest rates and yield curves, the construction of the yield curve, and therefore the interest rate model, is an essential part of this study. An interest rate model is defined as a probabilistic description of how interest rates can change over time. Many models have been developed and improved upon over the last few decades to describe the behaviour of interest rates in general, and the yield curve in particular, based on probability theory and stochastic processes (Audley et al., 2012). Interest rate models themselves have developed significantly from the initial models. The information provided in this study relates to interest rate models and it provides the background to the bootstrap (static) model used to derive the spot rate yield curve. The key difference between the interest rate models and the static model used is that, whereas interest rate models describe the evolution of interest rates over time, a bootstrap model provides an accurate reflection of the current observed yield curve in the market (Fabozzi, 2012).

In practice, market participants have access to a multitude of term structure models, ranging from static models (Nelson & Siegel, 1987), first generation dynamic models (Cox et al., 1985), to the second and third generation no-arbitrage models (LIBOR market models) (Musiela & Rutkowski, 1997). Most of these models use a specific set of variables as inputs and they produce a specific output (Cochrane & Piazzesi, 2005).

It is possible to classify term structure models in many different ways depending on the underlying assumptions, the number of factors that the model evaluates, and the ultimate purpose of the model. Dynamic models fall into two broad categories, namely equilibrium models and no-arbitrage models. Static models can use the same sub-classification, but it is immaterial this type of model as the model only depicts the current observed market at any given point in time.

The following sections provide an overview of the evolution of term structure models in academic literature.



3.7.1 Dynamic models

The dynamic class of term structure models describes the evolution of interest rates (specifically the short rate) through time. These models were developed using statistical and probabilistic approaches to solve the question of how interest rates can change over time (Joslin et al., 2011). The practical application of these models was to enable market practitioners to price derivative instruments. Dynamic models generally require calibration and they are computationally intensive (Bauer et al., 2012).

3.7.1.1 Equilibrium models

The equilibrium models use stochastic processes to model the term structure and the output of these models is the yield curve (Longstaff, 1989). Under the expectations theory the long-term rates are determined by the current and future short-term rates. So, if it is possible to find a mathematical description of the evolution of the short-term rates, we can use that information to forecast long-term rates (Diebold & Li, 2006; Marsh, 1980). The original one-factor models evolved by studying the statistical processes that short-term rates follow, based on the assumption that all other rates in the term structure are related to the short rates (Hull & White, 1993).

In the Rendleman and Bartter (1980) model the change in the short-term interest rate is reflected as the long-term trend in interest rates, plus a measure of volatility - or noise - was adjusted using a random variable. This model is not robust and does not provide for all of the permutations of the term structure.

According to Klebaner (2012) the Wiener process, also called Brownian motion, can be described as a type of Markov stochastic process. It is in essence a series of normally distributed random variables. For later points the variances of these variables increase, thereby demonstrating that it is more uncertain to predict the value of the process as time increases.

In the Vasicek (1977) model the concept of mean reversion is introduced. Despite the fact that it is a one-factor model, it is popular due to the simplicity and ease of implementation (Chiarella & Kwon, 2001) When the mean reversion term is introduced to the equation it is



possible to achieve negative interest rates in the Vasicek model. Although Vasicek (1977) entitled his paper 'An equilibrium characterisation of the term structure', he did not expressly make any assumptions to solve for the instantaneous short rate (Al-Saadony et al., 2013).

Interest rates, unlike other types of financial prices, cannot rise indefinitely, as at very high rates of interest all economic activity will slow down and will eventually cease. This will force interest rates lower, thereby stimulating economic activity. Similarly, interest rates do not usually go below zero, thus interest rates are limited to a range of values. Interest rates tend to revert to a long run average value (Schmidt, 1996).

In 1985 Cox, Ingersoll, and Ross introduced the CIR model to describe the evolution of interest rates. The CIR model is an extension of the Vasicek model, with the addition of the constraint that it is not possible for interest rates to go below zero (Cox et al., 1985).

It is important to note at this stage that, although these models were developed as single factor term structure models, they do not fit the yield curve well on an empirical basis. The parameters in the models can be adjusted or calibrated to roughly fit the current yield curve, but on an on-going basis over time these models are poor tools to use for forecasting interest rates (Rainer, 2009). For an interest rate model to accurately describe the evolution of interest rates over time the model must incorporate the statistical properties of the components of the interest rate market, such as the drift, the volatility and mean reversion qualities of interest rates (Andersen et al., 2004).

Whereas the equilibrium models use various parameters to estimate the yield curve, the noarbitrage class of models use the current yield curve as an input to derive a mathematical description of the yield curve.

3.7.1.2 No-arbitrage models

No-arbitrage models are constructed so that the value produced by the model is exactly consistent with the term structure observed in the market (Buraschi & Corielli, 2005). This is in contrast with equilibrium models, where the term structure evolves from a statistical process.



The Ho-Lee model uses a normal distribution to describe the evolution of the whole yield curve, thus it is easy to implement and calibrate to fit the exact price of bonds comprising the yield curve at any point in time. However, the model is neither mean reverting nor does it return only positive rates. It is therefore not widely used by practitioners to model the yield curve (Ho & Lee, 1986).

An early example of a model that allows for mean reversion and only positive rates is the Black-Derman-Toy (BDT) model, which was initially developed for use in the Goldman Sachs investment bank during the 1980s and was later published in 1990. The BDT model incorporates the mean-reverting characteristic of interest rates, as well as log-normal price changes (Black et al., 2018). The model assumes that the short rate follows a mean-reverting log-normal process and can easily be represented using a binomial tree.

The first Hull-White model, developed in 1990, was a one-factor model that described the evolution of the short rate in a normal probability distribution that can be transcribed to a lattice (Hull & White, 1990, 1996). The attractiveness of the Hull-White model is that it allows practitioners the ability to price interest rate derivative contracts analytically. In the two-factor form of the Hull-White model, the rate of the mean reversion of the short rate is governed to some extent by the volatility of the short rate (Hull & White, 1994).

3.7.2 Static models

There exists a class of interest rate models that complies with the criteria for both equilibrium and no-arbitrage models. These are so-called static yield curve models. The single purpose of static models is to capture all of the information contained in the term structure at a specific point in time as accurately, or as simply, as possible by using actual market data (Qizhi, 2009).

This class of model does not attempt to describe the evolution of rates over time. The focus is rather on fitting a spot rate model to the observed information available in the market. This stems from the requirement of market participants to have a single valuation framework for all instruments when fitting yield curves (Bolder, 2015).



3.7.2.1 Bootstrapping the zero-coupon rate curve

In the previous section an implicit assumption was made that the term structure of interest rates exists so that there is an infinite number of maturities of bonds. In this continuum, the zero-coupon curve can be represented by the function of the continuous variable *T*. However, in the markets there are only a finite number of discrete maturities available. The term bootstrap describes a self-contained process that is able to complete without external input (Hagan & West, 2008). This method of deriving the yield curve is based on the assumption that the theoretical price of a bond is equal to the sum of all the cash flows of the bond discounted at the zero-coupon rate for each flow. The yield curve is then derived by using the shortest known rate and discounting each successive cash flow at the calculated rate. This process does sometimes require that interest rates are interpolated, as the dates of the cash flows seldom correspond exactly (Hagan & West, 2007).

The bootstrap models (methodologies) described in this section all have in common that their objective is to theorise an empirical model of the yield curve that fits to the currently observed information available in the market. Ron (2000) stated that there is no unique solution for completing the term structure of the yield curve from a given set of rates. The problem of 'under-fitting' or 'over-fitting' a yield curve generally results from including too many instruments with similar maturities and different coupon structures, or including only instruments that mature at similar times. There are, however, some guidelines that can be used as criteria when discussing the efficacy of the constructed curve.

3.7.2.2 Nelson Siegel model

Nelson and Siegel (1987) described a parsimonious model for yield curves. They concluded that using a model that can fit various shapes of the yield curve (that has only three interest rate components and a decay factor) can predict the price of long-term Treasury bonds with 96% accuracy. The rationale for using this second order model is that it can adequately capture the relationship between yield and maturity without resorting to a model that requires more parameters. The authors' original objective was to develop a class of models that is motivated by, but not necessarily dependent on, the expectations theory of the term structure of interest rates.



Since its development the Nelson-Siegel (NS) model has been widely used by central bankers and market participants, due to the tractability and simplicity of the model. Svensson (1995) proposed that an additional term be added to the Nelson-Siegel model to increase the flexibility and to improve the fit of the NS curve, thus creating the Nelson-Siegel-Svensson model (NSS). Diebold and Li (2006) revisited the original Nelson-Siegel model and illustrated that the time-varying factors may be interpreted as factors that correspond to level, slope and curvature, and that these factors can normally be estimated with high efficiency. They suggested using the ten-year rate as the level, the ten-year rate minus the three-month rate as the slope, and the difference between these two rates and the two-year rate as the curvature parameters. However, in their work on calibrating the NSS parameters, Gilli et al. (2010) found that the estimated parameters (level, slope and yield) can be unstable, as these factors were not inputs to the model. However, they can be solved using linear equations. The NS model can become badly conditioned in certain ranges of the parameters (when the level and slope becomes roughly equal) thereby implying that many different values of the parameters will give similarly good fits for the curve.

3.7.2.3 Hagan West convex monotone model

As referenced by Ron (2000), there are many different models available to the practitioner to determine, or construct, the yield curve depending on the requirements that the practitioner has for the use of the curve. However, in almost all cases, the initial starting point for the construction of a yield curve, or application of a yield curve model, is the current (observed) interest rates in the market. It is important to explain the model used in this study to analyse the term structure of interest rates and how the yield curve, as well as specific points on the yield curve, can change over time.

Hagan and West (2007) were the first to promulgate the monotone convex model. They found that interpolation algorithms used in financial markets to construct yield curves suffered from problems: they posit unreasonable expectations, or are not even necessarily arbitrage free. Moreover, many methods resulted in hedging strategies that were not intuitively reasonable. The authors argued that the interpolation algorithm should be intimately connected to the bootstrap itself. Hagan and West (2007) introduced two new



interpolation methods, the monotone convex method and the minimal method, which they believed overcome many of the stated problems.

In the South African bond market (as in all other bond markets), two basic functions are used: a capitalisation function (future value) denoted as C(t,T), and a discount function (present value) denoted as Z(t,T), where t is the present time, and T the maturity date. It then follows that an investment I made today will have a future value of $I \times C(t,T)$, and that the present value of the investment can be calculated as $Z(t,T) \times I \times C(t,T) = I$. The condition that C(t,T) > 1 for T > t, seems rather obvious, but it will only hold true if interest rates are positive. The discount function and the capitalisation function are both equal to 1 if T = t, that is for an investment made today, maturing today, the maturity value of the investment is equal to the value invested. It can then be seen that Z(t,T) decreases in T as C(t,T) increases in T.

It appears as if there are interest rates observable in the market that could immediately provide us with the capitalisation function and discount function, but in fact, these zerocoupon bonds are rarely traded in the market. Thus, the continuum of these discount functions and capitalisation functions needs to be derived from the observed information using a bootstrapping process. The following relationships hold true for a continuously compounded risk-free rate r at time t for maturity at time T, denoted r(t,T):

$$C(t,T) = exp(r(t,T)(T-t))$$
 Eq 3-4

$$r(t,T) = \frac{1}{T-t} \ln C(t,T)$$
 Eq 3-5

$$Z(t,T) = exp(-r(t,T)(T-t))$$
 Eq 3-6

$$r(t,T) = -\frac{1}{T-t} \ln Z(t,T) \qquad \qquad \text{Eq 3-7}$$

Where, $r_i = r(t_i)$ for $1 \le i \le n$, and the rates $r_1, r_2, r_3, ..., r_n$ are known at the ordered times $t_1, t_2, t_3, ..., t_n$. As mentioned above, the discount function decreases in *T*. This argument is central to the monotone convex method, and although it appears to be obvious, this is not necessarily enforced in all bootstrapping methodologies. The forward rate is described as the rate that applies to an investment/borrowing made at time t_1 and maturing at time t_2 .

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This is denoted by $f(0; t_1, t_2)$ and the forward rate is expressed as a function of the rates as:

$$f(0; t_1, t_2) = \frac{r_2 t_2 - r_1 t_1}{t_2 - t_1}$$
$$= -\frac{\ln(Z(0, t_2)) - \ln(Z(0, t_1))}{t_2 - t_1}$$
Eq 3-8

If we denote the instantaneous forward rate of a tenor *t* as f(t), then $f(t) = \lim_{\epsilon \downarrow 0} f(0; t, t + \epsilon)$, for whichever *t* this limit exists. We then have:

$$f(t) = -\frac{d}{dt} \ln(Z(t))$$

= $\frac{d}{dt} r(t)t$
Eq 3-9

The advantage of the unameliorated monotone convex bootstrap algorithm is that the following criteria are met:

- (i) Forward rates calculated from the bootstrapped curve are positive;
- (ii) Forward rates are continuous;
- (iii) Interpolation is done on a maximum of three known points prior to and three known points after the interpolated point; and
- (iv) The bootstrapped forward curve is stable.

The ease of implementation, as well as the accuracy of this curve fitting model, makes the Hagan West convex monotone model the ideal choice for use in this study (Du Preez, 2012).

3.8 SUMMARY

In their article 'A history of interest rates' Stucki and Homer (1964) traced the evolution of interest rates from Mesopotamia in 3000 B.C. to the modern day. The evolution of interest rates and the study of the behaviour of interest rates has come a long way. Changes in



perception, economic realities, global circumstances and a myriad of other effects are reflected in the interest rates charged on loans and the interest rates earned on deposits. Different methodologies have been used to study the impact that various factors have on interest rates and on an economy, with varying degrees of accuracy and with different objectives in mind. There are a limited number of approaches that can be used to accurately reflect the effect of changes on interest rates, each of these with its own disadvantages and advantages. The methods identified in past studies are the following:

- (i) Measure the impact of new information on individual instruments.
- (ii) Observe the impact of new information on a constructed portfolio of instruments.
- (iii) Measure the effect of new information on a series of synthetically constructed constant maturity instruments.
- (iv)Analyse the impact of new information for specific points on the zero-coupon curve directly.

The term structure of interest rates has historically been used by academics, practitioners and spectators (sometimes each with their own interpretation of the concept) as a construct to describe the changes of interest rates over time. Although there are various term structure models, the final application of the information extracted from the term structure should dictate which specific model is used. Dynamic term structure models take as initial inputs the current market data and produce probabilistic models of how interest rates can change over time. Static models use stochastic processes to model the term structure and the output of these models is the yield curve.

Although the Hagan-West ameliorated monotone convex algorithm is not widely used in academia, it was used in this study due to its practical application and almost exact fit to observed data. This made the model an ideal choice for the purpose of bootstrapping a zero-coupon curve in an environment where there are significant gaps in the maturity structure of the bonds.



CHAPTER 4 LITERATURE REVIEW OF STUDIES THAT USED THE EVENT STUDY METHODOLOGY

4.1 INTRODUCTION

Originally applied in accounting and finance, the event study methodology expanded its application to almost all business disciplines including management, economics, marketing, information technology, law, political science, operations and supply chain management.

The literature in accounting and finance emphasises the statistical fundamentals and provides the guidelines for application in all other fields. This study falls within the finance and investment discipline. Therefore the focus of this literature review is on research pertaining to the field of financial markets and event studies, specifically emerging market event studies. Within the emerging market research, the emphasis is on interest rates or bond markets and the impact thereon of economic and political events.

This study analysed three major strands of literature.

First, literature was reviewed relating to the importance of relevant news that may have had an impact on sovereign bond prices. News is released daily from various sources for market participants to monitor. Headline news can be categorised into various different themes or classes that can explain price behaviour.

Second, literature on the South African sovereign bond markets was reviewed to identify studies that examined the impact of news in bond market interest rates.

Third, literature was reviewed to find reverse event studies, specifically those that linked headline news to changes in the sovereign bond zero-coupon yield curve.

4.2 IMPORTANCE OF EVENT STUDIES IN INVESTMENT MANAGEMENT

The event study methodology is a well-known research method and it is regularly used as an analytical tool in financial research (Fama, 1991). This method has become an important



part of finance studies and can be described as a simplistic method. The methodology has many variations, as well as special issues and applications (Peterson, 1989).

Event study methodology has an extensive history and this was proved by MacKinlay (1997), who found that event study methods were used in research as early as 1933, when Dolley (1933) examined stock price reactions to stock splits. There are several earlier studies similar to that of Dolley (1933) proving that this method of research has been used for several decades (Ashley, 1962; Barker, 1956). However, it was the two formative papers by Ball and Brown (1968) and Fama et al. (1969) that gave rise to the modern event study methodology that is known and used today (Corrado, 2011). These studies were ground-breaking and important in finance, as they implemented the market model patterned on the then recently developed Capital Asset Pricing Model (CAPM), which was created by Sharpe (1964).

Adding to the importance of using event studies as a statistical tool in finance were studies by Modigliani and Miller (1958) and Modigliani and Miller (1963). The authors conducted research in the field of corporate finance, specifically capital structure concerns and dividend policy. Fama et al. (1969) followed these studies with their event study of stock splits, thus paving the way for a large number of successive event studies in finance.

Burnwal and Rakshit (2019) studied the effect of stock split announcements on share price behaviour and the market liquidity of stocks of companies. In the case of stock splits, the effect (price change, change in volatility, volume or liquidity, as well as many more variables) that can be measured around the event provided insight with respect to corporate policy decisions. The usefulness of event studies in corporate finance stems from measuring the impact of the event around the event date (or time), which provides insight into how a firm's shareholders are affected by the corporate event (Kothari & Warner, 2007).

The importance of event studies in the field of corporate finance can also be seen in the large number of event studies in finance and management: corporate acquisitions (Cai et al., 2011; Cao et al., 2005; Chatterjee, 1986; Chatterjee et al., 1992; Seth, 1990; Shelton, 1988; Singh & Montgomery, 1987; Wan & Wong, 2009); control changes (Jarrell et al., 1988;



Jensen & Ruback, 1983; Jensen & Warner, 1988; Warner et al., 1988; Worrell et al., 1986); earnings announcements (Beaver, 1968) and corporate events(Beaver, 1968; Becher, 2009; Cai et al., 2011; Cao et al., 2005; Jensen & Ruback, 1983; Ritter, 1991; Wan & Wong, 2009; Warner et al., 1988; Worrell et al., 1986).

This large body of literature over several decades shows how important event studies are in financial economics. The application found its origin in considering the impact of different macroeconomic announcements (such as inflation, unemployment and industrial production) on stock prices (Mcqueen & Roley, 1993). Evidence from the literature confirms that macroeconomic news has substantial effects on stock prices and volatility (Fleming & Remolona, 1999a; Rossi, 1998).

Many different underlying assets have been analyzed through the lens of event study methodology. Regarding the use of event studies in stock splits and corporate finance, it is clear from the evidence that stock prices were the most popular asset class used in these studies (Armitage, 1995; Binder, 1998). Other asset classes have also been investigated, namely fixed income or bonds (Maul & Schiereck, 2016; Rossi, 1998), commodities (Roache & Rossi, 2010) and foreign exchange (Anderson et al., 2003; Ehrmann & Fratzscher, 2005; Galati & Ho, 2003). All of these studies examined certain events that may have had an impact on the performance of the underlying asset.

4.3 BASIC PREMISE OF THE EVENT STUDY METHODOLOGY

The basic methodological premise of the event study method is an empirical process that measures the impact of new information on the price of an asset (Dutta, 2014). Given the importance of event study methodology's key components, it is worth re-examining the literature already discussed in previous chapters.

4.3.1 Defining the event of interest

In terms of the discussion in 2.3., in this study the classification of the event of interest can broadly be defined as new relevant information that may be financially sensitive, consequently it may have an impact on the price of an asset (Von Groll et al., 2011). The



two central themes of interest in this study are macroeconomic and political news announcements, as discussed in 2.4. There are several studies on the financial impact of these two news categories, with different asset classes being investigated. For the purposes of reviewing the literature of event studies, the studies were grouped into specific events (as discussed in 4.4) as well as economy-wide events (as discussed in 4.5). Gürkaynak and Wright (2013) caution researchers on the choice of event, as the choice will have consequences for the length of the event window. They state that some events will require longer event windows, whereas global news will require shorter event windows to exclude confounding effects. The premise of event study involves linking the events to abnormal return behaviour. This leads to the next key component of event studies, namely the consideration given to the length of the event window.

4.3.2 Consideration of the length of the event window

Modern event studies can broadly be grouped into two types according to the length of the event window. Short-horizon event studies use a short sampling interval or event window, which is shorter than one year. Long-horizon event studies use a long sampling interval or event window of one year or longer (Kothari & Warner, 2007). Short-horizon event studies focus on the effect of an event on securities prices over a short time period around the event, such as a two day $(-t_1, t_0)$ period (Bonnier & Bruner, 1989; Lummer & McConnell, 1989) and a three day $-t_{1,}t_{1}$ period (Chen, 2013; DeFond & Zhang, 2009; Small et al., 2007). Kothari and Warner (2007) conducted a comprehensive survey of over 500 studies published in five of the top finance and accounting journals from 1974 to 2005. They found that the properties of the event studies reviewed were different depending on the time period and sample firm characteristics. They also established that, compared with short-term event studies, longterm event studies suffered from several limitations. Inferences from long-horizon tests require extreme caution, due to the lack of reliability of the method (Brown & Warner, 1980; Kothari & Warner, 1997). Evidence from event studies with a short-term event window produces statistically reliable results. Longer event windows may increase contagion (Pištora, 2014). Long-horizon event studies that cover months or years before or after an event date are also reported in several research papers, such as a 36-month window (Hertzel et al., 2002; Loughran & Ritter, 1995) and a 60-month window (Teoh et al., 1998a).



4.3.3 Appraisal of the impact of the event

For macroeconomic and political events of interest, studies using short-term event windows are the most appropriate, as the surprise of new information is quickly incorporated into the asset's prices around the event date. The impact of the event results is measured by calculating the abnormal return over the event window. Dutta (2014) assesses different parametric and nonparametric testing procedures for measuring short-run abnormal performance. They found that non-parametric tests are better for detecting short-run anomalies. The process of assessing the impact in a reverse event study is outlined in the research methodology section of CHAPTER 5.

Various models and methods for measuring abnormal performance in an event study have been promulgated in academic literature (Brown & Warner, 1985; MacKinlay, 1997).

4.4 FIRM-SPECIFIC EVENTS APPLIED IN EVENT STUDIES

A firm-specific event, such as company policy change announcement, can impact the value of the firm's equity or debt (Durnev et al., 2001). An event study can be a useful tool for measuring the impact of the firm-specific event. The impact of an event on the value of the equity (section 4.4.1.1 to 4.4.1.8) and the value of the debt (section 4.4.2.1 to 4.4.2.4) of a firm is discussed in greater detail below.

The next section structures the literature reviewed to support the importance of event study methodology in finance. For the purpose of this study, the researcher grouped event studies according to the definition of the event applied in the discipline of finance. The following section discusses firm-specific events and economy-wide events and how these events were analysed using the event study methodology to gain insight to asset price behaviour after such an event.

4.4.1 The value of a firm's share price given a firm-specific event

These types of news announcements are specific to the firm under analysis. They include events such as stock splits, dividend policy, merger announcements, acquisitions, earnings announcements, corporate control changes and Initial Public Offerings (IPOs) (MacKinlay,



1997). The effects of these firm-specific events on a company's share price are discussed in more detail below.

4.4.1.1 Stock split investigations

Stock split event studies analyse the effect of a stock split announcement on the stock price performance and liquidity of the shares. Studies after the seminal paper of Fama et al. (1969) relating to stock split investigations include those by Bar-Yosef and Brown (1977), Charest (1978) and Grinblatt et al. (1984). Copeland (1979) and Lamoureux and Poon (1987) studied liquidity changes following stock splits. A weakness of some of these earlier studies is that they did not control for the potential influence that other information at the time of the stock split event date may have had on the stock price, particularly when using long-horizon studies (Eckbo, 2008). In addition, these studies did not differentiate between the stock split announcing company and the control company. More recent event studies on stock splits and stock dividend announcements have addressed these weaknesses (Burnwal & Rakshit, 2019). Ikenberry et al. (1996) studied firms listed on the New York Stock Exchange (NYSE) and found that investors mostly under-react to split announcements and the highest excess performance was found in low book-to-market stocks. They further observed that firms splitting stock to very low prices generated a positive return in the short run after the announcement, but a negative return in the long run. Contrary to many stock split studies associated with the wealth effect of stock splits, a study by Mishra (2012) analysed the Indian stock market and found evidence of a negative effect on stock returns and a positive effect on liquidity.

4.4.1.2 Dividend policy

Dividend policy impacts the future performance of a firm and is of great importance (Miller & Modigliani, 1961). The importance of this firm-specific event is highlighted as a key objective in financial management. For a financial manager it is imperative to define the optimal dividend policy that will maximize shareholders wealth. An event study by Suwanna (2012) examined the effect of dividend announcements using a sample of 60 Thai companies listed on the Stock Exchange of Thailand. The study found a significant upward move in stock prices after a dividend announcement.



4.4.1.3 Merger announcements

Several event studies have been conducted on mergers and a partial list of early studies include Becher (2009), Eckbo (1983), Eckbo and Wier (1985), Fee and Thomas (2004), Lubatkin (1987), Shahrur (2005) and Stillman (1983). A recent study by Klein (2020) proved that there are still several benefits in using event studies to analyse the effects of mergers.

4.4.1.4 Acquisitions

The importance of event studies regarding corporate acquisitions is reflected in several event studies (Cai et al., 2011; Cao et al., 2005; Chatterjee, 1986; Chatterjee et al., 1992; Mulherin & Womack, 2015; Seth, 1990; Shelton, 1988; Singh & Montgomery, 1987; Wan & Wong, 2009).

Studies which concluded that acquisitions are wealth-reducing events for the acquirer include those by Lys and Vincent (1995) and Bruner (1999). Gregory (1997) concluded that the long-run post-acquisition performances of UK acquiring firms are significantly negative. Various studies were conducted on the impact of mergers and acquisitions on long-run company performance. Irani (2015) used an anticipation-adjusted event study method to investigate the consequences of early merger and acquisition anticipations on the outcome of a takeover. Agrawal and Mandelker (1990) conducted research on the effect of an announcement and completion of a takeover bid. They found that the role of institutional ownership in monitoring managers is important and observed negative effects of anti-takeover charter amendments on shareholders wealth.

4.4.1.5 Earnings announcements

One of the first studies on earnings announcements was by Beaver (1968) with the focus on the information value of the content of earnings announcements. Earnings management practices before IPO and seasoned equity offerings (SEO) includes a paper by Loughran and Ritter (1997) that examined pre-issue earnings management that explain the long-run under-performance of seasoned equity issues. There is also a negative relation between pre-issue discretionary current accruals and post-issue earnings and stock returns (Teoh et al., 1998b). Another paper by Teoh et al. (1998a) provides evidence that issues with



unusually high accruals in the IPO year experience poor stock return performance in the three years thereafter.

4.4.1.6 Corporate control changes

Studies investigating corporate control changes include those by (Jarrell et al., 1988; Jensen & Ruback, 1983; Jensen & Warner, 1988; Warner et al., 1988; Worrell et al., 1986).

4.4.1.7 Initial Public Offerings (IPOs)

Event study methodology was also extensively used in analysing the performance of initial public offerings (IPOs) and the effects they had on shareholders' wealth. Researchers used this methodology to analyse the long-run performance of IPOs in different countries. Ritter (1991) investigated the long-run performance of IPOs by using a sample of US firms. He found that IPO's appeared to be over-priced. Studies by Loughran and Ritter (1995); (Loughran & Ritter, 1997) concluded that IPOs and seasoned equity offerings (SEOs) were poor long-run investments for the period under investigation. An event study that investigated the characteristics of lock-in agreements in the UK on the behaviour of stock returns around the lock-in expiry dates found evidence of negative abnormal stock returns at and around lock-in expiry dates (Espenlaub et al., 2001). Australian studies provided further evidence on the poor long-run performance of IPOs (Das et al., 2016; Lee et al., 1996).

4.4.1.8 Other firm-specific events and firm value

Other firm-specific event studies include but are not limited to: obtaining new bank loans or loan renewals (Lummer & McConnell, 1989); selecting an auditor and determining if auditor reputation matters (Weber et al., 2008); an appointment of a new CEO with financial expertise (Defond et al., 2005); top executive changes (Bonnier & Bruner, 1989); sudden CEO vacancy and economic consequences (Lambertides, 2009); compensation plan policy (DeFusco et al., 1990); impact of name changes on company value (Mase, 2009); and advertising campaigns (Kim & Morris, 2003).



4.4.2 The value of a firm's debt and firm-specific events

Corporate bonds are used to finance companies through debt. The impact of events can have an effect on a firm's value, shareholders' wealth and bondholder's wealth. Maul and Schiereck (2016) conducted a comprehensive survey of corporate bond events. They found 118 research papers that applied event study methodology where bond instruments were used for analysis. Some of the key areas affecting a firm's value through debt are discussed in more detail below.

4.4.2.1 Ratings

The rating afforded to a firm's bonds is the principal source of information for investors regarding the relative quality and marketability of the firm's issues (Pinches & Singleton, 1978). As potential investments are assessed in terms of risk and reward, any changes to the risk profile of the issuer. or of the issue, will impact the price of the investment (Rego et al., 2009). Miyamoto (2016) found that the prices of stocks listed on the Tokyo Stock Market reacted to rumours (rather than to the actual change event) of rating changes in the debt issued by Japanese companies during the period 2001 to 2007. De Souza Murcia et al. (2013) analyzed the impact of the informational content of ratings announcements in the Brazilian economy and concluded that there were statistically significant abnormal returns, and that these returns were asymmetrical, with negative information having a greater effect than positive information on the price of the stock.

4.4.2.2 Debt issuance

Modigliani and Miller (1958) stated that the optimal corporate capital structure for a firm, in terms of the ratio of the debt to the equity of the firm, is one of the factors in determining the total market value of the firm. The studies performed in this area have had varied goals in mind. Kaur and Srivastava (2017) and Kapoor and Pope (1997) investigated the effects of the issuance of debt on the value of equity, whilst a study by Ivanov (2014) investigated the accuracy of the pricing of initial debt offerings. The perceived riskiness of the debt will influence the required return on the firm's equity. If the debt is considered risky, investors will require higher returns on the equity (Kapoor & Pope, 1997). Datta et al. (1997) observed that initial public offers of straight debt were under-priced when the debt was rated as



speculative grade, and over-priced when rated as investment grade. In analyzing the effect of bond issuance announcements on share price returns, M'ng et al. (2019) concluded that there is a significant effect on the share price resulting from the announcement of bond issuance. The authors analyzed the data of three Asian markets, namely Malaysia, Singapore and Thailand. Godlewski et al. (2011) concluded that there is a negative reaction in the stock markets when a company announces debt financing arrangements in the Russian market.

4.4.2.3 Mergers and acquisitions (M&As)

Mergers and acquisitions are described by Bruner (2004) as one of the most aggressive change-agents in the business economy. Simões et al. (2012) investigated the relationship between abnormal positive returns and the announcement of M&As. They observed that there is an effect, and interestingly this effect took place five days after the announcement in Chile and Argentina, and on the same day as the announcement in Brazil. This led the authors to conclude that the Brazilian market is more efficient. In their study on the effect of M&As in the Indian market Rani et al. (2015) found that share prices started to react prior to any announcement taking place (positive abnormal returns), and that after the announcement the market then corrected, thus negating the positive abnormal returns. An event study that analysed the wealth effects of M&A announcements in the Turkish financial markets found that there were significant positive abnormal returns after the announcement (Akben-Selcuk, 2015).

4.4.2.4 Leveraged buyout (LBO)

Many studies established that bondholders face a risk of loss in the event of an LBO (Asquith & Wizman, 1990; Billett et al., 2008; Crabbe, 1991; Warga & Welch, 1993). Baran and King (2010) confirmed that there is a transfer of wealth from bondholders to stockholders in their study of LBO transactions from 1981 to 2006. Okamoto et al. (2011) examined the price effects of event-risk protection using the LBO of Bell Canada Enterprises. They found that an exogenous shift in event-risk protection is priced by the market. Billett et al. (2008) found proof that change-in control covenants in bonds play an important role in the decision to undertake an LBO. They used a sample of 18 LBO deals and 49 bonds and observed



positive returns in response to change of control covenant protection bonds, as opposed to bonds without this protection.

4.5 ECONOMY-WIDE EVENTS APPLIED IN EVENT STUDIES

Economy-wide events are used in big sample event studies that examine the effect of a specific occurrence on security prices. These types of events include key macroeconomic announcements that are comprised of inflation, unemployment, interest rates, consumer confidence, retail sales, and economic growth. There are also other announcements that have a broader impact on securities, such as legal, regulatory, political or other events. The impact of these events can apply to different types of securities or asset classes (Dutta, 2014).

4.5.1 Macroeconomic announcements

Macroeconomic announcements include different variables that have an impact on security prices, such as news about the 'real' economy and also news about monetary policy (Beechey & Wright, 2009). Research studies that analysed three key economic variables (inflation, interest rates and GDP growth) using event study methodology are described and reviewed below.

4.5.1.1 Inflation

Inflation is one of the key variables in economics, and countries prefer to keep inflation at a stable low rate (Hummel, 2007). Event studies allow the researcher to measure the effect of inflation events on the prices of different securities. Different aspects of the impact of inflation can be studied using this method.

An event study by del Camino Torrecillas and Jareño (2013) concluded that the impact of inflation news on stock returns had a negative effect in the short term, but that the effect became positive in the long term.

Neumann and Von Hagen (2002) conducted an event study to determine the effectiveness of inflation targeting by studying inflation and interest rate performance both before and after



inflation targeting was introduced to the industrialised countries being studied. The events for their study included oil price shocks after 1978 and 1998. They found that inflation targeting proved to be a useful strategy for reducing the level and volatility of inflation. However, a study by Levin et al. (2004) which included emerging market countries found that, even though these countries achieved lower inflation by adopting inflation targeting, the volatility of inflation remained high due to the susceptibility of the countries to global economic fluctuations.

An event study by Jalil and Rua (2016) studied historical news announcements during the second quarter of 1933, when the recovery from the Great Depression started. They identified the key events that shifted inflation expectations in financial markets, which played a causal role in stimulating the economic recovery.

Gürkaynak et al. (2005) looked at the long-term forward interest rates' response to data releases and monetary policy surprises to see whether inflation expectations were anchored. Gürkaynak et al. (2006) continued the study with long-term forward interest rates and inflation and the impact of macroeconomic data releases and monetary policy announcements. They found that US long-term forward nominal interest rates and inflation compensation were significantly sensitive to data releases and policy announcements, whilst in Canada and Chile the long-term inflation expectations were less sensitive.

Inflation-linked bonds were introduced to the UK in the early 1980s and to the US in 1997. Inflation compensation gives a clear indication of long-term inflation expectations. This is a valuable tool for investors. Since the launch of these financial instruments there has been an increase in macroeconomic research and event studies that analysed inflation compensation (Gürkaynak, Levin, et al., 2010; Gürkaynak, Sack, et al., 2010). A related study for the Euro area was conducted using inflation swaps in the place of inflation compensation (Beechey et al., 2011).

4.5.1.2 Interest rates

Smirlock (1986) investigated the effect of inflation announcements on long-term interest rates in the US. He found that unexpected inflation increases had a positive effect on long-



term rates. Smirlock (1986) justified this phenomenon by reasoning that an unexpected inflation increase will ultimately increase long-term rates, as there will be a higher demand for borrowings, and consequently a higher cost of such borrowings. This finding was confirmed by Roley (1982b), Roley (1982a) and Cornell (1983). Strongin and Tarhan (1990) found that unanticipated variances in the money supply generated an interest rate response in the same direction. They reported that the effect can be observed for both short-term and long-term rates.

Hardouvelis (1988) analysed the response of interest rates (specifically the Fed Funds effective rate, three-month Treasury bill rate and the twenty-year Treasury bond rate) and foreign exchange rates to the new information contained in fifteen US macroeconomic news series. Although the result of this study confirms the study by Smirlock (1986) (for example: an unanticipated increase in money supply leads to an increase in interest rates and an appreciation of the Dollar), Hardouvelis (1988) did not use daily data. He recommended the use of intra-day data to accurately capture the effect of new information on a more granular basis.

Cook and Korn (1991) studied the relationship between the US employment report, the anticipation of new policy decisions resulting from the report, and interest rates in the United States. The US unemployment report contains three elements that are closely monitored by market participants: the non-farm payroll, the unemployment rate and the revision of the previous month's unemployment figure. The authors concluded that the strong reaction from the interest rate market to unexpected deviations from the anticipated unemployment numbers was due to the market anticipation of monetary policy changes as a result of the unexpected change in the unemployment numbers.

Several studies by Balduzzi et al. (1996) and Balduzzi et al. (1998) investigated the effects of economic news announcements on the prices, bid-ask spreads and trading volume of the three-month Treasury bill, two- and ten-year note, and the 30-year bond. They used high frequency trading data in their study and observed that the bid-ask spread widened immediately on release on the information, but then returned to normal levels within 5 to 15 minutes. The trading volume was significantly higher than during non-announcement times.



Regarding the price of the Treasury bill, ten of the economic variables had a significant effect on the prices of the notes and bonds, thereby confirming previous assumptions that longterm rates are more susceptible to economic surprises than short-term rates (Cornell, 1983; Dwyer & Hafer, 1989; Urich & Wachtel, 1981, 1984).

4.5.2 Other announcements

Although the effect of macroeconomic and political news announcements has been a primary study area, there are various event studies that investigated the effect of other variables.

4.5.2.1 Regulatory news announcements

Schipper and Thompson (1983) examined the economic impact of a group of merger-related regulatory changes in the US which occurred during 1966–1970. A study on the effects of new legislation was conducted in 1985 by Schumann (1988). He used the event study methodology to measure the net effect of two take-over statutes passed by the New York State legislature. Marshall and Anderson (2009) investigated the impact that stronger regulations had on take-over returns in New Zealand. New Zealand moved from a weak regulatory environment to one that is governed by prescriptive legislature. Paleari and Redondi (2005) used an event study and time-varying beta estimation to examine the impact of regulations on risk and return. More recently a study (that used a dataset of 17 different take-over laws and court decisions from 1965 through to 2014) measured the variation in take-over laws and their long-term impact on hostile activity over time (Cain et al., 2017).

4.5.2.2 Legal and governance changes

Studies that relate to corporate governance include one by Small et al. (2007) which examined the market reaction to congressional agreements on the passage of the Sarbanes-Oxley Act of 2002 (SOX) and found that as a firm's size increases the negative impact of the passage of SOX decreased. Other corporate governance event studies include, but are not limited to, governance and shareholder initiatives and shareholder wealth (Andres et al., 2007; Karpoff et al., 1996); firm value (Black & Khanna, 2007; Carter et al., 2003; Chhaochharia & Grinstein, 2007); acquirer returns (Masulis et al., 2007); insider



trading (Betzer & Theissen, 2009); dividend pay-out policy (Gugler & Yurtoglu, 2003); board effectiveness and independence (Gupta & Fields, 2009; John & Senbet, 1998); and information efficiency (Cai et al., 2006).

4.5.3 Political events

Political risk impacts global markets and such event risks have become important in recent research. It can be said that unexpected political events can create uncertainty and risk in economies (Snowberg et al., 2013). A socioeconomic study by Parker (Parker, 2007) found that there is a significant link between the social mood and trust in government for stock market participants but not for non-stock market investors. This suggests that public mood towards politics is a factor in investment decision making. Political events can be far reaching and this section of the literature review substantiates this statement. Many political event studies investigated stock markets within different countries.

Brooks et al. (1997) studied the effects of major political change on stock market volatility in South Africa using daily data from three key South African indices, namely the All Share Index, the Industrial Index and the Gold Index for a ten-year period (1986 to 1996).

Mei and Guo (2004) examined the impact of political uncertainty and election cycles on financial crises using a panel of 22 emerging markets. They concluded that these countries experienced economic turmoil and financial crises during periods of political election and government transition.

An event study on the Nepalese stock market found that unanticipated political events generated positive abnormal returns and that negative events resulted in negative abnormal returns during the post-event period (Dangol, 2008). Chan and Wei (1996) investigated the impact of political news on stock market volatility in Hong Kong using a sample of blue-chip and red-chip shares. They found that adverse political news resulted in negative returns for the blue-chip shares and that good political news led to positive returns. Contrary to the findings on the blue-chip shares, they observed that neither good nor bad political news had an impact on the red-chip shares. The authors concluded that red-chip stocks can be considered to be safe haven equity investments that will protect investors against political



uncertainties (Chan & Wei, 1996). Similar results were found in the Argentinian stock markets, where a study included the country's economic stewardship, national elections, rebellion, wars and terrorist attacks as political shocks in the event study (Carnahan & Saiegh, 2021). Zach (2003) studied the Israeli stock market and found that returns on the Tel Aviv Stock Exchange and dually-listed stocks (stocks traded in Israel as well as the US) were severely impacted following political events.

Leigh et al. (2003) studied the build up to the second US-Iraq war. They showed that every 10% increase in the probability of war led to a \$1 increase in the spot price of oil and the S&P dropped by 1.5%. The pending war between US and Afghanistan in early 2003 also led to lower stock prices and higher oil futures prices (Rigobon & Sack, 2005). Guidolin and La Ferrara (2007) studied the relationship between civil war and the value of firms in Angola and concluded that war may lead to higher stock prices due to conflict-generated entry barriers.

Investigating 13 different tweets, news and announcements relating to the US-China trade war for an event study on the Swedish Stock Market, Gappel and Erlandsson (2020) found that the stock market was not affected by these announcements, as only three of the 169 samples of stocks showed significant abnormal returns.

A short-window event study was used by Nisar and Yeung (2018) to explore the relationship between politics-related sentiments regarding a UK-based political event and the FTSE100 index. The study used a sample of over 60 000 tweets.

4.6 POLITICAL EVENT STUDIES THAT FOCUS ON BONDS IN EMERGING MARKETS

Fitzpatrick (1983) developed a conceptual framework to assess political risk in international businesses, the focus being on adverse government actions that can vary over time. Prior to the study the definition and assessment of political risk was uncoordinated due to the absence of a conceptual framework. This study drew together previous work as the initial step in creating the conceptual framework required for further studies.



There is a lack of event studies in the sphere of emerging market countries, especially with respect to bond markets and political news events. A few emerging markets studies that analysed the impact of macroeconomic news are discussed below. However, no political studies relevant to this research on bond markets in emerging markets could be found.

Vasishtha et al. (2006) used an event study to investigate the effect of fiscal and macroeconomic news on sovereign bond spreads, interest rates and exchange rates in three emerging market countries, namely Brazil, Poland and Turkey. They found that budget news had a substantial impact on country sovereign bond spreads and interest rates during weak economic periods.

A key research paper is that by Andritzky et al. (2007) which used an event study to investigate the impact of macroeconomic announcements on emerging market bonds. The authors found that individual domestic data and policy announcements had systematic influences on international bond spreads for emerging market countries. They concluded that volatility increases if a policy announcement is unclear and is open to alternative interpretations, which signals additional risk to investors. Another key finding was that such announcements are of less importance for countries with more transparent policies and higher credit ratings.

Pištora (2014) conducted a series of event studies using macroeconomic surprises. He studied the impact on Czech, Polish and Hungarian government bonds and sovereign credit default swaps. He found that daily changes in bond spreads are driven by inflation shocks. The study also showed that volatility is impacted by both good and bad news.

Bekaert et al. (2014) derived a political risk measure from the sovereign yield spreads within an event study framework. They considered the impact of global economic conditions, country-specific economic factors, liquidity of bonds within the country and political risk. In their study a political risk spread was extracted using political risk ratings.



4.7 REVERSE EVENT STUDIES

When one compares the traditional event study approach to the reverse event study approach, the method can be described as one where the starting point is abnormal returns. The end point links the specific event to such a return, as opposed to specifying a list of dates *a priori* and then testing for their significance. One allows the data to identify the important dates and then links the news categories to such dates.

The reverse event study method was recently developed, thus there are few research papers available on this methodology. This method has mostly been applied in the field of finance.

Ellison and Mullin (2001) studied the effect of President Clinton's health care reform proposal on declining pharmaceutical stock prices. Using isotonic regression they found that most of the decline occurred gradually. Similarly, (Hilliard et al., 2018) studied the market impact of a US supreme court ruling regarding the Patient Protection and Affordable Care Act. Bech and Lengwiler (2012) examined the changing dynamics of the yield curve with respect to the financial crisis during 1998 to 2011.

Kugler and Weder di Mauro (2009) used a reverse event approach to investigate defined large currency appreciations and then observed patterns that could possibly be matched to significant geopolitical events. Janner and Schmidt (2015) used reverse event study methodology to test the association between bond prices and corporate news announcements for firms listed in the prime segment of the German stock market. Janner and Schmidt (2015) is the closest research related to this investigation, in that it used a similar methodology to that employed in this study on the impact of news on corporate bond markets. Janner and Schmidt (2015)described the quantitative news content analysis as a linguistic classification algorithm that assigns each announcement to a specific news category. This approach allowed the researchers to draw comparisons with respect to size and time of impact. The researchers firstly determined the economically significant returns (ESAR's) and then matched the bond data with the event data. The reverse event study method was used by Willard et al. (1995) to relate significant changes in the unit price of gold expressed in Greenbacks to important events during the American Civil War.



4.8 SUMMARY

Gürkaynak and Wright (2013) stated that event studies can solve many questions in finance. There are numerous variations of the event study methodology, but all event studies follow a basic method of identifying the event(s) of interest, determining the event window around the event date and then appraising the abnormal returns after news releases relating to the event(s) of interest. The influx of new information in the public domain causes a reaction. In some cases this reaction can be an over- or under-reaction if the news is unanticipated. This is explained by the risk of the uncertainty regarding the future impact of such information on the price of the asset. The literature reviewed shows that the event study methodology has been widely used with success.

In a strong form efficient market, the classical EMH dictates that the market will react to new information (almost instantaneously and uniformly) and that the asset will then trade at or near a new level. However, this theory is not supported by the studies investigated, which show that there are information asymmetries, under- and over-reactions, as well as longer term effects on asset prices that the EMH in its strong form does not allow for. Thus, the semi-strong form of the EMH appears to be a more appropriate theory for explaining and understanding the empirical realities reflected in the studies.

The literature review on event studies shows that there are few studies that used the reverse event study methodology to identify specific dates of interest and then to subsequently link these event dates back to headline news categories.



CHAPTER 5 RESEARCH METHOD

5.1 INTRODUCTION

The purpose of this study was to link the impact of specific identifiable news events to explicit changes in the sovereign bond yield curve through observation of the zero-coupon yield curve. The impact of the identified news events on the sovereign bond yield curve was quantified by applying the reverse event study method.

This chapter describes the research design, methods and data properties for the analysis. The chapter has four main sections. The first outlines the research hypotheses that relate to the literature and research objectives; the second describes the data and data properties; the third addresses the data analyses within the broad framework of the reverse event study methodology; and the fourth and final section explains the statistical analyses of the identified abnormal returns. The statistical hypotheses are formulated in the broad framework of the reverse event study methodology and they are linked back to the research hypotheses. The chapter concludes with a discussion of the quality and rigour of the research methodology and design, which is followed by a statement on the research ethics applied in this study.

5.2 RESEARCH HYPOTHESES

The research null hypotheses are formulated to answer the research problem based on the research objectives and literature review.

The sovereign bond yield curve is regarded as the domestic interest rate risk-free curve. As such, it is used for the pricing, valuation and risk determination of financial instruments, or derivatives thereof, that are dependent on a benchmark interest rate. As increased volatility is generally an indication of increased risks, analysing yield curve returns and volatility can provide key information on the efficiency and transparency of the bond market. This leads to the first research hypothesis:

1. There are no significant abnormal bond returns associated with periods of increased volatility in the sample period.



The sovereign bond yield curve represents the collective sum of all information available across all levels relating to the sovereign issuer. Any changes in this body of knowledge are reflected in price level changes on the sovereign bond yield curve. The types of information that lead to bigger changes in returns are studied and analysed. This forms the basis of the second research hypothesis:

2. Abnormal government bond returns cannot be associated with specific news categories.

Not all news elicits equal responses from investors across all maturities. The extent of the change in the sovereign bond yield curve, and indeed the specific tenor that is affected by the news, is influenced by the type of news being released. This leads to the third research hypothesis:

3. There is no difference in abnormal government bond returns for headline news releases across the different news categories.

In line with the above hypothesis, changes in bond returns are not necessarily symmetrical. For each node of the zero-coupon yield curve the upward change in the yield or decrease in the yield indicates the reaction of the financial markets to news. The strength of the reaction to certain news types can be seen as the difference between the abnormal increases in the yield and the abnormal decreases in the yield, which leads to the fourth research hypothesis:

4. There are no differences between abnormal increases and abnormal decreases in yields for each of the nodes.

Changes in the sovereign bond spread are important for international investors in South African sovereign bonds. The sovereign bond spread is a reflection of the perceived sovereign risk of the issuer compared to the US government. News announcements are likely to change the risk perception. This leads to the fifth research hypothesis:



5. Specific abnormal event dates do not have an impact on the term structure of the South African sovereign bond spread.

The semi-strong form of EMH asserts that the efficiency of a security's price changes is a reflection of publicly available material information. The reaction of the South African sovereign spread to new information within one business day leads to the sixth research hypothesis:

6. The South African sovereign bond spread does not react quickly and efficiently to new information.

The above research hypotheses were tested using different statistical hypotheses and statistical tests, as described in this chapter.

5.3 DATA

Selecting a sample that best represents the population being studied is necessary to make inferences on the population (Wagner et al., 2012). The data in this section include two types namely, the data relating to the instruments used in the construction of the zero-coupon yield curve and the headline news announcements.

5.3.1 Target population

The data target population comprises all sovereign debt issued by the South African government and all headline news relating to South Africa.

5.3.1.1 Government bonds

The target population of sovereign debt issued by the South African government can be separated into domestically issued bonds (ZAR denominated debt) and internationally issued bonds (denominated in other currencies). Only domestically issued government bonds, listed and included in the GOVI Bond Index, were considered as inputs to the study.



Table 5-1 shows the fixed-coupon sovereign bonds that were issued by the South African government and were listed on the JSE during the time period under review.

Table 5-1

Target population of South African sovereign bonds

RIC Code	Name	Coupon	Maturity date
ZAR206=	R206	7.50%	15 January 2014
ZAR201=	R201	8.75%	21 December 2014
ZAR203=	R203	8.25%	15 September 2017
ZAR204=	R204	8%	21 December 2018
ZAR207=	R207	7.25%	15 January 2020
ZAR208=	R208	6.75%	31 March 2021
ZAR212=	2.75 ILB 31JAN22	2.75%	31 January 2022
ZAR2023=	R2023	7.75%	28 February 2023
ZAR197=	5.5 ILB 07DEC23	5.50%	07 December 2023
ZAI2025=	2 ILB 31JAN25	2%	31 January 2025
ZAR186=	R186	10.50%	21 December 2026
ZAR210=	2.6 ILB 31MAR28	2.60%	31 March 2028
ZAI2029=	1.88 ILB 31MAR29	1.88%	31 March 2029
ZAR2030=	R2030	8%	31 January 2030
ZAR213=	R213	7%	28 February 2031
ZAR2032=	R2032	8.25%	31 March 2032
ZAI2033=	1.88 ILB 28FEB33	1.88%	28 February 2033
ZAR202=	3.45 ILB 7DEC33	3.45%	07 December 2033
ZAR2035=	R2035	8.88%	28 February 2035
ZAR209=	R209	6.25%	31 March2036
ZAR2037=	R2037	8.50%	31 January 2037
ZAI2038=	2.25 ILB 31JAN38	2.25%	31 January 2038
ZAR2040=	R2040	9%	31 January 2040
ZAR214=	R214	6.50%	28 February 2041
ZAR2044=	R2044	8.75%	31 January 2044
ZAI2046=	2.5 ILB 31MAR46	2.50%	31 March 2046
ZAR2048=	R2048	8.75%	28 February 2048
ZAI2050=	2.5 ILB 31DEC50	2.50%	31 December 2050

Source: RefinitivEikon (2020)

Note. A complete list of South African sovereign bonds in issuance during the sample period 1 January 2010 to 31 December 2019.

5.3.1.2 Short-term interest rates

The population for short-term interest rates comprises exchange quoted, OTC quoted and on-screen displayed rates for periods shorter than one year. The time periods range from the overnight rate (the SABOR as quoted on the SARB website), the overnight rate (ON) (JIBAR as quoted on the JSE website), to the overnight FX rate, which is implied by the FX ON swaps quoted interbank and traded through the EBS system. Several rates can be observed for each specific tenure. These are quoted by market participants of different credit



quality and are offered on different products. Only observable and on-screen quoted or displayed rates were considered for inclusion in the study.

5.3.1.3 News announcements

The target population comprises all daily headline news announcements relating to South Africa from 1 January 2010 to 1 January 2020. All news wires related to real time news were included.

5.3.1.4 US Government bonds

The US government issues benchmark bonds on a regular basis depending on the tenor being issued. The shorter maturities (2-, 5-, 7-year notes) are issued monthly, whereas the longer maturities (10- and 20-year bonds) are issued quarterly in the February to November cycle. The new issue for every tenor is referred to as the on-the-run issue. These bonds are more liquid and trade at a premium to the off-the-run bonds. The availability of a large number of bonds with regular maturities provided the opportunity to create several yield curves for any specific date, which were similar, but that may have had small differences. This was as a result of the choice of bonds included in the bootstrap. To pre-empt any discrepancies being introduced, the par yield curve rates for constant maturity points (as published by the official US Treasury) were used as the US government sovereign par yield curve.

5.3.2 Sampling instruments

Selecting a sample is the process of obtaining information about a target population by examining only a part of it. It is important that the sample is without any bias and that it is representative of the target population's characteristics so that it may provide reliable results.

5.3.2.1 Government bonds

The sample of government bonds used in the study was selected from all listed fixed-coupon government bonds during the period 2010 to 2020 (provided in Table 5-2). The sample included in the FTSE/JSE government bond index (GOVI), as these bonds are considered



to be domestic benchmark bonds. That means that some of the bonds initially selected matured during the period under review. Such bonds were excluded on maturity and new bonds were included in the sample as the GOVI index rebalanced based on the underlying constituents.

Table 5-2

Government bonds selected for inclusion in the curve

RIC Code	Name	Coupon	Maturity date
ZAR206=	R206	7.50%	21 January 2014
ZAR203=	R203	8.25%	15 September 2017
ZAR207=	R207	7.25%	15 January 2020
ZAR208=	R208	6.75%	31 March 2021
ZAR186=	R186	10.50%	21 December 2026
ZAR213=	R213	7.00%	28 February 2031
ZAR209=	R209	6.25%	31 March 2036
ZAR2040=	R2040	9.00%	21 January 2040
ZAR2048=	R2048	8.75%	28 February 2048
0 0 0 0			

Source: RefinitivEikon (2020)

On any one day of calculating the zero-coupon yield curve a total sample of between five and nine bonds from Table 5-2, the SABOR, and the 3-month and 6-month JIBAR were included. These bond YTMs were used as raw data inputs in the zero-coupon rate model to construct the daily zero-coupon rate yield curve over a ten-year period. The derivation of a zero-coupon yield curve was discussed in section 3.7.2.1. However, the selection of bonds for inclusion in the bootstrap was based on the following factors:

- Liquidity in the specific issue at time of inclusion. Bonds that were included in the GOVI bond index are more liquid than bonds that are not in the GOVI index.
- Amount in issuance at the time of inclusion. As referenced in section 3.3, the full
 outstanding amount of a specific bond is not necessarily issued on the first issue date
 of the bond, but rather, issues are tapped throughout the tenor of the bond. Thus, the
 issued amount for a specific bond will generally increase over time.
- Maturity structure of the bonds selected for inclusion. Ideally, bonds included in the bootstrap would be equally spaced over the term for which the zero-coupon curve was derived. However, this was not always possible, and thus bonds were also selected on the maturity structure of the bonds. Bonds that had a maturity of less than one-year at the end of the calculation period were excluded from the bootstrap.



• The close YTM value of each of the bonds used as input to the bootstrap was used to calculate the zero-coupon rates.

5.3.2.2 News announcements

The news data consisted of daily news announcements relating to South Africa from 1 January 2010 to 31 December 2019. The news search functionality included in the Reuters system allows users to filter news headlines based on relevancy using the data provider's news monitor function. The filters used are:

South Africa [ZA] AND Economic Indicators; AND Economic News AND Monetary/Fiscal News; AND Central Bank news; NOT Commentaries; NOT Sport.

All available news providers and sources that produced relevant news headlines were included, as it was imperative that all headline news announcements relating to South Africa, both domestic and international, were included in the sample of news during the event window.

The following news sources available in Reuters' news monitor function were included in the sample of headline news announcements:

- 1. News wires that relate to real time financial news
- 2. Global press that contains over 6000 publications and more than a 20-year history
- 3. Web news that contains news from global websites
- 4. Breaking news alerts
- 5. Research
- 6. Filings
- 7. Transcripts
- 8. Press releases

The headlines were exported as raw data and comprise the sample used in the headline news classification.



5.3.2.3 US government bond yield curve

The instruments used for the US government bond yield curve were the constant maturity par yield curve points, based on the closing market bid prices on the most recently auctioned US Treasury securities in the US OTC market. The bootstrap method used to derive the par yield curve is a monotone convex method, and the points published are the constant maturity points for maturities specified by the US Treasury.

5.3.3 Units of analysis

The study aimed to investigate the association between abnormal price returns of the South African government bond yield curve and headline news categories. The study's units of analysis relate to the zero-coupon yield curve derived from the South African government bonds and the spread of the zero-coupon yield curve nodes relative to the US government bond yield curve nodes. For news, all headline news released daily during the 10-year sample period were included as units of analysis of the study.

5.3.3.1 Government bonds

The static term structure model of Hagan and West (2008), namely the unameliorated monotone convex bootstrap method, was used to construct the zero-coupon spot rate curve for each given set of bond yields for all specified dates.

Hagan and West (2007) introduced the monotone convex method of interpolation. This was one of the first models specifically designed to interpolate and bootstrap the yield curve simultaneously. According to Du Preez (2012), the Hagan-West bootstrap model is considered the best fit model for accuracy in the South African context. The Hagan-West monotone convex bootstrap algorithm fits a curve to any number of nodes, provided that the inputs to the algorithm are continuously compounded zero-coupon rates. These rates are not directly observable in the markets. They need to be derived from the current YTMs (trading yields) of the bonds that are quoted in the markets. The process of the bootstrap method is discussed next.



This study used the closing yields on every trading day of the specific sample of bonds as the raw inputs for the bootstrap model. The zero-coupon input rates were derived by following the logical development that the quoted price of the bond in the market is the sum of the discounted coupon flows and the discounted value of the final redemption value using the quoted yield as discount rate. As can be seen in Eq 5-1, the spot rates $Z(t, t_i)$ were required to determine the price. However, the spot rates represent the information the researcher was trying to extract from the bond price. This can be simplified to the present value of an annuity certain, plus the present value of the final redemption value and can mathematically be written as:

$$[\mathbb{A}]Z(t, t_{ssd}) = \sum_{i=0}^{N} p_i Z(t, t_i)$$
 Eq 5-1

Where for each bond,

[A] ssd	= =	rounded price of the bond the standard settlement period for bonds
p_0	=	$e\frac{c}{2}$, where $e = 1$ or 0, i. e. cum or ex next coupon
p_i	=	$\frac{c}{2}$, where $0 < i \le N-1$
p_N	=	$1 + \frac{c}{2}$
Ν	=	The number of coupon payments left
t_i	=	The number of coupon payments left date of the coupon flow <i>i</i>
		zero coupon rate from t to t_i

Hagan and West (2008) proposed that a model be imposed on the bond price. Such a model can determine the spot rate for the maturity date of the bond by using an iterative process. This process converges after 10-20 iterations and the spot rates for the nodes (nodes are initially set as the maturity dates for the bonds included in the bootstrap) are thus derived as inputs for the monotone convex algorithm. The model imposed makes r_N the zero-coupon risk-free rate for the specific bond used in the calculation, the subject of the equation:



$$r(t_N) = -\frac{1}{T_N} \left[\ln \left([\mathbb{A}] Z(t, t_{ssd}) - \sum_{i=0}^{N-1} p_i Z(t, t_i) \right) - \ln p_N \right]$$
 Eq 5-2

Where for each bond,

$r(t_N) T_N [A] ssd$	= = =	the risk-free rate for the period t_N time to maturity for the bond rounded price of the bond the standard settlement period for bonds
p_0	=	$e\frac{c}{2}$, where $e = 1$ or 0, i. e. cum or ex next coupon
p_i	=	$\frac{c}{2}$, where $0 < i \le N-1$
p_N	=	$1 + \frac{c}{2}$
	= = =	The number of coupon payments left date of the coupon flow i zero coupon rate from t to t_i

As first guess in this iteration process it is suggested that the YTM of the bond is used.

The bootstrap process proceeds as follows:

- i. Select the bonds to be included in the bootstrap.
- ii. Create a first provisional curve by estimating the zero-coupon rates for each node point (i.e. first guess of the $r(t_N)$ for each bond to be used in the bootstrap). The input required is a continuously compounded spot rate.
- iii. Using the estimates provided in step ii, use the interpolator algorithm and find the first estimated curve.
- iv. Using the results of the estimated curve, test to see if the prices of the bonds used as inputs to the bootstrap process' can be recovered from the derived zero-coupon curve. If not, then use the latest results as the next step in the iteration to derive the next estimated curve. Continue this process until the prices for the input bonds can be exactly recovered from the fitted curve.

Once a zero-coupon curve was generated for each day of the study period, the same method was used to interpolate specific constant maturity points. The constant maturity points are



referred to as the nodes of interest in this study. These were selected based on the Basel Committee on Banking Supervision's (BIS, 2016) recommendation of time buckets. The nodes of interest were determined at liquid tenor points to analyse interest rate risk. The study used the standardised approach of 19 buckets, as shown in Table 5-3.

Table 5-3

The maturity schedule with 19-time buckets for notional repricing cash flows repricing at t^{CF}.

	Time bucke	t intervals (N	I: months; Y:	years)				
Short- term rates	Overnight (0.0028Y)	O/N< <i>t^{CF}</i> ≦1M (0.0417Y)	1M< t ^{CF} ≦3M (0.1667Y)	3M< <i>t^{CF} ≦6M</i> (0.375Y)	6M< t ^{CF} ≦9M (0.625Y)	9M< t ^{CF} ≦1Y (0.875Y)	1Y< t ^{CF} ≦1.5Y (1.25Y)	1.5Y< <i>t</i> CF ≦2Y (1.75Y)
Medium- term rates	2Y< t ^{CF} ≦3Y (2.5Y)	3Y< <i>t</i> CF ≦4Y (3.5Y)	4Y < <i>t^{CF}</i> ≦ 5Y (4.5Y)	5Y< <i>t^{CF}</i> ≦6Y (5.5Y)	6Y< <i>t^{CF}</i> ≦7Y (6.5Y)			
Long- term rates	7Y< <i>t</i> CF ≦8Y (7.5Y)	8Y < t ^{CF} ≦ 9Y (8.5Y)	9Y < t ^{CF} ≦ 10Y (9.5Y)	10Y< <i>t</i> CF ≦ 15Y (12.5Y)	15Y< <i>t</i> CF ≦ 20Y (17.5Y)	t ^{CF} > 20Y (25Y)		

Note. The number in brackets is the time bucket's midpoint

The units of analysis were the zero-coupon node points, selected from the points in Table 5-3, namely the overnight; 3-month; 6-month; 1-year; 2-year; 5-year; 10-year; 15-year and 20-year points.

5.3.3.2 News announcements

For the units of analysis all of the headline news announcements released during the sample period were used.

5.3.3.3 US government bond yield curve

The specific US Treasury par yields gathered from the US Treasury website and used in this study were the 1-month, 3-month, 6-month, 1-year, 2-year, 5-year, 10-year and 20-year constant maturity par yields.



5.3.4 Units of observation

The units of observation were the actual datasets used in the statistical data analysis. The final dataset consisted of the abnormal event dates, changes in zero-coupon yield (expressed as daily return rate) for the event dates, the corresponding basis point change (the basis points were deemed to be more logical from a market perspective) and the categorised event window headline news.

5.3.4.1 Government bonds

The units of observation relating to the government bonds were the daily returns of the zerocoupon yields at the specified nodes.

5.3.4.2 News announcements

For the units of observation, only the headline news announcements released during the event window were used to identify the news categories that related to abnormal return event dates.

5.3.4.3 South African sovereign spread

The units of observation for the sovereign spread were the differences between the derived South African zero-coupon yields on the nodes and the US government bond curve on the nodes.

5.3.5 Strength and weaknesses of the data

Measurement bias can be caused by the distortion of data and changes in the way the data is collected (Saunders et al., 2009). However, it is noted that the continuity of the companies that provide data is dependent on their credibility and therefore their collection methods are considered to be accurate and credible. It can therefore be assumed that the sources used by the researcher to obtain data for this study were free from bias, as the data providers are reputable international financial data providers.



The strength of the news and South African yield data was dependent mainly on the news and price data tool collection instruments. Refinitiv Financial Solutions (Refinitiv) was used to source the news and South African yield data. US government par yield curve rates were sourced directly from the official website of the US Department of the Treasury. Therefore, the reliability and strength of the collected data were dependent on the strength of Refinitiv. Refinitiv is a reliable and reputable American-British global provider of financial market data and financial information that provides data obtained from more than 2 000 global sources, thus ensuring that the timeliest and most accurate price data is reflected. The news announcements were distributed via the newswire, thereby ensuring a real-time database. The information was released as the events arose.

Secondary data, namely the bond closing yield data, and the headline news items that were collected from Refinitiv, and the US government par yield curve rates data, were collected over the same sample period.

5.3.6 Data collection

Deciding on the source from which to collect data is an important first step in the research process, as validity and reliability of the database from which the data are obtained influences the study's credibility (Wagner et al., 2012). In the following section the data collection tools used in this study are described.

5.3.6.1 Data collection resources

Refinitiv was used as the main data collection tool for both the South African bond yields and news items. The data used were the daily historical yield data price quotes and news announcements provided through Eikon newswire services by Refinitiv. Refinitiv provides a set of software products through the Eikon interface that can be customised by users. Thomas Reuters launched Eikon in 2010 as a replacement for Reuters 3000 Xstra, which was Reuter's previous electronic trading platform. In 2018 Thomson Reuters sold a 55% stake of its financial and risk business to Blackstone, after which the division was rebranded as Refinitiv. The name 'Refinitiv' was born out of the combination between the 160-year-old Reuters brand and the new business objective to enable 'definitive' action in financial



markets. Refinitiv has a global reach providing information, data, insights and technology that assists clients in decision-making with respect to investing, trading and risk management.

Thomson Reuters still maintains ownership of the Reuters news division and Refinitiv pays an annual fee to retain access to the Reuters newswire services. Thomson Reuters is a chief international provider of news data on a wide range of topics, such as economics, finance, politics and technology. The news available from Reuters is sourced from more than 2 600 full-time journalists over 200 bureaus. The news sources include the global press, newswires and web-based news, including that of Reuters' major rival Bloomberg. The use of Refinitiv enabled the collection of financial market-related news that covered the entire spectrum of South African news due to the underlying extensive network of journalists and news sources. Thomson Reuters' articles are time-stamped with the date and time of the news event release. This was a critical feature as it enabled each event's date and time to be documented for validating the yield reaction to the news event.

US par bond yield data was sourced from the official website of the US Department of the Treasury. This website is used by a multitude of practitioners and researchers across the globe. The data can be downloaded as a daily time-series from 1990.

5.3.7 Data characteristics

For this study a set of nine nodes was selected from the zero-coupon yield curve to represent the South African sovereign yield curve, namely the overnight, 3-month, 6-month, 1-year, 2-year, 5-year, 10-year, 15-year and 20-year zero-rates over a ten-year sample period from 1 January 2010 to 31 December 2019.

An exploratory analysis of the data was important as a starting point for the complete analysis. The natural log of the daily zero-rate returns was used for the analysis:



$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right)$$
 Eq 5-3

Where:

 P_t = zero-coupon rate at time t

 P_{t-1} = zero-coupon rate at time t - 1

The continuously compounded daily return series comprises 2 497 observations. One observation was lost due to differencing the zero-coupon rates.

The descriptive statistics of the daily return rates for all the nodes were calculated to provide insight regarding the data's characteristics.

The Shapiro-Wilk test for normality was performed to test if the data could be described as a sample from a normal distribution. The Shapiro-Wilk test is one of several normality tests available. The equation for the test statistic of the Shapiro-Wilk test is:

$$W = \frac{\left(\sum_{i=1}^{n} a_{i} x_{(i)}\right)^{2}}{\sum_{i=1}^{n} (x_{i} - \overline{x})^{2}}$$
 Eq 5-4

Where:

 $x_{(i)}$ = is the *i*th smallest number in the sample

 \bar{x} = is the mean of the sample

$$a_i = \frac{m^T V^{-1}}{C}$$

 $C = ||V^{-1}m|| = (m^T V^{-1} V^{-1}m)^2$

The cut-off values for the test statistic W are determined using a Monte Carlo simulation. The hypothesis tests for the Shapiro-Wilk are:

H₀: The test population is normally distributed H₁: The test population is not normally distributed

The null hypothesis can be accepted if the *p*-value of the test is higher than 0.05, and the null hypothesis can be rejected if the *p*-value is lower than .05.



5.4 OUTLINE OF REVERSE EVENT STUDY FRAMEWORK

Event studies can be designed and applied to reflect specific research questions (Ederington et al., 2015b). The broad outline of the reverse event study methodology framework was followed to achieve the objectives set out in this study.

The research philosophy that is most appropriate for this study is positivism. Positivism is a philosophical line of thought that seeks to establish cause and effect relationships by obtaining objective knowledge about a subject matter (Ponterotto, 2005). This knowledge can be reduced to empirical indicators which can be explained using a logical analysis (Sale et al., 2002).

This study is premised on the fact that there is an objective reality that enables the possibility of obtaining results on the variables the study aims to examine. In addition, positivism is appropriate to quantitative studies, because it deals with scientific methods of handling the data which are independent of any researcher (Bahari, 2010). This aligns with the ontological position of quantitative studies, namely there is only one truth: an objective reality that exists independent of human perception (Sale et al., 2002).

Positivism is appropriate for this study due to the study's quantitative nature, which uses scientific data analysis methods, and the fact that the researcher is independent of the study. This study seeks to establish the effect that market news has on Bitcoin prices and therefore aligns with the philosophical assumptions of positivism.

The basic methodological premise of an event study and a reverse event study is an empirical process that measures the impact of new information on the price of an asset (Dutta, 2014). The underlying assumption of the event study methodology is based on the EMH theory, in that the market processes information in an efficient manner and it can be assumed that the effects of an event will immediately be reflected in the price of an underlying security. This allows the researcher to observe the economic effects of an event over a relatively short period of time (Bowman, 1983). Conversely, when a period of abnormal volatility is observed there must have been new information that was being assimilated by the market (Pynnönen, 2005). The reverse event study allows the researcher



to analyse all news releases simultaneously during the event window. The reverse event study approach assigns news announcements to abnormal returns. This study applied a similar method of the reverse event study approach used by Janner and Schmidt (2015) on the German corporate bond market.

Outline of the reverse event study analysis used in the study:

- 1. Determine the abnormal return event dates
 - a. Data distributional properties:
 - i. Investigation of stationarity of the time series
 - ii. Investigation of mean of the time series (constant or non-constant)
 - iii. Determination of ARIMA order (p, d, q) for the time series
 - iv. Investigation of the non-constant volatility of the time series
 - v. GARCH models applied
 - vi. Assumptions and use of statistical distributions employed in GARCH models applied
 - b. Determine points of excess or unexplained volatility using GARCH models
 - i. Use autoregressive models to identify the abnormal return dates
 - 1. GARCH (1, 1)
 - 2. EGARCH (1, 1)
 - 3. GJR-GARCH (1, 1)
 - c. From the conditional volatility forecasts, and by using the Chebyshev inequality, construct two bands of two conditional standard deviations around the mean (one for positive changes and one for negative changes) to identify the respective abnormal return dates
- 2. Actual returns of abnormal event dates expressed as basis points
- 3. Use abnormal basis points and match abnormal event dates to event window news classification
 - i. Define the event window
 - ii. Identify and categorise news events using supervised text classification
 - iii. Manual relevance and reliability check of headline news data
- 4. Quantify the impact of the news on the rates
 - i. Link the abnormal returns to the classified news categories



- 5. Analyse the impact of the identified event
 - i. Use multiple linear regression with forward selection to determine which categories are significant indicators of abnormal returns.

5.5 ABNORMAL RETURNS

5.5.1 Abnormal return event dates: Comparison of econometric models to determine abnormal returns

As described by Kothari and Warner (2007) there have been new developments in the event study methodology regarding the estimation of abnormal returns and statistical significance testing. Several recent event studies address the issue of autoregressive conditionally heteroskedastic effects (ARCH) of the residuals persistent after models have been fit to financial time series data and have applied GARCH models to address this problem (Brockett et al., 1999; Cam & Ramiah, 2012; Sabet et al., 2012).

In line with the main objective of this study, the impact of news on the South African yield curve was analysed using the broad framework of the reverse event study methodology. The researcher used three econometric models namely, the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, as introduced by Engle (1982); the Exponential GARCH (EGARCH) model by Nelson and Cao (1992); and the Glosten, Jagannathan and Runkle (GJR-GARCH) model introduced by Glosten et al. (1993). These models were used to estimate the volatility embedded in the South African yield curve over a ten-year sample period from 1 January 2010 to 31 December 2019. The natural logs of the daily zero-rate returns were used as inputs for the analysis. The models allowed the researcher to relate the modelled volatilities back to the daily return data to determine abnormal returns during the sample period, and thereby identify the news that may have contributed to the abnormal return behaviour (reverse event-study). This was done by assessing and studying the news around the identified abnormal event data points.

5.5.1.1 Investigating time series data for stationarity

Before fitting any of the GARCH models, the daily returns for the nodes were imported as time series data into R, and an exploratory investigation was made into the data distributional properties as the starting point for the analysis.



The first step was to determine suitable parameter sets for the econometric models by testing for stationarity. Non stationarity of the time series data complicates the usage of the GARCH models, therefore stationary data is preferred. Stationary time series data has the following characteristics:

- The mean of the series is constant, and not a function of time
- The covariance of the i^{th} and $(i+m)^{\text{th}}$ term is not a function of time (autocorrelation)
 - If autocorrelation is present determine an appropriate autoregressive or moving average model
- The variance is not a function of time.

A way to objectively determine stationarity is to conduct an Augmented Dickey and Fuller (ADF) unit root test. In the ADF test the null hypothesis is that there is a unit root present in the time series, which implies that the data series is non-stationary. The alternative hypothesis is stationarity. If the null hypothesis is rejected then the data series is stationary. If the *p*-value > .05, then accept the null hypothesis, data has a unit root and is non-stationary. If the *p*-value \leq .05 then reject the null hypothesis, data does not have a unit root and is stationary.

H₀: A unit root is present in an autoregressive time series (non-stationarity).H₁: A unit root is not present in an autoregressive time series (stationarity).

ADF test equation:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \cdots$$
 Eq 5-5

Where:

Δy_t	=	the change in the observed variable
y_{t-1}	=	the observed variable at time $t-1$
$\alpha + \beta t$	=	parameters of linear regression of Δy_t against t
γ	=	the test variable, test if $-1 < 1 + \gamma < 1$
δ_i	=	the lag(s) specified

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5.5.1.2 Investigating the data for constant mean

Stationarity of time series should be verified (Divisekara et al., 2020). The Kwiatkowski– Phillips–Schmidt–Shin (KPSS) test gauges if the data is stationary around a mean (stochastic) or linear trend (deterministic), or is non-stationary due to a unit root. The test statistic is given by:

$$k_0 = \frac{T^{-2} \sum_{t=1}^{T} S_t^2}{T^{-1} \sum_{t=1}^{T} e_t^2}$$
 Eq 5-6

Where:

 $k_0 =$ the KPSS test statistic $e_t^2 =$ square of the residuals of the regression $S_t^2 =$ long run variance of the time series

The hypothesis tested can be formulated as: H₀: Series is level (or trend) stationary or has no unit root H₁: Series is non-stationary or has unit root

The null hypothesis can be rejected if the test statistic is greater than the critical value which is taken from the KPSS table found in (Kwiatkowski et al., 1992) and the *p*-value is less than alpha (5%).

5.5.1.3 Test for autocorrelation

In another government bond study (Subhani et al., 2009) investigated the ACF and PACF plots for autocorrelation. A time series is a sequence of measurements of the same variable(s) made over time. It is helpful to uncover patterns in the data to select the correct model for analysis. By looking at the Autocorrelation Function (ACF) plot as well as the associated statistical significance at every lag, the ACF plot gives a visual pattern of the data to determine if there is autocorrelation in the data or the extent to which previous observations influence current observations. The ACF plot is therefore a bar chart of the serial correlation in data that changes over time. The Partial Autocorrelation Function



(PACF) plot is a plot of the partial serial correlation coefficients between the time series and lags of itself.

The equation used to calculate the ACF is given by:

$$\rho(k) = \frac{\widehat{Cov}(y_t, y_{t-j})}{\widehat{Var}(y_t)}$$

$$= \frac{\frac{1}{n-k} \sum_{t=k+1}^n (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \bar{y})^2}}$$
Eq 5-7

Where:

 $\rho(k) = autocorrelation$ $\bar{y} = the mean of the time series ([<math>\bar{y} = E[y_t]$) $\gamma_t = observation at time t$

The equation used to calculate the PACF is given by:

$$\widehat{\phi_{hh}} = corr(y_{t+h} - \hat{y}_{t+h}, y_t - \hat{y}_t), \quad h \ge 2$$
 Eq 5-8

Where:

 $\widehat{\phi_{hh}}$ = the partial autocorrelation for *h* lags

 γ_{t+h} = observation at time t+h

5.5.1.4 Investigating the data for constant variance (homoskedasticity vs heteroskedasticity)

To detect heteroskedasticity in the data the researcher referred to the ACF plots of the squared returns. If the ACF plot for returns and squared returns indicate a high level of autocorrelation that does not decrease over time the time series exhibits non-constant



volatility or heteroskedasticity. For a stationary time series, the ACF will drop to zero relatively quickly, while the ACF of non-stationary data decreases slowly.

The ARCH test is used to test for dynamics of the second moment effects. Financial time series data generally have periods of relatively low volatility and periods or clusters of high volatility. The Engle (1982) ARCH-Lagrange Multiplier test (ARCH-LM) was performed as an additional test to the ACF plots. The ARCH-LM test is the standard test to detect autoregressive conditional heteroskedasticity. If the test results show that the residuals are heteroskedastic then the squared residuals are autocorrelated.

H₀: There is no existing ARCH up to the order q in the residuals (Homoskedastic). H₁: There is existing ARCH up to the order q in the residuals (Heteroskedastic).

ARCH-LM equation:

$$\hat{e}_t^2 = \gamma_0 + \gamma_1 \hat{e}_{t-1}^2 + v_t$$
 Eq 5-9

Where:

 \hat{e}_t^2 = squared residuals \hat{e}_{t-1}^2 = squared residuals lagged v_t = white noise error process

Under the null hypothesis a large test statistic and a small *p*-value is indicative of a rejection of the null hypothesis, in favour of the alternative hypothesis. Thus, a *p*-value larger than the alpha level of 5% would be a failure to reject the null hypothesis.

5.5.1.5 Determination of the most appropriate autoregressive integrated moving average model (ARIMA)

Given the outcome from the investigation of the stationarity of the data, an autoregressive integrated moving average model (ARIMA) was run in the statistical programme R (Hyndman et al., 2020; Hyndman & Khandakar, 2008). The function used a combination of unit root tests, minimization of the Akaike Information Criterion (AIC), Bayesian Information



Criterion (BIC) and Maximum Log Likelihood Estimation (MLE) to obtain the most appropriate ARIMA model to fit to the data.

The determination of the ARIMA order p, d, q for the time series data was essential before fitting an econometric model, where p is given as the autoregressive component, d is seen as the order of differencing required, and q is a moving average component. The general ARIMA (p, d, q) model is then given by:

$$\phi_p(B)(1-B)^d Y_t = \Theta_q(B)\epsilon_t \qquad \qquad \text{Eq 5-10}$$

Where:

B = backshift operator where $By_t = y_{t-1}$ ϕ_p = Lag order *p*

 ϵ_t = residuals (assumed to follow a normal distribution)

The Box-Ljung statistical test was a further validation of the ARIMA models used and tests were performed on the residuals of the ARIMA suggestions for each time series associated with a given node.

The Box-Ljung Q-Statistic equation:

$$Q(k) = n(n+2) \sum_{m=1}^{k} (\hat{\rho}_m^2 / (n-m)), m = 1,2,3 \dots$$
 Eq 5-11

Where:

Q(k) = test statistic n = number of observations in the series $\hat{\rho}_m$ = estimated autocorrelation at lag m; m = 1,2,3...kk = lag; k = 1,2,3...

Under the null hypothesis a large test statistic and a small *p*-value is indicative of a rejection of the null hypothesis, in favour of the alternative hypothesis.

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H₀: There residuals are independently distributed

H₁: The residuals are not independently distributed; exhibit serial correlation

5.5.1.6 Description of the GARCH models

Bollerslev (1986) introduced the GARCH models with the aim of capturing leptokurtic returns and volatility clustering. Despite the success of GARCH models, these models have been criticized for failing to capture the leverage effect present in squared residuals (Liu & Hung, 2010). The limitation of the standard (symmetrical) GARCH is that the conditional variance is a function only of the magnitudes of the lagged mean corrected returns. This limitation is overcome by introducing more flexible volatility modelling by accommodating the asymmetric responses of volatility to positive and negative mean corrected returns. This more recent class of asymmetric GARCH models includes the Exponential GARCH (EGARCH) model and GJR-GARCH model. The data used in these models are predifferenced (the price change is considered rather than the yield). Thus, the *d*-term in the ARIMA models is completed prior to using the data as input for the GARCH models. The R package Rugarch was used to fit the GARCH models (Ghalanos, 2020).

5.5.1.6.1 The GARCH (*p*, *q*) model (sGARCH)

The GARCH (1, 1) model specification is given by:

$$y_{t+1} = \mu_{t+1} + \epsilon_{t+1} \qquad \qquad \text{Eq 5-12}$$

$$\epsilon_{t+1} = z_{t+1} \sqrt{\sigma_{t+1}^2} \qquad \qquad \text{Eq 5-13}$$

$$\sigma_{t+1}^2 = \omega + \alpha_1 \epsilon_t^2 + \beta_1 \sigma_t^2$$
 Eq 5-14

Where:

 y_{t+1} = value of the time series variable at time t + 1

 μ_{t+1} = mean of the variable at time t + 1

 ϵ_{t+1} = value of the residual at time t+1

- z_{t+1} = random value from the specified distribution
- σ_{t+1}^2 = variance of the time series variable at time t + 1

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- ω = constant parameter
- α_1 = GARCH reaction parameter
- β_1 = GARCH persistence parameter

In Eq 5-14 the variance is written as a function of exogenous variables with an error term, where the error term follows a predetermined distribution that is specified when the model is fitted. As σ_{t+1}^2 is the one-period ahead forecast variance it is conditioned on previous information. Each successive variance is dependent on the previous conditional variances, but independent of the conditional mean. The conditional variance equation as specified in Eq 5-14 is a function of three terms namely:

- A constant term ω .
- Information about volatility from the previous period, measured as the lag of the squared residual from the mean equation ϵ_{t-1}^2 (the ARCH term).
- Last period's forecast variance σ_{t-1}^2 (the GARCH term).

The use of a GARCH model to model the variance in the daily returns allows for the inclusion of a moving average component in the model, which allows modelling the conditional change in the variance over time as well as changes in time dependent variance. The (p, q) in GARCH (p, q) refers to the number of lag variances to include in the model (the first term in parentheses) and the number of lag residual errors to include in the model (the second term in parentheses).

This specification is often interpreted in a financial context, where an agent or trader predicts this period's variance by forming a weighted average of a long-term average (the constant), the forecasted variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the asset return was unexpectedly large in either the upward or the downward direction, then the trader will increase the estimate of the variance for the next period. This model is also consistent with the volatility clustering often seen in financial returns data, where large changes in returns are likely to be followed by further large changes.

There are two equivalent representations of the variance equation that can assist in interpreting the model:



If there is a recursive substitution for the lagged variance on the right-hand side of Eq 5-14, then the conditional variance can be expressed as a weighted average of all of the lagged squared residuals:

$$\sigma_t^2 = \frac{\omega}{(1-\beta)} + \alpha \sum_{j=1}^{\infty} \beta^{j-1} \times \epsilon_{t-j}^2$$
 Eq 5-15

5.5.1.6.2 The EGARCH model (eGARCH)

The exponential GARCH model (EGARCH) was proposed by Nelson (1991). The specification for the conditional variance is given by:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{\epsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}}$$
 Eq 5-16

Where:

y_k	=	the size effect at time k
ϵ_{t+1}	=	value of the residual at time $t + 1$
σ_{t-j}^2	=	variance of the time series variable at time $t - j$
ω	=	constant parameter
α_i	=	coefficient that captures the sign effect
β_i	=	deterministic parameter

The log of the conditional variance implies that the leverage effect is exponential (rather than quadratic) and forecasts of the conditional variance are guaranteed to be non-negative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$, the impact is asymmetric if $\gamma_i \neq 0$.



5.5.1.6.3 The GJR GARCH model (gjrGARCH)

The Glosten et al. (1993) threshold GARCH or TGARCH model specifies the conditional variance by:

$$\sigma_t^2 = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \epsilon_{t-i}^2 + \sum_{k=1}^r \gamma_k \epsilon_{t-k}^2 \Gamma_{t-k}$$
 Eq 5-17

 $\Gamma_t = 1$ if $\epsilon_t < 0$ and 0 otherwise.

Where:

\mathcal{Y}_k	=	leverage term at time <i>k</i>
ϵ_{t+1}	=	value of the residual at time $t + 1$
σ_{t-j}^2	=	variance of the time series variable at time $t - j$
ω	=	constant parameter
α1	=	GARCH reaction parameter for AR = p
β_j	=	deterministic parameter for observation <i>j</i>
γ_k	=	leverage term, the extent to which variance is influenced by type of innovation

In this model, sudden increases in the underlying series, $\epsilon_{t-i} > 0$, and sudden decreases, $\epsilon_{t-i} < 0$, have differential effects on the conditional variance; upward changes have an impact of α_i and decreases have an impact of $\alpha_i + \gamma_i$, if $\gamma_i > 0$, decreases in the underlying series increases volatility, and there is a leverage effect for the *i*-th order. If $\gamma_i \neq 0$, the influx of new information is asymmetric.

5.5.1.7 Statistical distributions employed in the GARCH models

To specify the appropriate GARCH model to fit to the data, the conditional distribution of the error term (residuals) ϵ_t must be specified. To this end the nine distributions in Table 5-4 were investigated for each of the nodes (time series) and the most appropriate distribution model for each specific node was then used in the analysis.



Table 5-4

Distributions for the residuals term in the GARCH model

Distribution	Parameters
Normal distribution	Mean and variance (μ, σ^2)
Skewed normal distribution	Location, scale and shape (ξ, ω, α)
Student's t-distribution	Degrees of freedom (v)
Skewed Student's t-distribution	Location, scale and shape (ξ, ω, α)
Generalized error distribution	Location, variance and shape (μ, σ^2, B)
Skewed generalized error distribution	Location scale and shape (ξ, ω, α)
Normal inverse gaussian distribution	Location, scale, asymmetry and tail $(\mu, \delta, \beta, \alpha)$
Generalized hyperbolic distribution	Asymmetry, scale, location $(\lambda, \alpha, \beta, \delta, \mu)$
Johnsons SU distribution	$(\gamma,\xi,\delta>0,\lambda>0)$

Note. Distributions available for application for use in the GARCH models offered by the statistical package. Distributions were fitted individually and assessed for suitability.

As the impact of an incorrect distribution could be that the residuals of the GARCH model exhibit excess kurtosis and skewness, all the distributions were fitted on all the nodes so that the optimum distribution for each node could be determined. The information criterion provides a measure of the balance between the goodness of fit and the parsimonious specification of the model fitted. For any collection of similar models, the model with the lower criterion and least number of parameters was preferred. The decision regarding which distribution to use for each node was based on the following information criteria.

(i) Akaike information criterion (AIC or Akaike)

The AIC estimates the quality of the fit of statistical models to data by assessing the prediction error. It produces a value that can be consistently interpreted across models. The lower the AIC value, the better the model.

(ii) Bayesian information criterion (BIC)

BIC is similar to the AIC in that the criterion assesses the likelihood function. In the BIC it is acknowledged that the likelihood can be increased by simply adding more parameters, but that this will result in overfitting. The BIC introduces a penalty term for increasing the number of parameters. Similar to the AIC, a model with a lower value of the BIC is preferable.

(iii) Hannan-Quinn information criterion

The Hannan-Quinn information criterion assess the order of an autoregression based on the law of iterated logarithm. In this case the penalty function decreases fast if the estimator is consistent and as the size of the sample increases.



5.5.1.8 Identification of the abnormal return dates

As abnormal returns will by definition be returns that have an excessive return when scaled relative to normal returns, these returns can be readily identified by visually inspecting a plot of the returns. The Chebyshev theorem in Eq 5-20 states that for any numerical data set at least 75% of the data will lie within two standard deviations from the mean (Clements et al., 2012; Saw et al., 1984). The equation for the theorem is given by:

$$P(|X - \mu| \ge k\sigma) \le \frac{1}{k^2}$$
 Eq 5-18

Where:

 μ = the mean of the distribution σ = the standard deviation of the distribution k = a constant, where k>1

The bounds imposed by the Chebyshev theorem are quite loose. However, for the purpose of identifying possible abnormal returns, the methodology is sufficient to produce workable results. The abnormal returns will almost certainly form part of the data that falls outside of the two standard deviations bound, and as the returns are both positive and negative, a two standard deviation band is placed both above and below the mean. Therefore, a minimum of 75% of data will lie within the two standard deviation bounds. Thus, points outside of these bounds can be seen as abnormal return points (dates). The dates that coincide with these excessive return points were then extracted and used as inputs to the next step in the process.

The date identification process was applied using all three econometric models namely, GARCH, EGARCH and GJR-GARCH. The results of all of the models were combined per node (time series). Once the abnormal returns for positive and negative changes in the returns per node were extracted, the positive returns for all nodes were combined (the same process was followed for the negative returns, and all the unique dates for all nodes from all of the models for the returns were identified.



5.5.2 Determination of abnormal returns

After the abnormal return dates were identified using the three GARCH-models, each date represented an abnormal return movement in the daily return of the node on that specific date. As the daily return values were very small and thus cumbersome to display, the daily returns were expressed as basis points, and these basis points were used in the subsequent analysis.

5.5.2.1 Abnormal return basis points

The abnormal return basis points were calculated as the absolute difference between the zero-coupon yield for each node on the abnormal return date and the zero-coupon yield for the same node on the prior trading date, multiplied by a factor of 10 000. A basis point therefore represents a change of 0.01% change in the zero-coupon yield for the node. As shown in Eq 5-21.

$$BPS = (ZCY_t - ZCY_{t-1}) \times 10\ 000$$
 Eq 5-19

Where:

 ZCY_t = Zero-coupon yield on event date

 ZCY_{t-1} = Zero-coupon yield on business day prior to event date

5.5.2.2 Defining the event window for news

Fleming and Remolona (1999a) asserted that nnews, and particularly surprise news announcements, have an immediate impact on treasury yields. This statement supported the researcher's decision to implement a short event window. The researcher had to identify the event window for news released around the event date. As the bond data collected reflected the closing yield-to-maturity, news that was released after closing time, or even very close to closing time, was only reflected in the market YTM on the following trading day. The event window must of necessity therefore, at the very least, be two days. This study implemented a three-day event window (T_{-1} , T_0 , T_{+1}) of trading dates. All headline news released during the event window was analysed and categorised. The three-day event



window comprised the trading day before (T_{-1}) the event date, (T_0) and (T_{+1}) the trading day after the event.

To be able to include news that was released on non-trading days (over weekends or during public holidays) these announcements were allocated to the first trading day after the release date. The determination of the event time window was consistent with other bond market studies. More specifically, it was the same time period as that used in the study on bond markets using bond yields by Ederington et al. (2015a).

5.6 TEXT ANALYSES AND NEWS CLASSIFICATION

The main purpose of classification is to break a subject into smaller, more manageable and specific parts. Smaller subcategories help us make sense of the information. In this study a series of news events, or information, from various sources was organized and divided into groups of related topics, namely specific news categories. Being able to organize and systematize information is valuable in so many ways. It also provides an efficient structure for reviewing information from general to specific topics (Borko, 1962).

In traditional event studies the event date is defined *ex-ante* as the date of the announcement of the pre-determined event, described as day T_0 and the date is known at the outset. Johnston (2007) states that identifying the content of the news released on the event date is important because the content is unknown to the market, this new information may or may not have an impact on asset prices. As many news items are released on a daily basis by different news sources, investors and issuers are interested in understanding which of these news articles may affect the prices of government bond yields. For this study, given the large number of news items that were released daily during the ten-year period reviewed, the researcher used another approach to determine the association between different news categories and abnormal government bond returns. This study followed a similar approach to that of Janner and Schmidt (2015) who used a reverse event study to identify the abnormal returns. They then linked the different news categories to the identified abnormal return event dates. In this study the researcher examined the links between abnormal price changes in the South African yield curve and headline news categories. A positive



change in the yield is the result of negative perceptions of the news by market participants and vice versa.

News released in the form of headline news was identified and then grouped into different categories. The taxonomy developed was represented as a network of related concepts or categories of headline news. Each category used specific keywords relevant to that category to define the category (Mellouli et al., 2010).

5.6.1 Pre-classification

The algorithms used in the analysis were supervised machine-learning algorithms. Thus, these models required a training set to be calibrated and then applied the knowledge gained from the training set to the test set. To provide a training set, the news headlines had to be pre-classified. For the pre-classification nine categories were identified for the analysis, of which only seven (namely economic, emerging markets, political, international, currency, credit and commodity news) categories were used in the final analysis. The other two categories used were 'other' and 'unclassified', where the headline could not be classified into one of the seven other categories by the machine-learning algorithm. The pre-classification procedure used a Naïve Bayes classification model, coupled with unique keywords, or key phrases, to allocate headline news items to a category.

The Naïve Bayes classifiers do not represent one single algorithm, but rather a family of algorithms that share a common principle. The Naïve Bayes classifiers assume that each feature or variable (or keyword) in a class (or news category) is independent of other features in the same class, and that all features are equal in their contribution to the outcome. Thus, no keyword is more important than any other keyword and the probability of getting a keyword in any article is the same for all keywords in a class. The Naïve Bayes classifier is applied by extracting the so-called tokens (stem words) for each word in an announcement and assigning a unique integer ID to each token. The token integer IDs for the keywords are then compared to the token IDs of the announcement. The announcement is then assigned to the class with the most keyword token IDs in the announcement. Several studies have applied the Naïve Bayes classifier method to headline news (Takahashi et al., 2007; Wongsap et al., 2018) In the pre-classification phase, where ties are encountered, the announcements are manually reviewed and assigned to the most appropriate category.



This initial allocation was used as the basis for the document term matrix (corpus) training set, to which the supervised machine-learning algorithms were applied. The same seven themes constituting the classes of the taxonomy used for the pre-classification were used. The importance and relevance of each category was:

- South African economic headline news
 Words used for the categorisation of economic headline news included words relating to economic variables and concepts, e.g., CPI, PPI, GDP, etc.
- South African political headline news
 Words used for the categorisation of political headline news included words relating to statements made by political figures at the time and politically related words, e.g., minister, strikes, etc.
- iii. South African sovereign credit rating news
 Words relating to credit rating headline news announcements made by rating agencies, e.g., Moody's, Fitch, etc.
- iv. International news references to South Africa
 Words relating to international headline news that referenced South Africa and other international occurrences that related to events in South Africa.
- Emerging market news
 Words relating to emerging market headline news that were relevant to or had an impact on South Africa.
- vi. Commodities news Words that related to commodities and commodity headline news in South Africa.
- *vii.* South African Rand currency news.Words that related to news regarding the South African currency, namely the Rand.
- viii. Other news
 News relating to companies and other entities that was not considered relevant and did not have an influence on the South African government bond markets.
- ix. Unclassified news

News that was not categorised under any of the specified categories automatically formed part of the unclassified news category. The unclassified news was also considered to be irrelevant with no influence on the South African government bond markets.



5.6.2 Supervised machine-learning for text classification

The process of hand-labelling text has been applied successfully in the social sciences fields, thereby assisting researchers to find and classify the answers to many different questions (Baumgartner et al., 2012; Jones et al., 2009). This process, also known as manual coding, when used with large volumes of text data can become extremely time consuming. For this reason researchers have started using machine-learning algorithms for text analysis and coding. Machine learning provides the researcher with a tool for systematically and efficiently coding and examining text. RTextTools is widely used as a statistical software and data analysis tool that provides a start-to-finish product for conducting supervised machine learning with textual data. It offers a complete package for text classification by interfacing with existing text pre-processing routines and machine-learning algorithms and analytics functions (Jurka et al., 2013).

5.6.2.1 Five-step process for news classification as performed in RTextTools

The core functionalities of the RTextTools statistical program are explained in this section.

5.6.2.1.1 Creating a document-term matrix

The document-term matrix is the input required by the statistical package, RTextTools. The raw text input is then changed so that the text is broken down into tokens, which are used as matrix entries, similar to the process described in the pre-classification procedure (see 5.6.1). In the matrix each headline news item represents a row in the matrix and the column entries for each row are the individual words or tokens. The document-term matrix records a count of the occurrence of each of the terms in the original text. The corpus, which comprises the headline news data that is loaded to create the document-term matrix, consists of the raw news data and the pre-classification results.

The functionality of the document-term matrix allows for the pre-processing of text in the corpus. This pre-processing process assists with the supervised machine learning, where words are reduced to their stem and punctuation, as well as general English stop words (such as prepositions, pronouns and conjunctions) are removed. The pre-processing of the



text is necessary, as it reduces the number of terms and it also simplifies the terms used in the classification algorithms.

5.6.2.1.2 Creating a container

The document-term matrix is then passed to a container that partitions the matrix and performs functions required by the statistical package. The container is a simple wrapper function that uses the document-term matrix as input and then applies certain functions so that the text is parsed to a list of objects that will be provided to the machine-learning algorithms. The matrix container separates the data into train and test sparse matrices, corresponding to vectors of train (the manual pre-classification codes), test classification codes and a character vector of term label names. The functions that the container accepts are the machine-learning algorithm models used to analyse the data. These models are described next.

5.6.2.1.3 Training models

The training model function takes each algorithm and uses the algorithm to classify the headline news. For the purpose of creating a training set, the first 50 000 news announcements were used to train the machine-learning algorithms. The following three algorithms were applied in this study:

- Support Vector Machine (Meyer et al., 2014)
 - SVM is a linear model for classification that uses supervised machine-learning. The basic premise is that the algorithm separates data by finding points equidistant from an initial separation line. These points are referred to as the vectors, and by changing the slope of the line, the classification is completed when the fitted line has a slope so that all of the points are approximately the same distance from the separation line (the hyperplane).
- Scale linear discriminant analysis (Peters et al., 2012)
 - The SLDA algorithm maximizes the distance between the means of the different classes, whilst simultaneously minimizing the distance between the mean of a class and the elements assigned to the class. Thus, the algorithm assigns elements to a specific class where these two conditions are met.



- Boosting (Jurka et al., 2013)
 - The boosting-type algorithms is one class of machine-learning algorithms that uses several weaker (inefficient) classifications and then combines them to get a strong classification. By creating an ensemble of weak learners the algorithm is able to combine these into strong (more accurate) learners.

5.6.2.1.4 Classifying data using trained models

The training set in the container is used as the basis for the machine-learning algorithms to classify the test set into categories. In each instance of headline news, the consensus code for the algorithms is used as the input for the robustness and reliability check. The consensus code is the category assignment on which two or more of the supervised machine learning algorithms agree. The categorised news articles for the abnormal event dates are then extracted for both the yield increases and decreases. The news categorisation is collated for each abnormal date event window. Thus, two sub-samples of the categorised news are created, a collection of news for all increases in yield unique to abnormal event windows, and the same applies for abnormal decreases in the yield.

5.6.2.1.5 Text analytics

The analytics functionality of the RTextTools package provides the researcher with insight regarding the allocations of the headlines to the various categories. The analytics function provides a summary by label (theme/topic), by algorithm, by document and the ensemble summary. This enables the researcher to perform the next step, which is the checking of robustness and reliability with respect to the categorisation performed by the machine-learning algorithms. This process is described in the next section.

5.6.3 Qualitative robustness and reliability check of news classifications

The starting point of the manual reliability check is the sub-sample of the abnormal events window of headline news. The sorting algorithm is not totally accurate in its classification, therefore a reliability check needs to be done to ensure relevant news items are classified in the correct news categories.



The categories of 'other' and 'unclassified' headline news were manually inspected for potential classification errors, where headline news that should have been classified into one of the categories by the algorithm had been incorrectly classified as 'other' or 'unclassified'. Incorrect classifications were corrected by recoding the headline news item manually.

The 'other' category was specifically categorised with keywords and key phrases that related to news that was not necessarily relevant to the study and could therefore be excluded, for example: bank, banks, banking, ETF and ETP, to name a few. Where headlines included news that was deemed relevant to the study those items were manually recoded to the correct category. After the manual review of the 'other' category, the headlines that remained in the 'other' category were excluded from the sample.

During the classification process all headline news that could not be categorised by the machine-learning algorithm into one of the eight categories created (economic, political. credit, emerging markets, international, commodity, currency or other) were by default allocated to the category 'unclassified'. The 'unclassified' category was manually reviewed by inspecting each headline and, where required, then allocating the headline to the appropriate category. Some headlines had no relevance and were therefore left in the 'unclassified' category. After the manual review of the 'other' and 'unclassified' categories, the news items left in these categories were excluded from the sample.

For improved reliability Janner and Schmidt (2015) applied a manual control process for messages that were assigned to a category with less than 95% matching probability. For this study a similar manual control process was applied to the seven news categories assigned by the machine-learning algorithms. The researcher sifted through the noise (defined as news and information that was irrelevant to the South African bond markets) and was then left with only those headline news articles that were relevant to the changes in South African yield returns. The following steps were followed to ensure that the final sample for analysis was reliable and relevant to the study:



- 1. Read through all the news per category and identify any exclusions that should be removed from each of the categories.
- 2. Read through all the news per category and recode any of the news that was incorrectly coded by the algorithm.
- 3. Exclude exact duplicates of specific headlines.
- 4. Keep different announcements of the same type of news which appeared during the event window as this is indicative of the perceived relative importance of the news announcement.

The news categories used for the supervised machine-learning algorithms are important, as the categories needed to be sufficiently different for the algorithms to assign a headline to a specific category. The categories can be summarised as follows:

Economic news: The economic news category included headline news of South African economic news relating to inflation, growth, unemployment, interest rates and any statements made by the governor of the South African Reserve Bank (SARB). The researcher excluded economists' opinions or polls, as well as economic research and market reports.

Political news: The political news category included headline news that could be viewed as political with respect to South Africa. Political headline news included strikes, nationalisation, land reform, corruption and government interference, as well as statements made by the president or other political figures and visits made by the president to other countries. The researcher excluded opinions, polls and research reports.

Credit rating: The credit rating news category included all headline news articles that related to statements on South Africa's sovereign credit rating and credit outlook made by rating agencies such as S&P, Fitch and Moody's. The researcher excluded credit rating news that related to companies or other entities.

Emerging market: Emerging market news included all news that related to emerging markets. This included such news that could affect South African investments, for example,



the follow on effects of the Greek crisis of 2009 and the sales of emerging market assets. The researcher excluded emerging market stock or company news.

International news: International news included statements made by the IMF, and news from major economies such as the US, UK and Japan. Also included was news from global markets that could have an impact on South African investments and the South African yield curve. The researcher excluded opinions, polls and research reports.

Commodity news: Commodity news included news that could impact South African investments. The news included the headline news relating to changes in the price of gold, platinum, silver, coal, copper and oil. The researcher excluded opinions, polls, research reports and commodity company news.

Currency: This category included news relating to currency movements that could affect investments in South Africa. For example, statements made about the Rand by the governor of the Reserve Bank. The researcher excluded news reporting on the movements in the Rand.

5.7 LINKING ABNORMAL RETURNS TO NEWS CATEGORIES

In the reverse event study methodology the sample data is reduced in each successive step. This funnel process led to a final data sample that comprised the abnormal event dates, the price change returns (for these abnormal event dates), the basis point change (which is the price change expressed in a market-related format), and the news categories (groups) with the different frequencies of classifications for the specific event windows around the event dates. The event windows for the news categories included only news on actual trading days and excluded the dates of weekends and public holidays, although news released on those dates was included.

Using the arithmetic mean of price changes, the news frequency counts and the price change percentages were expressed in basis points. An analysis was performed to compare the abnormal return for the event dates of the different nodes and the different categories of news.



5.7.1 Explanatory power of news for abnormal returns

The analysis proceeded by investigating the explanatory power of the news relative to the abnormal returns. In the research results the researcher provided a summary of the percentage of news in each category on an aggregate level over all of the event dates, which were then broken down to a per node level for all event dates.

5.7.2 Influence of news on abnormal returns

The next step in the analysis was to investigate the influence that a specific news category had across each node for the sample period. The researcher provided a summary of the number of abnormal days per node in which a specific news category was more influential than other categories. The influence was measured as the number of articles in a specific category that were released during the event window.

5.7.3 Comparison between increase and decrease news events

The study compared abnormal returns of increase event dates with abnormal returns and decrease event dates. To determine if the means of the increase event basis points were statistically different a one-way Welch's analysis of variance (ANOVA) test was applied. The Welch ANOVA statistical test was the best fit for the data as it does not require the assumption of equal variances and equal sample sizes to hold.

Under the null hypothesis a p-value < .05 is indicative of a rejection of the null hypothesis. For large p-values there is insufficient evidence to reject the null hypothesis, thus one can assume that there is a difference between the means of the groups. For this comparison, there were only two groups, namely increase basis points and decrease basis points for the various nodes of the yield curve. The purpose of the test was to determine whether there was a statistically significant difference between increase basis points and decrease basis points across the yield curve.

H₀: the means of the different groups are the same H₁: at least one sample mean is not equal to the other groups



5.7.4 Yield curve comparison to identify shared abnormal event dates for short-, medium- and long-term yield curve nodes

For the analysis the yield curve was divided into short term (ON, 3M and 6M), medium term (1Y, 2Y and 5Y) and long term (10Y, 15Y and 20Y) nodes. The objective was to find common dates amongst all the nodes for a specific term and then identify and link the news categories to the specific event dates and basis points of the abnormal event date. This analysis highlighted where on a specific date news had different impact across the different nodes in a specific term.

5.7.5 Statistical analysis of the relationship between abnormal returns and news categories

The analysis comprises several statistical tests that considered the association between the different news categories and abnormal returns for each node in the event window period.

5.7.5.1 Descriptive statistics of the abnormal returns

The descriptive statistics provide a summary of the statistical properties of the abnormal return variable. The mean, median and mode provide measures of central tendency and standard deviation and variance represent measures of variability, minimum and maximum values, kurtosis, a measure of the of whether the data are heavy-tailed or light-tailed relative to a normal distribution and skewness, a measure of the lack of symmetry.

5.7.5.2 Correlation matrix of the news categories

To determine if a relationship existed between the set of independent variables (news categories measured as counts) the correlation matrices for the respective nodes were constructed. A correlation matrix for a set of variables was used to determine whether a relationship existed between the variables. The coefficient indicated both the strength of the relationship as well as the direction (positive vs. negative correlations).

5.7.5.3 Multiple linear regression

Multiple linear regression is a type of model that is fit to data to describe the relationship between a group of variables, the independent variables, and dependent variable. The



multiple linear regression model fitted for the dependent variable, the abnormal basis point change in each of the nodes could be seen as a linear function of the independent variables (the counts of headline news categories). The relationship could then be expressed as shown in equation Eq 5-22.

$$Y_t = \beta_0 + \sum_{i=1}^m \beta_i X_{it} + \epsilon_t$$
 Eq 5-20

Where:

- Y_t = The value of the dependent variable at time *t*
- β_0 = The intercept or constant term
- β_i = The coefficient for independent variable *i*
- X_{it} = The value of independent variable *i* at time *t*
- ϵ_t = The residual or error term at time *t*

Using the data for each abnormal event day for each node, Eq 5-22 was then used to solve for the β_i using the ordinary least squares (OLS) method for each node. For a multiple linear regression model to provide reliable results there are important assumptions that need to be met, specifically relating to the error term. These assumptions are described in 5.9.4. in more detail.

Outliers are data points with a large residual for the multiple linear regression model fitted, and as these outliers can influence or skew the model fitted, they need to be identified. An influence plot was used to identify outliers, and the plot showed the residual, leverage and the circle size which is the square root of Cook's D statistic as a measure of the influence of the point (Fox, 2015). Outliers with a large residual and influence were excluded from the linear regression fit process, as these observations unduly influenced the results of the model fitted.

The specific methodology used to select the most appropriate multiple linear regression model for each node was to use forward selection, based on the contribution to the AIC of the specific independent variable on the total AIC (Yamashita et al., 2007). The method proceeded as follows:



- 1. Determine the model statistical results for the model with no independent variables, specifically observe the AIC for the model (this is the null model).
- 2. Systematically add each independent variable to the null-model based on the level of correlation of the independent variable to the dependent variable, and at each step compare the AIC for the new model with one additional variable added to the previous model.
- 3. Select the multiple linear regression model with the lowest AIC as the optimal model.
- 4. Confirm that the selected model complies with the assumptions for the linear regression models.

In some cases the assumption of normality of the residuals were violated. In these cases the absolute value of the standardised residuals were greater than three. This was then corrected by removing some of the outlier values and refitting the stepwise selection multiple linear regression model. The specific nodes where this process was applied are discussed in section 6.4.4.1.1 and 6.4.4.2.1.

5.8 ANALYSIS OF THE SOVEREIGN SPREAD ON ABNORMAL EVENT DATES

The sovereign spread was calculated as the difference between the South African zerocoupon yield and the US government par yield. The influence of comparing a zero-coupon rate and a par rates had no impact on the study, as the aim was to understand how the spread changed, rather than to determine the absolute level of the spread. The spread was calculated by comparing the nodes in one of the currency yield curves with the yield of the equivalent node in the other currency. The change in the spread was then calculated as the spread on the event date minus the spread on the business day prior to the event date. Where the event date fell on a US non-trading day the next US trading day rate was used, and where the day prior to the event date fell on a non-business day in the US the previous US business day was used to determine the prior day spread.

5.8.1 Descriptive statistics of the sovereign spread

The descriptive statistics for the change in the sovereign spreads for abnormal increase event dates and for abnormal decrease event dates were calculated. The descriptive



statistics were then analysed and the main statistical features of the change in sovereign spreads were then discussed. The US Treasury par yield curve used did not have an overnight node or a 15-year node. As proxy for the overnight US node, the researcher used the 1-month US node to calculate the sovereign spread for the South African overnight node. For the 15-year node, the node was discarded from the sovereign spread analysis, as interpolating the 15-year US point from the 10-year and 20-year nodes introduced the possibility of interpolation errors.

5.8.2 Statistical analysis of the sovereign spread

To determine if the means of the abnormal sovereign spreads across node periods were statistically significantly different, a one-way analysis of variance (ANOVA) test was used. The ANOVA test compares the means of two or more groups. In this study, the ANOVA compared the change in the sovereign spread across all nodes of the yield curve.

The Welch ANOVA does not require that the assumption of equal variances hold and is thus considered robust and can be used where there are differences in the sample sizes and where the assumption of equal variances is found to be violated. The sample of the difference between the sovereign spread the day before (PSpread) and on the event date (ESpread) across all nodes was tested.

Under the null hypothesis a p-value < .05 is indicative of a rejection of the null hypothesis, and so one can assume that there is a difference between the means of the groups.

H₀: The means of the different groups are the same

H₁: At least one sample mean is not equal to the other groups

The ANOVA/Welch ANOVA tests indicates that there are differences in the means but does not specify which of the means differ from the other means. To determine the differences between groups (groups of the sovereign spread for the various nodes), *a post hoc* pairwise comparison test, the Games-Howell test, was performed. The test was used to compare all the combinations of the groups and provides confidence intervals and associated *p*-values



for the differences between group means, showing whether the differences were statistically significant or not.

5.9 ASSESSING THE RIGOUR OF THE RESEARCH DESIGN

The study followed a reverse event study structure of analysis and used the underlying assumptions of the Efficient Market Hypothesis as a starting point. The statistical techniques used in the analysis included both parametric and non-parametric statistical tests, multi-variate regression analysis and other statistical models. The yield curve model used in this study could also easily be extended to longer term periods and to other samples, thereby giving the researcher control over the choice of instruments to sample. The time frame chosen included periods of abnormal price behaviour, which was ideal for achieving the objectives of this study.

5.9.1 Confirming the accuracy of the zero-coupon yield curve

The zero-coupon yield curve was derived from the actual marked-to-market closing yield-tomaturities of the selected bonds included in the bootstrap. To verify that the zero-coupon curve was accurate, the bond yields that were used as inputs to the bootstrap process were then used in the South African GCH-formula to calculate the actual all-in price for the bonds on the day on which the price change was observed. Using the derived zero-coupon yield curve, the zero rates were then used to calculate the present values of the cash flows for each of the bonds. As the all-in price of the bonds the present value of all future cash flows of the bonds discounted at the YTM, the present value should be equal to the present value calculated using the zero-coupon rates derived from the bootstrap process. The South African market calculates the all-in price for bonds for a specific settlement date rounded to five decimal places for a nominal of 100. Using the methods above, the differences between the calculated bond prices and the derived bond prices were then analysed.

5.9.2 Significance test of abnormal returns

The Wilcoxon signed rank test was performed to confirm that the abnormal returns were indeed statistically different from the sample returns. The test is a nonparametric statistical hypothesis test to compare two related samples without assuming them to follow a normal



distribution. If the null hypothesis is rejected then stationarity of the data series can be assumed . If the *p*-value > .05, then accept the null hypothesis, the two data samples are non-identical. If the *p*-value \leq .05, then reject the null hypothesis, data samples are from identical distributions.

H₀: The abnormal returns and the normal returns are identical populations H₁: The abnormal returns and the normal returns are non-identical populations

5.9.3 Text analysis analytics and reliability check

For the text analysis a two-step process was followed to ensure a robust and reliable final data sample. Firstly, the analytics function provided an understanding of the classifications for each category, for the algorithms used and a summary per document. Secondly, a manual relevance and reliability check was employed with respect to each classified category using the machine-learning process. Each headline news item per category was reviewed with respect to its classification and was either considered as correct or needed to be either excluded or recoded. After this process, the final sample for statistical analysis completely represented all news that was relevant during the event window for each abnormal date.

The analytics functionality of the RTextTools package provided the researcher with insight into the allocations of the headlines to the various categories. The analytics function provided a summary by label (theme/topic), by algorithm, by document and the ensemble summary.

The label summary provided statistics for each unique label in the classified data. This included the number of documents that were manually coded with that unique label, the number of documents that were coded using the ensemble method, the number of documents that were coded using the probability method, the rate of over- or under-coding with each method, and the percentage of documents that were correctly coded using the ensemble respectively.



The algorithm summary provided a breakdown of each algorithm's performance for each unique label in the classified data. This included metrics such as precision, recall, F-scores, and the accuracy of each algorithm's results.

The document summary provided all the raw data available for each document. It displayed by document, each algorithm's prediction, the algorithm's probability score, the number of algorithms that agreed on the same category, which algorithm had the highest probability score for its prediction, and the original category classification of the document.

i. Testing algorithm accuracy

Using the create analytics function in the RTextTools package, the precision, recall and F-scores for analysing algorithmic performance at the aggregate level was produced. Precision refers to how accurate the classifications by the algorithms were. For example, in the context of classifying economic news, precision told us what proportion of economic news was truly about economic news (based on the humanassigned labels).

Precision is defined as the ratio between the correct predictions and the total predictions yielded by the algorithm. Precision is computed using the following equation:

$$Precision = \frac{T_p}{T_p + F_p}$$
 Eq 5-21

Where:

 T_p = True positive F_p = False positive

Recall refers to the proportion of news in a class which the algorithm correctly assigned to that class. To explain further, it measured the percentage of actual economic news that the algorithm correctly classified as economic news. The recall



is defined as the ratio between the correct predictions made by the model and the total number of true and false labels. Recall is computed using the equation:

$$Recall = \frac{T_p}{T_p + F_n}$$
 Eq 5-22

Where:

 T_p = True positive F_n = False positive

F-score is a metric used in multi-class classifications that produces a weighted average of both precision and recall, where the highest level of performance is equal to 1 and the lowest 0. The metric is an effective measure of the performance of the model. F-score is computed using the equation:

$$F - Score = \frac{2 * Recall * Accuracy}{Recall + Accuracy}$$
 Eq 5-23

ii. Ensemble agreement

The ensemble agreement refers to whether multiple algorithms make the same prediction concerning the class of an event (that is, did the different machine algorithms used assign the same label to the text).

From the quantitative analysis the consensus code for each headline news item was identified for the event window of the abnormal event dates. This resulted in a broad classification of the headline news, which provided the starting point for the researcher to sift through the headline news articles to only capture the relevant and important news items. A qualitative reliability and relevance check was performed on the sub-sample abnormal event date news. The news categories were sorted and each headline news item was



checked for relevance. The first categories checked were 'other' and 'unclassified'. Where the machine-learning algorithm could not assign certain news items to the specified news categories it marked those items as 'unclassified'. The reason for checking the categories 'other' and 'unclassified' was to ensure that any news items that had been incorrectly coded by the algorithm could be manually recoded and assigned to the correct news category. The second step was to review the specified news categories (currency, commodities, international, economic and emerging markets) from the perspective of qualitative relevance and quality of content. The headline news items in the different categories were sorted and then checked item by item. Headline news that was not relevant was excluded and news that was incorrectly coded by the algorithm into the wrong category was manually recoded for the correct category.

5.9.4 Checking the multiple linear regression model against OLS assumptions

The quality of the linear regression model should be investigated based on the underlying assumptions of an ordinary least squares (OLS) regression. The assumptions of the OLS regression were investigated to validate the quality and use of the linear regression using diagnostic tools described by (Ernst & Albers, 2017). The assumptions are:

- Assumption I: Linearity visual inspection of the residuals plots that show the variability of the residual values with predictor variables. In an ideal situation the residual will show no fitted pattern. In addition to the linearity, multi-collinearity is an important requirement for a model to be parsimonious. Multi-collinearity is where there is correlation in the independent variables. The measure used for multicollinearity is the Variance Inflation Factor (VIF) which should not be above 10.
- Assumption II: Normality visual inspection utilising the Q-Q plot showing the distribution of residuals across the model. For the assumption of normality to hold true, the normal probability plot of residuals should approximately follow a straight line with acceptable standardized residuals between -3 and +3.
- Assumption III: Independence both a residual plot (to inspect the autocorrelation of the residuals) and the Durbin-Watson statistic were used. For the Durbin-Watson test, the statistic should be between 1.5 and 2.5 to assume that autocorrelation is not problematic. Values outside this range could, however, be a cause for concern.



Assumption IV: Homoskedasticity – the sub-populations of the residuals(ε_i) of the models are expected to have equal variance. The assumptions of homoskedasticity and normality combined, specify that the residuals of the models should follow a normal distribution with a mean of zero and some constant variance. The scatterplot of the residuals and the fitted values for each of the nodes was used to assess the homoskedasticity of each model.

5.9.5 Sovereign spread

To determine if the medians are significantly different from zero a two-sided t-test or a twotailed nonparametric Wilcoxon-sign ranked test was performed.

H₀: The median equals zero

H₁: The median does not equal zero

The tests provided the basis for further analysis of the sovereign bond spread.

As a check for using the Welsch ANOVA in the sovereign bond spread analysis, the Levene test was used for testing if the sovereign bond spreads of all nodes had equal variances (homogeneity). The test is a simple one-way analysis of variance on the absolute values of the differences between each observation and the mean of its group is tested.

Under the null hypothesis a p-value < .05 is indicative of a rejection of the null hypothesis, and unequal variances are not assumed.

- H₀: Variance is equal across groups
- H₁: Variance is not equal across groups

In the event of the null hypothesis being rejected it confirms the use of the Welsch ANOVA in the sovereign bond spread analysis.



5.10 RESEARCH ETHICS

The research in this study did not use sensitive personal information, interviews or incorporate people's opinions and beliefs. The study contained no data or names of individuals that could have an impact on the South African political environment, international landscape, emerging market countries, macroeconomic variables and credit ratings. The 'bag of words' used in the Naïve Bayes Classifier that may contain names of individuals is available from the researcher on request. The bag of words only has relevance with respect to the Naïve Bayes Classifier, as it was used to sort news into initial categories for quantitative analysis. The focus of the study was not on specific words, individuals or opinions, but rather on the impact of different news categories on the South African sovereign yield curve.

The secondary data used was at all times kept confidential and safe. All raw data is available from the researcher. This study relied on the analysis of publicly available price/yield and interest rate data, as well as news headlines that were categorised using a machine-learning algorithm. A reliability and relevance check was performed to ensure that the correct relevant news frequencies were reflected in the data. Data once collected was saved safely without altering data sets. The researcher tested all results to ensure that study results were error free. Data sources were displayed within the document. Where data modification was essential the modification was clearly indicated and explained.

The study was mostly quantitative in nature, where the abnormal return event dates were identified using GARCH-models. For the text classification a quantitative machine-learning process was used, which was followed with a qualitative manual reliability and robustness check. A quantitative multiple regression model was used, to establish the relationship between news categories and abnormal yield returns. Another quantitative analysis tool, ANOVA, was used for the sovereign bond spread analysis.

5.11 SUMMARY

This chapter described the methodology applied in the research to answer the six stated research hypotheses. The research method used was the reverse event study methodology to first identify abnormal price changes and second, to assign news related to abnormal 140



events into seven specific news categories. Thereafter a statistical analysis was undertaken to identify the association between the news items and the abnormal events.

The abnormal returns were identified as the dates on which the daily price changes exhibited abnormal volatility. The price changes from the zero-coupon yield curve were used as input to several GARCH models. This analysis addressed the first research hypothesis, which was to test whether there was a change in bond returns during periods (days) of increased volatility.

The news headlines collected were classified into seven different categories using a Naïve Bayes classification model, coupled with several machine-learning algorithms. This procedure was followed by a manual reliability and robustness check. The relationship between the abnormal returns and the news events released during the event windows was then analysed to determine the relevance of specific news categories and the influence of these categories on the yields. From this part of the analysis the researcher was able to answer the second and third research hypotheses relating to whether abnormal returns were linked to news event categories and whether there was a difference in the impacts of different news categories on the yield curve.

The abnormal change in bond prices is not necessarily symmetrical and an analysis was performed to investigate the differences between abnormal increases and abnormal decreases for each node. This relates to the fourth hypothesis.

The sovereign bond spread was determined as the difference between the zero-coupon yields of the South African market and the US government par yield curve. This part of the analysis linked back to the fifth and sixth hypothesis on investigating the sovereign bond spread and news across the yield curve.

Finally, at each step of the processes outlined above, the results obtained from applying a specific model or method were verified by using relevant statistical methods to confirm the veracity of the outputs.



CHAPTER 6 ANALYSIS OF DATA

6.1 INTRODUCTION

The flow of the analyses followed the order of the research hypotheses as follows: Firstly, the daily changes of the zero-coupon yields (as derived from the closing prices of the bonds) were used as inputs to the GARCH econometric models and the abnormal price change dates were identified; second, the abnormal price change dates were then used to collect the categorised news within the event windows for the dates identified; third, the association between the news categories and the price changes were then investigated and tested; fourth, the difference of the extent of the change of abnormal increases and decreases in yields for each node was investigated; fifth, the potential impact of the news on the abnormal price change dates on the sovereign spread was examined; lastly, market efficiency as observed in the reaction of the sovereign spread within one trading date.

The methods described in the previous chapter were applied to perform the analyses.

6.2 ANALYSIS TO DETERMINE ABNORMAL RETURNS

For this study a set of nine nodes was selected to represent the yield curve, namely the overnight, 3-month, 6-month, 1-year, 2-year, 5-year, 10-year, 15-year and 20-year zero-rates. The time series data used consisted of a 10-year sample of zero-coupon rates calculated using the Hagan-West model as described over a spectrum of nodes in the zero-coupon yield curve. Each node comprises 2 498 observations over the period from 1 January 2010 to 31 December 2019. As each instance of the analysis for the abnormal returns related to event dates for which either an increase or a decrease was observed, the data was split between abnormal event dates for the increases and the decreases. In addition to the split between the increases and the decreases, each instance of the analysis investigated the effect for all nine nodes. Therefore, where the tables or figures cannot succinctly be represented in the text, only a sub-selection is shown. The rest of the information (whether in table format or figures) is provided in the relevant appendix. For Chapter 6 all additional tables and figures are provided in Appendix A and their numbers are preceded by 'A'.

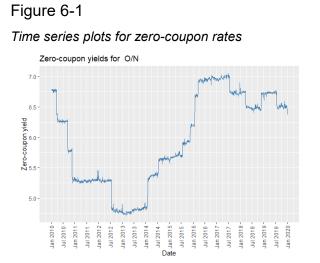


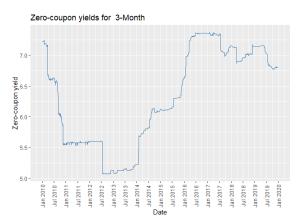
6.2.1 Data properties

The initial exploration of the properties of the data was mostly undertaken through a visual inspection of the plots of the data over time.

6.2.1.1 Zero-coupon yield data properties

Figure A-1 in Appendix A depicts the time series plots for the zero-coupon rates for all nodes. The sub-selection of the overnight and 3-month rates in Figure 6-1 exhibit almost discrete changes, whereas the other node points show more gradual changes. The general trend in the rates was downwards for the first period (approximately two years), followed by a period of relatively stable rates over the next three years), whereafter the rates increased sharply and then gradually decreased again towards the end of the timeframe.





Note. Daily zero-coupon yields for selected nodes (O/N and 3-month) over the entire sample period plotted as time series.

6.2.1.2 Zero-coupon daily return data properties

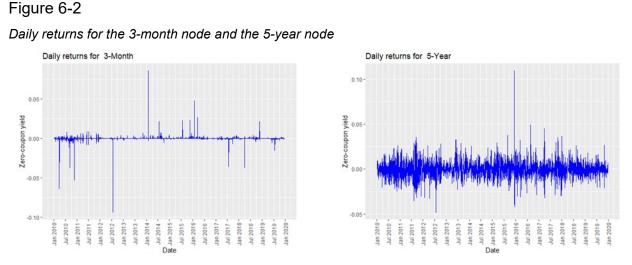
The plots for the daily return series are shown in Figure A-2 and illustrate periods of low volatility followed by periods of high volatility, as reflected in the daily price changes. This is the heteroskedastic effect of non-constant volatility which is often observed in financial time series data and is referred to as volatility clustering. In Figure 6-2, the difference in the 3-month daily return series and the 5-year daily return price series shows how the short-term prices tend to show very small daily changes, interspersed with short periods of larger

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changes. By comparison, the longer time series exhibit greater daily variation in the prices. The spikes seen on the daily return charts are the points where abnormal changes occurred. These points were identified using the GARCH processes, as discussed in section 6.2.2.5.



Note. Daily returns of zero-coupon yields for selected nodes (3-month and 5-year) over the entire sample period.

6.2.1.3 Descriptive statistics for the daily returns

The descriptive statistics in Table A-1 show that the means for the daily price changes are very close to zero and that the standard deviations for the nodes are relatively low. An extract from the detailed descriptive statistics is provided in Table 6-1, which shows that the kurtosis for the short-term nodes (overnight, 3-month and 6-month) is extremely high, with the 3-month node having the highest kurtosis of all the nodes. The high kurtosis is indicative of fat tails in the data. Visual inspection shows that it is unlikely that the data is normally distributed.

Table 6-1

Descriptive statistics for short term nodes

	O/N	3-Month	6-Month
Mean	-0.00003	-0.00003	-0.00002
Variance	0.00003	0.00001	0.00002
Stdev	0.00506	0.00374	0.00438
Skewness	-3.86678	-4.51881	-4.06821
Kurtosis	109.99512	341.27329	147.53369

Note. Extract from descriptive statistics Table A-1 showing some of the key statistics for the short term nodes indicating that it is unlikely that these observations are normally distributed.



The results for the Shapiro-Wilk test investigating the normality of daily returns can be found in Table 6-2. The results show that the null hypothesis is rejected for each of the nodes and indicates that the data is not normally distributed.

Table 6-2

Shapiro-Wilk test results

Shapiro-Wilk				
Node	W	<i>p</i> -value	Result	
O/N	0.533066	< .001	Reject H0	
3-Month	0.146185	< .001	Reject H0	
6-Month	0.423828	< .001	Reject H0	
1-Year	0.720678	< .001	Reject H0	
2-Year	0.861625	< .001	Reject H0	
5-Year	0.942713	< .001	Reject H0	
10-Year	0.930612	< .001	Reject H0	
15-Year	0.901151	< .001	Reject H0	
20-Year	0.852523	< .001	Reject H0	

Note. Results from Shapiro Wilk test for normality performed on the daily returns for all nine nodes indicating that none of the data samples follow a normal distribution.

6.2.2 Econometric models

As discussed in 6.2.1.2, the return data exhibits some volatility clustering, which is indicative of heteroskedasticity, a phenomenon generally observed in financial time series data. Variants of the ARCH model, namely GARCH, EGARCH and GJR-GARCH, were used to model the time-dependent changes in the volatility. Even though three models were used and the results were compared, the comparison was not a specific objective of the study. The results of all three GARCH models were used to determine the abnormal volatilities and the specific event dates. Thus, if one of the models indicated an abnormal event date, the date was included as an abnormal event date. The results of the investigation into the stationarity of the time series allowed for more accurate forecasts of the time series using the GARCH models.

6.2.2.1 Results of investigation for stationarity

The investigation for stationarity in the different nodes' time series was performed by assessing each of the three stationarity conditions, namely a mean that is constant over



time, constant variance and constant autocorrelation. The time series used was the daily price changes for each node, as discussed in 5.3.7. Due to the way in which the returns were calculated, the data could be considered as having been differenced once. The ADF unit root test statistic showed that the null hypothesis could be rejected for the time series. Thus, the hypothesis that the data time series is non-stationary could be rejected and one could assume stationarity. Table 6-3 summarizes the ADF results for all nodes where the *p*-value for all nodes is < .0001.

Table 6-3

		,
Node	t-Statistic	<i>p</i> -value
ON	-53.216	< .0001
3-month	-50.264	< .0001
6-month	-52.255	< .0001
1-year	-56.074	< .0001
2-year	-56.512	< .0001
5-year	-46.336	< .0001
10-year	-51.37	< .0001
15-year	-50.974	< .0001
20-year	-49.444	< .0001
Mate Disself	C	

Augmented Dickey-Fuller (ADF) unit root test

Note. Results from Augmented Dickey-Fuller test performed on the daily returns for all nine nodes indicating that stationarity can be assumed for all nine nodes.

6.2.2.2 Results of investigating the constant mean condition

Given that the descriptive statistics show that the means of the daily returns were very small, there could still be some trend in the mean. This was investigated using the KPSS test, as discussed in 5.5.1.2.

From the results of the KPSS test in Table 6-4, stationarity in the short-term nodes cannot be assumed. Whereas in the nodes from the 1-year to the 20-year periods there is insufficient evidence to say that the nodes are not stationary, therefore the long term nodes can assumed to be stationary. The results of the KPSS test motivates for some form of autoregressive and moving average model to be applied to the longer-term nodes.



Critical Values

Table 6-4

KPSS statistical test results

		Test Statistic	<i>p</i> -value	10%	5%	2.50%	1%	Result
O/N	Level	0.55990	.02713	0.347	0.463	0.573	0.739	Reject H0
	Trend	0.32897	< .0001	0.119	0.146	0.176	0.216	Reject H0
3-Month	Level	0.78804	.0073	0.347	0.463	0.573	0.739	Reject H0
	Trend	0.45395	< .0001	0.119	0.146	0.176	0.216	Reject H0
6-Month	Level	0.65511	.0156	0.347	0.463	0.573	0.739	Reject H0
	Trend	0.42560	< .0001	0.119	0.146	0.176	0.216	Reject H0
1-Year	Level	0.29268	.134	0.347	0.463	0.573	0.739	Fail to reject H0
	Trend	0.24541	< .0001	0.119	0.146	0.176	0.216	Reject H0
2-Year	Level	0.13850	.2812	0.347	0.463	0.573	0.739	Fail to reject H0
	Trend	0.12211	.0924	0.119	0.146	0.176	0.216	Fail to reject H0
5-year	Level	0.06926	.3753	0.347	0.463	0.573	0.739	Fail to reject H0
	Trend	0.06727	.3202	0.119	0.146	0.176	0.216	Fail to reject H0
10-Year	Level	0.17520	.2390	0.347	0.463	0.573	0.739	Fail to reject H0
	Trend	0.03380	.5872	0.119	0.146	0.176	0.216	Fail to reject H0
15-Year	Level	0.10530	.3240	0.347	0.463	0.573	0.739	Fail to reject H0
	Trend	0.07966	.2490	0.119	0.146	0.176	0.216	Fail to reject H0
20-Year	Level	0.02788	.4410	0.347	0.463	0.573	0.739	Fail to reject H0
	Trend	0.02796	.6463	0.119	0.146	0.176	0.216	Fail to reject H0

Note. Results for KPSS statistical tests performed on the daily returns for all nine nodes.

6.2.2.3 Results of investigating the autocorrelation condition

A visual pattern of the data was given by the ACF-plot and PACF-plot for each node to determine if autocorrelation is present in the data. For a stationary time series, the ACF plot will drop to zero relatively fast, while for a non-stationary time series the ACF remains significant for six or more lags and will then slowly decrease. The ACF-plot and PACF-plot for the returns and the squared returns for each node are provided in Figure A-3 for comparison purposes. The longer-term nodes exhibit autocorrelation for shorter lags (less than 5 days) and there is an indication from the ACF and PACF plots that the return data has some autocorrelation. An autoregressive model with varying lags was used to remove autocorrelation from the data. The results obtained from investigating the ADF, ACF and PACF confirmed stationarity, but some order of differencing might be required for some of the nodes. Given the results regarding the stationarity of the data, an autoregressive integrated moving average model (ARIMA) was tested on the data to find the most suitable



parameters (p, d, q), where: p refers to number of autoregressive terms, d refers to the number of non-seasonal differences required for stationarity and q indicates the number of lagged forecast errors in the equation. Table 6-5 shows the ARIMA function results and the most appropriate ARIMA model applicable for each node.

Table 6-5

Auto ARIMA results for all nodes

Node	AIC	BIC	Log-likelihood	ARIMA (<i>p, d, q</i>)
O/N	-18,903.16	-18,868.22	9,457.58	(5,1,0)
3-month	-20,447.52	-20,412.59	10,229.76	(5,1,0)
6-month	-19,664.40	-19,623.64	9,839.20	(5,1,0)
1-year	-17,245.06	-17,233.42	8,624.53	(0,0,1)
2-year	-15,418.95	-15,407.30	7,711.47	(0,0,1)
5-year	-16,058.38	-16,040.91	8,032.19	(2,0,2)
10-year	-15,768.38	-15,745.09	7,888.19	(0,0,3)
15-year	-15,869.69	-15,852.22	7,937.84	(1,0,1)
20-year	-15,461.88	-15,438.59	7,734.94	(1,0,2)

Note. The table shows the optimal ARIMA results with the lowest information criterion.

The Box-Ljung test results confirmed that the ARIMA models used were the best fit for the data. The results in Table A-2 and Table A-3 show that for all nodes the *p*-values were >.05 for most of the lags investigated. Where the *p*-value of the Box-Ljung test was below the alpha level of 5%, autocorrelation was present in the residuals. As can be seen in the tables, there are a number of nodes where some of the lags of the Box-Ljung test indicate autocorrelation. It is acceptable that for most of the nodes on any given lag the autocorrelation cannot be confirmed.

6.2.2.4 Results of investigating constant variance condition

The ARCH-LM test results confirm that heteroskedasticity of the data is present in all nodes. From the results in Table 6-6 it is evident that the null hypothesis is rejected and that ARCH effects are present in the data. It can therefore be concluded that the data of all nodes are likely heteroskedastic.



Table 6-6

Node	Lag	Statistic	<i>p</i> -value
O/N	1	135,543	< .001
3-month	1	426,267	< .001
6-month	1	154,721	< .001
1-year	1	18,541	< .001
2-year	1	10,204	< .001
5-year	1	3,873.2	< .001
10-year	1	9,358.9	< .001
15-year	1	24,645	< .001
20-year	1	71,816	< .001

Engle's ARCH-LM test for heteroskedasticity

Note. Results of the Engle's ARCH LM test for heteroskedasticity indicating the presence of heteroskedasticity in all nodes.

6.2.2.5 GARCH models

An important specification in the GARCH models is the conditional distribution of the error term. The most appropriate distribution will result in lower excess kurtosis and skewness of the residuals after fitting the appropriate model. The detailed results presented in Table A-4 show the most relevant distributions for each node time series.

From the findings, the student's t-distribution, or t-distribution, is the distribution most likely to not lead to excess skewness and kurtosis. However, not all the nodes had the same result, with the 3-month and 6-month nodes favouring the generalized error distribution. The 2-year to 20-year nodes had mixed results from the information criteria, with some of the criteria indicating the t-distribution, and others indicating the geometric hyperbolic distribution or the Johnson's SU distribution. However, as these differences were small (in the 4th and 5th decimal on the information criteria), the t-distribution was used for all nodes except the 3-month and 6-month nodes.

Using the GARCH models and specifications described, the R Rugarch statistical package was used to fit the ARMA-GARCH models to the node data using the appropriate statistical distribution. For the overnight, 3-month and 6-month nodes the time series was differenced once more prior to applying the GARCH models, as per the output of the ARIMA model investigation above. A summary of the model specifications for each node is provided in Table 6-7.



Table 6-7

Node	ARMA	Distribution
	(p, q)	
O/N	(5, 1)	Student's t
3-Month	(5, 1)	Generalized error
6-Month	(5, 1)	Generalized error
1-Year	(0, 1)	Student's t
2-Year	(0, 1)	Student's t
5-year	(2, 2)	Student's t
10-Year	(0, 3)	Student's t
15-Year	(1, 1)	Student's t
20-Year	(1, 2)	Student's t

Final distributions for the GARCH models to be fit

Note. Distributions and ARMA orders used in the GARCH models fitted for all nodes.

The Aikaike Information Criterion (AIC) is a measure of the goodness of fit of an estimated statistical model. The AIC values were calculated for each of the three GARCH models to fitted to the daily price change data. A summary of the AIC for all of the models is given in Table 6-8, and can be used to compare the models. As can be seen from Table 6-8, there is very little difference between the AIC for the different models for each of the nodes, with the exception of the 3-month and 6-month e-GARCH model. Table A-5 provides a full list of all of the information criteria of the models. The lowest AIC is an indication of the best model fit for the data. The researcher used all three models to identify the abnormal return points that could be linked back to the event dates.

Table 6-8

AIC results for the GARCH models fit

Nodes	sGARCH	eGARCH	gjrGARCH
O/N	-9.089071	-9.072505	-9.088354
3-month	-6.282696	-14.31689	-6.072298
6-month	-6.535763	-12.54349	-6.666175
1-year	-7.698385	-7.710028	-7.697907
2-year	-6.617049	-6.637178	-6.616265
5-year	-6.643630	-6.643542	-6.643389
10-year	-6.565237	-6.566264	-6.564523
15-year	-6.631917	-6.637988	-6.632199
20-year	-6.524474	-6.525283	-6.523849

Note. AIC results for the GARCH models fit for all nodes. sGARCH refers to the standard GARCH (p,q) model.

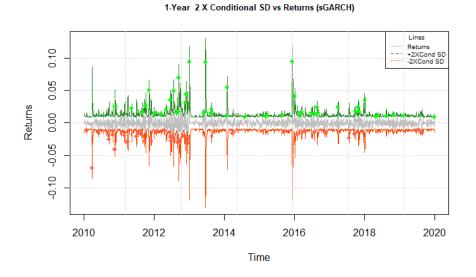


6.2.3 Identification of the abnormal return dates

From Eq 5-15 the conditional variance at time t of the GARCH (1, 1) model is described as the weighted average of the 1-period lagged residuals, the conditional variance will therefore change for every day, and as a result the Chebyshev inequality has to be re-calculated every day for each time series (node).

Figure 6-3

Conditional volatility and the returns of the 1-year node for the GARCH model



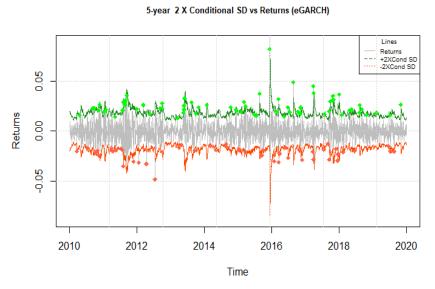
Note. The points in green represent the dates on which the return exceeded two standard deviations. Similarly, the red points indicate dates on which the return were lower than two standard deviations.

In Figure 6-4, Figure 6-5 and Figure 6-6 the two standard deviations plotted around the mean return of the 1-year, 5-year and 20-year nodes are shown, with the marked points illustrating occurrences where the actual returns are higher than the upper band, or lower than the lower band. Each of the points in the graphs represents an abnormal return event date. The conditional volatility and return plots for all other nodes are shown in Appendix A



Figure 6-4

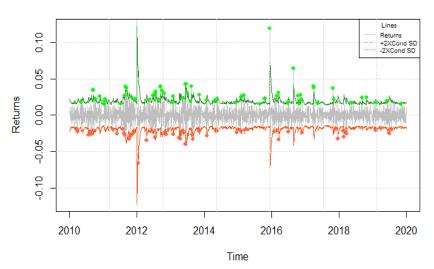
Conditional volatility and the returns of the 5-year node for the eGARCH model

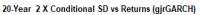


Note. The points in green represent the dates on which the return exceeded two standard deviations. Similarly, the red points indicate dates on which the return were lower than two standard deviations.

Figure 6-5

Conditional volatility and the returns of the 20-year node for the gjrGARCH model





Note. The points in green represent the dates on which the return exceeded two standard deviations. Similarly, the red points indicate dates on which the return were lower than two standard deviations.

All the dates with abnormal returns, either positive (higher than the upper 2 standard deviation band) or negative (lower than the lower 2 standard deviation band) were identified



using all three GARCH models and the dates were combined per node to isolate the unique dates.

Table 6-9 shows an extract of the identified unique dates for the negative returns in 2010 for the 2-year node.

Table 6-9

Extract of the negative returns and the model that led to the discovery of the date

2-year node for abnormal decreased returns			
Unique down date	Model that identified the abnormal return date		
28/01/2010	sGarch gjrGarch		
25/03/2010	sGarch eGarch gjrGarch		
26/03/2010	sGarch eGarch gjrGarch		
03/06/2010	sGarch eGarch gjrGarch		
09/06/2010	sGarch eGarch gjrGarch		
17/08/2010	sGarch eGarch gjrGarch		
09/09/2010	sGarch eGarch gjrGarch		
17/09/2010	sGarch eGarch gjrGarch		
18/10/2010	sGarch eGarch gjrGarch		
19/11/2010	sGarch eGarch gjrGarch		
01/12/2010	eGarch		

Note. Extract of the 2-year node unique decrease dates for the 2010 sample period.

Table 6-10 shows an extract of the unique dates for 2010 positive returns for the 2-year series. These two tables (regarding negative and positive returns in 2010) illustrate that, for any specific date (whether a single model identified the date as an abnormal return date or all of the models identified the date as an abnormal return date) the date was included in the study.

Table 6-10

Extract of the positive returns and the model that led to the discovery of the date

2-year node for abnormal increased returns		
Unique down date	Model that identified the abnormal return date	
22/04/2010	sGarch eGarch gjrGarch	
04/05/2010	sGarch gjrGarch	
17/11/2010	sGarch eGarch gjrGarch	
29/11/2010	sGarch eGarch gjrGarch	

Note. Extract of the 2-year node unique increase dates for the 2010 sample period.



All dates identified from all three GARCH models were used as event dates to link the news events released during the event window per node. Abnormal increases in the return dates per node (news associated with a negative perception) and abnormal decreases in the return dates per node (news associated with a positive perception) were shown. All the dates for abnormal increases across all the nodes were then collated in one table, and the unique dates from all nodes were identified as inputs for the determination of the event window news as the next step in the analysis. The same process was used to determine the news event window for the abnormal decrease dates. The total data set comprised 2 498 yield observations per node, and 2 497 log price change observations per node, of which only 226 were identified as being unique 'up' (increase) abnormal dates, and 231 unique 'down' (decrease) abnormal dates. Combining the unique up and down dates eliminated duplicates. There were 457 unique abnormal return dates. Thus, there were some dates on which some nodes experienced abnormal increases, whilst on the same date other nodes experienced abnormal decreases.

The final sample for the abnormal return dates for the purpose of news classification was the collection of the 457 unique abnormal return dates. The basis point change was calculated for each of these dates for each of the nodes as the zero-coupon yield on the abnormal return business day (expressed as a percentage) less the zero-coupon yield on the business day immediately preceding the abnormal return date (expressed as a percentage) multiplied by 10 000.

A visual inspection of the time series plots in Figure A-1 for the overnight, 3- and 6-month nodes clearly shows that the interest rates for these nodes show discrete jumps. Fitting GARCH models to these nodes consequently resulted in an overestimation of the heteroskedasticity of the daily returns. In Figure A-2 the daily returns for the overnight, 3- and 6-month nodes clearly shows the very specific dates on which the abnormal daily returns were experienced, but the GARCH models identifies several other abnormal daily return dates in addition to these specific dates. The result is that in addition to clearly identifiable abnormal returns, the GARCH models also highlight several noisy points for inclusion in the abnormal return dates series. The inclusion of these noisy smaller abnormal returns and decreased

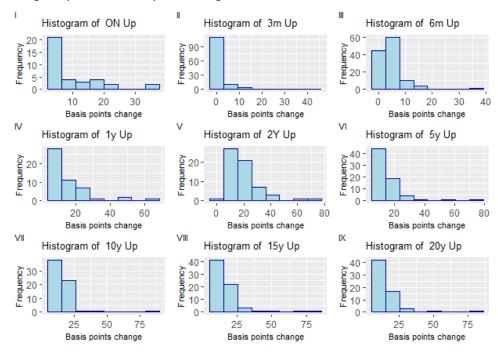


the standard deviation of the observations. However, as the true abnormal returns were identified, for the purpose of the analysis the results obtained were sufficient.

6.2.3.1 Descriptive statistics of the abnormal return basis points

From the descriptive statistics of the abnormal returns for both the increase event dates and the decrease event dates, the 3- and 6-months nodes have more observations than the other nodes. The histograms in Figure 6-7 (for the increase event dates) and Figure 6-8 (for the decrease event dates) indicated that there are relatively few observations that can be seen as outliers. The means for the abnormal increase event date basis points were all higher than zero, with the means for the 3- and 6-month nodes being the lowest.

Figure 6-6



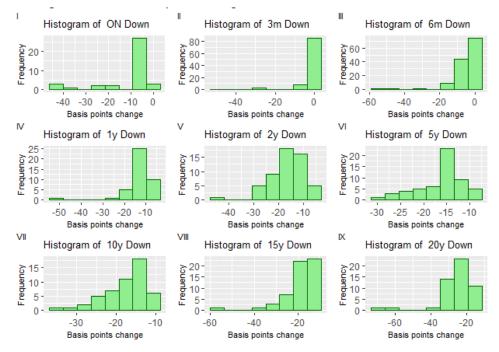
Histogram plots for basis point change for abnormal increase event dates

Note. Basis point change for abnormal increase event dates for all nodes

Figure 6-8 shows the basis point changes for abnormal decrease event dates. Again the means for the 3- and 6-month nodes were the closest to zero, The behaviour of the 3- and 6-month nodes is then different from the other nodes for both the abnormal increase and decrease event dates.



Figure 6-7



Histogram plots for basis point change for abnormal decrease dates

Note. Basis point change for abnormal decrease event dates for all nodes

The complete descriptive statistics is provided in Table A-6 (for the increases) and Table A-7 (for the decreases). An extract of the descriptive statistics in Table 6-11 and Table 6-12 show that the number of observations for the nodes follow the same pattern, with approximately 36 for increase event dates (38 for decrease event dates) observations in the Overnight, increasing almost three-fold to the 3- and 6-month nodes, and then decreasing again to the 1-year node and beyond. The range of the abnormal basis points shows a skew towards the increases as the range for the increases in the basis points for the abnormal return dates are higher than the range for the decrease dates, hinting at more severe reactions to the perceived negative news than to the positive news.



Descriptive statistics for the abnormal return increase dates expressed in basis points

	ON	3M	6M	1Y	2Y	5Y	10Y	15Y	20Y
n	36	127	120	50	61	70	64	70	64
mean	9.73056	2.51146	4.44145	15.3849	20.0248	15.6768	16.5961	16.8851	16.1196
sd	8.04409	5.2001	4.54368	11.8015	12.4506	9.83669	10.2571	11.8043	10.0401
range	31.1	43.099	36.518	56.6874	72.5861	65.4057	74.1062	70.8249	70.8686
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Note. Extract of the descriptive statistics in Table A-6.

Table 6-12

Descriptive statistics for the abnormal return decrease expressed in basis points

			6M	1Y	2Y	5Y	10Y	15Y	20Y
n	38	100	131	42	54	56	51	57	51
mean -	11.042	-3.81	-5.4847	-12.9883	-17.0125	-16.265	-17.729	-18.7244	-25.376
sd 12	2.2298	7.99644	7.35411	7.06705	6.88854	4.76948	5.58772	7.66317	9.96204
range	43	49.5	55	45.0352	39.0838	20.8357	24.5788	44.141	54.2117

Note. Extract of the descriptive statistics in Table A-7.

6.3 TEXT ANALYSIS AND NEWS CLASSIFICATION

The value of text analysis tools for news classification lies in their ability to organize and structure news automatically by assigning subject or theme categories to deliver meaningful data and thereby solve problems. For this study headline news announcements from 1 January 2010 to 31 December 2019 were used to associate news categories to the abnormal returns identified above.

6.3.1 Data properties

The full sample of news announcements comprised 92 051 individual headline announcements released during the study period. Each headline announcement in the dataset was assigned to the date on which the announcement was made. The newswire that released the announcement and a unique ID key was assigned to each announcement for the purpose of the analysis. In the full sample, some headline announcements are labelled 'Diary'. As these items were only calendar entries they were removed from the sample, leaving 88 848 items. Not all of the announcements were in English. As part of the initial data clean-up, 24 newswire services that released announcements in languages other than English were removed from the full sample, which reduced the sample to 84 341 items. The newswire services that were excluded are listed in Table A-8.



6.3.2 Descriptive statistics

The headline news announcements comprised a total of 84 341 items published by 683 sources. The most prolific newswire source was Reuters, with 32 986 announcements attributed to the source, which represents approximately 39% of the total sample. The top ten sources reported approximately 70% of the total news, and the top 50 sources provided approximately 90% of all of the announcements used in the sample. The news announcements released per year are shown in Table 6-13. The year with the highest number of announcements released was 2015, with almost five times the number of announcements as the year with the lowest count, 2012. There is no obvious reason for the high frequency of news releases in 2015.

Table 6-13

News announcements released per year

Year	Count
2010	8 570
2011	5 132
2012	4 581
2013	6 119
2014	6 404
2015	21 738
2016	7 447
2017	7 262
2018	8 617
2019	8 471
Total	84 341

Note. Break-down of all news counts per year.

6.3.3 Initial text pre-classification into categories

The initial text classification into categories was done using a Naïve Bayes classification algorithm. The Naïve Bayes result is a response vector that shows the category to which each headline was assigned.

Table 6-14 provides a summary for the categories created by the Naïve Bayes algorithm for the training set used in the supervised machine-learning algorithms. The large number of announcements allocated to the unclassified category was expected, as not all of the news released during the course of a business day could easily be assigned to one of the seven specified categories.



Naive	Raves	categorisation	summar	for	the	trainina	set
IVAIVE	Dayes	calegonsalion	Summary	101	uic	uannny	SEL

Category	Count
Commodities	3 089
Credit rating	278
Currency	4 726
Economic	4 474
Emerging Market	5 807
International	1 837
Other	2 208
Political	3 093
Unclassified	24 488
Total	50 000

Note. Break-down of the training set news counts per category.

Following the initial text pre-classification, the results of the pre-classification were used as the input dataset for the supervised machine-learning document term matrix.

6.3.4 Document term matrix

The headline news announcements were imported as a data matrix into the RTextTools software package. The rows of the matrix represent the 84 341 daily headline news items that were analysed over the 10-year period. Table 6-15 shows an extract of the corpus used to create the document matrix and classification categories. The 'Class Code' heading shown in the table is the output vector from the pre-classification step, and 'Class Name' lists the category associated with each 'Class Code'.

Table 6-15

Extract of headline news corpus

Date	Newswire	News Headline	Class	Class
			Code	Name
03 01 2010	REUTES	SPDR Gold Trust holdings stable at 1,133.622 tonnes	s 3	Com
04 01 2010	REUTES	African Markets - Factors to watch on Jan 4	9	Unc
04 01 2010	REUTES	Gold rise 2 pct as Dollar weakens	3	Com
04 01 2010	REUTES	Platinum hits 16-month high on weak dlr, ETF talk	1	Oth

Note. The extract shows the input data used as training set for the text analysis.



No further manipulation or analysis was performed on the document term matrix. The supervised machine-learning models require that the document term matrix is used as the input to the container functionality of the statistical package.

6.3.5 Creating a container and training the model

The container required by the RTextTools package is a wrapper class used for specifying the training set for the supervised machine-learning models. A training size range of 1:50 000 was specified as the quantity of headline news items to be used for training the models. The full range of 1 to 84 341 headline news items was included for classification. Using their unique algorithms, each model then 'learns' how the data is classified for the training set and applies the 'learned' approach to classifying the test set. The analytics provided by the statistical package represent the output from the text classification using the supervised machine-learning algorithms.

6.3.6 Text analytics

The label summary statistics for each category of classified data is given in Table 6-16. In the label summary statistics two categories were excluded from the study, namely 'other' (which had a consensus percentage code of 84.27%) and 'unclassified' (which had a percentage consensus code of 119.46%). The 'other' category included news that could not immediately be identified as being relevant to the study. Items in this category were excluded. All news items that were not categorised into one of the specified categories were automatically assigned to the unclassified category. The large number of unclassified headline news items (16 610) reflects the large volume of news and information that was irrelevant to the South African bond markets and could therefore be described as noise. For the news categories included in the study the percentage consensus was high, with emerging markets having the lowest coding percentage of 32.13%.



Full name	Code	Manual Coded	Consensus coded	% Consensus coded
Commodities	Com	1 377	1 396	101.38
Credit	Cre	2 756	2 531	91.84
Currency	Cur	1 154	800	69.32
Economic	Eco	4 647	3 934	84.66
Emerging market	EMM	1 111	357	32.13
International	Int	501	503	100.40
Other	Oth	2 996	2 525	84.28
Political	Pol	3 189	2 452	76.89
Unclassified	Unc	16 610	19 843	119.46

Label summary statistics

Note. Summary of the supervised machine learning text analysis results. Consensus coded refers to the code assigned by two or more of the supervised machine learning algorithms.

Table 6-17 provides the performance of each of the algorithms across every category. For the three algorithms that were used, namely SVM, SLDA and Logitboost, the best precision results of precision scores were obtained by the SVM algorithm. The overall performance, as determined by the F-score, was also obtained by the SVM algorithm. Again, the emerging market category had the lowest performance when comparing the recall and F-score percentages.

Table 6-17

Algorithm summary

	SVM Precision	Recall	Fscore	SLDA Precision	Recall	Fscore	Logitboost Precision	Recall	FScore
Commodities	0.85	0.84	0.84	0.76	0.77	0.76	0.77	0.84	0.8
Credit rating	0.99	0.91	0.95	0.98	0.89	0.93	0.99	0.92	0.95
Currency	0.91	0.65	0.76	0.77	0.61	0.68	0.92	0.6	0.73
Economic Emerging	0.93	0.78	0.85	0.89	0.7	0.78	0.86	0.8	0.83
market	0.87	0.26	0.4	0.53	0.29	0.37	0.89	0.25	0.39
International	0.79	0.71	0.75	0.55	0.73	0.63	0.78	0.7	0.74
Other	0.79	0.77	0.78	0.74	0.6	0.66	0.74	0.56	0.64
Political	0.87	0.66	0.75	0.83	0.62	0.71	0.88	0.64	0.74
Unclassified	0.82	0.97	0.89	0.79	0.94	0.86	0.8	0.96	0.87

Note. Summary of supervised machine learning algorithm text analysis performances.



The precision value expresses the ratio of the number of items coded in a specific category by the machine-learning algorithm to the ratio in the same category from the test set. Higher precision scores indicate the ability of the algorithm to correctly assign an announcement to the correct category. The recall scores indicated the accuracy of the assigned items, showing what percentage of the items assigned to the category should actually fall in the category. For example, a recall score of 80% indicated that 80% of the items classified in a specific category actually did belong to that category based on the pre-classification results. The F-score is a weighted measure that combines the precision and recall scores. This study used the consensus code assigned by all three of the algorithms as shown in Table 6-18, which shows the ensemble agreement coverage and recall of the three algorithms applied. For a 3-ensemble agreement, 88% of the data was classified with 87% accuracy. All of the above tests were run to test the accuracy of the classifications relating to the nine categories of the headline news dataset.

Table 6-18

Ensemble agreement

_	Ensemble coverage	Ensemble Recall
1	1	0.84
2	0.99	0.85
3	0.88	0.87

6.3.7 Classification of identified abnormal returns event date news

The sub-sample of abnormal return event dates created for further analysis was drawn from the consensus category classification performed by the machine-learning algorithms. The total number of headline news items for all identified abnormal return dates using the 3-day event window of headline news was then extracted to form the abnormal return news sample. For the abnormal increase in yield returns a total of 11 593 headline news items were classified over the 10-year period for all of the respective nodes. For the abnormal decrease in yield returns a total of 15 061 news items were classified over the 10-year period for all of the respective nodes. For the abnormal for all of the respective nodes. Table 6-19 shows the total number of news items classified per category.



Table	6-19
-------	------

Category	Headline news items (Increase)	Headline news items (Decrease)
Commodity	900	1 323
Credit rating	118	131
Currency	1 319	1 286
Economic	1 469	1 697
Emerging Market	1 460	1 810
International	508	654
Other	423	590
Political	741	1 317
Unclassified	4 655	6 253
Total	11 593	15 061

Headline news items classified per category prior to manual reliability check

Note. Supervised machine learning text classification results divided into increase and decrease event dates.

6.3.8 Manual reliability check

The starting point of the manual reliability check was the sub-sample of the event window headline news. The sub-sample of headline news items was further reduced by first manually inspecting the categories of 'other' and 'unclassified' headline news.

At the conclusion of the manual review of the 'other' and 'unclassified' categories, news headline items left in those categories were excluded from the event window news sub-sample. Table 6-20 summarizes the number of headline news items that remained in the sub-sample after the exclusion of the headlines that had been assigned to these two categories.

For improved reliability a relevance check (as outlined and described in 5.6.3) was applied manually to the final sub-sample for analysis. The final sub-sample of the analysis is summarized in Table 6-20:



Final sample

	Increase returns	Decrease returns
Total sub-sample	11 593	15 061
Excluding Unclassified and Other	5 078	6 843
Manual exclusions	3 959	5 450
Final sample after manual exclusions and recoding	2 556	2 768

Note. Final sample of the news used as the input for the regression analysis.

The break-down of the final sub-sample of headline news items classified per category after the manual reliability check is shown in Table 6-21. After the qualitative manual check of all the news items in the sub-sample was completed, the number of news items was considerably reduced. A substantial amount of news was released on a daily basis during the study period, but not all of the news was relevant or important to the South African bond markets. The currency, commodities, emerging markets and international categories were the four categories that had the highest numbers of items that were either excluded or recoded, namely 98%, 87%, 74% and 56% respectively. The political, economic and credit categories had much lower exclusion and recoding percentages, namely 29%, 34% and 26% respectively. A brief explanation of the process and reasoning for excluding certain news items from these categories is provided in 6.3.8.1 to 6.3.8.7.

Table 6-21

Category	Headline news items (Increase)	Headline news items (Decrease)
Commodity	141	137
Credit	89	94
Currency	22	37
Economic	1 021	1 052
Emerging Market	428	394
International	245	263
Political	610	791
Total	2 556	2 768

Headline news items classified per category post the manual reliability check

Note. Breakdown of final sample of news per category used in the regression analysis.



6.3.8.1 Headline news category: Currency

The currency headline news items were qualitatively filtered using a manual relevance check. It was found that many of the headline news items that had been assigned to the currency category were either general news items (see item 1 in Table 6-22) or they addressed some other topic, such economic news (see item 2 in Table 6-22) or they related to company news (see item 3 in Table 6-22). Such news items were excluded from the final sample.

The currency-related headline news that was considered for further analysis included headline news items on the South African Rand and news relating to interventions in the exchange rate, as well as news releases or comments on the Rand exchange rate by the Reserve Bank, government officials or other groups (see items 4 and 5 in Table 6-22).

Table 6-22

Extract of news items excluded and included in the headline news category: Currency

Item	Date	Result	Newswire	Headline news item
1	22 02 2010	Excluded	REUTES	S.Africa's Rand edges up, stocks seen up
2				S.Africa's Rand firms a bit vs dlr before
	23 02 2010	Moved to Eco	REUTES	GDP data
3				BRIEF-Central Rand Gold says early trial
	01 03 2010	Excluded	REUTES	mining
4	15 04 2011	Remains Cur	REUTES	S. Africa's X against competitive currency
				devaluation
5	14 05 2010	Remains Cur	REUTES	S.Africa's X group against Rand
				intervention

Note. Extract of currency category manual robustness check.

6.3.8.2 Headline news category: Commodities

For commodity news, various headline news items that were not relevant to the South African bond market were excluded. Examples: news items that related to company news (see item 1 in Table 6-23), news relating to gold funds (see item 2 in Table 6-23), Euro-coal news (see item 3 in Table 6-23), news relating to South Africa maize production (see item 4 in Table 6-23) and other news not directly relevant to the South Africa bond markets (see item 5 in Table 6.15).



The commodity headline news included was news on changes in the spot price of gold, platinum, silver, copper and palladium (see item 6 in Table 6-23) iron ore (see item 7 in Table 6-23) and oil prices (see item 8 in Table 6-23).

Table 6-23

Extract of news items excluded and included in the headline news category: Commodities

ltem	Date	Result	Newswire	Headline news item
1	22 02 2010	Excluded	REUTES	BRIEF-ARM sees 2.5 mln/T of export coal from GGV
2	24 02 2010	Excluded	REUTES	SPDR Gold Trust holding steady at 1,106.987/T
3	26 02 2010	Excluded	REUTES	Euro Coal-Apr S.Africa coal trades at \$85/T
4	26 02 2010	Excluded	REUTES	INTERVIEW-SAfrica maize farmers urge u-turn
5				ANALYSIS-Somali pirates set to gain from Asia coal
	01 03 2010	Excluded	REUTES	boom
6	07 05 2010	Excluded	REUTES	PRECIOUS-Gold hovers above \$1,200 after rally
				near record high
7	18 05 2010	Excluded	REUTES	ANALYSIS-Iron ore prices set to slip but not for long
8	10 11 2011	Excluded	REUTES	Oil prices likely to stay constrained - S.Africa

Note. Extract of commodity category manual robustness check.

6.3.8.3 Headline news category: Emerging markets

Various emerging market headline news items released on a daily basis that were not relevant in the South African context and specifically the South African bond markets were excluded. Examples: general emerging market news releases on the stock markets (see item 1 in Table 6-24), emerging market news not relevant to the South African bond market (see item 2 in Table 6-24).

Emerging market news that related to South Africa and which may have impacted the South African bond market was included (see items 3 and 4 in Table 6-24).



ltem	Date	Result	Newswire	Headline news item
1	26 01 2010	Excluded	REUTES	EMERGING MARKETS-Stocks drop sharply, Hungary to
				launch bond
2	29 01 2010	Excluded	REUTES	China reiterates goals for curbing climate change
3	25 02 2010	Remains EMM	BBCMON	Chinese, South African foreign ministers hold talks
4	26 01 2010	Remains EMM	MEHRNA	Iran seeks enhanced ties with S. Africa: minister

Extract of news items excluded and included in the headline news category: Emerging markets

Note. Extract of emerging market category manual robustness check.

6.3.8.4 Headline news category: International

For international news, news that was not relevant to the South African bond markets was excluded. Examples: company news (see item 1 in Table 6-25) and news such as the climate deal (see item 2 in Table 6-25).

Examples of items included as international news were headline news items released by the IMF (see item 3 in Table 6-25) and specific global market news (see item 4 in Table 6-25).

Table 6-25

ltem	Date	Result	Newswire	Headline news item
1	02 03 2010	Excluded	REUTES	ArcelorMittal loses challenge to EU carbon market
2	05 03 2010	Excluded	REUTES	EU tempers hopes of binding climate deal this year
3	09 03 2010	Remain Int	ASSPRE	IMF chief says world must prepare for next crisis
4	17 03 2016	Remain Int	REUTES	GLOBAL MARKETS-Dollar dives as Fed pulls in rate hike

Note. Extract of international category manual robustness check.

6.3.8.5 Headline news category: Political

For classifying political news, the names of government officials, such as the president of the country, were used in the process. Not all news relating to the president and his aides was relevant to the South African bond markets and was therefore excluded. Examples: a statement by the IFAD President (see item 1 in Table 6-26), news relating to strikes (see item 2 in Table 6-26), nationalisation (see item 3 in Table 6-26) and statements made by the president included (see item 4 in Table 6-26). News regarding the president sacking the



finance minister (see item 4 in Table 6-26) was included, as this event affected the South African bond market.

Table 6-26

Extract of news items excluded and included in the headline news category: Political

ltem	Date	Result	Newswire	Headline news item
1	04 05 2010	Excluded	ECLPCM	South Africa : IFAD President urges African leaders to
				invest in agriculture
2	13 05 2010	Excluded	REUTES	UPDATE 2-SAfrica transport strike hits more industries
3	17 09 2010	Excluded	REUTES	Mine nationalisation unlikely to move at ANC summit
4	10 12 2015	Remain Pol	COUREP	President sacks the finance minister

Note. Extract of political category manual robustness check.

6.3.8.6 Headline news category: Economic

Current and relevant economic news released within the event window was important as it could lead to abnormal returns. Economic news items were filtered and sorted for relevance. Examples of exclusions: economists' views or reports (see item 1 in Table 6-27), economic calendars (see item 2 in Table 6-27) and research reports (see item 3 in Table 6-27).

All economic news released on a specific day was included. Examples of inclusions: interest rates (see item 4 in Table 6-27), Inflation data (see item 5 in Table 6-27), growth (see item 6 in Table 6-27).

Table 6-27

Extract of news items excluded and included in the headline news category: Economic

lten	n Date	Results	Newswire	Headline news item			
1	24 02 2010	Excluded	ALLENG	Interest Rates 'Too High for Too Long'			
2	02 03 2010	Excluded	OSTSEL	DJ UK Political, Economic Calendar - Week Ahead			
3				Research and Markets: South Africa Retail Report			
	10 05 2010	Excluded	BSW	Q2			
4	13 05 2010	Remain Eco	REUTES	S.Africa's cbank leaves repo rate steady at 6.5 pct			
5	29 09 2010	Remain Eco	REUTES	S.African CPI slows to 3.5 pct y/y in August			
6				UPDATE 2-S.Africa's Q3 GDP growth data			
	23 11 2010	Remain Eco	REUTES	disappoints			

Note. Extract of economic category manual robustness check.



6.3.8.7 Headline news category: Credit

In this category, headline news categorised as credit may also have included credit rating information relating to other countries and companies. Those headline news items were excluded. Example of exclusions: Fitch rating on Middle East and North Africa (see item 1 in Table 6-28), Fitch ratings of South African companies (see item 2 in Table 6-28).

Credit rating news relating to South Africa's sovereign bond rating by the rating agencies Fitch, Moody's and Standard and Poor were included (see items 3, 4 and 5 in Table 6-28).

Table 6-28

ltem	Date	Result	Newswire	Headline news item
1	07 04 2011	Excluded	REUTES	TEXT-Fitch release on Middle East & N. African banks
2	05 07 2011	Excluded	REUTES	TEXT-Fitch:Stable outlook for South African corporates
3	09 11 2011	Remain Cre	REUTES	Moody's puts S.Africa's A3 rating on negative
4	13 01 2012	Remain Cre	REUTES	Fitch cuts S.Africa's outlook to negative
5	08 12 2015	Remain Cre	MISTNW	Fitch Downgrades South Africa to 'BBB-'; Outlook Stable
		-		

Note. Extract of credit category manual robustness check.

6.4 RESULTS OF ASSESSING THE RIGOUR OF THE RESEARCH DESIGN

Within the broad reverse-event study framework, the first part of the study was to determine abnormal returns of the various nodes of the yield curve. It was important to confirm that the derived zero-coupon yield curve was accurate, which was confirmed. The accuracy of the zero-coupon yield curve needed to be tested to show that the abnormal returns were significantly different from the population sample, as abnormal returns were the starting point of the analysis. The second part of the study concerned the text analysis and classification process, which provided the news frequencies allocated to the different categories. The news classification used a quantitative and a qualitative approach. The third part of the study concerned the linking of abnormal returns to specific news categories. The final data sample was investigated to ensure that the appropriate statistical regression model was applied. Finally, for the sovereign bonds a spread analysis of the data sample was performed to ensure that the appropriate statistical ANOVA model was used. The tables and figures



relating to the results of assessing the rigour of the research design can be found in Appendix C, and all of their label numbers are preceded by C.

6.4.1 Confirming the accuracy of the zero-coupon yield curve

As described in section 3.7.2.3 the bootstrap of the zero-coupon yields from the coupon bearing bonds used a mathematical model. The inputs to the calculation were the mark-to-market yield to maturity for each of the bonds included in the bootstrap for the specific date. The Hagan-West bootstrap model employed to derive the yield curve solves the bootstrap algorithm iteratively by adjusting the zero-coupon rates, so that the collection of zero-coupon rates calculated by the algorithm equates to the bond price determined from the GCH-formula. The accuracy of the zero-coupon rates was then verified by examining the difference between the actual price (price of the bond calculated using the GCH formula) and the derived price (price for the bond calculated using the zero-coupon yields). In Table C-1 the descriptive statistics of the differences between the calculated price and the derived price for each bond are provided. The mean of the differences for each bond is only observed in the seventh decimal place for bond prices expressed in 100 nominals.

To test if the bond prices (both calculated and derived) were normally distributed, a Shapiro-Wilk test for normality was performed on the standardised prices. The results of the Shapiro-Wilk tests can be seen in Table C-2. As the prices were not normally distributed a Wilcoxon rank-sum statistical test was used to ascertain if there were statistically significant differences between the calculated prices and the derived bond prices. The results of the Wilcoxon rank-sum tests are supplied in Table C-3. They show that there were no statistically significant differences between the calculated bond prices and the derived bond prices.

6.4.2 Abnormal returns statistical test results

The study identified abnormal event dates and the returns from the abnormal return dates were referred to as the abnormal returns. The Wilcoxon signed ranked test (as described in 5.9.2) results affirmed that the abnormal returns were statistically different from the corresponding data population. The results of the test are provided in Table C-4. for increase



event dates and Table C-5 for decrease event dates. At a 95% confidence interval, p-values for all nodes are < .05 therefore it could be concluded that the abnormal returns of both the increase and decrease event dates were from non-identical populations and that the returns were significantly different from the population (normal return) sample.

6.4.3 Text analysis and reliability check

The results of the text analytics were described in 6.3.6 where it was stated that 88% of the full sample of text data was classified with 87% accuracy. This quantitative news classification process was the starting point of the final sample of news used for further analysis. Only the headline news items identified during the event window of the abnormal return dates were taken through a further qualitative process (described in 6.3.8) to ensure that only the most relevant and applicable news items were categorised.

6.4.4 Diagnostic tests for the multiple linear regression model assumptions

Different visual inspections were conducted with respect to the final data sample of the basis points and news categories for each node to confirm that the linear regression assumptions were met. The diagnostic tests conducted were VIF, testing for multicollinearity, and the Durbin-Watson test to confirm independence of the residual error terms. The standardized residuals were also reported.

6.4.4.1 Results of diagnostic tests for increases in basis point changes

The stepwise selection method employed to solve for the optimal multiple linear regression model was a semi-autonomous procedure, after which the researcher verified the results by testing for compliance to the linear regression model assumptions.

6.4.4.1.1 Outlier treatment for increase event dates

Outliers are defined as observations that lies an abnormal distance from other observations, and in this study the researcher used the influence plot to identify outlier values. The influence plots for the increase event dates in Figure B-2, shows the index number of the outliers, and in Table 6-29, the number of outliers removed per node is given.



Number of outliers excluded per node for increase event dates

	Number of outliers excluded
ON	0
3M	1
6M	1
1Y	0
2Y	1
5Y	3
10Y	1
15Y	3
20Y	2

Note. Number of outliers that were removed before fitting the linear regression model as identified using an influence plot.

6.4.4.1.2 VIF – Multicollinearity for increase event dates

The VIF for the nodes with more than one statistically significant independent variable is provided in Table 6-30. VIF for all nodes appears to be in an acceptable range, namely close to 1 and not above 10.

	Com	Cre	Cur	Eco	ЕММ	Int	Pol
ON	1.158	1.237	2.166	1.582	2.333	1.582	1.221
3M	1.247	1.154	1.078	1.325	1.752	1.244	1.223
6M	1.084	1.214	1.677	1.832	2.216	1.795	1.366
1Y	1.108	1.813	1.974	1.766	2.062	1.387	1.926
2Y	1.533	2.776	1.069	2.083	2.104	1.435	2.137
5Y	1.253	1.618	1.489	1.455	1.230	1.329	1.458
10Y	1.293	1.868	1.385	1.384	1.430	1.266	1.509
15Y	1.513	1.821	1.141	1.505	1.209	1.126	1.508
20Y	1.108	1.745	1.087	1.162	1.271	1.030	1.465

Table 6-30

VIF test for multicollinearity for increase dates

As the VIF is a measure of the multicollinearity, it is not possible to show the VIF for some of the nodes where the optimal linear regression comprises a single independent variable. The possibility of multicollinearity was verified by referring to the correlation matrixes for all the independent variables for all nodes, and it was confirmed that there were no correlations higher than .8.



6.4.4.1.3 Durbin-Watson – Independence of residual error terms for increase event dates

The Durbin-Watson (DW) statistic for all nodes is provided in Table 6-31. The DW statistic for all the nodes were between the acknowledged thresholds of 1.5 and 2.5, this indicates no serious autocorrelation in the data.

Table 6-31

Durbin-Watson test for independence for increase event dates

statistic	DW	<i>p</i> -value
ON	2.1798	.640
3M	1.7438	.117
6M	1.5584	.069
1Y	1.7918	.271
2Y	1.5170	.058
5Y	1.8802	.334
10Y	1.5687	.073
15Y	1.8781	.342
20Y	1.5911	.089

6.4.4.1.4 Standardised residuals for increase event dates

The standardised residuals for all nodes are provided in Table 6-32. The acceptable range for standardised residuals is between +3 and -3. All nodes are in the acceptable range, therefore the normal distribution of the residuals can be assumed.

Table 6-32

Standardised residuals for increase event dates

	Lowest	Highest
ON	-1.915	2.253
3M	-1.914	3.077
6M	-0.957	2.653
1Y	-1.723	3.060
2Y	-2.254	2.567
5Y	-1.868	1.724
10Y	-1.567	2.880
15Y	-1.929	2.607
20Y	-1.526	2.468



The outliers identified and removed using the Cook's Distance in the diagnostic tests, were excluded in all the regression models. The number of outliers removed in each instance are shown in Table 6-29 and Table 6-34. Similar to the diagnostic tests performed for the abnormal increase basis points: in the abnormal decrease basis points, where outliers affect the final model fit, the outliers were removed from the sample used for the multiple linear regression model selection.

6.4.4.1.5 Homoskedasticity of the residuals

The homoskedasticity assumption for linear regression models checks if the variance of the error term is constant, as non-constant variance could be an indication that the estimators used are not the most efficient. When looking at the scatterplots in Figure B-4 and the definition of the heteroskedasticity, the variance of the residuals increased as the predicted value of the basis points increased in some instances, but this in line with expectations, as the data used in the regression were by definition the extreme moves. A linear model is unlikely to capture all the variability in the data, as for the most extreme moves very few observations were noted.

6.4.4.2 Results of diagnostic tests for decrease in basis point changes

Similar to increase event dates, the stepwise selection method has been employed to solve for the optimal multiple linear regression model after which the researcher verified the results by testing for compliance to the linear regression model assumptions

6.4.4.2.1 Outlier treatment for decrease event dates

The influence plots for the decrease event dates in Figure B-3, shows the index number of the outliers, and in Table 6-33, the number of outliers removed per node is given.



Number of outliers excluded per node for decrease event dates

	Number of outliers excluded
ON	0
3M	4
6M	6
1Y	0
2Y	0
5Y	0
10Y	0
15Y	0
20Y	0

Note. Number of outliers that were removed before fitting the linear regression model as identified using an influence plot.

6.4.4.2.2 VIF – Multicollinearity for decrease event dates

Similar to the increase nodes, the VIF for the decrease nodes with more than one statistically significant independent variable is provided in Table 6-34. VIF for all nodes appears to be in an acceptable range, namely above 1 and not above 10.

Table 6-34

VIF test for multicollinearity for decrease event dates

	Com	Cre	Cur	Eco	EMM	Int	Pol
ON	1.535	1.390	1.309	1.664	1.509	1.108	1.319
3M	1.389	1.122	1.245	1.573	1.412	1.164	1.141
6M	1.398	1.121	1.170	1.422	1.139	1.130	1.111
1Y	1.279	1.130	1.516	1.820	1.114	1.229	1.089
2Y	1.300	1.077	1.135	1.348	1.212	1.062	1.261
5Y	1.128	1.133	1.191	1.243	1.068	1.142	1.179
10Y	1.400	1.082	1.318	1.257	1.187	1.142	1.138
15Y	1.164	1.628	1.214	1.289	1.070	1.011	1.654
20Y	1.102	1.649	1.443	1.387	1.553	1.278	1.804

As indicated for the decrease event dates, the possibility of multicollinearity was verified by referring to the correlation matrixes for all the independent variables for all nodes, and it was confirmed that there were no correlations higher than .8.



6.4.4.2.3 Durbin-Watson – Independence of residual error terms for decrease event dates

The Durbin-Watson statistic for all nodes is provided in Table 6-35. The threshold for the Durbin-Watson test statistics is values should lie between 1.5 and 2.5 to indicate no autocorrelation, values outside this range could potentially indicate that there is autocorrelation present.

Table 6-35

statistic	DW	<i>p</i> -value
ON	2.4171	.884
3M	1.6393	.086
6M	1.6289	.071
1Y	2.5237	.911
2Y	1.5293	.044
5Y	1.4842	.045
10Y	1.7689	.229
15Y	1.7426	.171
20Y	1.3932	.025

Durbin-Watson test for independence for decrease event dates

From Table 6-35 above, the 1-, 5- and 20-year nodes' DW statistic fall outside the range of 1.5 to 2.5. As the observations used in the analysis were the abnormal price change event dates, and the observations did not represent a regular time-series, the possible autocorrelation as indicated by the Durbin-Watson test statistic did not represent big enough deviation from the threshold value to be cause for concern.

6.4.4.2.4 Standardised residuals for decrease event dates

Table 6-36 shows the standardised residuals for all nodes. The acceptable range for the standardised residuals is between +3 and -3. Apart from the 1-year node, all nodes appear to be in an acceptable range.



	Lowest	Highest
ON	-2.519	1.754
3M	-2.980	1.697
6M	-2.897	1.760
1Y	-3.976	1.360
2Y	-2.915	1.464
5Y	-2.625	1.633
10Y	-2.298	1.801
15Y	-2.626	1.424
20Y	-2.764	2.022

Standardised residuals for decrease event dates

Table 6-36

6.4.4.2.5 Homoskedasticity of the residuals

The scatterplots for the residuals against the predicted values is given Figure B-5. From the inspection of the plots, once again some of the scatterplots indicated that heteroskedasticity could be present in some of the nodes, but similar to the scatterplots for the increase in basis points, the presence of heteroskedasticity was mostly due to the uneven number of observations for all fitted values.

6.4.5 Sovereign spread assumption test

As described in 5.8.2 the Levene test confirmed that the Welch ANOVA be used to test the sovereign spread and is considered the most appropriate and robust test. The results from the Levene test of homogeneity of variances showed that the null hypothesis can be rejected with the all the *p*-values < .05. The population variances for the sovereign spread on the day prior to the news release, and the during the event window are different.



Test of homogeneity of variances

Levene test

		Levene Statistic	df1	df2	<i>p</i> -value
Difference between Espread and Pspread	Based on Mean	3.313	8	382	.001
	Based on Median	3.046	8	382	.002
	Based on Median and with adjusted df	3.046	8	283	.003
	Based on trimmed mean	3.147	8	382	.002

Note. Results of homogeneity of variances for all sovereign spread data.

6.5 SUMMARY

This chapter described the processes followed to generate the final data sub-samples for the abnormal event dates, the news related to the abnormal event dates, the classification of the news into different categories, and how the news was linked to the abnormal event dates through basis point changes. It also discussed the methods used to test the rigour of the study, which confirmed the validity of the research processes used.

The first step of the reverse event study was to identify abnormal event dates by applying three GARCH models using daily return data for each node of the yield curve over the sample period. Based on the Chebyshev inequality, the two standard deviations were calculated every day for each time series. Occurrences outside the two standard deviation bands could be identified as the abnormal event dates. There was a total of 457 unique abnormal return dates, consisting of 226 dates for increases in yield returns and 231 dates for decreases in yield returns.

The second part of the analysis was the text classification of the headline news items. The full sample of news for the study period comprised 92 051 headline news items that were classified using a quantitative text analysis to categorise news into seven different categories: economic, commodities, credit, currency, emerging markets, international and political news. News items released on the identified news dates underwent a manual



reliability and relevance check. The total number of news items for increase event dates was 2 556 and for decrease event dates it was 2 768. The text analytics indicates that 88% of the full sample of text data is classified with 87% accuracy, and needs to be further verified and checked by applying a manual process to the news items categorised using the quantitative text analysis process.

The results of assessing the rigour of the design were reported by confirming the accuracy of the zero-coupon yield curve nodes. It was then confirmed that the returns on the abnormal return dates were statistically significant when compared to the corresponding data population. The multiple regression diagnostics were validated using the Levene test, which confirmed that the Welch ANOVA test was the appropriate statistical test to use.



CHAPTER 7 RESEARCH RESULTS

The research method outlined in chapter 5 used the broad framework of the reverse event study methodology to (1) determine abnormal event dates, and (2) analyse and classify news announcements released during the event window of each identified event date. Chapter 6 provides the data analysis results of the abnormal event dates and the news classification. The results formed the final sample for analysis. The results of linking the abnormal returns to news categories are provided in chapter 7. The tables and figures relating to these final research results can be found in Appendix B and their labels are preceded by B.

7.1 RESULTS OF LINKING NEWS CATEGORIES TO ABNORMAL RETURNS

By using the price changes, the news frequency counts and price changes expressed as basis points, the researcher was able to link abnormal returns to different news categories by applying both descriptive and inferential statistical analysis methods to make inferences regarding the impact of news on the South African yield curve. For the sovereign bond spread analysis the research results were divided into two, namely the descriptive analysis and the inferential statistical analysis.

7.1.1 Descriptive analysis

The following section describes the descriptive analysis results. The tables reflect the contribution of the seven relevant news categories for each specified node of the yield curve.

7.1.1.1 Overall aggregate explanatory power of news categories

The aggregated contribution of the news tables provides the frequency of the headline news items per category for all nodes of the South African yield curve. The number of news items in the tables shows the aggregate number of headline news items per news category associated with each node over the 10-year sample period.

Table 7-1 shows the aggregated number of headline news items in each category for all of the event windows for the identified abnormal yield increases for each node. On aggregate, it was evident from the table that economic news provided the highest contribution for all

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nodes of the yield curve, followed by political news and emerging market news. A similar trend was observed for the aggregate number of headline news items for the abnormal decrease event dates as presented in Table 7-2.

Table 7-1

	Com	Cre	Cur	Eco	EMM	Int	Pol	Total
ON	87	42	33	732	384	219	564	2 061
3M	234	78	51	1 086	510	279	651	2 889
6M	78	63	39	918	396	285	525	2 304
1Y	21	114	21	666	327	234	465	1 848
2Y	63	105	24	714	312	231	420	1 869
5Y	111	78	30	681	393	204	480	1 977
10Y	114	78	42	846	366	180	432	2 058
15Y	135	69	39	768	333	228	465	2 037
20Y	72	78	12	609	327	222	426	1 746

Aggregated contribution of news for abnormal increases in yields

Note. The total number of headline news articles classified per category for the full sample period.

Table 7-1 and Table 7-2 show that the economic news category contributes the largest frequency of news for all nodes on abnormal increase and decrease event dates. The political news category shows the second largest contribution in most nodes, but not in all of the nodes. The currency news category had virtually no impact, except for a few items in the short-term nodes.

Table 7-2

Aggregate contribution of news for abnormal decreases in yields

	Com	Cre	Cur	Eco	EMM	Int	Pol	Total
ON	57	72	18	660	315	174	702	1998
3M	210	24	60	1068	267	192	774	2595
6M	141	66	69	1146	384	216	900	2922
1Y	60	69	24	873	267	126	366	1785
2Y	84	105	21	762	261	186	510	1929
5Y	60	102	24	795	378	231	438	2028
10Y	90	81	33	810	300	234	483	2031
15Y	153	81	30	1080	309	216	912	2781
20Y	72	81	24	669	282	183	735	2046

Note. The total number of headline news articles classified per category for the full sample period.



7.1.1.2 Contribution of the news categories per node

This section investigates each node of the yield curve to provide a deeper insight regarding the contribution of the different news categories. Table 7-3 provides a summary per node for increase event dates. It shows the period that had the highest number of news items releases in each of the news categories. For example, the overnight (ON) node 37 on abnormal event dates was identified using the GARCH process. From the analysis the yield increases on that day can be explained by linking the news to different relevant news categories. In the ON example, one day (2.7%) can be linked to commodity news headlines, one day (2.7%) to credit rating news, and 20 days to economic news (54.1%), emerging markets seven days (18.9%), three days for international news (8.1%), five days for political news (13.5%) and zero for currency news. For the abnormal event dates, the news categories with the highest frequencies of news releases were identified as having the highest contribution. For the ON-node (on each of the 37 days) a news category was identified as having the most news items during the event window. Table 7-3 provides a summary which shows that economic news had the highest contribution for all of the nodes. Political and emerging market news had similar impacts, as reflected in their ranking as the second and third highest categories.



Contribution of the news: a summary per node for increase event dates

	Com	Cre	Cur	Eco	EMM	Int	Pol	Total
O/N	1	1	0	20	7	3	5	37
O/N Perc	2.7%	2.7%	0.0%	54.1%	18.9%	8.1%	13.5%	
3-month	2	1	1	37	6	3	11	61
3-month Perc	3.3%	1.6%	1.6%	60.7%	9.8%	4.9%	18.0%	
6-month	2	0	0	38	3	6	7	56
6-month Perc	3.6%	0.0%	0.0%	67.9%	5.4%	10.7%	12.5%	
1-year	1	0	0	21	2	4	8	36
1-year Perc	2.8%	0.0%	0.0%	58.3%	5.6%	11.1%	22.2%	
2-year	1	0	0	23	4	3	7	38
2-year Perc	2.6%	0.0%	0.0%	60.5%	10.5%	7.9%	18.4%	
5-year	2	0	0	22	7	2	6	39
5-year Perc	5.1%	0.0%	0.0%	56.4%	17.9%	5.1%	15.4%	
10-year	1	0	0	29	3	1	9	43
10-year Perc	2.3%	0.0%	0.0%	67.4%	7.0%	2.3%	20.9%	
15-year	2	0	0	28	6	2	8	46
15-year Perc	4.3%	0.0%	0.0%	60.9%	13.0%	4.3%	17.4%	
20-year	1	0	0	22	8	4	9	44
20-year Perc	2.3%	0.0%	0.0%	50.0%	18.2%	9.1%	20.5%	
Total	3.3%	0.5%	0.3%	60.0%	11.5%	7.0%	17.5%	

Note. Summary showing number of days and percentage on which a specific category had the highest count.

Table 7-4 groups the number of event dates (for which abnormal decrease returns were observed per node) into the news category that had the most news items released on a specific date. For the overnight node 36 event dates were identified, on which 660 (see Table 7-2) economic news articles were released. Economic news had the most articles on one of the total of 19 days. A total of 702 total political articles (for the overnight node) were released over the 36 event dates, which represents the most articles released during the study period, namely nine days out of the 36. This demonstrated that most of the political articles were either published on days where other news was released, or that most of the political articles were clustered around a few event dates.



Table 7-4

Contribution of the news: a summary per node for decrease event dates

	Com	Cre	Cur	Eco	EMM	Int	Pol	Total
O/N	0	1	1	19	4	2	9	36
O/N Perc	0.0%	2.8%	2.8%	52.8%	11.1%	5.6%	25.0%	
3-month	1	0	0	32	1	3	20	57
3-month Perc	1.8%	0.0%	0.0%	56.1%	1.8%	5.3%	35.1%	
6-month	1	1	3	41	5	0	13	64
6-month Perc	1.6%	1.6%	4.7%	64.1%	7.8%	0.0%	20.3%	
1-year	0	1	0	27	4	0	4	36
1-year Perc	0.0%	2.8%	0.0%	75.0%	11.1%	0.0%	11.1%	
2-year	0	3	0	26	2	2	7	40
2-year Perc	0.0%	7.5%	0.0%	65.0%	5.0%	5.0%	17.5%	
5-year	0	2	0	26	5	2	6	41
5-year Perc	0.0%	4.9%	0.0%	63.4%	12.2%	4.9%	14.6%	
10-year	0	2	0	28	4	4	7	45
10-year Perc	0.0%	4.4%	0.0%	62.2%	8.9%	8.9%	15.6%	
15-year	0	1	0	30	3	4	9	47
15-year Perc	0.0%	2.1%	0.0%	63.8%	6.4%	8.5%	19.1%	
20-year	0	1	0	20	4	3	11	39
20-year Perc	0.0%	2.6%	0.0%	51.3%	10.3%	7.7%	28.2%	
Total	0.49%	2.96%	0.99%	61.48%	7.90%	4.94%	21.23%	

Note. Summary showing number of days and percentage on which a specific category had the highest count.

7.1.1.3 Explaining news categories per node for an abnormal increase in yield returns Table 7-5 is an extract of the two-year node that shows a selection of the abnormal event dates and numbers (or frequencies) of news items released during the event window (T₋₁, T, T₊₁) and the basis point movement on the abnormal event date. The table shows the categories that had the most articles for specific abnormal increase event dates.



			'			,				
EventDate	Com	Cre	Cur	Eco	EMM	Int	Pol	Total	Most articles	Bps
22 04 2010	4	0	0	5	2	2	0	13	Eco	15
04 05 2010	4	0	0	8	5	3	9	29	Pol	13.2
17 11 2010	5	0	1	22	12	1	1	42	Eco	12.3
29 11 2010	3	0	0	7	5	3	1	19	Eco	29.9
07 01 2011	0	0	0	2	3	0	0	5	EMM	12.8
21 01 2011	0	0	0	12	1	0	1	14	Eco	20.1
13 05 2011	0	0	1	10	3	0	2	16	Eco	34.1
05 08 2011	1	0	0	1	8	6	0	16	EMM	15.1
12 09 2011	0	0	0	1	0	7	0	8	Int	20.8
08 11 2011	0	5	0	6	0	2	1	14	Eco	40.8
10 11 2011	1	6	0	15	0	0	7	29	Eco	31.5
15 11 2011	0	3	0	6	2	4	2	17	Eco	41.3
14 03 2012	0	0	0	2	0	0	0	2	Eco	13.7

Table 7-5

Extract of news classification per event date for two-year node on increase event dates

7.1.1.4 Mean price change and basis points of each node

In Table B-3 and Table B-4 (see Appendix B) the mean of the price change and basis point change for each of the abnormal return dates per node per news category was analysed. The mean basis point per news category provided an indication of the value of the price change impact for the specific news category. The highest contribution per news category per node was determined as the highest number of articles per category per node. The analysis was based on the number of changes in the news frequencies and the impact was assessed using the mean basis point calculation.

During abnormal increase news events (see Table B-3) it can be seen that , from ON to the 6M (the short end of the yield curve) the economic news category had the highest contribution, with mean basis points of 12.04 (ON), 4.79 (3M) and 6.24 (6M). The mean basis points were linked to a Rand value for the basis point change of R3.30, R117.54 and R301.06 per million nominal respectively. From 1Y to 20Y (medium and long ends of the yield curve), the category with the highest contributions (which explains abnormal returns) was the political news category, with the mean basis points of 21.43 (1Y), 28.59 (2Y), 25.64 (5Y), 22.41 (10Y), 24.15 (15Y) and 23.12 (20Y). These points were linked to a Rand value



for the basis point change of R2 006.76, R5 353.01, R11 940.95, R20 776.48, R33 382.85 and R42 195.09 respectively.

Figure 7-1 provides graphs of the various news categories and the association between the basis points and news for different nodes of the yield curve. It is clear that economic news, followed by emerging markets and international news, were the main news categories that had an impact on the short end of the yield curve. Political news, followed by economic news, were the highest contributors in the medium and long ends of the yield curve.



Influence of different news categories on increase event dates



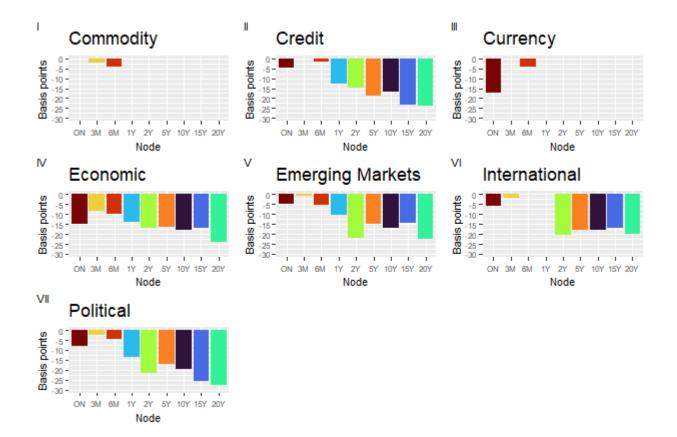
Table B-4 shows that for decrease news events in the ON to 1Y (the short end of the yield curve) the economic news category had the highest contribution (to explain abnormal returns), with the mean basis points of 15.04 (ON), 8.35 (3M), 9.90 (6M) and 14.13 (1Y). The points were linked to a Rand value of the basis point change of R4.12, R204.91, R477.19 and R1 323.48 per million nominal respectively. For the 2Y node the emerging market news category had the highest contribution, with 21.96 basis points and a Rand



value of R4 112.05 per million nominal. The 5Y node shows credit as the highest contributing news category, with 18.66 basis points and a Rand value of R8 690.99 per million. In the 10Y, 15Y and 20Y (long end of the yield curve), political news showed the highest contributions, with the mean basis points of 19.35 (10Y), 25.63 (15Y) and 27.72 (20Y). These points were linked to a Rand value per basis point of R17 938.06, R35 429.25 and R50 591.72 respectively. This was confirmed visually in Figure 7-2, where the different graphs show the association between the basis points and news for different nodes of the yield curve. Economic news is the main news category that had an impact on the short end of the yield curve, in the medium-term emerging market news and credit news stand out and political news had the biggest contribution in the long end of the yield curve.

Figure 7-2

Influence of different news categories on decrease event dates





7.1.1.5 Comparison between absolute increase basis points and decrease basis points

From the ANOVA results in Table 7-6 it can be seen that the 20Y node was the only node with a statistically significant difference between the means for the absolute values of the abnormal increase basis points and the decrease basis points. A visual inspection of Figure 7-3 shows that the absolute values of the decrease basis points were higher than the increase basis points. The graphs for all of the other nodes are provided in Figure B-1 (see Appendix B).

Table 7-6

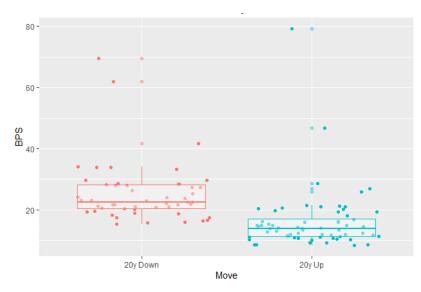
ANOVA results comparing means of increase and decrease basis points for all nodes comprising the yield curve

Node	n	statistic	DFn	DFd	<i>p</i> -value	method
ON	74	0.3	1	64.32752	.586	Welch ANOVA
3M	227	1.98	1	161.8112	.161	Welch ANOVA
6M	251	1.86	1	219.3166	.174	Welch ANOVA
1Y	92	1.45	1	81.92273	.233	Welch ANOVA
2Y	115	2.65	1	95.71289	.107	Welch ANOVA
5Y	126	0.19	1	104.2212	.661	Welch ANOVA
10Y	115	0.57	1	101.0102	.453	Welch ANOVA
15Y	127	1.12	1	119.4734	.292	Welch ANOVA
20Y	115	24.33	1	107.6995	< .001	Welch ANOVA



Figure 7-3

20-year node: Comparison of abnormal returns in basis points for increase and decrease event dates



Note. A scatter- and box-plot, indicating the differences in the dispersion and means of the absolute values for the abnormal increase and decrease in basis points for the 20-year node.

7.1.1.6 Results of comparing significant dates that occurred across the short-, medium- and long-term nodes of the yield curve.

The impact of different news categories on different parts of the curve were analysed further by grouping the nodes into short-, medium- and long-term, with the short-term nodes being the overnight, 3- and 6-month nodes, the medium-term nodes being the 1-, 2- and 5-year nodes, and the long-term nodes being the 10-, 15- and 20-year nodes. All common abnormal dates across all three nodes for each of the periods were analysed to determine the effect of the news category on the basis points of the different tenors. There were no dates observed (for either the increases or the decreases) that influenced all three of the periods.

Table 7-7
Common abnormal return dates for increases in the short-term tenors

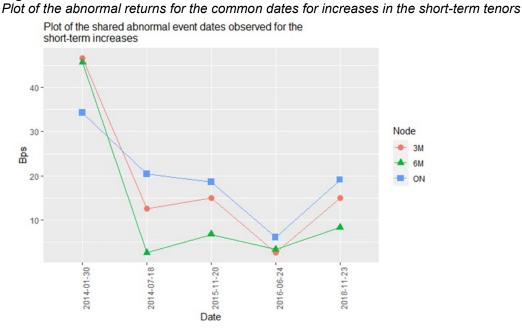
Dates	News	ON	3M	6M	
30/01/2014	Eco	34.3	46.7	45.8	
18/07/2014	EMM	20.4	12.5	2.5	
20/11/2015	Eco	18.6	15.0	6.7	
24/06/2016	Int	6.0	2.5	3.3	
23/11/2018	Eco	19.1	15.0	8.3	

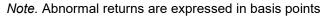
Note. News impact on the short term-tenors of the yield curve with the impact expressed in basis points.



For the short-term abnormal increase event dates (see Table 7-7 and Figure 7-4), the overnight point showed the biggest reaction to news in all of the dates. The economic news category showed three shared event dates with the highest basis point movements. Emerging market news and international news also shared common dates in the short-term nodes.

Figure 7-4





For the medium-term abnormal increase event dates, the longest maturity (5-year) showed the greatest reaction to the news. The medium-term period comprised only three common abnormal return dates in three different news categories, being economic, political and international news, which was observed across the three medium-term tenors, as shown Table 7-8 and Figure 7-5.

Table 7-8

Common abnormal return dates for increases in the medium-term tenors

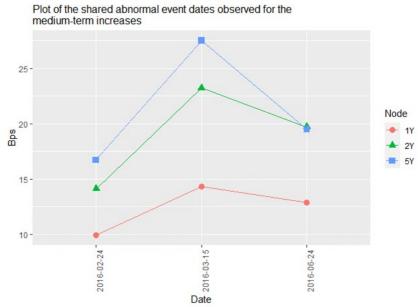
Dates	News	1Y	2Y	5Y
24/02/2016	Eco	9.9	14.1	16.7
15/03/2016	Pol	14.3	23.2	27.5
24/06/2016	Int	12.9	19.7	19.5

Note. News impact on the medium-term tenors of the yield curve with the impact expressed in basis points.



Figure 7-5

Plot of the abnormal returns for the common dates for increases in the medium-term tenors



Note. Abnormal returns are expressed in basis points

The long-term period comprised ten shared abnormal event dates. There were no clear differences in the basis point moves of the tenors that made up the long term. The long-term period showed the single biggest change for an abnormal event date increase for all of the increases analysed. On 12 December 2015 the 20-year node increased by 125 bps, while the 10- and 15-year nodes increased by 105 bps and 103 bps respectively, as illustrated in Table 7-9 and Figure 7-6. For the long-term period mostly the economic and political news categories were assigned to these dates.



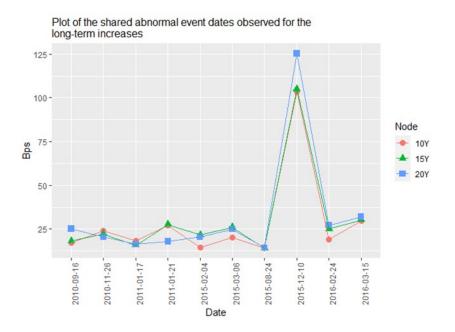
Dates	News	10Y	15Y	20Y
16/09/2010	Pol	17.1	18.3	25.1
26/11/2010	Eco	24.2	22.3	20.6
17/01/2011	Eco	18.5	15.8	16.3
21/01/2011	Eco	27.1	27.6	17.9
04/02/2015	Eco	14.7	21.6	20.6
06/03/2015	Pol	20.4	26.1	24.9
24/08/2015	EMM	14.3	14.0	14.4
10/12/2015	Pol	103.5	105.1	125.3
24/02/2016	Eco	19.1	25.1	27.2
15/03/2016	Pol	29.6	30.3	32.1

Common abnormal return dates for increases in the long-term tenors

Note. News impact on the long-term tenors of the yield curve with the impact expressed in basis points.

Figure 7-6

Plot of the abnormal returns for the common dates for increases in the long-term tenors



The shared dates for short-term abnormal decreases are shown in Table 7-10 and Figure 7-7, and consist of six observations. There is no single node that has a consistently larger reaction on the shared dates, compared to the other nodes for the short-term period. Economic news was the only category linked to these shared dates.



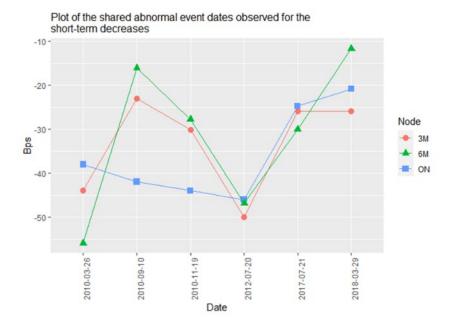
Common abnormal return	dates for decreases	in the short-term tenors
------------------------	---------------------	--------------------------

Dates	News	ON	3M	6M	
26/03/2010	Eco	-38.0	-44.0	-56.0	
10/09/2010	Eco	-42.0	-23.0	-16.0	
19/11/2010	Eco	-44.0	-30.1	-27.8	
20/07/2012	Eco	-46.0	-50.0	-46.9	
21/07/2017	Eco	-24.7	-25.9	-30.0	
29/03/2018	Eco	-20.8	-25.8	-11.6	

Note. News impact on the short-term tenors of the yield curve with the impact expressed in basis points.

Figure 7-7

Plot of the abnormal returns for the common dates for decreases in the short-term tenor



Note. Abnormal returns are expressed in basis points

For the medium-term decreases Table 7-11 and Figure 7-8 show that the 5-year node exhibited the largest reaction to news on the shared abnormal event dates, mainly with regard to the economic news category (three observations), followed by political news (two shared observations) and one credit category observation.



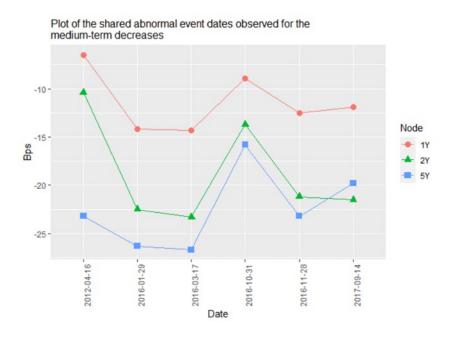
Dates	News	1Y	2Y	5Y
16/04/2012	Eco	-6.5	-10.4	-23.2
29/01/2016	Eco	-14.2	-22.5	-26.3
17/03/2016	Pol	-14.3	-23.3	-26.7
31/10/2016	Pol	-8.9	-13.7	-15.8
28/11/2016	Cre	-12.5	-21.2	-23.2
14/09/2017	Eco	-11.9	-21.5	-19.8

Common abnormal return dates for decreases in the medium-term tenors

Note. News impact on the medium-term tenors of the yield curve with the impact expressed in basis points.

Figure 7-8

Plot of the abnormal returns for the common dates for decreases in the medium-term tenors





In the long-term period, as can be seen in Table 7-12 and Figure 7-9, there was no dominant node for the abnormal event dates. The news categories for the long-term period included economic (four observations), political (three observations), and with the emerging markets, international and credit news categories each showing one shared observation across the nodes.



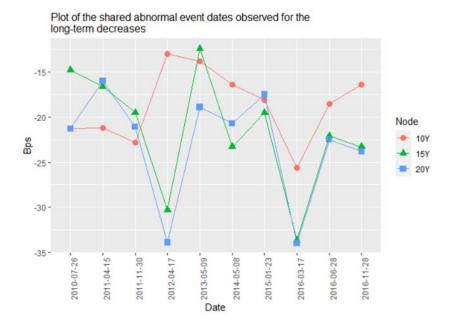
Dates	News	10Y	15Y	20Y
26/07/2010	Eco	-21.3	-14.8	-21.3
15/04/2011	EMM	-21.2	-16.6	-16.0
30/11/2011	Eco	-22.8	-19.5	-21.1
17/04/2012	Eco	-13.0	-30.3	-33.9
09/05/2013	Eco	-13.8	-12.4	-18.9
08/05/2014	Pol	-16.4	-23.3	-20.7
23/01/2015	Pol	-18.1	-19.5	-17.5
17/03/2016	Pol	-25.6	-33.6	-34.0
28/06/2016	Int	-18.5	-22.1	-22.5
28/11/2016	Cre	-16.4	-23.3	-23.8

Common abnormal return dates for decreases in the long-term tenors

Note. News impact on the long-term tenors of the yield curve with the impact expressed in basis points.

Figure 7-9

Plot of the abnormal returns for the common dates for decreases in the long-term tenors



7.1.2 Statistical tests that examined the link between news and abnormal returns

7.1.2.1 Correlation matrices for news categories

The correlation matrices for each node were calculated using the number of observations per news category per event date and the basis point per event date. Increase event dates for all yield curve nodes are presented in Table B-1. The results of the correlation matrices



showed that for the overnight, there was moderate correlation between the economic, currency and emerging market categories (.3), with the emerging market and currency and international categories showing strong correlation (<math>p > .5). The 3-month node correlation matrix showed moderate correlation between the emerging market category, the commodity, economic and international categories, and moderate correlation between the economic and political categories. For the 6-month node there was a strong correlation between the international and emerging market categories, and moderate correlation between the international and emerging market categories.

The 1-year node correlation matrix showed strong correlation between the credit and political categories and between the currency and emerging market categories. There were moderate correlation between the currency and economic and international categories and between the economic and emerging markets and political categories. The correlation matric of the 2-year node showed strong correlation between the credit and political categories, and between the commodity and emerging market categories, and moderate correlation between the credit and economic categories. The 5-year node correlation matrix showed moderate correlation between the international and currency and emerging market categories.

The 10-year node correlation matrix showed strong correlation between the credit and political categories and moderate correlation between the emerging market and currency and economic categories, and between the international and currency categories. The matrix showed strong correlation between the credit and political categories. The 15-year node correlation matrix showed strong correlation between the commodity and economic and emerging market categories. The correlation matrix of the 20-year node showed strong correlation between the credit and political categories and emerging market categories.

The decrease event dates correlation matrices for all of the yield curve nodes are presented in Table B-2. For the overnight node, a moderate correlation (.3) was observedbetween the news categories for the currency and commodity categories; emerging market



and economic categories and the political and credit categories. The 3-month node correlation matrix showed a moderate correlation between commodities, emerging market and economic news categories. The 6-month node showed moderate correlation between the economic and commodity news categories. The 1-year and 2-year node showed moderate correlation between economic and commodity news categories, whilst there are no significant correlations between the different news categories for the 5-year node. The 10-year node exhibited moderate correlation between currency and commodity news. The only two nodes that exhibit strong correlation (p > .5) are the 15-year and 20-year nodes and the correlation is noted between the credit and political news categories.

7.1.2.2 Results of multiple linear regression

The process employed to fit the multiple linear regression model(s) was described in section 5.7.5.3. The two following sections present the results of the regression models and they discuss some of the processes subsequently employed to achieve the optimal linear regression model.

In all cases discussed in the next two sections, the independent variables are the number of news items in each specific news category that were observed on each of the identified abnormal return dates. The dependent variable is the basis point move calculated for each of the abnormal return dates.

7.1.2.2.1 Increase dates multiple regression results

For each of the increase nodes the final multiple linear regression model (applying forward selection) was fitted, as shown in Table 7-13.



Results of multiple linear regression for all nodes of the yield curve for increase event dates

Node		Intercept	Com	Cre	Eco	EMM	Int	Pol	Mode
ON	Coeff	0.000	-0.287		0.520				
	<i>p</i> -value	1.000	.049		.001				.001
	RVal								.348
	AdjR								.308
3-Month	Coeff	0.000	-0.389		0.306	0.561	0.191		
	<i>p</i> -value	1.000	<.001		.001	<.001	.036		<.001
	RVal								.657
	AdjR								.632
6-Month	Coeff	0.000				0.169			
	<i>p</i> -value	1.000				.222			.222
	RVal								.029
	AdjR								.001
1-Year	Coeff	0.000			0.409				
	<i>p</i> -value	1.000			.015				.015
	RVal								.167
	AdjR								.142
2-Year	Coeff	-0.000						0.613	
	<i>p</i> -value	1.000						<.001	<.001
	RVal								.376
	AdjR								.358
5-Year	Coeff	-0.000					0.284	0.288	
	<i>p</i> -value	1.000					.087	.083	.045
	RVal								.176
	AdjR								.124
10-Year	Coeff	0.000						0.614	
	<i>p</i> -value	1.000						<.001	<.001
	RVal								.377
	AdjR								.361
15-Year	Coeff	0.000		0.299				0.573	
	<i>p</i> -value	1.000		.019				<.001	<.001
	RVal								.618
	AdjR								.598
20-Year	Coeff	0.000						0.823	
	<i>p</i> -value	1.000						<.001	<.001
	RVal								.678
	AdjR								.670

Note. Coefficients in table are the standardised or beta coefficients for all independent variables



For the overnight node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differed significantly from zero. The economic (p<.001) and commodity (p<.05) news categories were selected as predictors of the abnormal change in the basis points for the node and explain 30.8% of the variance in the dependent variable. Economic news was a stronger predictor of the change in basis points with a positive relationship between the economic news and increase in the abnormal basis points moves for the overnight node.

For the 3-month node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The commodity (p<.001), economic (p<.05), emerging market (p<.001) and international (p<.05) news categories were selected as the predictors of the abnormal increase in basis points, and explained 63.2% of the variance in the dependent variable. The emerging market news category emerged as the strongest predictor for the 3-month node abnormal increase in basis points.

For the 6-month node, the F test for the final regression model indicated that there were no statistical significant linear relationships between the independent variables and the dependent variable.

For the 1-year node, the F test for the final regression model indicated statistical significance (p<.05), indicating that at least one of the beta coefficients differed significantly from zero. The economic (p<.05) news category was selected as predictor of the abnormal change in the basis points for the node and explain 14.2% of the variance in the dependent variable

For the 2-year node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The political (p<.001) news category was selected as the predictor of the abnormal increase in basis points, and explained 35.8% of the variance in the dependent variable.

For the 5-year node multiple linear regression, the F test for the final model indicated statistical significance (p < 0.05), indicating that at least one of the beta coefficients differ



from zero. The two categories selected for the final model were international and political, with neither of the predictors indicated to be statistically significant (p>0.05). The two news categories as predictor variables explained 12.7% of the variance in the basis points, the dependent variable.

For the 10-year node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The political (p<.001) news category was selected as the predictor of the abnormal increase in basis points, and explained 36.1% of the variance in the dependent variable.

For the 15-year node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The credit (p<.05) and political (p<.001) news categories were selected as the predictors of the abnormal increase in basis points, and explained 59.8% of the variance in the dependent variable. The political news category emerged as the strongest predictor for the 15-year node abnormal increase in basis points.

For the 20-year node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The political (p<.001) news category was selected as the predictor of the abnormal increase in basis points, and explained 67.0% of the variance in the dependent variable.

For all of the increase nodes, the political news category was included in five of the nine regression equations, the economics news category in three of the nine, and the categories of commodity and credit news, as well as international news and emerging market news, were included in two regression equations each. The political news category was selected as the independent variable for all nodes longer than two years. The independent variables selected were statistically significant for the ON, 3-month, 6-month and 1-year nodes. Four news categories (economic, commodities, international and emerging markets) were completely excluded by the forward selection model in the medium and long-term nodes (2-years to 20-years), with the exception of the international news category, which was selected for the 5-year node.



7.1.2.2.2 Decrease dates multiple regression results

The results of the multiple linear regression for the decrease dates are shown in Table 7-14. For the abnormal decreases, the stepped forward selection method of fitting the multiple linear regression model did not converge to a feasible solution for all of the nodes. The linear regression model for the 1-year and 2-year nodes could not be solved using the forward selection method. For these nodes a multiple regression analysis was performed, which included all of the independent variables.

Table 7-14

Node		Intercept	Com	Cre	Cur	Eco	EMM	Int	Pol	Model
ON	Coeff	0.000		0.270		-0.645				
	<i>p</i> -value	1.000		.047		<.001				<.001
	RVal									.457
	AdjR									.423
3- Month	Coeff	-0.000					-0.544			
	<i>p</i> -value	1.000					<.001			<.001
	RVal									.296
	AdjR									.282
6- Month	Coeff	0.000				-0.515		0.385		
	<i>p</i> -value	1.000				<.001		.002		<.001
	RVal									.305
	AdjR									.280
1-Year	Coeff	0.000	-0.158	0.091	0.039	-0.167	-0.097	0.358	-0.164	
	<i>p</i> -value	1.000	.429	.628	.859	.485	.602	.076	.376	.570
	RVal									.178
	AdjR									036
2-Year	Coeff	0.000	-0.242	0.112	-0.049	0.117	0.138	-0.121	-0.276	
	<i>p</i> -value	1.000	.214	.523	.783	.550	.460	.490	.153	.701
	RVal									.130
	AdjR									066
5-Year	Coeff	0.000							-0.293	
	<i>p</i> -value	1.000							.067	.067
	RVal									.086
	AdjR									.062

Results of multiple linear regression for all nodes of the yield curve for decrease event dates



40

10- Year	Coeff	0.000	-0.428		
	<i>p</i> -value	1.000	.004		.004
	RVal				.183
	AdjR				.164
15- Year	Coeff	-0.000		-0.759	
	<i>p</i> -value	1.000		<.001	<.001
	RVal				.576
	AdjR				.566
20- Year	Coeff	0.000		-0.650	
	<i>p</i> -value	1.000		<.001	<.001
	RVal				.423
_	AdjR				.407

Note. Coefficients in table are the standardised or beta coefficients for all independent variables

For the overnight node, the F test for the final regression model indicated statistical significance (p<.001). The economic (p<.001) and credit (p<.05) news categories were selected as predictors of the abnormal change in the basis points for the node and explain 42.3% of the variance in the dependent variable. Economic news was a stronger predictor of the change in basis points for the overnight node.

For the 3-month node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The emerging market (p<.001) news category was selected as the strongest predictor of the abnormal decrease in basis points, and explained 28.2% of the variance in the dependent variable.

For the 6-month node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The economic (p<.001) and international (p<.05) news category were selected as predictors of the abnormal decrease in basis points, and explained 28% of the variance in the dependent variable. The economic news category came out as the strongest predictor for the 6-month node.



For the 1-year, 2-year and 5-year nodes, the F test for the final regression model indicated that there were no statistical significant linear relationships between the independent variables and the dependent variable.

For the 10-year node, the F test for the final regression model indicated statistical significance (p<.05), indicating that at least one of the beta coefficients differ from zero. The economic (p<.001) news category was selected as predictor of the abnormal decrease in basis points, and explained 16.4% of the variance in the dependent variable. The economic news category came out as the strongest predictor for the 10-year node.

For the 15-year and 20-year node, the F test for the final regression model indicated statistical significance (p<.001), indicating that at least one of the beta coefficients differ from zero. The political (p<.001) news category was selected as the strongest predictor of the abnormal decrease in basis points for both the nodes, and explained 56.6% and 40.7%, respectively of the variance in the dependent variable.

Overall, the fit of the linear regression models to the abnormal decrease basis points was somewhat similar to the linear regression models' fit to the abnormal increase basis points, in that the longer-term nodes showed a linear relationship between political news and the basis points changes.

7.2 RESULTS OF SOVEREIGN BOND SPREAD ANALYSIS

7.2.1 Descriptive statistics of the sovereign bond spread

The descriptive statistics for the change in the sovereign spreads for abnormal increase event dates and for abnormal decrease event dates are shown in Table B-5 and Table B-6 respectively. When reviewing the descriptive statistics and the spread charts in Figure B-4 and Figure B-5, it appears as if the means and medians for the shorter periods (ON, 3-month, 6-month and 1-year) is lower than the means and medians for the longer periods for both the increases and decreases in abnormal returns yields. The range for the abnormal change in prices is larger for the increases than the range for the decreases, thereby indicating that the reaction to perceived negative events results in a larger immediate reaction.



7.2.2 Statistical analysis of the sovereign spread

The descriptive statistics in Table B-5 and Table B-6 show that there are differences between the nodes when looking at the mean (or median) of the sovereign spread on event dates. The mean for the sovereign spread in the overnight node for abnormal increases is 9.361 (median 6.8), whereas the mean for the 1-year node is 18.426 (median 13.32). The 1-year mean is almost double that of the overnight mean, the same for the medians. Given that the variance of the sovereign spreads for these two nodes were 81.454 and 228.43 respectively, the statistical significance of the differences in the means were determined using an ANOVA.

The starting point of the analysis was to determine if the medians were statistically different from zero as the basis for further analyses of the sovereign bond spread. The results for the two-sided t-test and a two-tailed Wilcoxon-sign ranked test are presented in Table 7-15 and Table 7-16 with *p*-values < .001 for the respective nodes. The null hypothesis are rejected and as such it can be confirmed that for all nodes the median is statistically different from zero.

Table 7-15

Node	T-test		
	<i>p</i> -value	Min Confidence	Max Confidence
Overnight	< .001	-16.13933802	-7.540661979
3-month	< .001	-8.351875514	-2.805267343
6-month	< .001	-10.14898923	-5.101804421
1-year	< .001	-15.97982674	-10.85902075
2-year	< .001	-19.82058167	-15.07115206
5-year	< .001	-17.63129344	-13.52885103
10-year	< .001	-19.4259595	-14.82290573
15-year	< .001	-22.3761765	-15.73387909
20-year	< .001	-27.05044028	-19.87322383

Results of the two-sided t-test

Note. Results showing that medians of the sovereign spread increase and decrease event dates are statistically different for each node.



Node	Wilcoxon signed rank test
	<i>p</i> -value
Overnight	<.001
3-month	< .001
6-month	< .001
1-year	< .001
2-year	< .001
5-year	< .001
10-year	< .001
15-year	< .001
20-year	< .001

Note. Results showing that medians of sovereign spread for increase and decrease event dates are statistically different for each node.

As discussed in the methodology section 5.9.5, the Welch ANOVA was used to determine whether there were statistically significant differences in the means of the sovereign spread for the abnormal increase dates and the abnormal decrease dates. The Welch ANOVA completely removes the concern of the violation of the assumption of homogeneous variances. The results of the tests are presented in Table 7-17. The *p*-value for both the increases and decreases indicate that there were statistically significant differences between the means of the nine nodes.

Table 7-17

Results of the Welch ANOVA for the sovereign spread

Move	n	statistic	DFn	DFd	<i>p</i> -value
Increases	391	20.41	8	147.7985	<.001
Decreases	396	14.49	8	154.3085	< .001

A Games-Howell *post hoc* test was performed to determine which of the nodes' mean of the sovereign spread was statistically significantly different from the other nodes. The results of the Games-Howell test (see Table 7-18) show that for abnormal increases there is a statistically significant difference between the means of the short-term nodes (ON, 3-month and 6-month) and the 1-year and longer nodes (although the difference between the ON node and the 1-year node is not statistically significant). The differences in the means can be seen in Figure 7-10, with the short-term nodes demonstrating lower means than the longer-term nodes.

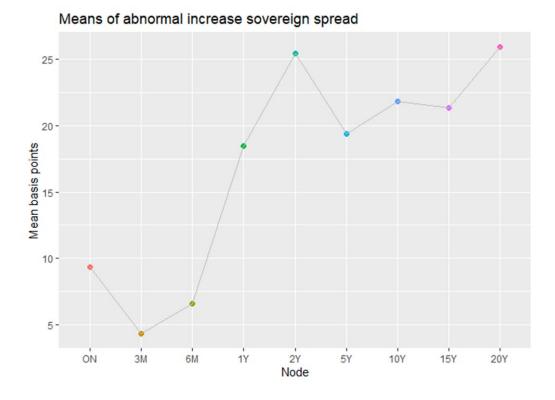


Games-Howell post-hoc test for abnormal increases on the sovereign spread

Var 1	Var 2	Mean Diff	Conf Low	Conf high	<i>p</i> -value
ON	3M	-5.031	-10.912	0.849	.153
ON	6M	-2.754	-8.496	2.988	.832
ON	1Y	9.065	-0.504	18.635	.077
ON	2Y	16.057	5.545	26.569	< .001
ON	5Y	10.016	1.161	18.871	.015
ON	10Y	12.468	3.150	21.787	.002
ON	15Y	11.967	1.223	22.710	.018
ON	20Y	16.553	6.594	26.511	< .001
3M	6M	2.277	-2.239	6.793	.806
ЗM	1Y	14.096	5.105	23.088	< .001
3M	2Y	21.088	11.092	31.084	< .001
3M	5Y	15.047	6.836	23.258	< .001
3M	10Y	17.499	8.788	26.210	< .001
3M	15Y	16.998	6.767	27.229	< .001
ЗM	20Y	21.584	12.185	30.982	< .001
6M	1Y	11.819	2.912	20.726	.003
6M	2Y	18.811	8.891	28.731	< .001
6M	5Y	12.770	4.654	20.886	< .001
6M	10Y	15.222	6.601	23.843	< .001
6M	15Y	14.721	4.565	24.876	.001
6M	20Y	19.307	9.991	28.622	< .001
1Y	2Y	6.992	-5.347	19.331	.673
1Y	5Y	0.951	-10.076	11.978	1.000
1Y	10Y	3.403	-7.989	14.795	.989
1Y	15Y	2.902	-9.645	15.448	.998
1Y	20Y	7.487	-4.414	19.388	.542
2Y	5Y	-6.041	-17.877	5.795	.783
2Y	10Y	-3.589	-15.762	8.584	.990
2Y	15Y	-4.090	-17.338	9.158	.986
2Y	20Y	0.496	-12.149	13.141	1.000
5Y	10Y	2.452	-8.377	13.281	.998
5Y	15Y	1.951	-10.100	14.001	1.000
5Y	20Y	6.536	-4.834	17.907	.660
10Y	15Y	-0.501	-12.885	11.882	1.000
10Y	20Y	4.085	-7.640	15.809	.971
15Y	20Y	4.586	-8.264	17.436	.967



Figure 7-10 Plot of the mean of the sovereign spread for each node for abnormal increase



For the sovereign spread for abnormal decreases, the 3-month and 6-month nodes' means are statistically different from the means of the other nodes. In it can be seen that the means for these two nodes are not as extreme as the means for the longer-term nodes.

From the results of the ANOVA, as summarised in Table 7-19, the means of the sovereign spread are significantly different for the short-term from the means of spread for the long-term nodes.



Games-Howell post-hoc test for abnormal decreases on the sovereign spread

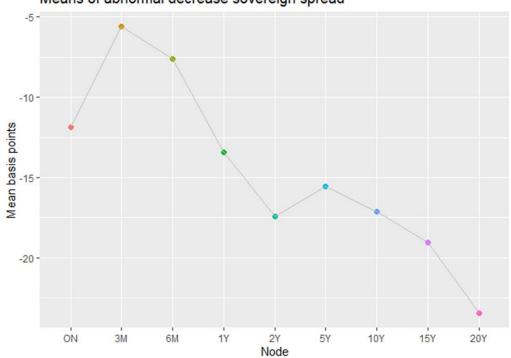
		Mean	Conf	Conf	
Var 1	Var 2	Diff	Low	high	P. Adj
ON	3M	6.261	-1.862	14.385	.263
ON	6M	4.215	-3.720	12.149	.738
ON	1Y	-1.579	-9.526	6.367	.999
ON	2Y	-5.606	-13.424	2.212	.350
ON	5Y	-3.740	-11.350	3.870	.803
ON	10Y	-5.284	-13.056	2.487	.422
ON	15Y	-7.215	-15.806	1.376	.171
ON	20Y	-11.622	-20.462	-2.781	.002
3M	6M	-2.047	-7.970	3.876	.974
3M	1Y	-7.841	-13.794	-1.887	.002
3M	2Y	-11.867	-17.629	-6.105	< .001
3M	5Y	-10.002	-15.451	-4.552	< .001
3M	10Y	-11.546	-17.237	-5.855	< .001
3M	15Y	-13.476	-20.314	-6.639	< .001
3M	20Y	-17.883	-25.058	-10.709	< .001
6M	1Y	-5.794	-11.466	-0.122	.041
6M	2Y	-9.820	-15.288	-4.353	< .001
6M	5Y	-7.955	-13.088	-2.821	< .001
6M	10Y	-9.499	-14.890	-4.108	< .001
6M	15Y	-11.430	-18.030	-4.830	< .001
6M	20Y	-15.836	-22.789	-8.883	< .001
1Y	2Y	-4.026	-9.534	1.482	.334
1Y	5Y	-2.161	-7.343	3.022	.917
1Y	10Y	-3.705	-9.138	1.728	.430
1Y	15Y	-5.636	-12.257	0.986	.159
1Y	20Y	-10.042	-17.014	-3.071	.001
2Y	5Y	1.866	-3.087	6.818	.953
2Y	10Y	0.321	-4.896	5.539	1.000
2Y	15Y	-1.609	-8.065	4.847	.997
2Y	20Y	-6.016	-12.834	0.802	.126
5Y	10Y	-1.544	-6.409	3.321	.984
5Y	15Y	-3.475	-9.662	2.712	.685
5Y	20Y	-7.882	-14.452	-1.312	.008
10Y	15Y	-1.931	-8.326	4.464	.988
10Y	20Y	-6.337	-13.099	0.425	.083
15Y	20Y	-4.407	-12.123	3.309	.668

For the sovereign spread for abnormal decreases, the 3-month and 6-month nodes' means are statistically different from the means of the other nodes. In Figure 7-11 it can be seen that the means for these two nodes are not as extreme as the means for the longer-term nodes.



Figure 7-11

Plot of the mean of the sovereign spread for each node for abnormal decrease



Means of abnormal decrease sovereign spread

7.3 SUMMARY AND CONCLUSION

This chapter started with an exploratory analysis that linked abnormal returns to specific news categories.

On aggregate and per node, the economic news category reflected the highest percentage of news items, followed by political news and emerging market news across all nodes of the yield curve for increase and decrease event dates. It was observed that for abnormal event dates the shorter tenor nodes (ON, 3M, 6M) had many small basis point changes relative to the longer tenor nodes that reflected higher basis point changes.

Apart from the 20-year node, the comparison of the abnormal increase and decrease basis points showed no statistical basis to distinguish between the increase and decrease. Thus, it appears that the effect of news is symmetrical on all of the other observed nodes.

Specific news categories were linked to shared dates in groups (short-, medium- and longterm) of the yield curve nodes. These shared dates were determined as common dates on



which a significant impact was observed on all of the nodes comprising the specific term of the yield curve.

The results of the multiple linear regression models fit for the abnormal increase event dates showed that news associated with abnormal changes differed for the shorter tenors and news associated with abnormal changes in the medium and longer tenors (2- to 20-year nodes). For the medium and longer tenors, political news was the dominant news category, whereas for the shorter tenors there was no dominant news category. In the abnormal decrease event dates the distinction was not as clear as with the increases. However, the political news category was dominant for the 15- and 20-year nodes. The multiple linear regression models fitted to the abnormal event dates delivered statistically significant fit results, except for the 1- and 2-year decrease data sets, for which no feasible model could be fitted.

The investigation into the effect of abnormal price changes on the sovereign spread led to the conclusion that the impact of abnormal increases is higher for longer tenor nodes than for shorter tenor nodes. For abnormal decreases the mean for the 3- and 6-month nodes differed statistically from the means of the other nodes. For both the increase and decrease event dates the sovereign spread appeared to change more for the longer nodes.



CHAPTER 8 CONCLUSION AND RECOMMENDATIONS

8.1 INTRODUCTION

This chapter presents the main findings of the study. It concludes with future research suggestions.

8.2 SHORT SUMMARY OF THE STUDY

The study applied the broad framework of the reverse event study methodology to link specific news categories to identified abnormal returns observed in the South African sovereign bond market during the period 1 January 2010 to 31 December 2019. The foundation of event studies (and reverse event studies) lies in the efficiency of the market. EMH assumptions, namely those that relate to the ability of the market to reflect new information in the form of asset price changes, are relevant to this study.

The abnormal price change dates were identified using three GARCH models for the daily price changes in the derived zero-coupon sovereign yield curve. These abnormal event dates were then separated into dates for which the price change was positive for daily returns (increases) and dates for which prices reflected a negative change in the daily returns (decreases). For each of the identified dates in the relevant event window the headline news (which had been categorised using supervised machine-learning algorithms) was collated.

The relationship between the abnormal daily price changes (expressed in basis points) and the headline news event window was then quantified using a multiple linear regression model. The independent variables were the different news categories, and the dependent variables were the basis points.

The sovereign spread was included in the analysis as this spread is an indication of the market's perception of country risk.



8.3 KEY EMPIRICAL FINDINGS AND RESEARCH HYPOTHESES

This section details the results of the empirical investigation of the research hypotheses.

8.3.1 Abnormal return dates

These analyses related to the first research hypothesis, namely to test whether there was a change in bond returns during periods (days) of increased volatility. The bond returns could not be used directly for this purpose, therefore the bonds were used as inputs to a static yield curve model to construct the zero-coupon yield curve. Daily price changes were then calculated for selected nodes as the difference in the yield for the node between two consecutive trading days.

This study used the event study methodology, which can also be applied to a reverse event study framework. As discussed by Pynnönen (2005), in regression-based event studies GARCH models can be efficiently used to predict event period volatility. In this study the abnormal return dates were identified as the dates on which the daily price changes exhibited volatility in excess of two conditional standard deviations. The deviations were identified by using the price changes from the zero-coupon yield curve as input to several GARCH models and the Chebychev inequality as applied in the study by Clements et al. (2012). The returns for the identified dates were then grouped as increase abnormal returns or decrease abnormal returns.

The results of the analysis differed from node to node, although for all nodes the identified dates and returns were shown to be statistically different from the returns for dates not included in the study. Smaller basis point returns were included in the abnormal returns samples for the shorter tenor nodes. The reason was that the short-term tenor interest rates had different repricing characteristics when compared to the medium- and long-term tenor rates. The short-term rates exhibited insignificant changes from day-to-day, which remained fairly constant (or very range-bound) until the rates almost discretely changed in level, where they then remained until the next change. The sample for the abnormal returns for the short-term tenors was characterized by the inclusion of several small basis point events.



Table 8	3-1
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Range	ON	3M	6M	1Y	2Y	5Y	10Y	15Y	20Y
(0, 5]	36.1%	88.3%	67.3%	0.0%	0.0%	0.0%	2.4%	2.2%	2.3%
(5, 15]	41.7%	6.7%	23.6%	60.0%	29.7%	36.8%	28.6%	24.4%	9.3%
(15, 20]	11.1%	1.7%	7.3%	11.4%	13.5%	36.8%	33.3%	40.0%	27.9%
(20, 100]	11.1%	3.3%	1.8%	28.6%	56.8%	26.3%	42.9%	40.0%	67.4%
Total	36	60	55	35	37	38	42	45	43

Percentage of increase abnormal returns in different ranges

Table 8-1 and Table 8-2 show the number of small basis point moves, expressed as a percentage of the total number of observations for the increase abnormal event dates and the decrease abnormal event dates respectively.

Table 8-2

Percentage of decrease abnormal returns in different ranges

Range	ON	3M	6M	1Y	2Y	5Y	10Y	15Y	20Y
(-5, 0]	31.4%	85.7%	50.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
(-15, -5]	45.7%	3.6%	34.9%	74.3%	41.0%	55.0%	38.6%	43.5%	0.0%
(-20, -15]	2.9%	0.0%	7.9%	20.0%	25.6%	22.5%	27.3%	30.4%	23.7%
(-100, -20]	20.0%	10.7%	6.3%	5.7%	33.3%	22.5%	34.1%	26.1%	76.3%
Total	35	56	63	35	39	40	44	46	38

As the samples for the abnormal event date returns consisted of 63 observations, these small values were left in the analysis. From the tables above it is evident that the larger moves tended to occur in the longer tenors.

The rigour of the study was confirmed at each step of the process. In the case of the zerocoupon yield curve constructed from the raw bond yields, the accuracy of the zero-coupon curve was confirmed by comparing the price calculated (using the closing YTM of the bond) for a specific settlement date with the price calculated for the bond for the same settlement date, but using the zero-coupon curve to discount all future cash flows. The Wilcoxon signed rank test was then used to compare the abnormal returns per node with the other returns for the node over the sample period. In all cases it was confirmed that the abnormal returns were from statistically different populations compared to those relating to the other returns for each node.



The returns (expressed in basis points) on the dates that were identified (using the conditional volatilities of the daily returns) were shown to be statistically significant. For the first research hypothesis it can therefore be confirmed that there is indeed a significant change in returns on dates on which the volatility is higher.

8.3.2 News categories

Several studies investigated the relationship between macroeconomic news and the sovereign bond yield curve in developed economies (Altavilla et al., 2017; Balduzzi et al., 2001a; Benamar et al., 2019; Faust et al., 2007; Fleming Michael J., 1997; Fleming & Remolona, 1999b; Green, 2004; Gürkaynak et al., 2007; Hansen et al., 2019; Hördahl et al., 2018; Lombardi et al., 2019; Pasquariello & Vega, 2007). There is a definite literature gap regarding emerging markets, with only a few studies that focused on macroeconomic news and the bond market in emerging market economies (Andritzky et al., 2007; Pistora & Hausenblas, 2015; Vasishtha et al., 2006). The researcher was unable to find studies that investigated the effects of other types of news categories on the yield curve in emerging markets.

The second research hypothesis postulated that there is no relationship between abnormal government bond returns and specific news categories. In section 8.3.1 the process of identifying and selecting the abnormal returns was discussed. The categorisation and linking of the news categories to the abnormal returns follows in this section.

The aggregate of usable headline news announcements for the sample period comprised 84 341 items. These were used as the final sample in the quantitative text analyses. The sample period covered the ten-year period from 1 January 2010 to 31 December 2019. During this period 26% of the total news headlines were released in 2015, with the volume of news published in each of the other years in the sample period ranging from 5%-10% of the total news. The headline news items were spread evenly across the news categories, with economic news in the highest news category (24%). The news categories of commodities, currency, emerging markets and political news ranged between 10% and 20% of the total. The credit and international news categories had less than 10% of the total observed news headlines.



The process followed to classify the news into the different categories was discussed in section 5.6. A Naïve Bayes classification model was used to initially classify a training set of the news headlines for the machine-learning algorithm. Takahashi et al. (2007) used the Naïve Bayes classification to analyse the reaction of stock prices to headline news. In this study the Naïve Bayes classification was used for only one step in the text classification process, namely to provide the training set which was then used in the supervised machine-learning algorithms. Jurka et al. (2013) described the machine-learning algorithms available in the RTextTools software package. Three machine learning algorithms were used to classify the final headline news data, of which the SVM algorithm provided the best results based on the precision score. Each of the news categories was measured for perceived accuracy using a recall and F-score percentage. The highest recall and F-score was for the credit news category.

The final sub-sample of the headline news items used in the analysis was then drawn from the news categories, which contained only the headline news items for the event window dates relating to abnormal increases and decreases. Finally, a manual review of the classification (that was performed by the supervised machine-learning algorithms) was undertaken to ensure that incorrectly classified news items were corrected.

A count was then performed for each event date to determine how many articles in each news category were released during each specific event window. The exploratory analysis associated specific abnormal moves with news categories that had the highest count of news articles during the event window period. The results of this analysis showed that economic and political news was associated with most of the abnormal price changes in most of the nodes.

The hypothesis that there is no link between the abnormal price changes and the different news categories can therefore be shown to be false, as there was indeed a relationship between abnormal price changes and the news categories.



8.3.3 Linking abnormal return basis points to different news categories

The third research hypothesis related to the relationship of different news categories to different tenors of the sovereign bond yield curve. From the second research hypothesis (confirming that there is a relationship between the abnormal price changes - or returns - and the news categories) the next objective was to formalise and express the relationship using a multiple linear regression model.

The multiple linear regression model was selected to express the relationship between the basis points and the different news categories. The specific selection method used was the forward stepwise selection model. Each node for abnormal increases and abnormal decreases was evaluated individually. In all cases, as part of the preliminary linear regression, the results were first assessed for compliance to the regression assumptions. Where the assumptions were violated the breach in the assumptions could be corrected in almost all the cases by eliminating one or two outlier observations.

The results for the multiple linear regression models fitted indicated that political news perceived as negative by market participants had a positive linear relationship with abnormal yield increases, as expressed in basis points. This relationship was observed for the 2-, 5-, 10-, 15- and 20-year nodes for abnormal increases. The final predictive multiple linear regression models for the abnormal increase event dates are provided in Table 8-3. The adjusted R^2 in the table is an indication of the variance percentage in the basis points, as explained by the model. In the case of the 1-year and 5-year nodes, the multiple linear regression explains less than 15% of the variation of the basis points. The 3-month node as well as the long-term nodes, specifically the 15- and 20-year nodes, have fairly strong adjusted R^2 of 63%, 60% and 67% respectively.



Table 8-3

Regression equations for the multiple linear regression models fit to the abnormal increase event date data

Node	Regression	<i>p</i> -value	Adj <i>R</i> ²
ON	$Bps = 5.796 - 1.475 \times Com + 0.707 \times Eco$.001	0.308
3M	$Bps = -2.279 - 1.041 \times Com + 0.439 \times Eco + 1.244 \times EMM + 0.477$	< .001	0.632
	\times Int		
6M	$Bps = 4.952 + 0.319 \times EMM$. 222	0.001
1Y	$Bps = 10.982 + 1.115 \times Eco$	< .001	0.142
2Y	$Bps = 17.284 + 1.575 \times Pol$	< .001	0.358
5Y	$Bps = 14.625 + 0.4 \times Int + 0.245 \times Pol$.045	0.124
10Y	$Bps = 16.77 + 1.854 \times Pol$	< .001	0.361
15Y	$Bps = 14.428 + 5.497 \times Cre + 1.796 \times Pol$	< .001	0.598
20Y	$Bps = 18.161 + 3.178 \times Pol$	< .001	0.67

Note. Regression equation for the linear regression models as shown in Table 7-13 with the beta coefficient shown in the table.

For the abnormal decrease nodes the multiple linear regression models fitted delivered mixed results, with some of the nodes not showing any linear relationship between the independent variables and the dependent variable (the basis points). The multiple linear regression equations for the abnormal decreases are shown in Table 8-4.



Table 8-4

Regression equations for the multiple linear regression models fit to the abnormal decrease event date data

Node	Regression	<i>p</i> -value	Adj R²
ON	$Bps = -1.664 + 2.094 \times Cre - 1.797 \times Eco$	< .001	0.423
ЗM	$Bps = 0.562 - 3.56 \times EMM$	< .001	0.282
6M	$Bps = -4.896 - 0.561 \times Eco + 1.601 \times Int$	< .001	0.28
1Y	$Bps = -12.806 - 0.837 \times Com + 0.387 \times Cre + 0.442 \times Cur - 0.186 \times Eco$	< .570	-0.036
	$-0.328 \times EMM + 2.052 \times Int - 0.203 \times Pol$		
2Y	$Bps = -16.913 - 1.116 \times Com + 0.313 \times Cre - 0.565 \times Cur + 0.133 \times Eco$	<.701	-0.066
	+ $0.309 \times EMM - 0.412 \times Int - 0.277 \times Pol$		
5Y	$Bps = -15.735 - 0.237 \times Pol$.067	0.062
10Y	$Bps = -14.95 - 0.488 \times Eco$.004	0.164
15Y	$Bps = -15.949 - 0.306 \times Pol$	< .001	0.566
20Y	$Bps = -22.164 - 0.345 \times Pol$	< .001	0.407

Note. Regression equation for the linear regression models as shown in Table 7-14 with the beta coefficient shown in the table.

The 1- and 2-year multiple linear regression analysis showed no linear relationship existed between the independent variables and the basis points. As in the abnormal decrease event dates, the long-term nodes showed that there was a linear relationship between the political news category and the basis points. For the 15- and 20-year nodes the regression model adjusted R^2 was 57% and 41%, indicating that a good proportion of the variance in the basis points was explained by the political news category.

The abnormal increase event dates, as well as the commodities, credit, emerging markets and international news categories, were included in two linear regression models as independent variables; the economic news category in three regressions; and the political news category was included in five regressions. For the abnormal decrease event dates, the 1- and 2-year node regressions were excluded. The credit, emerging markets and international news categories were included in one regression each, whereas the economic and political news categories were included in three regressions. Of the independent variables included in the different regression models, the political news category was most often selected as one of the regressors, followed by the economic news category. Thereafter



the other news categories were almost equally represented as regressors in the multiple linear regression models.

This research is consistent with the findings of Önder and Şimga-Mugan (2014), where economic and political news articles were found to be the main factors that influenced the fixed income markets in emerging markets. Regarding developed economies, Fleming and Remolona (1999b) studied the effect of economic news on the entire yield curve and found that the yield curve in the intermediate maturities (1 to 5 years) showed strong reactions to macroeconomic news announcements. Other studies which also found that significant yield changes tended to be at the intermediate maturities of the yield curve include those by Balduzzi et al. (2001b) and Faust et al. (2007). In this study multiple news categories were analysed. It was found that economic and political news items were the main contributors in both increase and decrease event dates. For both increase and decrease event dates economic news had a strong influence in the short term, whereas political news mostly influenced long-term rates.

The third research hypothesis raised the question of which news category or categories had a specific relationship with abnormal price changes. Table 8-3 and Table 8-4 show the news categories that had a significant linear relationship with the abnormal basis points. which news category or categories had a specific relationship with abnormal price changes.

8.3.4 Asymmetrical impact of information

The fourth research hypothesis related to the asymmetrical impact of information in sovereign bond markets. This was investigated by analysing the differences between the basis point moves for abnormal event dates for yield increases versus the absolute of the basis point moves for abnormal yield decrease event dates.

In accordance with the fourth hypothesis, changes in the abnormal bond returns were not necessarily symmetrical. For each node of the zero-coupon yield curve, both the upward change in the yield and decrease in the yield indicated the market's reaction to the news. The strength of the reaction to the news was seen in the extent of the move, as expressed in basis points.



When comparing the basis point moves in abnormal increases with the basis point moves in the abnormal decreases, the news category that caused the abnormal changes was not necessarily the same or even similar (for example, worse than expected CPI figures vs. better-than-expected CPI). In the ANOVA results only the 20-year node showed that the abnormal increase basis points were statistically different from the abnormal decrease basis points. This indicated that market yields increase more when news is bad (or is perceived as negative) than when the news is good or is perceived as positive. The ANOVA results for all of the other nodes indicated that the market reaction to perceived positive and perceived negative news was balanced.

The null hypothesis could be accepted and it confirmed that there were no statistically significant differences between abnormal increases and abnormal decreases in yields for each of the nodes, with the exception of the 20-year node.

8.3.5 Sovereign bond spread

The fifth research hypothesis investigated the sovereign bond spread and news across the yield curve. The sovereign bond spread was determined as the difference between the zerocoupon yields of the South African bond market and the US government par yield curve. The external perception of sovereign risk is priced in by market participants into the spread above the US government curve and reflects the market participants' perception of the relative riskiness of the sovereign issuer. Cuadra and Sapriza (2008) linked politically unstable economies with a higher level and volatility of sovereign interest rate spreads.

After comparing the abnormal event increases and sovereign spreads, the results showed that the short-term nodes were grouped together and the medium-and long-term nodes were grouped together. The analysis showed that the short-term nodes exhibited relatively smaller moves than the longer-term nodes, similar to the zero-coupon yield curve, where the greatest abnormal price changes (in terms of the basis point moves) were in the longer-term nodes. The 1-year point appears to act as the fulcrum in the sovereign spread, where the change in the basis points of the sovereign spread is smaller for periods shorter than the 1-year point and bigger for periods longer than the 1-year point.



For the abnormal decrease event dates, the sovereign spread comparison analysis results led to a similar conclusion to that regarding the abnormal increase event dates, in that the short-term nodes changed with relatively smaller margins than the longer-term nodes. The overnight node sovereign spread changed by a larger margin for the abnormal decrease dates compared to the abnormal increase dates. This means that the overnight node was more likely to be grouped with longer-term nodes, rather than with short-term nodes.

The fifth research hypothesis postulated that news has no impact on the sovereign spread. The analysis results of the sovereign spread rejected the hypothesis and showed that the sovereign spread for the different tenors reacted differently to the release of news and that longer-term tenors were likely to react more than shorter-term tenors.

8.3.6 Efficiency of the sovereign bond markets

The semi-strong form of EMH asserts that the efficiency of a security's price changes reflects publicly available material information. The reaction of the South African sovereign spread to new information within one business day led to the sixth research hypothesis, namely that the South African sovereign bond spread does not react quickly and efficiently to new information.

The efficiency of asset prices, as asserted by the semi-strong form EMH, points to a quick (or relatively so) assimilation of news in the price of the asset. The change in the sovereign spread, as measured in this study, used the sovereign spread on the event date and the sovereign spread on the business day immediately preceding the event date. Thus, if the market was inefficient the spread would not be changed or the change in the spread would be very small relative to the spread on the business day immediately preceding the event date. As the results of the spread analysis showed, the change in the spread ranged from 44 basis points to 119 basis points for the increase and 40 to 57 basis points for the decrease. As the changes occurred within one business day period the sovereign bond market could be considered efficient.



The sixth and final research hypothesis, that the market does not react efficiently and quickly to new information, could then be rejected. The alternative, that the market is efficient and can adjust quickly to new information, could be accepted.

8.4 MAJOR AREAS OF CONTRIBUTION

The study contributed to the body of literature regarding the impact of news events on sovereign bonds in emerging markets. The main aim of the study was to link the impact of changes in the sovereign bond yield curve to specific identifiable news events, and to investigate the resultant effect of such news events on the sovereign bond spread.

As large volumes of information are released daily in the form of news headlines the importance of understanding what is released and the market reaction to certain types of news is of considerable value to financial market participants. The categorisation of South African headline news was an important factor for analysing the changes of asset prices in response to news announcements. Being able to convert large quantities of unstructured news into structured and meaningful information using text analysis provided valuable insights that allowed accurate links to be made to abnormal behaviour in government bond returns.

This is the first study of its kind, as it measured the impact of headline news on the South African government bond yield curve. Thus, the study contributes to the body of literature in the field of South African fixed income investment management.

This study also contributes to the body of literature in the field of event study methodology, by using econometric models and applying the broad framework of the reverse event study methodology.

8.5 PRACTICAL IMPLICATIONS

As this is the first study that analyses the impact of news on daily bond yield curve data in the South African market (with both the South African Government Bond Index (GOVI) and



the Citi World Government Bond Index (WGBI) being included over the sample period) various domestic and international stakeholders will benefit from the results of the study.

Domestic and international Investors in the South African bond market are interested in what drives or moves the market. This study focused on abnormal event date returns and their association with various news categories. The multiple linear regression provided a description of the statistical relationship between abnormal basis points and news releases during the event window.

Foreign investors are interested in the changes in the sovereign spread. This study illustrated the sensitivity of the yield curve nodes. It found statistically significant differences between the different nodes on abnormal event dates. Understanding which tenors of the yield curve may be significantly impacted by specific news events may provide deeper insight regarding sovereign spreads, thereby potentially influencing investment decisions.

8.6 SUGGESTIONS FOR FUTURE RESEARCH

Several ideas for future research were suggested by the empirical findings of this study.

An informative line of research would be to extend the different news categories and also to investigate more themes within news sub-categories to provide further insight with respect to the impact of different types of news on the South African sovereign bond market.

This study used statistical analysis, specifically a multiple linear regression model, to investigate the relationship between the abnormal basis points and news from a linear perspective. Further research can be conducted using non-linear regression models as a fit for the final data samples.

In terms of other markets, the research can be extended by examining the impact of different news categories news on other asset classes, for example the exchange rate and stock markets.



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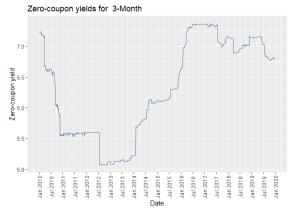


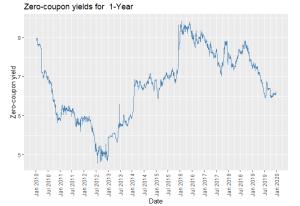
Appendix A

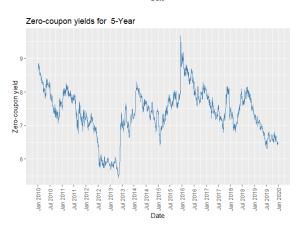
Figure A-1

Time series plot of the zero-coupon rates for all nodes

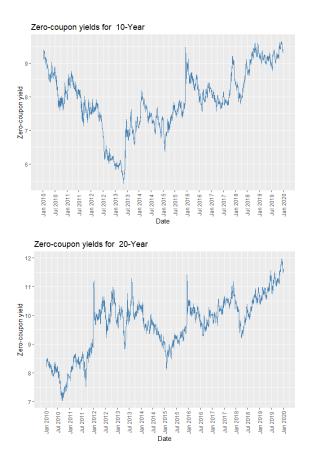












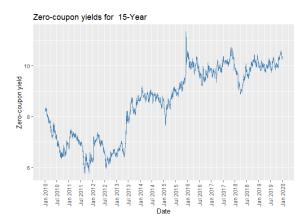
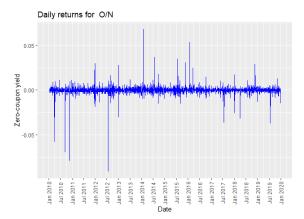
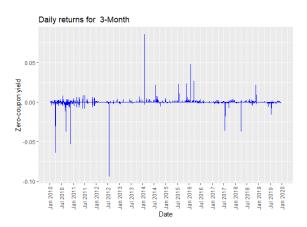


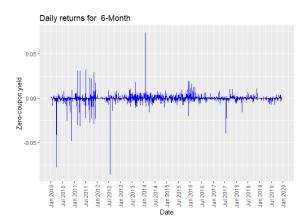
Figure A-2

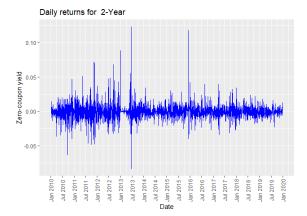
Daily change of the zero-coupon rates for all nodes

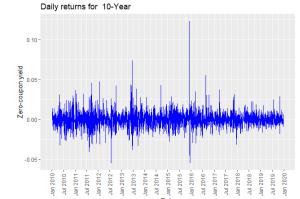


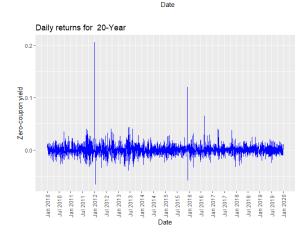


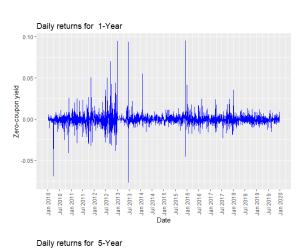


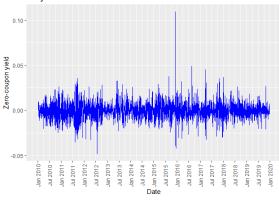


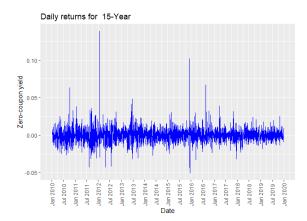














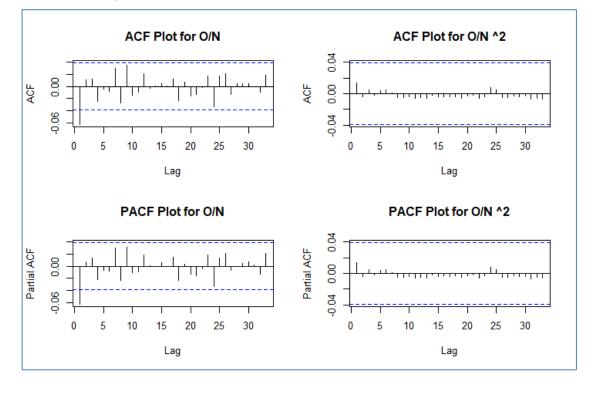
Descriptive statistics for the daily price changes for all nodes

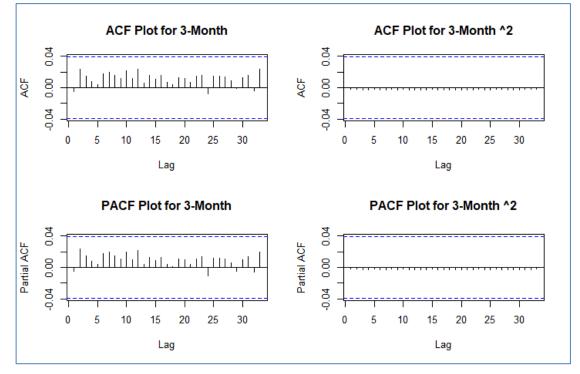
	O/N	3-Month	6-Month	1-Year	2-Year	5-year	10-Year	15-Year	20-Year
nobs	2497	2497	2497	2497	2497	2497	2497	2497	2497
NAs	0	0	0	0	0	0	0	0	0
Minimum	-0.09079	-0.09397	-0.08586	-0.07664	-0.08346	-0.04819	-0.05448	-0.05045	-0.06587
Maximum	0.06799	0.08561	0.07395	0.09520	0.12313	0.10931	0.12289	0.13877	0.20609
1. Quartile	-0.00147	-	-	-0.00288	-0.00501	-0.00549	-0.00545	-0.00520	-0.00568
3. Quartile	0.00149	-	-	0.00248	0.00452	0.00503	0.00515	0.00505	0.00568
Mean	-0.00003	-0.00003	-0.00002	-0.00007	-0.00009	-0.00011	0.00001	0.00009	0.00014
Median	-	-	-	-0.00011	-0.00017	-0.00028	-0.00019	-0.00001	0.00010
Sum	-0.06354	-0.06118	-0.05009	-0.16752	-0.22223	-0.27751	0.03060	0.23350	0.34600
SE Mean	0.00010	0.00008	0.00009	0.00015	0.00022	0.00020	0.00021	0.00020	0.00022
LCL Mean	-0.00022	-0.00017	-0.00019	-0.00037	-0.00053	-0.00049	-0.00039	-0.00030	- 0.00029
UCL Mean	0.00017	0.00012	0.00015	0.00024	0.00035	0.00027	0.00042	0.00049	0.00057
Variance	0.00003	0.00001	0.00002	0.00006	0.00012	0.00010	0.00011	0.00010	0.00012
Stdev	0.00506	0.00374	0.00438	0.00770	0.01112	0.00973	0.01031	0.01010	0.01093
Skewness	-3.86678	-4.51881	-4.06821	2.21145	1.46104	0.93755	1.05337	1.74639	3.21893
Kurtosis	109.99512	341.27329	147.53369	41.52652	17.89812	9.74462	11.39565	20.81458	57.41427



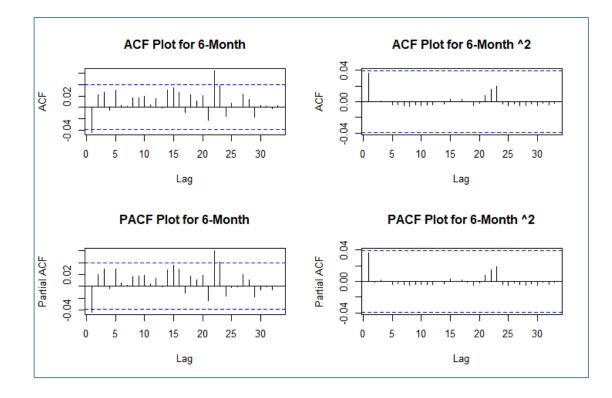
Figure A-3

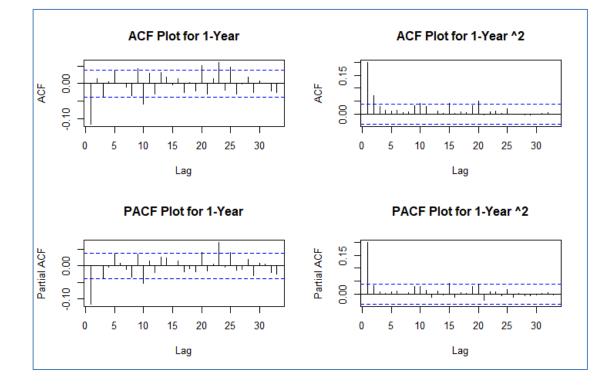
ACF and PACF plots for all nine nodes



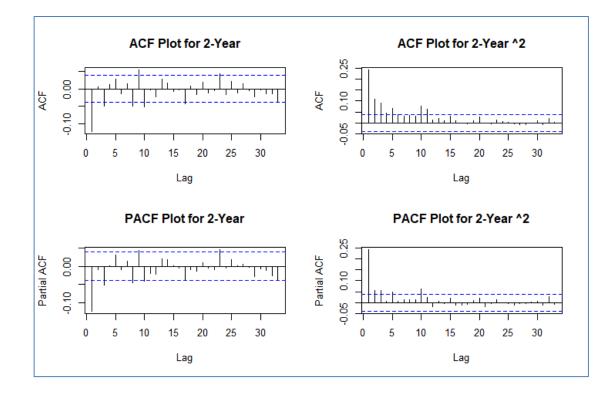


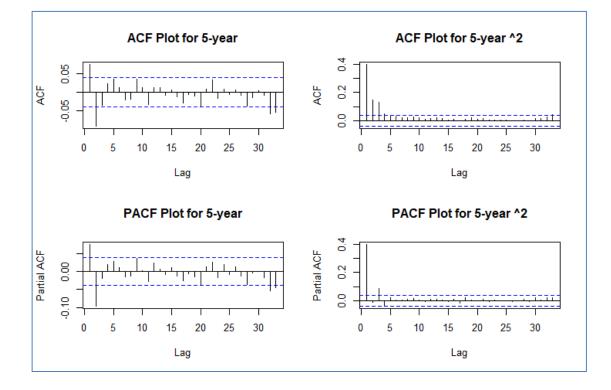




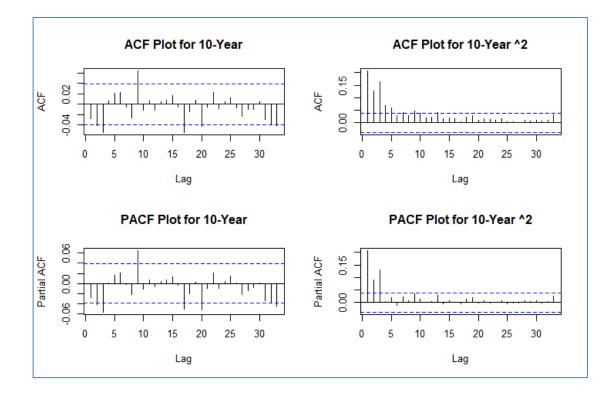


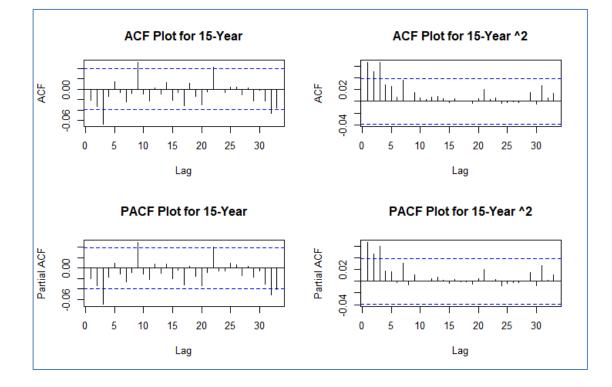




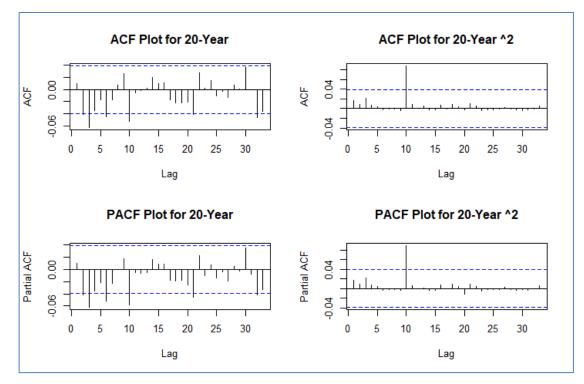












Note. Results for ACF and PACF plots performed on the daily returns and squared daily returns for all nine nodes



Results of the Box-Ljung test for serial autocorrelation overnight to 2-Year

	O/N		3-month		6-month		1-year		2-year	
Lag	statistic	p.value								
1	0.1339	.7144	0.7070	.4004	0.0598	.8068	0.2701	.6032	0.0012	.9718
2	2.1953	.3337	1.6293	.4428	0.0614	.9698	3.5605	.1686	5.9261	.0517
3	3.4858	.3226	2.1539	.5411	0.6859	.8765	3.6063	.3072	6.2493	.1001
4	6.1812	.1860	2.4443	.6546	1.3687	.8496	6.9718	.1374	8.4029	.0779
5	6.6279	.2498	3.4250	.6348	2.1211	.8322	7.0153	.2195	8.6534	.1237
6	6.7888	.3408	3.6980	.7175	2.1523	.9052	7.4663	.2799	8.8478	.1823
7	7.8417	.3468	4.9501	.6661	2.5705	.9217	10.0082	.1881	13.7437	.0559
8	7.8450	.4488	5.0100	.7565	2.5793	.9579	12.7378	.1212	18.4817	.0179
9	7.8452	.5498	5.5321	.7857	4.8520	.8470	19.7799	.0193	24.4186	.0037
10	7.8926	.6393	5.7832	.8331	8.0301	.6259	20.9740	.0213	24.7839	.0058
11	7.9027	.7220	6.3094	.8519	9.8987	.5395	22.3349	.0219	25.7992	.0070
12	8.1892	.7702	6.3881	.8953	10.2718	.5921	24.9207	.0152	27.7656	.0060
13	9.4552	.7378	6.4095	.9300	11.2928	.5863	26.1271	.0163	28.7644	.0071
14	9.5092	.7971	6.7837	.9427	11.6097	.6376	26.1292	.0249	28.8424	.0110
15	10.2302	.8050	7.0923	.9550	12.2927	.6567	26.4001	.0340	29.0970	.0156
16	10.7116	.8269	7.1759	.9697	13.3903	.6440	27.7776	.0336	33.9740	.0055
17	10.7137	.8711	7.6588	.9733	23.8044	.1248	27.7795	.0476	33.9775	.0085
18	11.3144	.8805	8.2206	.9752	27.6232	.0680	28.4084	.0561	34.4457	.0111
19	13.8213	.7940	8.4252	.9819	28.1488	.0806	33.9005	.0189	35.0549	.0138
20	14.4735	.8057	8.8724	.9843	28.1739	.1053	35.1278	.0194	35.2965	.0186

Note. Bold numbers indicate where H_0 is rejected thus on these lags there is still autocorrelation present



	5-year		10-year		15-year		20-year	
Lag	statistic	p.value	statistic	p.value	statistic	p.value	statistic	p.value
1	1.1416	.7670	0.1562	.6927	5.4229	.0199	1.3507	.2451
2	1.8767	.7584	1.1593	.5601	5.4621	.0651	1.7148	.4243
3	1.9648	.8540	2.7180	.4372	7.2992	.0629	2.8247	.4195
4	2.8755	.8243	2.7289	.6042	7.3716	.1175	2.8526	.5828
5	5.3758	.6142	3.9736	.5532	7.8835	.1628	3.9568	.5557
6	5.6711	.6840	14.3543	.0259	7.8835	.2468	7.9957	.2384
7	8.0750	.5266	14.6613	.0406	15.6144	.0289	12.0414	.0992
8	9.0070	.5314	14.7811	.0635	15.6858	.0471	12.1817	.1433
9	9.2910	.5950	14.9463	.0924	16.6303	.0548	12.2842	.1978
10	9.6394	.6476	15.0115	.1316	16.6788	.0818	12.4478	.2562
11	9.8563	.7056	15.0942	.1782	16.8170	.1134	13.8719	.2402
12	10.1320	.7525	15.4930	.2156	17.2017	.1422	14.1866	.2890
13	12.5585	.6364	15.6069	.2710	18.2511	.1482	14.6976	.3266
14	12.7141	.6935	23.7622	.0489	18.3690	.1905	15.2528	.3611
15	12.8202	.7481	24.5342	.0566	20.8942	.1402	16.1463	.3724
16	16.4821	.5589	24.5730	.0777	21.0957	.1749	17.0696	.3811
17	16.6453	.6139	29.9224	.0269	21.6358	.1991	17.8379	.3991
18	19.4494	.4928	30.0647	.0368	24.0352	.1539	22.1747	.2243
19	20.4654	.4920	31.2055	.0383	24.1314	.1912	24.0895	.1927
20	21.1258	.5130	31.4618	.0494	28.4249	.0997	24.1070	.2377

Results of the Box-Ljung test for serial autocorrelation for 5-Year to 20-Year

Note. Blue highlighted values indicate where H₀ is accepted thus on these lags there is still autocorrelation present



Analyses of the statistical distribution for the GARCH models

criterion	Distribution								
IC	norm	snorm	std	sstd	ged	sged	nig	ghyp	jsu
Akaike	-7.816	-7.858	-9.079	-	-9.010	-9.028	-9.028	-9.057	-9.057
Bayes	-7.802	-7.842	-9.065	-	-8.993	-9.010	-9.010	-9.039	-9.039
Hannan-Quinn	-7.811	-7.853	-9.074	-	-9.004	-9.021	-9.021	-9.051	-9.051
Akaike	-9.591	-9.707	-21.323	-22.487	-25.852	-19.441	-16.583	-12.726	-12.726
Bayes	-9.579	-9.693	-21.306	-22.468	-25.836	-19.423	-16.565	-12.705	-12.705
Hannan-Quinn	-9.587	-9.702	-21.317	-22.480	-25.847	-19.435	-16.577	-12.719	-12.719
Akaike	-8.578	-8.517	-10.172	-10.173	-18.251	-16.790	-10.785	-10.028	-15.720
Bayes	-8.566	-8.503	-10.158	-10.157	-18.237	-16.774	-10.768	-10.010	-15.704
Hannan-Quinn	-8.573	-8.512	-10.167	-10.167	-18.245	-16.784	-10.779	-10.021	-15.714
Akaike	-7.276	-7.281	-7.711	-7.710	-7.693	-7.693	-7.701	-7.708	-7.709
Bayes	-7.265	-7.268	-7.697	-7.694	-7.679	-7.676	-7.685	-7.689	-7.693
Hannan-Quinn	-7.272	-7.276	-7.706	-7.704	-7.688	-7.687	-7.695	-7.701	-7.703
Akaike	-6.414	-6.430	-6.635	-6.635	-6.623	-6.622	-6.633	-6.636	-6.636
Bayes	-6.403	-6.416	-6.622	-6.619	-6.609	-6.606	-6.617	-6.617	-6.620
Hannan-Quinn	-6.410	-6.425	-6.630	-6.630	-6.618	-6.617	-6.627	-6.629	-6.630
Akaike	-6.562	-6.569	-6.639	-6.639	-6.624	-6.625	-6.636	-6.640	-6.638
Bayes	-6.551	-6.555	-6.627	-6.624	-6.611	-6.610	-6.620	-6.622	-6.623
Hannan-Quinn	-6.558	-6.564	-6.634	-6.633	-6.619	-6.619	-6.630	-6.633	-6.632
Akaike	-6.446	-6.446	-6.563	-6.564	-6.539	-6.541	-6.558	-6.565	-6.562
Bayes	-6.434	-6.434	-6.550	-6.548	-6.525	-6.524	-6.542	-6.547	-6.547
Hannan-Quinn	-6.442	-6.442	-6.558	-6.558	-6.533	-6.535	-6.552	-6.558	-6.556
Akaike	-6.442	-6.471	-6.631	-6.631	-6.593	-6.595	-6.620	-6.632	-6.562
Bayes	-6.431	-6.457	-6.617	-6.615	-6.579	-6.579	-6.603	-6.614	-6.547
Hannan-Quinn	-6.438	-6.466	-6.625	-6.625	-6.588	-6.589	-6.614	-6.626	-6.556
	AkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-QuinnAkaikeBayesHannan-Quinn	Akaike -7.816 Bayes -7.802 Hannan-Quinn -7.811 Akaike -9.591 Bayes -9.579 Hannan-Quinn -9.587 Hannan-Quinn -9.587 Akaike -8.578 Bayes -8.566 Hannan-Quinn -8.573 Akaike -7.276 Bayes -7.276 Bayes -7.276 Bayes -7.276 Bayes -6.414 Bayes -6.403 Hannan-Quinn -6.410 Akaike -6.551 Hannan-Quinn -6.552 Bayes -6.551 Hannan-Quinn -6.558 Akaike -6.434 Hannan-Quinn -6.434 Hannan-Quinn -6.442 Bayes -6.442 Bayes -6.442 Bayes -6.431	Akaike-7.816-7.858Bayes-7.802-7.842Hannan-Quinn-7.811-7.853Akaike-9.591-9.707Bayes-9.579-9.693Hannan-Quinn-9.587-9.702Akaike-8.578-8.517Bayes-8.566-8.503Hannan-Quinn-8.573-8.512Akaike-7.276-7.281Bayes-7.265-7.268Hannan-Quinn-7.272-7.276Akaike-6.414-6.430Bayes-6.403-6.416Hannan-Quinn-6.562-6.569Bayes-6.551-6.555Hannan-Quinn-6.558-6.564Hannan-Quinn-6.558-6.564Hannan-Quinn-6.446-6.446Bayes-6.434-6.434Hannan-Quinn-6.446-6.446Bayes-6.434-6.434Hannan-Quinn-6.442-6.442Akaike-6.442-6.442Bayes-6.434-6.434Hannan-Quinn-6.442-6.442	Akaike-7.816-7.858-9.079Bayes-7.802-7.842-9.065Hannan-Quinn-7.811-7.853-9.074Akaike-9.591-9.707-21.323Bayes-9.579-9.693-21.306Hannan-Quinn-9.587-9.702-21.317Akaike-8.578-8.517-10.172Bayes-8.566-8.503-10.158Hannan-Quinn-8.573-8.512-10.167Akaike-7.276-7.281-7.711Bayes-7.265-7.268-7.697Hannan-Quinn-7.272-7.276-7.706Akaike-6.414-6.430-6.635Bayes-6.562-6.569-6.630Akaike-6.551-6.555-6.627Hannan-Quinn-6.558-6.564-6.634Akaike-6.434-6.434-6.550Bayes-6.434-6.446-6.563Bayes-6.434-6.446-6.563Bayes-6.434-6.446-6.553Bayes-6.434-6.446-6.553Bayes-6.434-6.446-6.553Bayes-6.434-6.446-6.553Bayes-6.434-6.446-6.553Bayes-6.434-6.446-6.553Bayes-6.434-6.446-6.553Bayes-6.434-6.442-6.471Bayes-6.431-6.457-6.631Bayes-6.431-6.457-6.617	Akaike-7.816-7.858-9.079-Bayes-7.802-7.842-9.065-Hannan-Quinn-7.811-7.853-9.074-Akaike-9.591-9.707-21.323-22.487Bayes-9.579-9.693-21.306-22.468Hannan-Quinn-9.587-9.702-21.317-22.480Akaike-8.578-8.517-10.172-10.173Bayes-8.566-8.503-10.158-10.157Hannan-Quinn-8.573-8.512-10.167-10.167Hannan-Quinn-7.265-7.268-7.697-7.694Hannan-Quinn-7.272-7.276-7.706-7.704Akaike-6.414-6.430-6.635-6.635Bayes-6.403-6.416-6.622-6.619Hannan-Quinn-6.551-6.555-6.627-6.624Hannan-Quinn-6.558-6.564-6.634-6.633Akaike-6.561-6.555-6.627-6.624Hannan-Quinn-6.558-6.564-6.634-6.633Akaike-6.446-6.446-6.6563-6.634Bayes-6.434-6.434-6.550-6.564Bayes-6.434-6.446-6.563-6.564Bayes-6.434-6.442-6.558-6.558Akaike-6.442-6.442-6.558-6.558Akaike-6.431-6.457-6.617-6.615	Akaike -7.816 -7.858 -9.079 - -9.010 Bayes -7.802 -7.842 -9.065 - -8.993 Hannan-Quinn -7.811 -7.853 -9.074 - -9.004 Akaike -9.591 -9.707 -21.323 -22.487 -25.852 Bayes -9.579 -9.693 -21.306 -22.468 -25.836 Hannan-Quinn -9.587 -9.702 -21.317 -22.480 -25.847 Akaike -8.578 -8.517 -10.172 -10.173 -18.251 Bayes -8.566 -8.503 -10.158 -10.157 -18.237 Hannan-Quinn -8.573 -8.512 -10.167 -10.67 -18.245 Akaike -7.276 -7.281 -7.711 -7.710 -7.693 Bayes -7.265 -7.268 -7.697 -7.694 -7.679 Hannan-Quinn -7.272 -7.276 -7.706 -7.704 -7.688 Akaike -6.414 -6.430 -6.635 -6.635 -6.623 Bayes -6.551 <td>Akaike-7.816-7.858-9.0799.010-9.028Bayes-7.802-7.842-9.0658.993-9.010Hannan-Quinn-7.811-7.853-9.0749.004-9.021Akaike-9.591-9.707-21.323-22.487-25.852-19.441Bayes-9.579-9.693-21.306-22.468-25.836-19.423Hannan-Quinn-9.587-9.702-21.317-22.480-25.847-19.435Akaike-8.578-8.517-10.172-10.173-18.251-16.790Bayes-8.566-8.503-10.158-10.157-18.237-16.744Hannan-Quinn-8.573-8.512-10.167-10.167-18.245-16.784Akaike-7.276-7.281-7.711-7.710-7.693-7.693Bayes-7.265-7.268-7.697-7.694-7.679-7.676Hannan-Quinn-7.272-7.276-7.706-7.704-7.688-7.687Akaike-6.414-6.430-6.635-6.635-6.623-6.622Bayes-6.403-6.416-6.622-6.619-6.618-6.617Akaike-6.551-6.555-6.627-6.624-6.611-6.610Hannan-Quinn-6.558-6.554-6.533-6.541-6.513-6.541Bayes-6.434-6.555-6.627-6.624-6.611-6.610Hannan-Quinn-6.558-6.558-6.558<!--</td--><td>Akaike -7.816 -9.079 - -9.010 -9.028 -9.028 Bayes -7.802 -7.842 -9.065 - -8.993 -9.010 -9.021 -9.021 Hannan-Quinn -7.811 -7.853 -9.074 - -9.004 -9.021 -9.021 Akaike -9.591 -9.707 -21.323 -22.487 -25.852 -19.441 -16.583 Bayes -9.579 -9.693 -21.306 -22.468 -25.836 -19.423 -16.565 Hannan-Quinn -9.587 -9.702 -21.317 -22.480 -25.847 -19.435 -16.577 Akaike -8.578 -8.517 -10.172 -10.173 -18.237 -16.774 -10.768 Bayes -8.566 -8.503 -10.167 -18.245 -16.764 -10.779 Akaike -7.276 -7.281 -7.711 -7.710 -7.693 -7.693 -7.701 Bayes -7.265 -7.268 -7.697 -7.694 -7.679</td><td>Akaike -7.816 -7.858 -9.079 - -9.010 -9.028 -9.028 -9.037 Bayes -7.802 -7.842 -9.065 - -8.993 -9.010 -9.021 -9.039 Hannan-Quinn -7.811 -7.853 -9.074 - -9.004 -9.021 -9.021 -9.051 Akaike -9.591 -9.707 -21.323 -22.487 -25.852 -19.441 -16.565 -12.726 Bayes -9.579 -9.693 -21.306 -22.468 -25.847 -19.435 -16.577 -12.719 Akaike -8.578 -8.517 -10.172 -10.173 -18.237 -16.774 -10.028 -10.028 Bayes -8.566 -8.503 -10.157 -18.237 -16.774 -10.768 -10.021 Akaike -7.276 -7.281 -7.711 -7.710 -7.693 -7.693 -7.701 -7.708 Bayes -7.265 -7.268 -7.697 -7.679 -7.676 -7.685 -7.689 Hannan-Quinn -7.272 -7.276 -7.706 -7</td></td>	Akaike-7.816-7.858-9.0799.010-9.028Bayes-7.802-7.842-9.0658.993-9.010Hannan-Quinn-7.811-7.853-9.0749.004-9.021Akaike-9.591-9.707-21.323-22.487-25.852-19.441Bayes-9.579-9.693-21.306-22.468-25.836-19.423Hannan-Quinn-9.587-9.702-21.317-22.480-25.847-19.435Akaike-8.578-8.517-10.172-10.173-18.251-16.790Bayes-8.566-8.503-10.158-10.157-18.237-16.744Hannan-Quinn-8.573-8.512-10.167-10.167-18.245-16.784Akaike-7.276-7.281-7.711-7.710-7.693-7.693Bayes-7.265-7.268-7.697-7.694-7.679-7.676Hannan-Quinn-7.272-7.276-7.706-7.704-7.688-7.687Akaike-6.414-6.430-6.635-6.635-6.623-6.622Bayes-6.403-6.416-6.622-6.619-6.618-6.617Akaike-6.551-6.555-6.627-6.624-6.611-6.610Hannan-Quinn-6.558-6.554-6.533-6.541-6.513-6.541Bayes-6.434-6.555-6.627-6.624-6.611-6.610Hannan-Quinn-6.558-6.558-6.558 </td <td>Akaike -7.816 -9.079 - -9.010 -9.028 -9.028 Bayes -7.802 -7.842 -9.065 - -8.993 -9.010 -9.021 -9.021 Hannan-Quinn -7.811 -7.853 -9.074 - -9.004 -9.021 -9.021 Akaike -9.591 -9.707 -21.323 -22.487 -25.852 -19.441 -16.583 Bayes -9.579 -9.693 -21.306 -22.468 -25.836 -19.423 -16.565 Hannan-Quinn -9.587 -9.702 -21.317 -22.480 -25.847 -19.435 -16.577 Akaike -8.578 -8.517 -10.172 -10.173 -18.237 -16.774 -10.768 Bayes -8.566 -8.503 -10.167 -18.245 -16.764 -10.779 Akaike -7.276 -7.281 -7.711 -7.710 -7.693 -7.693 -7.701 Bayes -7.265 -7.268 -7.697 -7.694 -7.679</td> <td>Akaike -7.816 -7.858 -9.079 - -9.010 -9.028 -9.028 -9.037 Bayes -7.802 -7.842 -9.065 - -8.993 -9.010 -9.021 -9.039 Hannan-Quinn -7.811 -7.853 -9.074 - -9.004 -9.021 -9.021 -9.051 Akaike -9.591 -9.707 -21.323 -22.487 -25.852 -19.441 -16.565 -12.726 Bayes -9.579 -9.693 -21.306 -22.468 -25.847 -19.435 -16.577 -12.719 Akaike -8.578 -8.517 -10.172 -10.173 -18.237 -16.774 -10.028 -10.028 Bayes -8.566 -8.503 -10.157 -18.237 -16.774 -10.768 -10.021 Akaike -7.276 -7.281 -7.711 -7.710 -7.693 -7.693 -7.701 -7.708 Bayes -7.265 -7.268 -7.697 -7.679 -7.676 -7.685 -7.689 Hannan-Quinn -7.272 -7.276 -7.706 -7</td>	Akaike -7.816 -9.079 - 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20-Year	Akaike	-6.259	-6.301	-6.515	-6.515	-6.464	-6.464	-6.496	-6.516	-6.509
	Bayes	-6.247	-6.287	-6.503	-6.501	-6.451	-6.449	-6.482	-6.500	-6.495
	Hannan-Quinn	-6.255	-6.295	-6.511	-6.509	-6.459	-6.458	-6.491	-6.510	-6.504

Note. Blue highlighted values indicate the absolute minimum as identified by each of the four-information criterion for each node



All information criterion results for all GARCH models fit for all nodes

Node		sGARCH	eGARCH	gjrGARCH
O/N				
	Akaike	-9.089071	-9.072505	-9.088354
	Bayes	-9.063419	-9.044521	-9.060371
	Hannan-Quinn	-9.079757	-9.062345	-9.078194
3-Month				
	Akaike	-6.282696	-14.31689	-6.072298
	Bayes	-6.257045	-14.28891	-6.044315
	Hannan-Quinn	-6.273383	-14.30673	-6.062138
6-Month				
	Akaike	-6.535763	-12.54349	-6.666175
	Bayes	-6.510112	-12.51551	-6.638192
	Hannan-Quinn	-6.52645	-12.53333	-6.656016
1-Year				
	Akaike	-7.698385	-7.710028	-7.697907
	Bayes	-7.684393	-7.693704	-7.681584
	Hannan-Quinn	-7.693305	-7.704102	-7.691981
2-Year				
	Akaike	-6.617049	-6.637178	-6.616265
	Bayes	-6.603057	-6.620855	-6.599942
	Hannan-Quinn	-6.611969	-6.631252	-6.610339
5-year				
	Akaike	-6.64363	-6.643542	-6.643389
	Bayes	-6.622643	-6.620223	-6.62007
	Hannan-Quinn	-6.63601	-6.635076	-6.634923
10-Year				
	Akaike	-6.565237	-6.566264	-6.564523
	Bayes	-6.546582	-6.545277	-6.543536
	Hannan-Quinn	-6.558464	-6.558644	-6.556904
15-Year		6 604047	6 607000	6 600400
	Akaike	-6.631917	-6.637988	-6.632199
	Bayes Hannan-Quinn	-6.615594	-6.619333	-6.613543
20-Year	nannan-Quinn	-6.625991	-6.631215	-6.625426
20-1 Cai	Akaike	-6.524474	-6.525283	-6.523849
	Bayes	-0.524474 -6.505818	-6.504296	-6.502862
	Hannan-Quinn	-6.517701	-0.504290 -6.517663	-6.516229
		-0.517701	-0.517003	-0.510229

Figure A-4

Conditional volatility and the returns of the overnight node for the GARCH model



O/N 2 X Conditional SD vs Returns (sGARCH)

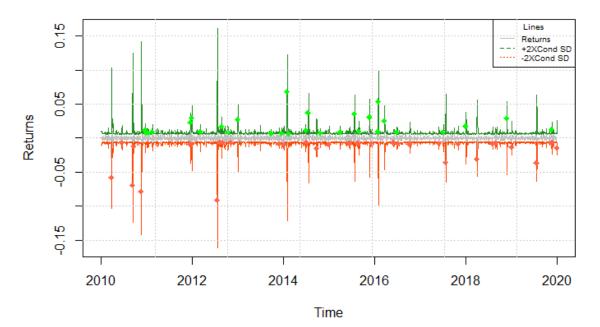


Figure A-5

Conditional volatility and the returns of the overnight node for the eGARCH model



O/N 2 X Conditional SD vs Returns (eGARCH)

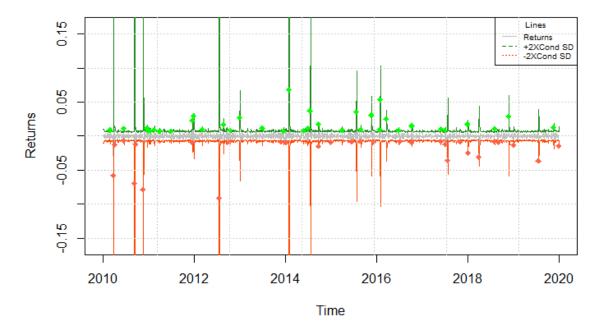
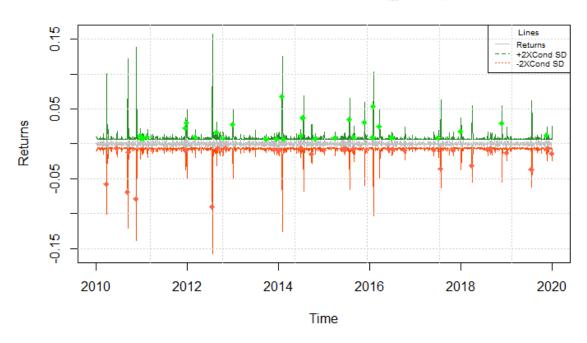


Figure A-6

Conditional volatility and the returns of the overnight node for the gjrGARCH model







Conditional volatility and the returns of the 3-Month node for the GARCH model



3-Month 2 X Conditional SD vs Returns (sGARCH)

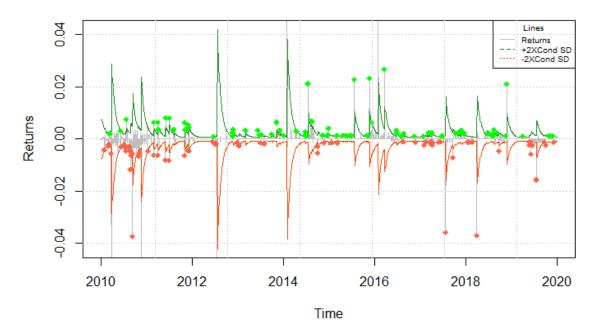


Figure A-8

Conditional volatility and the returns of the 3-Month for the eGARCH model

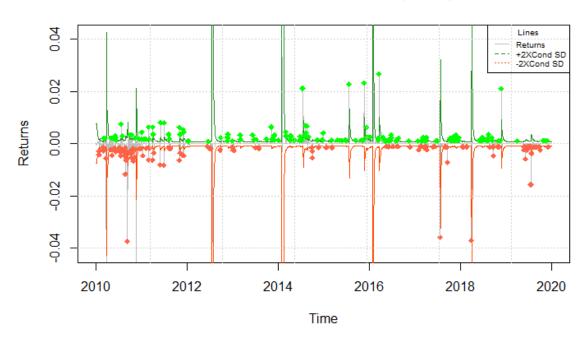




Figure A-9

Conditional volatility and the returns of the 3-Month node for the gjrGARCH model

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3-Month 2 X Conditional SD vs Returns (gjrGARCH)

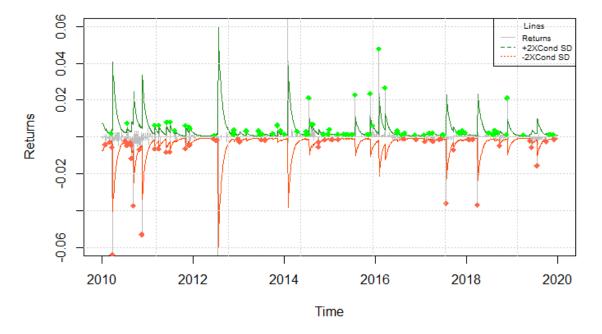
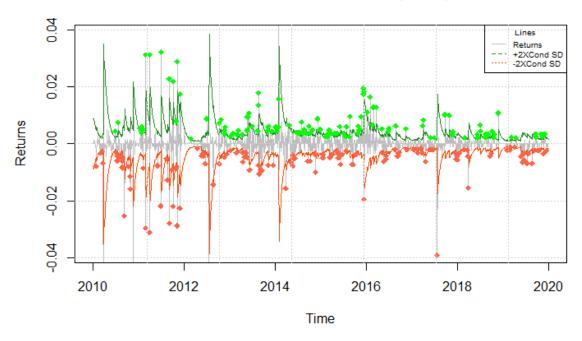
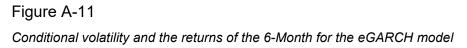


Figure A-10

Conditional volatility and the returns of the 6-Month node for the GARCH model



6-Month 2 X Conditional SD vs Returns (sGARCH)



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6-Month 2 X Conditional SD vs Returns (eGARCH)

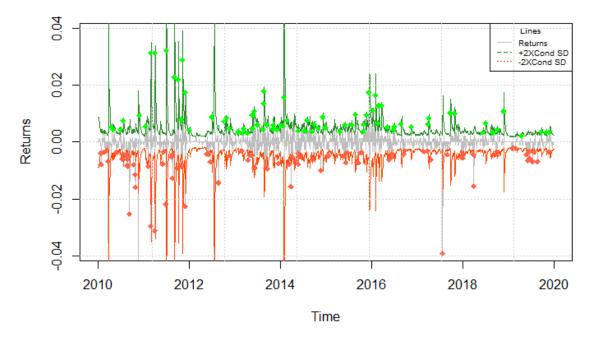
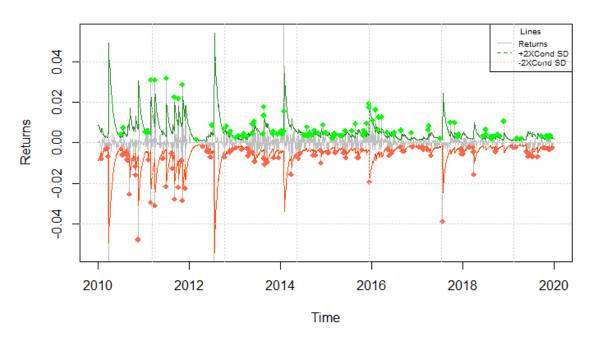
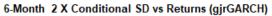
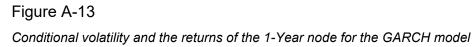


Figure A-12

Conditional volatility and the returns of the 6-Month node for the gjrGARCH model









1-Year 2 X Conditional SD vs Returns (sGARCH)

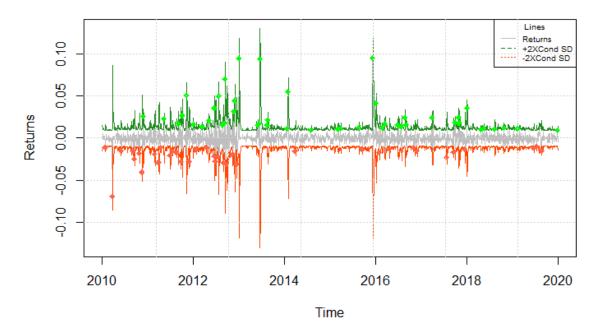


Figure A-14

Conditional volatility and the returns of the 1-Year for the eGARCH model

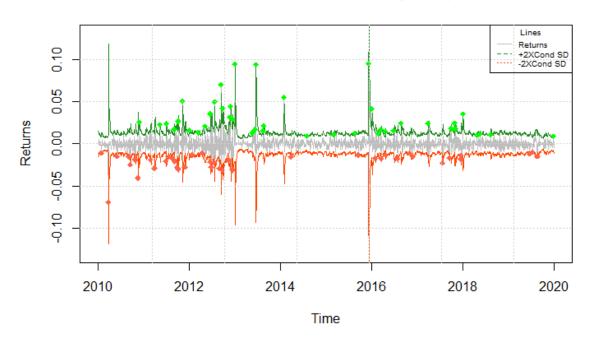




Figure A-15

Conditional volatility and the returns of the 1-Year for the gjrGARCH model



1-Year 2 X Conditional SD vs Returns (gjrGARCH)

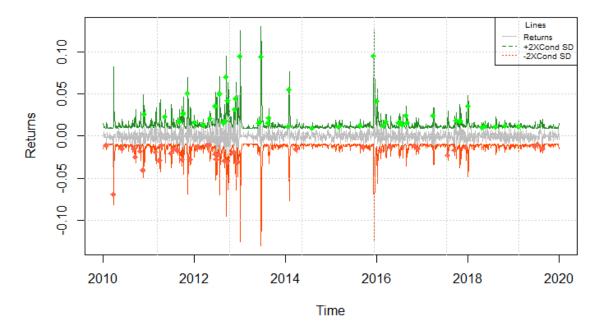
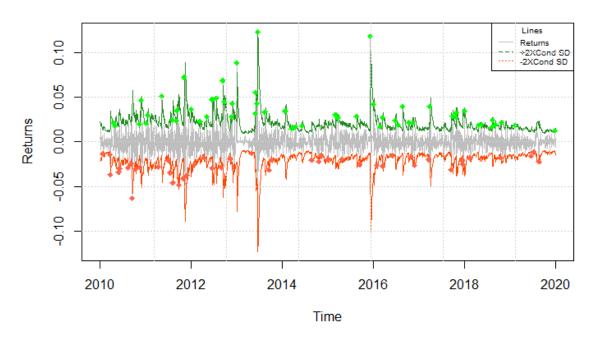
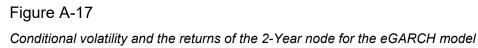


Figure A-16

Conditional volatility and the returns of the 2-Year node for the GARCH model



2-Year 2 X Conditional SD vs Returns (sGARCH)





2-Year 2 X Conditional SD vs Returns (eGARCH)

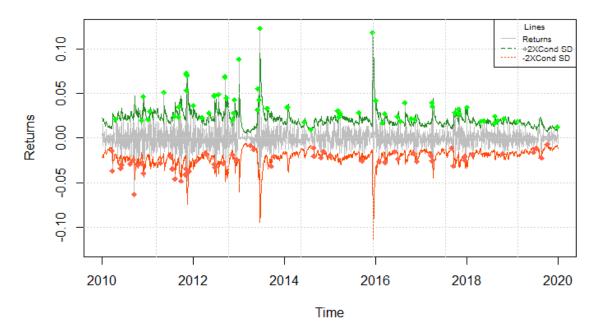
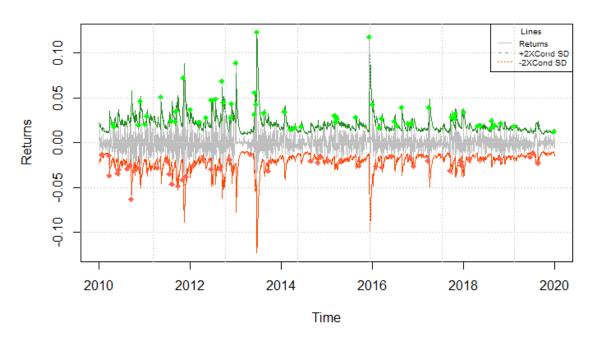


Figure A-18

Conditional volatility and the returns of the 2-Year node for the gjrGARCH model



2-Year 2 X Conditional SD vs Returns (gjrGARCH)



Conditional volatility and the returns of the 5-Year node for the GARCH model



5-year 2 X Conditional SD vs Returns (sGARCH)

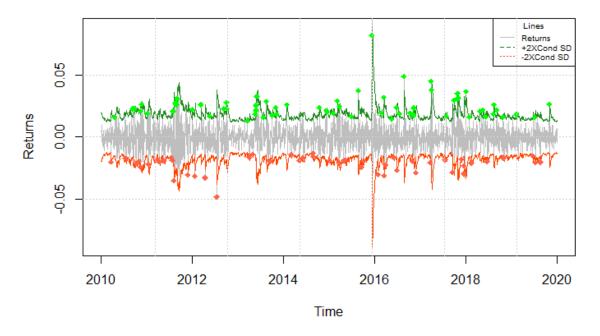
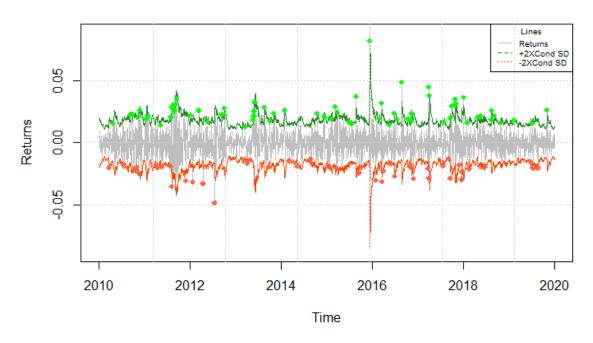
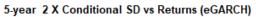


Figure A-20

Conditional volatility and the returns of the 5-Year node for the eGARCH model

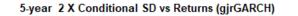






Conditional volatility and the returns of the 5-Year node for the gjrGARCH model





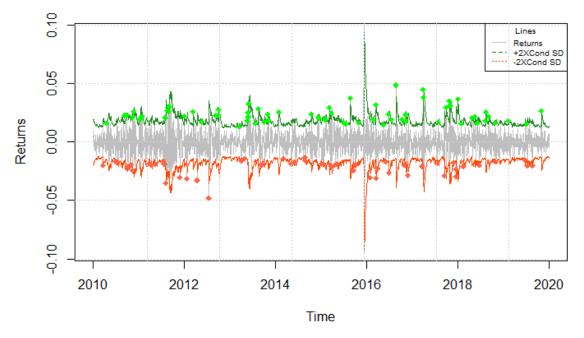
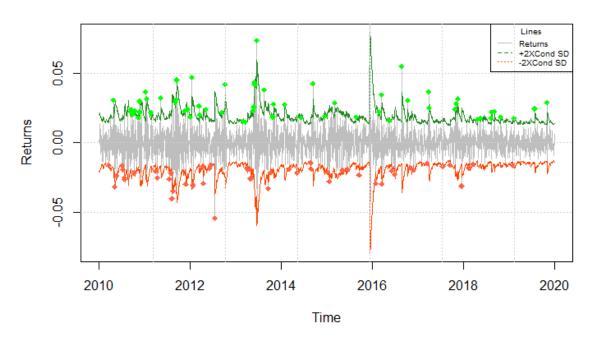


Figure A-22

Conditional volatility and the returns of the 10-Year node for the GARCH model



10-Year 2 X Conditional SD vs Returns (sGARCH)



Conditional volatility and the returns of the 10-Year node for the eGARCH model



10-Year 2 X Conditional SD vs Returns (eGARCH)

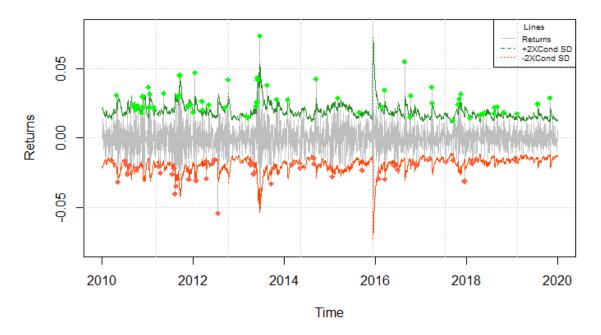
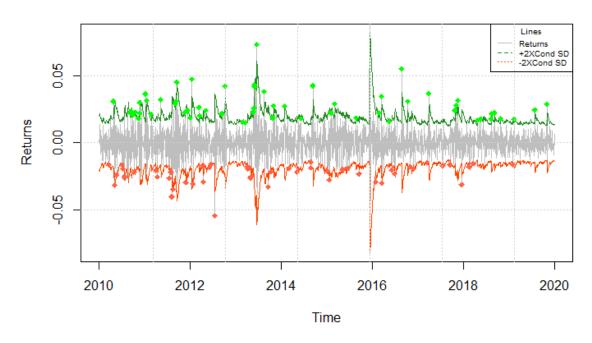


Figure A-24

Conditional volatility and the returns of the 10-Year node for the gjrGARCH model



10-Year 2 X Conditional SD vs Returns (gjrGARCH)



Conditional volatility and the returns of the 15-Year node for the GARCH model



15-Year 2 X Conditional SD vs Returns (sGARCH)

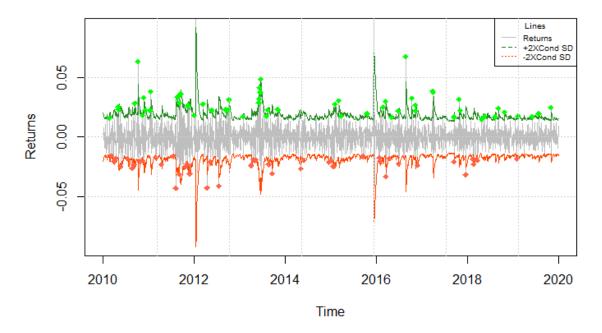
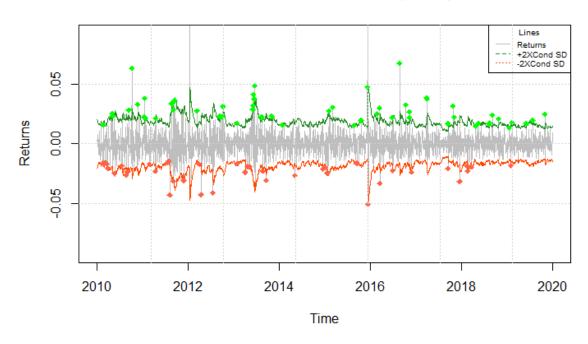


Figure A-26

Conditional volatility and the returns of the 15-Year node for the eGARCH model

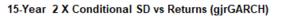


15-Year 2 X Conditional SD vs Returns (eGARCH)



Conditional volatility and the returns of the 15-Year node for the gjrGARCH model





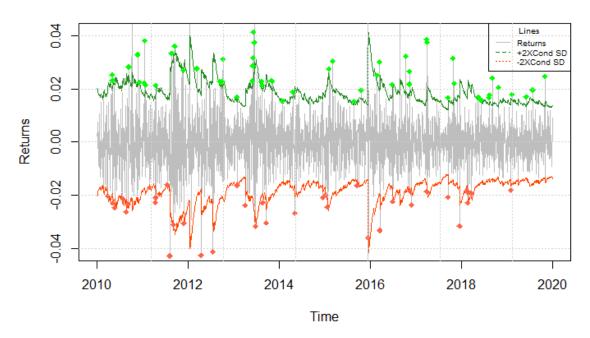


Figure A-28

Conditional volatility and the returns of the 20-Year node for the GARCH model

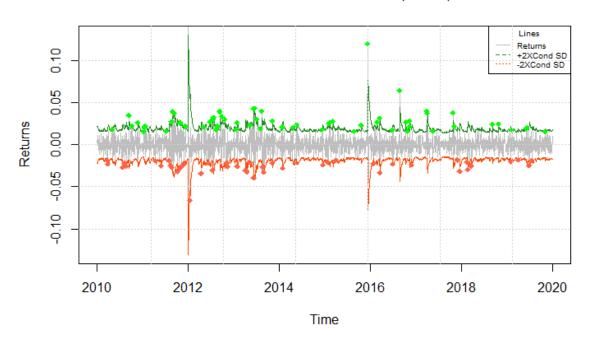




Figure A-29

Conditional volatility and the returns of the 20-Year node for the eGARCH model



20-Year 2 X Conditional SD vs Returns (eGARCH)

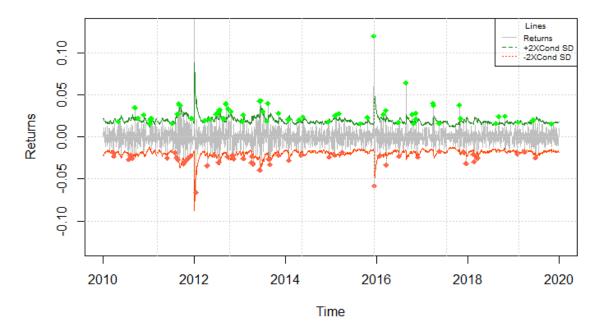
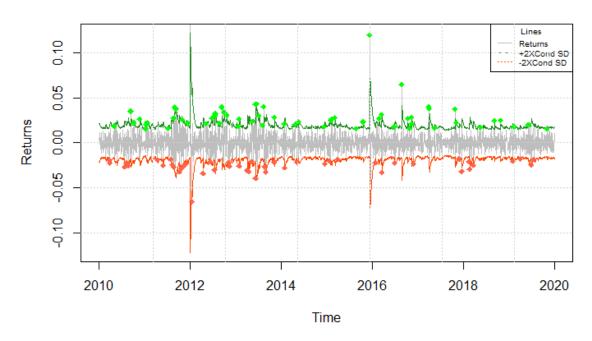


Figure A-30

Conditional volatility and the returns of the 20-Year node for the gjrGARCH model



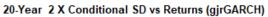


Table A-6

Descriptive statistics for basis points of abnormal dates for increases

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	ON	3M	6M	1Y	2Y	5Y	10Y	15Y	20Y
n	36	127	120	50	61	70	64	70	64
mean	9.73056	2.51146	4.44145	15.3849	20.0248	15.6768	16.5961	16.8851	16.1196
sd	8.04409	5.2001	4.54368	11.8015	12.4506	9.83669	10.2571	11.8043	10.0401
median	6	1.42177	2.84261	11.7291	16.2179	13.3971	13.7252	14.0421	13.9356
trimmed	8.37333	1.40618	3.46958	12.998	17.8282	13.7862	14.9427	14.3725	14.4246
mad	2.9652	0.86948	1.12556	6.44327	7.06414	4.07138	4.36919	4.37476	3.99519
min	3.2	0.47274	0.90026	5.37594	5.17702	6.33278	7.1115	7.62198	8.35792
max	34.3	43.5718	37.4183	62.0633	77.7631	71.7385	81.2177	78.4468	79.2265
range	31.1	43.099	36.518	56.6874	72.5861	65.4057	74.1062	70.8249	70.8686
skew	1.67323	5.58438	3.97876	2.10206	2.44702	3.57193	4.15046	3.42632	4.32249
kurtosis	2.23052	35.4756	22.2006	4.51128	7.50602	15.4845	22.3294	13.0931	22.8545
se	1.34068	0.46143	0.41478	1.66899	1.59414	1.17571	1.28214	1.41089	1.25502

Descriptive statistics for basis points of abnormal dates for decreases

	ON	3M	6M	1Y	2Y	5Y	10Y	15Y	20Y
n	38	100	131	42	54	56	51	57	51
mean	-11.042	-3.81	-5.4847	-12.9883	-17.0125	-16.265	-17.729	-18.7244	-25.376
sd	12.2298	7.99644	7.35411	7.06705	6.88854	4.76948	5.58772	7.66317	9.96204
median	-5.45	-1.5	-3.4	-11.6039	-15.7543	-14.78	-16.358	-17.6042	-22.538
trimmed	-8.7063	-1.8363	-3.8248	-12.0332	-16.5677	-15.954	-17.126	-17.4845	-23.723
mad	2.14977	0.88956	1.77912	3.92503	5.49871	2.84212	4.91967	5.07034	5.73922
min	-46	-50	-56	-51.1398	-43.7169	-28.778	-34.805	-53.8013	-69.591
max	-3	-0.5	-1	-6.10459	-4.6331	-7.942	-10.226	-9.66022	-15.38
range	43	49.5	55	45.0352	39.0838	20.8357	24.5788	44.141	54.2117
skew	-1.8288	-4.0914	-4.4693	-3.74685	-1.05629	-0.743	-0.9891	-2.22461	-2.6762
kurtosis	1.99093	17.1832	23.5358	17.483	2.38766	-0.1365	0.39836	6.49286	8.47178
se	1.98394	0.79964	0.64253	1.09047	0.93741	0.63735	0.78244	1.01501	1.39497

Table A-8Non-English newswires excluded



NUMBER	NEWSWIRE
1	REUSPB
2	REUTRA
3	CANPRE
4	APAECO
5	ITARTA
6	UKRGEN
7	AGENEN
8	CNNSTA
9	SUNIND
10	TARNEW
11	CPIFIN
12	SUNSRI
13	POLGOW
14	WISWAT
15	INVCON
16	EKACOM
17	SCODAI
18	CAPCOM
19	ECONBR
20	INSCLI
21	INDAWA
22	INEWSP
23	ETNEWS
24	ABVLAW

Note. Headline news announcements from non-English newswire sources that were excluded



Appendix B

Table B-1

News categories correlation matrices for all nodes of yield curve for increase event dates

ON	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.179	0.168	0.018	0.029	-0.132	0.020	-0.278
Cre	-0.179	1.000	0.064	-0.140	-0.212	-0.061	-0.076	-0.088
Cur	0.168	0.064	1.000	0.478	0.619	0.443	-0.006	0.273
Eco	0.018	-0.140	0.478	1.000	0.399	0.348	0.281	0.515
EMM	0.029	-0.212	0.619	0.399	1.000	0.561	-0.167	0.366
Int	-0.132	-0.061	0.443	0.348	0.561	1.000	-0.046	0.333
Pol	0.020	-0.076	-0.006	0.281	-0.167	-0.046	1.000	-0.012
Bps _	-0.278	-0.088	0.273	0.515	0.366	0.333	-0.012	1.000
3M	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.167	-0.019	-0.028	0.360	0.035	0.059	-0.193
Cre	-0.167	1.000	-0.029	-0.026	-0.230	-0.019	0.240	-0.043
Cur	-0.019	-0.029	1.000	0.150	0.235	0.145	0.029	0.271
Eco	-0.028	-0.026	0.150	1.000	0.338	0.115	0.324	0.592
EMM	0.360	-0.230	0.235	0.338	1.000	0.414	0.056	0.534
Int	0.035	-0.019	0.145	0.115	0.414	1.000	0.055	0.413
Pol	0.059	0.240	0.029	0.324	0.056	0.055	1.000	0.175
Bps	-0.193	-0.043	0.271	0.592	0.534	0.413	0.175	1.000
6M	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.097	-0.118	0.078	0.039	0.111	-0.015	-0.133
Cre	-0.097	1.000	-0.039	0.046	-0.166	-0.114	0.378	0.111
Cur	-0.118	-0.039	1.000	0.489	0.496	0.427	-0.062	0.324
Eco	0.078	0.046	0.489	1.000	0.503	0.294	0.289	0.350
EMM	0.039	-0.166	0.496	0.503	1.000	0.638	-0.041	0.601
Int	0.111	-0.114	0.427	0.294	0.638	1.000	-0.051	0.342
Pol	-0.015	0.378	-0.062	0.289	-0.041	-0.051	1.000	0.044
Bps _					0.011			
	-0.133	0.111	0.324	0.350	0.601	0.342	0.044	1.000
				0.350	0.601	0.342		
1Y _	Com	0.111 Cre	Cur				0.044 Pol	1.000 Bps
1Y Com				0.350	0.601	0.342		
-	Com	Cre	Cur	0.350 Eco	0.601 EMM	0.342 Int	Pol	Bps
Com	Com 1.000	Cre -0.151	Cur -0.121	0.350 Eco 0.061	0.601 EMM 0.071	0.342 Int 0.041 -0.021 0.399	Pol 0.016 0.632 -0.099	Bps -0.074 0.310 0.159
Com Cre Cur Eco	Com 1.000 -0.151	Cre -0.151 1.000	Cur -0.121 -0.037 1.000 0.459	0.350 Eco 0.061 0.283 0.459 1.000	0.601 EMM 0.071 -0.020 0.593 0.490	0.342 Int 0.041 -0.021 0.399 0.180	Pol 0.016 0.632 -0.099 0.345	Bps -0.074 0.310 0.159 0.409
Com Cre Cur	Com 1.000 -0.151 -0.121 0.061 0.071	Cre -0.151 1.000 -0.037 0.283 -0.020	Cur -0.121 -0.037 1.000 0.459 0.593	0.350 Eco 0.061 0.283 0.459 1.000 0.490	0.601 EMM 0.071 -0.020 0.593 0.490 1.000	0.342 Int 0.041 -0.021 0.399 0.180 0.497	Pol 0.016 0.632 -0.099 0.345 0.101	Bps -0.074 0.310 0.159 0.409 0.241
Com Cre Cur Eco	Com 1.000 -0.151 -0.121 0.061	Cre -0.151 1.000 -0.037 0.283	Cur -0.121 -0.037 1.000 0.459 0.593 0.399	0.350 Eco 0.061 0.283 0.459 1.000	0.601 EMM 0.071 -0.020 0.593 0.490	0.342 Int 0.041 -0.021 0.399 0.180	Pol 0.016 0.632 -0.099 0.345 0.101 0.014	Bps -0.074 0.310 0.159 0.409
Com Cre Cur Eco EMM	Com 1.000 -0.151 -0.121 0.061 0.071	Cre -0.151 1.000 -0.037 0.283 -0.020	Cur -0.121 -0.037 1.000 0.459 0.593	0.350 Eco 0.061 0.283 0.459 1.000 0.490	0.601 EMM 0.071 -0.020 0.593 0.490 1.000	0.342 Int 0.041 -0.021 0.399 0.180 0.497	Pol 0.016 0.632 -0.099 0.345 0.101	Bps -0.074 0.310 0.159 0.409 0.241



2Y	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.156	0.017	0.313	0.528	0.028	-0.052	-0.156
Cre	-0.156	1.000	-0.058	0.416	-0.125	0.019	0.671	0.465
Cur	0.017	-0.058	1.000	0.161	0.029	-0.181	-0.020	-0.083
Eco	0.313	0.416	0.161	1.000	0.323	-0.274	0.322	0.279
EMM	0.528	-0.125	0.029	0.323	1.000	0.260	0.166	-0.059
Int	0.028	0.019	-0.181	-0.274	0.260	1.000	0.031	-0.007
Pol	-0.052	0.671	-0.020	0.322	0.166	0.031	1.000	0.457
Bps	-0.156	0.465	-0.083	0.279	-0.059	-0.007	0.457	1.000
5Y	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.245	-0.180	0.126	0.079	-0.067	-0.059	-0.097
Cre	-0.245	1.000	-0.183	0.225	-0.183	0.026	0.519	0.405
Cur	-0.180	-0.183	1.000	0.302	0.262	0.356	-0.159	-0.067
Eco	0.126	0.225	0.302	1.000	0.117	0.295	0.275	0.228
EMM	0.079	-0.183	0.262	0.117	1.000	0.362	-0.123	-0.035
Int	-0.067	0.026	0.356	0.295	0.362	1.000	0.018	0.051
Pol	-0.059	0.519	-0.159	0.275	-0.123	0.018	1.000	0.673
Bps	-0.097	0.405	-0.067	0.228	-0.035	0.051	0.673	1.000
10Y _	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.243	-0.029	0.212	0.273	-0.126	0.009	-0.170
Cre	-0.243	1.000	-0.212	0.150	-0.093	0.119	0.537	0.350
Cur	-0.029	-0.212	1.000	0.204	0.312	0.361	-0.080	-0.075
Eco	0.212	0.150	0.204	1.000	0.433	0.165	0.011	0.127
EMM	0.273	-0.093	0.312	0.433	1.000	0.234	-0.061	-0.083
Int	-0.126	0.119	0.361	0.165	0.234	1.000	-0.027	0.052
Pol	0.009	0.537	-0.080	0.011	-0.061	-0.027	1.000	0.570
Bps _	-0.170	0.350	-0.075	0.127	-0.083	0.052	0.570	1.000
15Y _	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.199	0.164	0.398	0.351	0.064	0.083	-0.186
Cre	-0.199	1.000	-0.125	0.232	-0.085	0.120	0.544	0.457
Cur	0.164	-0.125	1.000	0.256	0.121	-0.178	-0.021	-0.130
Eco	0.398	0.232	0.256	1.000	0.233	-0.080	0.193	0.111
EMM	0.351	-0.085	0.121	0.233	1.000	0.176	0.016	-0.109
Int	0.064	0.120	-0.178	-0.080	0.176	1.000	0.038	-0.015
Pol	0.083	0.544	-0.021	0.193	0.016	0.038	1.000	0.489
Bps _	-0.186	0.457	-0.130	0.111	-0.109	-0.015	0.489	1.000



20Y	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.092	0.053	-0.072	0.234	0.062	0.029	-0.228
Cre	-0.092	1.000	-0.137	0.350	0.211	0.055	0.513	0.326
Cur	0.053	-0.137	1.000	-0.070	0.179	0.001	-0.003	-0.090
Eco	-0.072	0.350	-0.070	1.000	-0.020	-0.068	0.229	0.276
EMM	0.234	0.211	0.179	-0.020	1.000	0.144	-0.049	-0.023
Int	0.062	0.055	0.001	-0.068	0.144	1.000	0.004	-0.096
Pol	0.029	0.513	-0.003	0.229	-0.049	0.004	1.000	0.708
Bps	-0.228	0.326	-0.090	0.276	-0.023	-0.096	0.708	1.000

Table B-2

News categories correlation matrices for all nodes of yield curve for decrease event dates

ON _	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.174	0.442	0.239	-0.136	-0.034	-0.006	-0.117
Cre	-0.174	1.000	0.018	0.092	0.207	-0.092	0.458	0.211
Cur	0.442	0.018	1.000	0.064	0.009	-0.098	-0.055	-0.045
Eco	0.239	0.092	0.064	1.000	0.482	-0.245	0.163	-0.620
EMM	-0.136	0.207	0.009	0.482	1.000	-0.023	0.089	-0.088
Int	-0.034	-0.092	-0.098	-0.245	-0.023	1.000	-0.025	0.065
Pol	-0.006	0.458	-0.055	0.163	0.089	-0.025	1.000	0.099
Bps	-0.117	0.211	-0.045	-0.620	-0.088	0.065	0.099	1.000
3M	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.068	0.227	0.382	0.205	0.160	0.174	0.107
Cre	-0.068	1.000	-0.085	0.135	-0.160	-0.038	-0.056	-0.039
Cur	0.227	-0.085	1.000	0.230	-0.121	-0.206	-0.110	0.069
Eco	0.382	0.135	0.230	1.000	0.369	-0.043	-0.175	-0.327
EMM	0.205	-0.160	-0.121	0.369	1.000	0.244	-0.114	-0.547
Int	0.160	-0.038	-0.206	-0.043	0.244	1.000	0.074	0.085
Pol	0.174	-0.056	-0.110	-0.175	-0.114	0.074	1.000	0.117
Bps _	0.107	-0.039	0.069	-0.327	-0.547	0.085	0.117	1.000
6M	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.084	0.235	0.497	0.133	0.055	0.021	0.011
Cre	-0.084	1.000	0.003	-0.012	-0.051	-0.120	0.284	-0.044
Cur	0.235	0.003	1.000	0.134	-0.142	-0.234	-0.091	0.045
Eco	0.497	-0.012	0.134	1.000	0.258	0.131	0.059	-0.329
EMM	0.133	-0.051	-0.142	0.258	1.000	0.212	0.073	-0.225
Int	0.055	-0.120	-0.234	0.131	0.212	1.000	0.038	0.139
Pol	0.021	0.284	-0.091	0.059	0.073	0.038	1.000	-0.035
Bps _	0.011	-0.044	0.045	-0.329	-0.225	0.139	-0.035	1.000



1Y	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.154	0.122	0.448	0.132	0.165	0.008	-0.198
Cre	-0.154	1.000	0.180	-0.151	-0.049	-0.131	0.121	0.086
Cur	0.122	0.180	1.000	0.413	-0.179	-0.139	0.145	-0.089
Eco	0.448	-0.151	0.413	1.000	0.092	0.297	0.129	-0.160
EMM	0.132	-0.049	-0.179	0.092	1.000	0.027	-0.171	-0.107
Int	0.165	-0.131	-0.139	0.297	0.027	1.000	0.119	0.243
Pol	0.008	0.121	0.145	0.129	-0.171	0.119	1.000	-0.111
Bps	-0.198	0.086	-0.089	-0.160	-0.107	0.243	-0.111	1.000
2Y	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.171	-0.075	0.460	0.130	0.059	-0.033	-0.184
Cre	-0.171	1.000	0.120	-0.227	-0.041	0.002	-0.030	0.123
Cur	-0.075	0.120	1.000	-0.070	-0.017	-0.221	0.220	-0.062
Eco	0.460	-0.227	-0.070	1.000	0.170	0.099	0.104	-0.033
EMM	0.130	-0.041	-0.017	0.170	1.000	0.008	0.376	0.018
Int	0.059	0.002	-0.221	0.099	0.008	1.000	-0.049	-0.098
Pol	-0.033	-0.030	0.220	0.104	0.376	-0.049	1.000	-0.212
Bps _	-0.184	0.123	-0.062	-0.033	0.018	-0.098	-0.212	1.000
5Y _	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
5Y _ Com	Com 1.000	Cre -0.196	Cur 0.106	Eco 0.075	EMM -0.170	Int 0.116	Pol -0.036	Bps 0.074
-	-							· · · · ·
Com	1.000	-0.196	0.106	0.075	-0.170	0.116	-0.036	0.074
Com Cre	1.000 -0.196	-0.196 1.000	0.106 0.150	0.075 -0.232	-0.170 0.036	0.116 -0.029	-0.036 0.061	0.074 -0.071
Com Cre Cur	1.000 -0.196 0.106	-0.196 1.000 0.150	0.106 0.150 1.000	0.075 -0.232 -0.097	-0.170 0.036 -0.101	0.116 -0.029 -0.233	-0.036 0.061 0.169	0.074 -0.071 0.047
Com Cre Cur Eco	1.000 -0.196 0.106 0.075	-0.196 1.000 0.150 -0.232	0.106 0.150 1.000 -0.097	0.075 -0.232 -0.097 1.000	-0.170 0.036 -0.101 0.057	0.116 -0.029 -0.233 -0.144	-0.036 0.061 0.169 0.283	0.074 -0.071 0.047 -0.273
Com Cre Cur Eco EMM	1.000 -0.196 0.106 0.075 -0.170	-0.196 1.000 0.150 -0.232 0.036	0.106 0.150 1.000 -0.097 -0.101	0.075 -0.232 -0.097 1.000 0.057	-0.170 0.036 -0.101 0.057 1.000	0.116 -0.029 -0.233 -0.144 0.092	-0.036 0.061 0.169 0.283 0.120	0.074 -0.071 0.047 -0.273 0.017
Com Cre Cur Eco EMM Int	1.000 -0.196 0.106 0.075 -0.170 0.116	-0.196 1.000 0.150 -0.232 0.036 -0.029	0.106 0.150 1.000 -0.097 -0.101 -0.233	0.075 -0.232 -0.097 1.000 0.057 -0.144	-0.170 0.036 -0.101 0.057 1.000 0.092	0.116 -0.029 -0.233 -0.144 0.092 1.000	-0.036 0.061 0.169 0.283 0.120 -0.017	0.074 -0.071 0.047 -0.273 0.017 -0.144
Com Cre Cur Eco EMM Int Pol	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293
Com Cre Cur Eco EMM Int Pol	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017 EMM	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293
Com Cre Cur Eco EMM Int Pol Bps	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036 0.074	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169 0.047	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283 -0.273	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017 -0.144	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000 -0.293	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293 1.000
Com Cre Cur Eco EMM Int Pol Bps 	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036 0.074	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071 Cre	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169 0.047 Cur	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283 -0.273 Eco	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017 EMM	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017 -0.144	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000 -0.293 Pol	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293 1.000 Bps
Com Cre Cur Eco EMM Int Pol Bps 10Y Com Cre Cur	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036 0.074 Com 1.000 -0.133 0.445	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071 Cre -0.133 1.000 0.083	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169 0.047 Cur 0.445 0.083 1.000	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283 -0.273 Eco 0.213 -0.190 0.058	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017 EMM -0.058 -0.083 -0.042	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017 -0.144 Int 0.139 -0.126 -0.075	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000 -0.293 Pol 0.177 0.004 0.139	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293 1.000 Bps -0.124 0.066 0.005
Com Cre Cur Eco EMM Int Pol Bps 10Y Com Cre	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036 0.074 Com 1.000 -0.133	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071 Cre -0.133 1.000	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169 0.047 Cur 0.445 0.083	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283 -0.273 Eco 0.213 -0.190	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017 EMM -0.058 -0.083	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017 -0.144 Int 0.139 -0.126	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000 -0.293 Pol 0.177 0.004	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293 1.000 Bps -0.124 0.066
Com Cre Cur Eco EMM Int Pol Bps 10Y Com Cre Cur Eco EMM	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036 0.074 Com 1.000 -0.133 0.445 0.213 -0.058	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071 Cre -0.133 1.000 0.083 -0.190 -0.083	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169 0.047 Cur 0.445 0.083 1.000	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283 -0.273 Eco 0.213 -0.190 0.058 1.000 0.303	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017 EMM -0.058 -0.083 -0.042 0.303 1.000	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017 -0.144 Int 0.139 -0.126 -0.075 0.178 0.186	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000 -0.293 Pol 0.177 0.004 0.139 0.203 -0.091	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293 1.000 Bps -0.124 0.066 0.005 -0.428 -0.227
Com Cre Cur Eco EMM Int Pol Bps - 10Y Com Cre Cur Eco EMM Int	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036 0.074 Com 1.000 -0.133 0.445 0.213 -0.058 0.139	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071 Cre -0.133 1.000 0.083 -0.190 -0.083 -0.126	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169 0.047 Cur 0.445 0.083 1.000 0.058 -0.042 -0.075	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283 -0.273 Eco 0.213 -0.190 0.058 1.000 0.303 0.178	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017 EMM -0.058 -0.083 -0.042 0.303	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017 -0.144 Int 0.139 -0.126 -0.075 0.178 0.186 1.000	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000 -0.293 Pol 0.177 0.004 0.139 0.203 -0.091 0.190	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293 1.000 Bps -0.124 0.066 0.005 -0.428 -0.227 -0.276
Com Cre Cur Eco EMM Int Pol Bps 10Y Com Cre Cur Eco EMM	1.000 -0.196 0.106 0.075 -0.170 0.116 -0.036 0.074 Com 1.000 -0.133 0.445 0.213 -0.058	-0.196 1.000 0.150 -0.232 0.036 -0.029 0.061 -0.071 Cre -0.133 1.000 0.083 -0.190 -0.083	0.106 0.150 1.000 -0.097 -0.101 -0.233 0.169 0.047 Cur 0.445 0.083 1.000 0.058 -0.042	0.075 -0.232 -0.097 1.000 0.057 -0.144 0.283 -0.273 Eco 0.213 -0.190 0.058 1.000 0.303	-0.170 0.036 -0.101 0.057 1.000 0.092 0.120 0.017 EMM -0.058 -0.083 -0.042 0.303 1.000	0.116 -0.029 -0.233 -0.144 0.092 1.000 -0.017 -0.144 Int 0.139 -0.126 -0.075 0.178 0.186	-0.036 0.061 0.169 0.283 0.120 -0.017 1.000 -0.293 Pol 0.177 0.004 0.139 0.203 -0.091	0.074 -0.071 0.047 -0.273 0.017 -0.144 -0.293 1.000 Bps -0.124 0.066 0.005 -0.428 -0.227

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15Y	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.182	0.221	0.279	0.052	0.028	-0.052	0.212
Cre	-0.182	1.000	0.046	0.057	-0.037	-0.043	0.581	-0.565
Cur	0.221	0.046	1.000	0.310	-0.114	0.003	-0.073	0.136
Eco	0.279	0.057	0.310	1.000	0.170	0.023	0.192	-0.182
EMM	0.052	-0.037	-0.114	0.170	1.000	0.022	0.082	-0.088
Int	0.028	-0.043	0.003	0.023	0.022	1.000	0.049	-0.216
Pol	-0.052	0.581	-0.073	0.192	0.082	0.049	1.000	-0.759
Bps	0.212	-0.565	0.136	-0.182	-0.088	-0.216	-0.759	1.000
20Y	Com	Cre	Cur	Eco	EMM	Int	Pol	Bps
Com	1.000	-0.137	-0.066	0.158	0.157	-0.010	-0.039	0.248
Cre	-0.137	1.000	0.080	0.199	-0.113	-0.022	0.582	-0.470
Cur	-0.066	0.080	1.000	0.200	0.463	0.307	-0.091	-0.011
Eco	0.158	0.199	0.200	1.000	0.285	0.276	0.369	-0.331
EMM	0.157	-0.113	0.463	0.285	1.000	0.405	-0.042	0.020
Int	-0.010	-0.022	0.307	0.276	0.405	1.000	0.062	-0.093
Pol	-0.039	0.582	-0.091	0.369	-0.042	0.062	1.000	-0.650
	0.000	UIUUL	-0.031	0.000	0.0.12			

Table B-3

Mean price change and basis points per node for increase event dates

Node	News Category	Number of days	Mean Percentage change	Mean Basis point change	Rand value per basis point
ON	Com	1	0.01117	7.000	1.92
	Cre	1	0.00833	4.000	1.10
	Cur	0	-	-	
	Eco	20	0.02092	12.042	3.30
	EMM	7	0.01266	6.957	1.91
	Int	3	0.01219	6.500	1.78
	Pol	5	0.01415	8.460	2.32
3M	Com	2	0.00189	1.184	29.07
	Cre	1	0.00107	0.567	13.92
	Cur	1	0.00334	1.931	47.41
	Eco	37	0.00851	4.789	117.54
	EMM	6	0.00557	3.068	75.30
	Int	3	0.00310	1.958	48.06
	Pol	11	0.00511	3.196	78.44



Node	News Category	Number of days	Mean Percentage change	Mean Basis point change	Rand value per basis point
6M	Com	1	0.00438	2.750	132.65
	Cre	0	-	-	
	Cur	0	-	-	
	Eco	39	0.01172	6.241	301.06
	EMM	3	0.00900	4.783	230.73
	Int	6	0.00873	4.641	223.87
	Pol	7	0.00804	4.734	228.35
1Y	Com	0	-	-	-
	Cre	0	-	-	
	Cur	0	-	-	
	Eco	22	0.02918	15.290	1 431.86
	EMM	2	0.03592	17.696	1 657.20
	Int	4	0.01757	9.741	912.20
	Pol	8	0.03569	21.429	2 006.76
2Y	Com	0	-	-	-
	Cre	0	-	-	
	Cur	0	-	-	
	Eco	24	0.04089	21.900	4 100.43
	EMM	4	0.02829	14.383	2 693.03
	Int	3	0.02451	14.503	2 715.45
	Pol	7	0.04641	28.590	5 353.01
5Y	Com	0	-	-	-
	Cre	0	-	-	
	Cur	0	-	-	
	Eco	24	0.02327	12.497	5 820.90
	EMM	7	0.02239	12.058	5 616.15
	Int	2	0.02053	12.516	5 829.40
	Pol	6	0.04081	25.637	11 940.95
10Y	Com	1	0.01853	9.949	9 224.43
	Cre	0	-	-	
	Cur	0	-	-	
	Eco	29	0.02892	15.463	14 336.13
	EMM	3	0.02375	12.268	11 374.46
	Int	1	0.03075	16.517	15 313.89
	Pol	9	0.03749	22.409	20 776.48



Node	News Category	Number of days	Mean Percentage change	Mean Basis point change	Rand value per basis point
15Y	Com	2	0.02057	12.160	16 812.32
	Cre	0	-	-	
	Cur	0	-	-	
	Eco	28	0.03097	16.742	23 146.53
	EMM	6	0.02284	11.597	16 033.71
	Int	2	0.01860	11.396	15 755.35
	Pol	8	0.04061	24.146	33 382.85
20Y	Com	0	-	-	-
	Cre	1	0.02990	14.605	
	Cur	0	-	-	
	Eco	22	0.02474	13.201	24 096.69
	EMM	8	0.02756	13.959	25 478.78
	Int	4	0.02463	13.453	24 555.14
	Pol	9	0.03926	23.117	42 195.09

Table B-4

Mean price change and basis points per node for decrease event dates

Node	News Category	Number of days	Mean Percentage change	Mean Basis point change	Rand value per basis point
ON	Com	0	-	-	0.00
	Cre	1	-0.00679	-4.700	1.29
	Cur	1	-0.02539	-17.300	4.74
	Eco	19	-0.02547	-15.042	4.12
	EMM	4	-0.00848	-4.875	1.34
	Int	2	-0.00849	-5.700	1.56
	Pol	9	-0.01258	-7.962	2.18
3M	Com	1	-0.00305	-2.000	49.09
	Cre	0	-	-	0.00
	Cur	0	-	-	0.00
	Eco	32	-0.01354	-8.348	204.91
	EMM	1	-0.00179	-1.000	24.55
	Int	3	-0.00320	-1.967	48.27
	Pol	20	-0.00405	-2.645	64.92
6M	Com	1	-0.00594	-4.000	192.95
	Cre	1	-0.00200	-1.600	77.18
	Cur	3	-0.00670	-4.267	205.81
			200		



Node	News Category	Number of days	Mean Percentage change	Mean Basis point change	Rand value per basis point
	Eco	41	-0.01600	-9.892	477.19
	EMM	5	-0.00886	-5.360	258.55
	Int	0	-	-	0.00
	Pol	13	-0.00700	-4.654	224.49
1Y	Com	0	-	-	0.00
	Cre	1	-0.01553	-12.538	1 174.20
	Cur	0	-	-	0.00
	Eco	27	-0.02258	-14.132	1 323.48
	EMM	4	-0.01671	-10.265	961.29
	Int	0	-	-	0.00
	Pol	4	-0.02029	-13.410	1 255.80
2Y	Com	0	-	-	0.00
	Cre	3	-0.01908	-14.740	2 759.72
	Cur	0	-	-	0.00
	Eco	26	-0.02615	-16.691	3 125.08
	EMM	2	-0.03115	-21.962	4 112.05
	Int	2	-0.02663	-20.548	3 847.22
	Pol	7	-0.03147	-21.554	4 035.51
5Y	Com	0	-	-	0.00
	Cre	2	-0.02265	-18.659	8 690.99
	Cur	0	-	-	0.00
	Eco	26	-0.02267	-16.552	7 709.32
	EMM	5	-0.01928	-14.904	6 942.12
	Int	2	-0.02296	-17.805	8 292.95
	Pol	6	-0.02163	-17.106	7 967.57
10Y	Com	0	-	-	0.00
	Cre	2	-0.02001	-16.660	15 446.10
	Cur	0	-	-	0.00
	Eco	28	-0.02418	-18.106	16 787.03
	EMM	4	-0.02185	-17.159	15 908.79
	Int	4	-0.02374	-17.804	16 506.38
	Pol	7	-0.02434	-19.348	17 938.06
15Y	Com	0	-	-	0.00
	Cre	1	-0.02368	-23.345	32 276.04
	Cur	0	-	-	0.00
	Eco	30	-0.02363	-16.766	23 180.63
	EMM	3	-0.01848	-14.464	19 997.73
	Int	4	-0.01934	-16.728	23 128.16
	Pol	9	-0.02821	-25.626	35 429.25

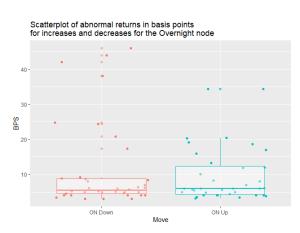


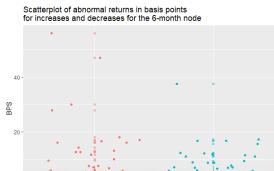
Node	News Category	Number of days	Mean Percentage change	Mean Basis point change	Rand value per basis point
20Y	Com	0	-	-	0.00
	Cre	1	-0.02367	-23.786	43 416.76
	Cur	0	-	-	0.00
	Eco	20	-0.02542	-23.796	43 434.84
	EMM	4	-0.02402	-22.432	40 946.25
	Int	3	-0.02159	-19.989	36 485.68
	Pol	11	-0.02932	-27.717	50 591.72

Figure B-1

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Comparison of absolute abnormal returns in basis points for increase and decrease event dates

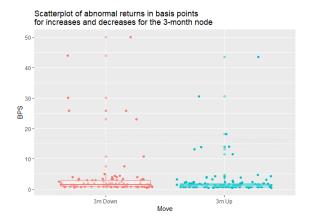


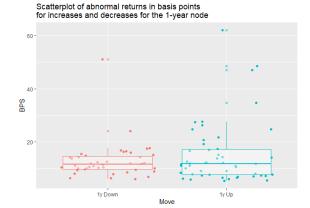


Move

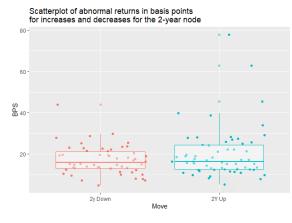
6m Up

6m Down

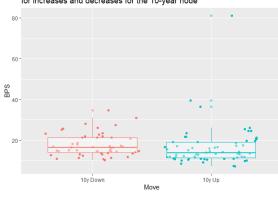




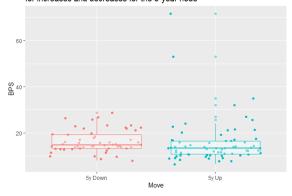




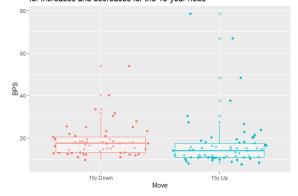
Scatterplot of abnormal returns in basis points for increases and decreases for the 10-year node



Scatterplot of abnormal returns in basis points for increases and decreases for the 5-year node



Scatterplot of abnormal returns in basis points for increases and decreases for the 15-year node



Scatterplot of abnormal returns in basis points for increases and decreases for the 20-year node

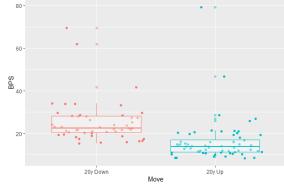




Table B-5

Descriptive statistics for sovereign bond spread on increase event dates

	ON	3M	6M	1Y	2Y	5Y	10Y	20Y
nbr.val	36	60	55	35	37	38	42	43
min	-6.1	-3.4	1.3	5.45	-0.563	2.28	1.586	5.16
max	38.3	48.7	46.8	77.281	94.937	88.237	101.463	124.339
range	44.4	52.1	45.5	71.83	95.5	85.957	99.878	119.179
sum	337	259.8	363.4	644.922	940.468	736.338	916.83	1114.294
median	6.8	2	4.4	13.32	22.127	16.975	19.246	22.666
mean	9.361	4.33	6.607	18.426	25.418	19.377	21.829	25.914
SE.mean	1.504	1.052	0.966	2.555	2.886	2.31	2.486	2.714
Cl.mean.0.95	3.054	2.105	1.936	5.192	5.852	4.681	5.021	5.477
var	81.454	66.372	51.278	228.43	308.075	202.845	259.644	316.688
std.dev	9.025	8.147	7.161	15.114	17.552	14.242	16.113	17.796
coef.var	0.964	1.882	1.084	0.82	0.691	0.735	0.738	0.687
skewness	1.453	3.659	3.521	2.171	2.174	2.983	2.852	3.842
skew.2SE	1.851	5.926	5.471	2.73	2.805	3.896	3.904	5.316
kurtosis	2.147	15.096	15.774	5.002	5.792	11.711	11.609	18.918
kurt.2SE	1.398	12.405	12.45	3.215	3.817	7.81	8.1	13.341

Table B-6

Descriptive statistics for sovereign bond spread on decrease event dates

	ON	3M	6M	1Y	2Y	5Y	10Y	20Y
nbr.val	35	56	63	35	39	40	44	38
min	-47	-50	-56	-50.14	-43.717	-26.778	-40.155	-64.94
max	-1	0	1.1	-5.861	-2.119	2.807	0.115	-8.513
range	46	50	57.1	44.279	41.598	29.585	40.27	56.427
sum	-414.4	-312.4	-480.4	-469.68	-680.389	-623.203	-753.475	-891.55
median	-6.4	-2	-4.2	-11.9	-16.21	-16.359	-16.357	-22.123
mean	-11.84	-5.579	-7.625	-13.419	-17.446	-15.58	-17.124	-23.462
SE.mean	2.116	1.384	1.262	1.26	1.173	1.014	1.141	1.771
Cl.mean.0.95	4.299	2.773	2.524	2.56	2.375	2.051	2.302	3.589
var	156.646	107.243	100.407	55.556	53.666	41.136	57.307	119.199
std.dev	12.516	10.356	10.02	7.454	7.326	6.414	7.57	10.918
coef.var	-1.057	-1.856	-1.314	-0.555	-0.42	-0.412	-0.442	-0.465
skewness	-1.644	-2.861	-2.975	-3.434	-1.05	0.658	-0.929	-1.331
skew.2SE	-2.067	-4.484	-4.933	-4.317	-1.387	0.88	-1.3	-1.738
kurtosis	1.458	7.651	10.011	14.12	2.665	0.255	1.378	3.205
kurt.2SE	0.937	6.089	8.415	9.077	1.798	0.174	0.982	2.138

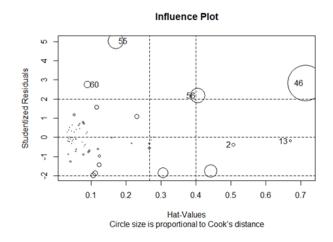


Figure B-2

<u>ON</u>

Influence plots for all the increase event date nodes

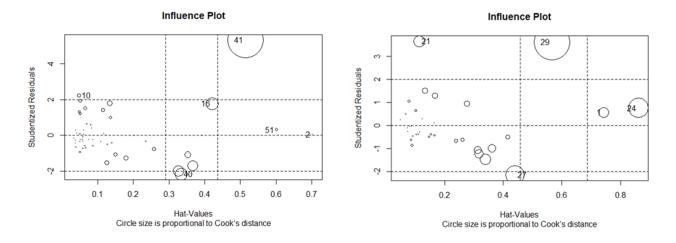
Influence Plot ო 30 18 2 G 2 Studentized Residuals 0 ~ 0 0 0 13 0 32 7 0 0 0 0 Ο Ņ 29 0.1 0.3 0.5 0.6 0.7 0.2 0.4 Hat-Values Circle size is proportional to Cook's distance



6-Month

<u>1-Year</u>

<u>3-Month</u>



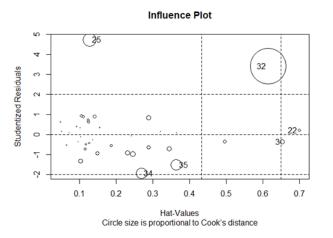


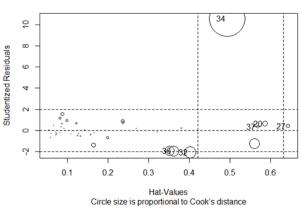
© University of Pretoria





<u>5-Year</u>

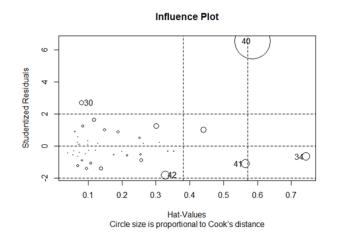


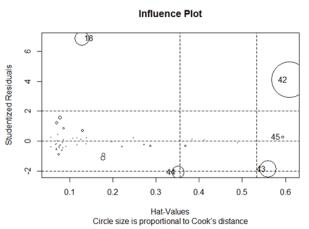


Influence Plot

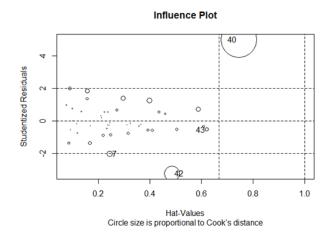












302

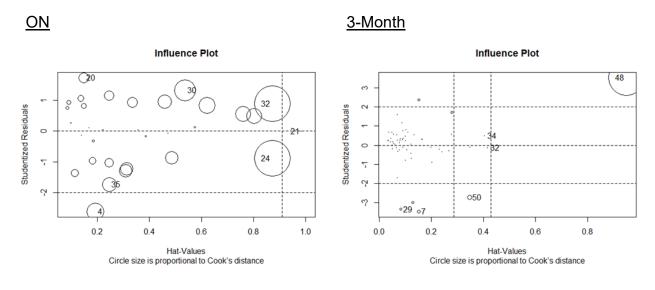
© University of Pretoria



Note. Studentized residuals versus model fitted values are provided, with the areas of the circles representing the observations proportional to the value Cook's distance. Vertical reference lines are drawn at twice and three times the average hat value, horizontal reference lines at -2, 0, and 2 on the Studentized-residual scale.

Figure B-3

Influence plots for all the decrease event date nodes

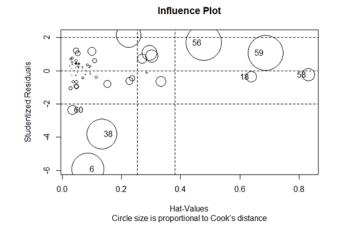


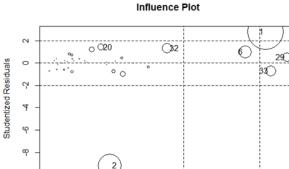
6-Month

1-Year

0.1

0.2





0.3

Hat-Values Circle size is proportional to Cook's distance

0.5

0.6

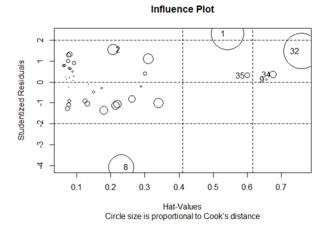
0.7

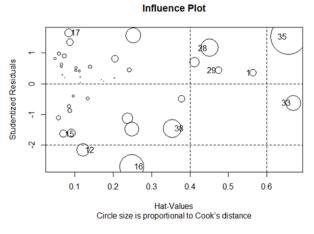
0.4





<u>5-Year</u>





40

(41

0.5

27

12

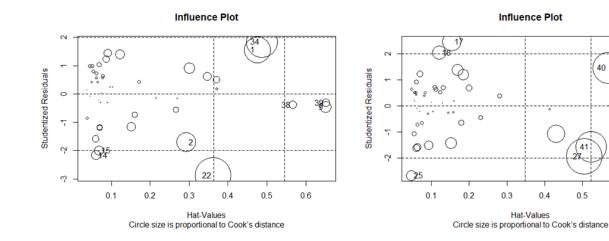
0.6

45

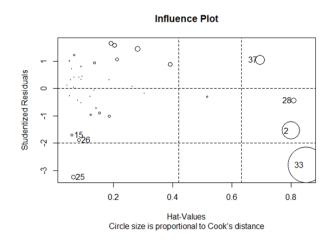
0.7

<u>10-Year</u>

<u>15-Year</u>





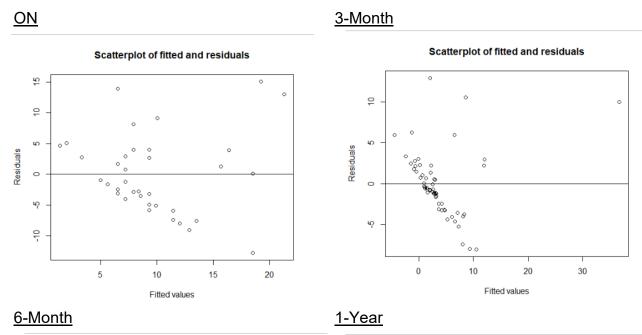




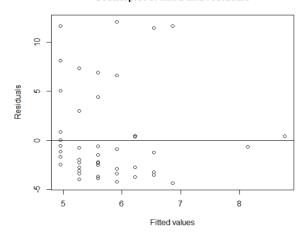
Note. Studentized residuals versus model fitted values are provided, with the areas of the circles representing the observations proportional to the value Cook's distance. Vertical reference lines are drawn at twice and three times the average hat value, horizontal reference lines at -2, 0, and 2 on the Studentized-residual scale.

Figure B-4

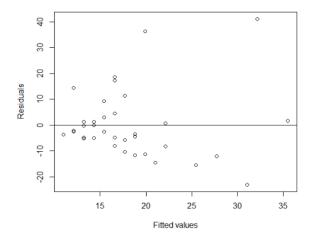
Scatterplots of the fitted linear regression model residuals versus fitted values for all nodes relating to increase event dates



Scatterplot of fitted and residuals



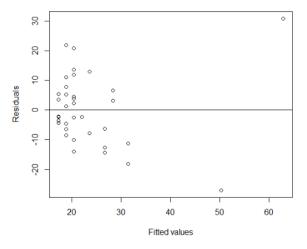
Scatterplot of fitted and residuals





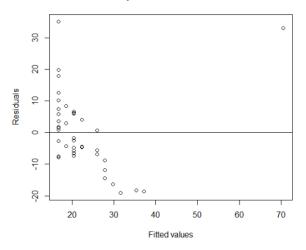


Scatterplot of fitted and residuals



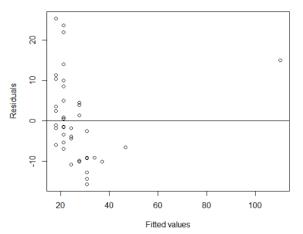


Scatterplot of fitted and residuals

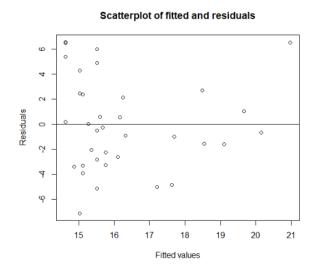




Scatterplot of fitted and residuals

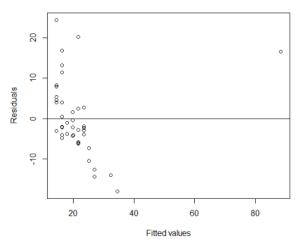


<u>5-Year</u>



<u>15-Year</u>

Scatterplot of fitted and residuals

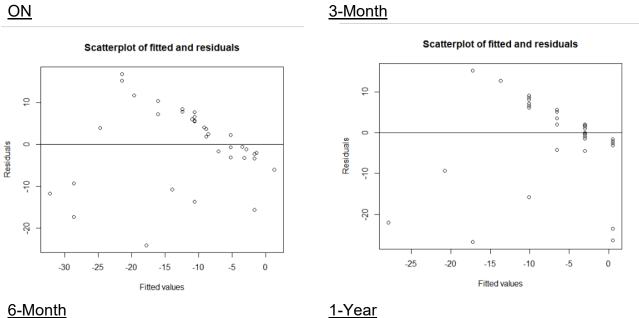




Note. Plots above were used as a tool to visually inspect the variance of the residuals. The horizontal line at zero is the theoretical mean of the residuals.

Figure B-5

Scatterplots of the fitted linear regression model residuals versus fitted values for all nodes relating to decrease event dates

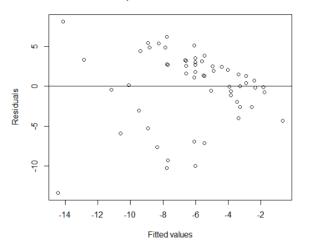


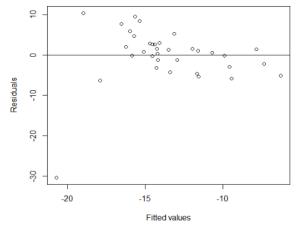
6-Month

Scatterplot of fitted and residuals



Scatterplot of fitted and residuals

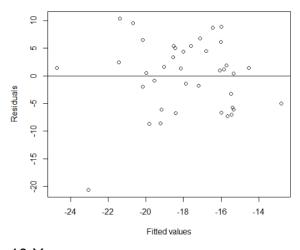






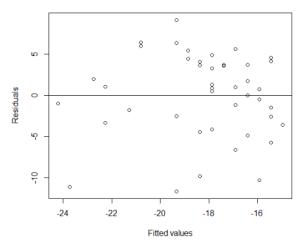


Scatterplot of fitted and residuals

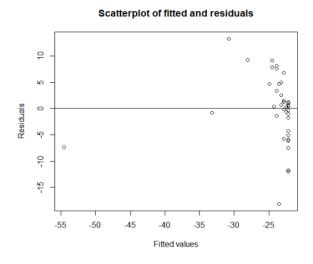




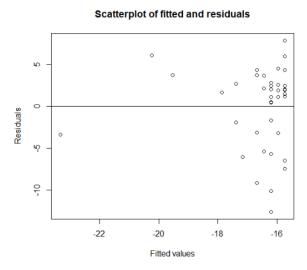
Scatterplot of fitted and residuals





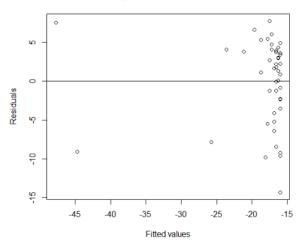


<u>5-Year</u>



<u>15-Year</u>

Scatterplot of fitted and residuals

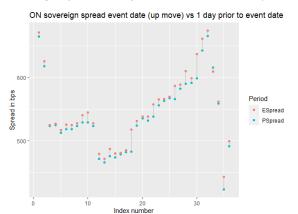




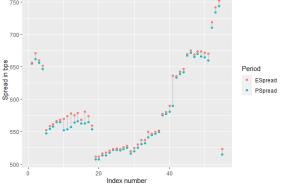
Note. Plots above were used as a tool to visually inspect the variance of the residuals. The horizontal line at zero is the theoretical mean of the residuals.

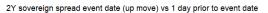
Figure B-6

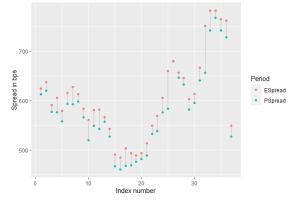
Sovereign spread comparison of event date (increase) and 1-day prior to event date

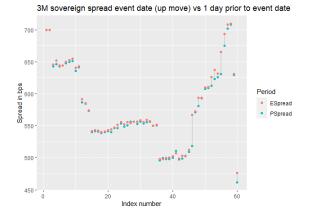


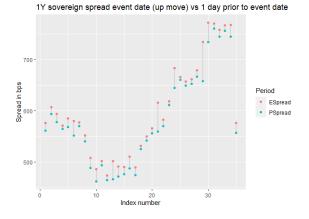


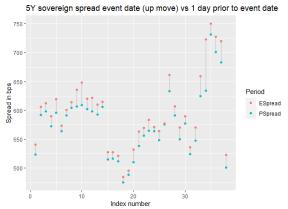






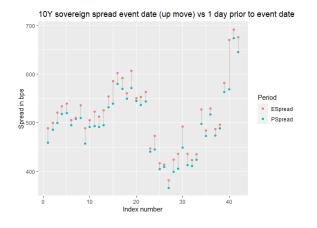












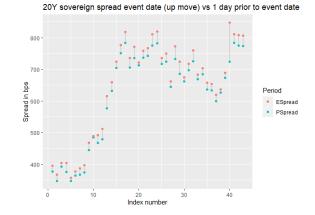
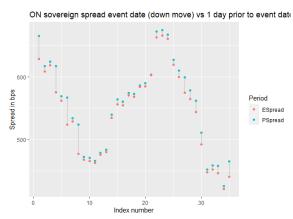
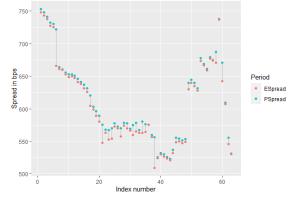


Figure B-7

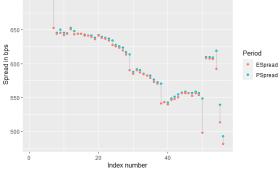
Sovereign spread comparison of event date (decrease) and 1-day prior to event date

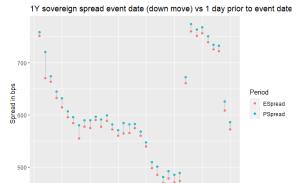


6M sovereign spread event date (down move) vs 1 day prior to event date



3M sovereign spread event date (down move) vs 1 day prior to event date





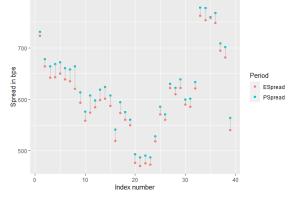
30

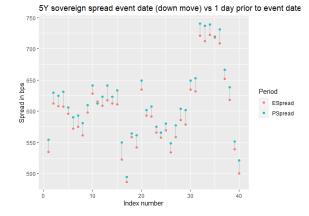
20 Index number

10

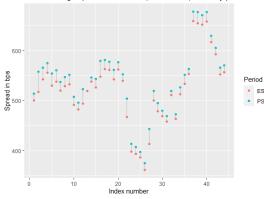


2Y sovereign spread event date (down move) vs 1 day prior to event date

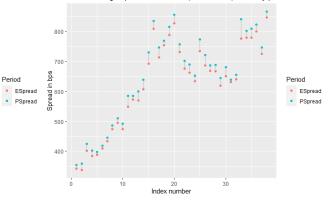




10Y sovereign spread event date (down move) vs 1 day prior to event dat



20Y sovereign spread event date (down move) vs 1 day prior to event dat





Appendix C

Table C-1

Descriptive statistics of the differences between the calculated bond prices and the derived bond prices

	R206	R203	R207	R208	R186	R213	R209	R2040	R2048
n	751	1501	1999	499	2498	1997	2498	1997	1248
mean	0.0000000	-0.0000000	-0.0000000	0.0000001	0.0000000	0.0000001	0.0000000	0.0000002	0.0000002
sd	0.0000000	0.0000000	0.0000014	0.0000039	0.0000027	0.0000034	0.0000040	0.0000118	0.0000065
median	0.0000000	0.0000000	-	0.0000001	0.0000000	0.0000000	-	0.0000000	0.0000000
trimmed	0.0000000	0.0000000	-0.0000000	0.0000001	-0.0000000	0.0000001	0.0000000	0.0000001	0.0000000
mad	0.0000000	0.0000000	0.0000000	0.0000038	0.0000000	0.0000000	0.0000000	0.0000000	0.0000018
min	-0.0000000	-0.0000000	-0.0000094	-0.0000095	-0.0000092	-0.0000160	-0.0000373	-0.0001172	-0.0000419
max	0.0000000	0.0000000	0.0000089	0.0000096	0.0000169	0.0000297	0.0000709	0.0002221	0.0000841
range	0.0000000	0.0000000	0.0000184	0.0000191	0.0000261	0.0000458	0.0001082	0.0003394	0.0001259
skew	0.13	-10.65	-0.39	-0.11	0.22	0.55	2.69	3.95	1.97
kurtosis	-0.45	223.74	15.54	-0.46	2.53	6.78	58.16	90.48	28.68
se	0.0000000	0.0000000	0.0000000	0.0000002	0.0000001	0.0000001	0.0000001	0.0000003	0.0000002

Note. The difference is calculated using the closing YTM for each bond and the GCH-formula and using the zero-coupon yield to each cash flow date and

discounting the cashflow to the settlement date.



Table C-2

Shapiro-Wilk test for normality for calculated and derived bond prices

Bond	Test statistic (w)	<i>p</i> -value
R206	0.936118975027414	< .001
R203	0.977172535421556	< .001
R207	0.984763803606323	< .001
R208	0.978349260114354	< .001
R186	0.940875290845861	< .001
R213	0.962618838363778	< .001
R209	0.971246800487446	< .001
R2040	0.955715372305998	< .001
R2048	0.909378093937548	< .001
R206m	0.936118975027415	< .001
R203m	0.977172535421654	< .001
R207m	0.984763805687532	< .001
R208m	0.978349294794852	< .001
R186m	0.940875294177261	< .001
R213m	0.962618843472459	< .001
R209m	0.971246807345451	< .001
R2040m	0.955715371701710	< .001
R2048m	0.909378144382247	< .001

Note. Shapiro-Wilk test for normality done on both the calculated (GCH-formula) and bond prices derived from the zero-coupon model.

Table C-3

Wilcoxon rank sum test comparing calculated versus derived bond prices.

Bond	statistic	p.value
R206	282 138	.987
R203	1 126 554.5	.998
R207	1 997 971.5	.999
R208	124 503	.999
R186	3 120 046.5	.999
R213	1 994 022.5	.999
R209	3 120 004	.999
R2040	1 994 014.5	.999
R2048	778 764	.999

Note. Two-sided Wilcoxon rank sum test with continuity correction.



Table C-4

Wilcoxon signed rank test comparing abnormal returns with normal returns in the sample for increase event dates

Increase	ON	3M	6M	1Y	2Y	5Y	10Y	15Y	20Y
<i>p</i> -value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
(pseudo)									
median	8.037864	1.999932	4.700013	15	22.09993	16.79996	20.30004	19.39996	24.09996
Mate Milesure	Λ								

Note. Wilcoxon signed ranked test with continuity correction with a 95% confidence interval

Table C-5

Wilcoxon signed rank test comparing abnormal returns with normal returns in the sample for decrease event dates

Decrease	ON	3M	6M	1Y	2Y	5Y	10Y	15Y	20Y
<i>p</i> -value	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
(pseudo)									
median	-6.59911	-2.50004	-5.05005	-12.45	-17.393	-15.9521	-17.6999	-16.9501	-22.8
Mate Milesus air	بيم المعتما بمعالية ما	4	14		C 1	I			

Note. Wilcoxon signed ranked test with continuity correction with a 95% confidence interval