Assessing the Impact of Risk Contagion on Value-at-Risk and the Alternative Application of a Bayesian Factor Based Approach

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy.

By

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Declaration

This is to certify that this thesis is the result of an original investigation. The material has not been used in the submission for any other qualification. Full acknowledgement has been given to all sources used.

Signed: ………………………………………… (Student)

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Abstract

The first part of this thesis focuses on the application of Value-at-risk (VaR) in defining a financial institution's exposure to systemic risk. Specifically, I apply an extension of it in the form of Delta-CoVaR as suggested by Adrian and Brunnermeier (2011) and then further developed by Castro et al (2014). In both cases, it is suggested that, rather than quantifying an institution's risk in isolation through its own VaR, you should consider the negative risk-spillover effects of all institutions on the whole financial system. Therefore, I assess the contribution of an individual institution to a region's systemic risk and this is done for a sample of 29 European banks and Insurance Companies. I note their individual systemic risk contributions in the first instance and assess their respective significance through bootstrapping. Furthermore, I note whether there is any significance in relation to the underlying sector, in particular the insurance sector, and country of origin of the company. Both are shown to be of importance to regulatory authorities in determining capital requirements for the largest institutional investors in the financial industry. The results suggest that the insurance sector is systemically important and that a high 1% individual VaR does not necessarily yield the largest contribution to the VaR of the whole system – thereby illustrating the importance of considering Delta-CoVaR.

Chapter 4 provides an extension to the preceding chapter in relation to providing further evidence of the need to consider interlinkages and coupling within the financial system. This is done through application of the Absorption Ratio (AR) to ten European banks and insurance companies. In this case, the AR does not appear to act as an early warning indicator of market turmoil. However, one principal component is identified as explaining 70 to 80% of the variability in the assets' returns for the period under review. A high AR suggests the stocks are more tightly coupled and provides evidence of interlinkages across two subsectors and a number of countries within Europe – thereby illustrating the extent of financial linkages.

Chapter 5 considers a methodology for deriving stock returns and VaR through the application of a Bayesian Network (BN). A network map is specified where the returns for three stocks are deemed to be conditionally dependent on two factors. The latter are defined having previously considered literature relating to the financial crisis and risk contagion. Subsequently, two factors are identified as influencing the individual stock returns – one relating to liquidity and the other relating to the market. Following application of the Gaussian Bayesian Network, regressions generate models for the said returns. The latter are then used to simulate time series of stock returns and those outcomes are compared to the original data series. The BN specification is found to be a satisfactory alternative for the modelling of stock returns. Furthermore, the resulting quantiles are shown to be more prudent estimates in relation to VaR calculations at the 5% level and, therefore, can result in increases in regulatory capital.

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Chapter 1:

Introduction

1 Introduction

1.1 Systemic Risk Defined

The risk of collapse of a financial system has been debated at length and the components and dimensions of systemic risk subsequently brought to the fore. A broad history of financial crises illustrates their extreme costs to the wider domestic economy and, at their worst, to the wider global economy - as evidenced by the 2008 crisis. Thereby, the need for increased awareness and more substantive and effective regulation around systemic risk is very high on the agenda. However, for such regulatory enhancement to be effective, one has to have greater clarity of what defines systemic risk and whether there are any key features or common attributes to the various financial failings of the past.

Without any context, a dictionary definition of the word systemic is "relating to a system as opposed to a particular part.[1]" In this case, the system could be the entire financial system as opposed to just one institution or sector within it. From an industry standpoint, the Bank for International Settlements (BIC) defines systemic risk as:

> "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy."

The words, "a risk of disruption" as opposed to catastrophic failure appear to underplay the significance of systemic risk but the subsequent impact is clarified in the potential *serious* negative consequences for the real economy resulting from the said disruption. Other definitions comment

[1] Oxford English Dictionary (2017)

on a likelihood or probability of *cumulative* losses resulting from an event. Whereby the event itself triggers a series of losses amongst the majority of financial institutions deemed to be the constituents of the financial system. Indeed, the latter are considered by Chan et al (2005) who describe systemic risk as "the possibility of a series of correlated defaults among financial institutions, typically banks, that occur over a short period of time, often caused by a single major event." However, the triggering event does not have to be a major one – from a moderate shock to the financial system you may witness significant volatility in asset prices, reduced liquidity in the markets and subsequent problems in the inter-bank markets. Furthermore, the shock or event itself may be confined to the financial system of one global region or then spread to multiple regions. The similarities appear to be the occurrence of a loss inducing event, however large or small and the repercussions spreading across the entire financial system and wider economy where both may be regarded as localised or global.

The spreading effect is what makes systemic risk so dangerous and harmful to the stability of any financial system and economy per se. It occurs because of the interlinkages that exist between financial institutions within and across regions. In order to articulate the objectives of this thesis, I firstly present some context to systemic risk through a discussion of the aforementioned spreading effect, the inter-linkages that exist within and between financial systems and the subsequent consequences of those inter-linkages. Furthermore, another consideration is the contagion effect as discussed and defined by Forbes and Rigobon (2002) and deemed appropriate given the empirical analyses presented in chapters three, four and five. Specifically, an important distinction is made between markets being highly correlated due to *continuing* strong linkages between markets and institutions as opposed to an *increase* in such linkages during and following financial crises.

1.2 The Spreading and Contagion Effects

Aside from the 2008 crisis, there are several instances in recent times where events have created a spread in losses across an entire financial system and wider ramifications for the economy as a whole. A suggested common underlying factor in relation to each financial crisis is the growth in consumer credit and bank lending. This is discussed by Allen and Gale (2007) in relation to Scandinavia who note that between 1985 and 1986, consumer and corporate borrowing increased by 40 percent in the region. Following a triggering event of the collapse in oil prices, upon which the region relied so heavily, the economy stalled, asset prices dropped, banks tightened lending and the housing market crashed. Many of the banks were left with loan balances linked to assets that had previously been severely overvalued. The government intervened to stem the crisis but it spread across the region's financial system and a recession followed - it did not have a global impact. A similar situation arose in Japan in the 1980s, where, once again there was a huge expansion in credit, asset prices rose and the Nikkei 225 market index reached an all-time high in 1989. A tightening in monetary policy in early 1990 led to a sharp and sudden rise in interest rates, the subsequent impacts being a significant drop in available credit, the markets and real estate values. Takeo and Kashyap (2004) argue that the Japanese economy had still not recovered by early 2003 and highlight the linkages between the wider economy and the financial system.

In contrast, impacts of other financial crises have spread far beyond their point of origination. The currency crisis arising in East Asia in 1997 is a prime example. Chang (1999) argues that the crisis stemmed from a dramatic upward valuation in many of the region's currencies during the 1990s due to record levels of growth, foreign portfolio and direct investment, which were ultimately not sustainable. Diao et al (2000) further add that a general lack of confidence in the region's regulatory controls and financial systems led to a sudden reversal of capital inflows where investors liquidated their positions in the various asset classes. The latter presented an enormous shock to the East Asian economies, subsequent devaluation in currencies, tightening of bank lending, rising interest rates and severe contraction of money supply from bank sources.

In terms of spread, there are several distinguishable sources in this example. For instance, the Thai Baht was the first of the currencies to devalue which subsequently impacted its competing neighbours in both the import and export markets – Thailand's goods became cheaper than those of Indonesia. Furthermore, imports to Thailand from Laos became more expensive and demand reduced – amounting to spreading across trading channels. Of greater relevance to this thesis, is the spread that existed across financial channels, as clarified by Walker (1998). Aside from the impact on chains of banks across the East Asia region the crisis created a lack of confidence in Emerging markets in general. A sell-off occurred across all emerging market investments – including those linked to South America and former Eastern European countries. Therefore, in relation to systemic risk, the currency crises of East Asia, Argentina (2001) and Russia (1998) represent occurrences of a trigger event as proposed by Schwarz (2008). Whereby, there is an economic shock or institutional failure, causing a chain of bad economic consequences. In all of the examples presented, financial institutions suffered significant losses and the global markets experienced excessive price volatility.

Having illustrated that significant market movements can affect other markets across regions and the globe, it is important to clarify whether, what appear to be highly correlated market movements, provide evidence of the existence of the contagion effect. Forbes and Rigobon (2002 p.2) define the latter as "a significant increase in cross-market linkages after a shock to one country (or group of countries)." If cross-market links do not increase significantly, but rather continue due to high levels of correlation, then the latter is more likely a further indication of persistent strong links across the global financial system as opposed to evidence of contagion. This thesis does not investigate differences in cross-market linkages pre and post financial crisis, rather it indicates that the financial crisis was so severe because of the mere existence of linkages and high correlations in the first instance.

1.3 Interlinkages in the Financial System

Given the severity and spread of the global crisis in 2008, it provides suitable examples to illustrate the interlinkages in the financial system. Essentially, the catalyst for it was the extent of the losses sustained through the defaults in the sub-prime domestic mortgage markets in the United States. Such losses ultimately created a domino effect and amplification across global financial markets. Preceding this, global stock markets had experienced several years of healthy prosperity, for instance, the FTSE-All-Share index reached an all-time high of 3490.17[2] as at 13th August 2007. For the subsequent crisis to have been so prolific, it suggests that a rise in US mortgage delinquency rates was not the only issue – indeed, the following discussion presents other critical factors.

[2] Bloomberg

1.3.1 The Demand for Securitised Products

One has to ask why borrowers, with a high probability of default, were given access to the funds in the first instance. Keys et al (2008) provide evidence to suggest that the increased demand for securitised products led to a decline in the credit quality of the underlying mortgagee. For example, in the United Kingdom, certain retail banks were offering mortgages based on 120% of annual gross salary and there was a significant increase in the buy-to-let mortgage market. In conjunction with very low costs of borrowing, there appears to have been a lax approach in determining a consumer's ability to repay. The resulting higher risk mortgages were packaged into securitised sub-prime debt products and the associated risks transferred to the investors. The increasing demand from the financial markets could only be satisfied through the granting of the underlying mortgages in the first instance within the retail sector. Thereby creating links between separate parts of the financial system – the retail banks issuing the mortgages, the investment banks repackaging the underlying debt into securitised products and the investors in the secondary markets buying said products from across the globe. Brunnermeier (2009, p.78) highlights the problem as follows:

> "The traditional banking model, in which issuing banks hold loans until they are repaid, was replaced by the originate and distribute banking model, in which loans are pooled, tranched and then resold via securitisation. The creation of new securities facilitated the large capital inflows from abroad."

1.3.2 Funding Operations

Financial institutions issuing loans for mortgages require access to appropriate funding as do the financial institutions investing in the related securitised debt products. This can be achieved through external borrowing of varying maturity. If borrowing costs are low, there is a propensity for shorter term borrowing which can involve the issuance of asset backed securities, commercial paper and medium-term notes in the money markets in return for cash. Such securities have maturities varying from one month to one year but financial institutions may also borrow on an overnight, weekly, fortnightly or monthly basis through the inter-bank sector of the money markets. Furthermore, investment banks may finance their activities through the repo[3] markets. According to Brunnermeier (2009), in the seven years leading up to the crisis, there was a doubling in the fraction of total investment banks financed by overnight repo instruments. Clearly, whatever the nature of the underlying security issuance in the money markets, linkages are created through the pool of investors willing to buy the said securities and the issuers with the funding requirements. Furthermore, there are linkages created between the retail banks and their customers in relation to funding – whereby funds are deposited by them into bank and building society interest bearing deposit accounts. The common factor across funding sources is their short-term maturity – the money market borrowings and issued securities require frequent refinancing and the retail banking customers can withdraw their deposits with minimum notice. A liquidity crisis across the financial system can arise in the event that the available funding pool of investors in the money markets diminishes and / or when retail banking depositors withdraw funds all at the same time.

[3] In a repo contract, a firm borrows money by selling an asset today (usually a T-Bill) and promising to repurchase it at a later date for a pre-specified price.

1.4 Consequences of the Interlinkages

Brunnermeier and Pedersen (2009) highlight the increasing occurrence of sub-prime mortgage defaults from as early as February 2007, resulting in rating downgrades of certain sub-prime products by Moody's, Standard and Poor's and Fitch. In addition, the mortgage issuers began recording significant losses on delinquency and defaults. A natural consequence was growing negative sentiment and concern over the true intrinsic value of the structured sub-prime debt products and decline in their market prices. For the investors, this meant a reduction in the value of assets on balance sheets and overall decline in net worth. This impact is presented by Duarte and Eisenbach (2015), where they refer to fire-sale spillovers and externalities. It is suggested that, in order to control leverage ratios, financial institutions had to sell off portions of their assets at the reduced market prices. The asset sell-off amounted to a "fire-sale" and the negative signals sent to the market acted as a catalyst for more and more institutions to sell off their devalued structured products – resulting in a loss spiral affecting many market participants.

The aforementioned declining asset values created issues with liquidity due to the impact on the leverage ratio. Indeed, Shleifer and Vishny (2011) allude to the rising ratios affecting the ability to raise new funds and refinance existing borrowing commitments through the money markets. Furthermore, banks often received overnight funding through collateral backed loans – with the collateral being the securitised debt products. With the true intrinsic values of the underlying securities being difficult to determine, their higher perceived inherent risk and a shrinking investor pool, there was even greater tightening in lending policies. Subsequently, financial institutions were forced to sell increasing amounts of assets to achieve short term funding goals. It became a self-perpetuating vicious circle of events made increasingly worse by the forced selling activity.

It is clear that issues around market liquidity and funding were significant in the 2008 crisis. Consistent with section 1.3.2 above, Adrian and Shin (2010) suggest that the difficulties arose because cheap funding costs in boom periods induce financial institutions to finance themselves with short term borrowing where there will be associated refinancing risk. In such a market environment, the lending institutions may underestimate risk and their exposures to associated losses. During a boom, this may contribute further to excessively rapid credit growth and relatively low regulatory capital provisions. In this case, as the financial crisis progressed all participants within the financial system were ill prepared for the consequences. In particular, through identifying greater risks than first anticipated, lenders either reduced lending or did so at much greater cost. Furthermore, other institutions ceased lending altogether. The latter is referred to by Brunnermeier (2009) as a hoarding externality. It reflects the concern that the lending banks had about strains on their own internal funding sources. Potentially, they could also require short term borrowing through the inter-bank markets. Given the uncertainty over availability of funds through that channel, it led to precautionary hoarding by the lending banks in order to fund their own operations in the short term. Subsequently, the liquidity spiral worsened with the shrinking appetite for new and refinanced issues of commercial paper and medium-term notes but also the short supply of funding on an overnight to monthly basis. The worst-case scenario was illustrated by Lehman Brothers, when, on September 15th 2008, the investment bank was declared bankrupt. Likewise, numerous other struggling banks were bailed out by respective governments, following their inability to lock in funding sources.

From a retail banking perspective, institutions were not only impacted by the lack of liquidity in the money markets but also through their retail customer base. As presented in section 1.3.2, the minimal notice period for withdrawals implies that if large numbers of customers wish to make withdrawals at the same time, there is a situation known as a bank run. This is what occurred in the case of Northern Rock in September 2007 – depositors converged on the bank's branches to withdraw their funds and the bank had insufficient cash to pay all withdrawal demands. The catalyst for the bank run was the media hype created by Northern Rock approaching the Bank of England for a short-term loan facility given its inability to source funding through the usual channels. Kaufman and Scott (2003) identify the issues this kind of failure creates within the financial system due to banks being interlinked financially. They lend to and borrow from each other through the inter-bank markets and if one bank defaults on its obligations to another, the latter is also then unable to meet its own obligations to other banks in the chain. What you see unfold is a domino effect of defaulting financial institutions.

1.5 Research Objectives and Contribution

Following the above discussion, it is clear that financial failures can be both localised and widespread in nature. The latter is a characteristic of spreading and risk contagion, the degree of severity being determined by respective links between the participants within the financial system. In practice, within industry, the concept of Value-at-Risk (VaR)[4] is widely used by individual institutions to measure their exposures to systemic risk, possibly because it is simple enough to apply. There are a number of ways to derive VaR – some involving the estimation of conditional volatility using ARCH and GARCH methodologies. It is apparent that such techniques are not favoured within industry because they are not well understood and do not result in transparency in risk management across the financials' sector. A method proposed by RiskMetrics *is* widely used

[4] maximum loss incurred by a single institution over a given horizon at a given confidence level

and its outputs lead to the setting aside of adequate regulatory capital to protect against insolvency. Given the indicated importance of correlations, inter-linkages and influences of financial institutions on each other, I suggest that it is inappropriate to quantify an institution's regulatory requirements based solely on its own individual VaR. Rather, the negative risk spillover effects of all institutions on the entire financial system should be considered. Furthermore, if current industry VaR measures do not adequately capture the potential severity of the exposure to systemic risk, is there a viable alternative which considers factors that are regarded as highly influential in the degree of spread? For example, the falling liquidity in the money markets as identified previously. Through this thesis, the intention is not to assess the respective advantages, disadvantages and applicability of the various ways to measure VaR. Rather, I aim to provide evidence to suggest that linkages need to be incorporated in any method. Furthermore, for this research to be of any use in practice, the suggested method must be capable of widespread application in industry. In gathering that evidence, I begin with a review of existing research in relation to the measurement of systemic risk and encompassing the key themes. Within this review, the VaR concept is discussed and one technique incorporating the impact of individual institutions on others is presented, namely CoVaR. In chapter 3, I not only add to the existing studies in relation to the application of CoVaR to UK and European data sets but, more importantly, illustrate the need to apply the technique across sub-groups of institutional investors. In particular, I aim to assess the impact of the insurance sector on the wider financial system – currently, literature suggests an emphasis on the impact of banks with an absence of data analysis in relation to insurance companies. Furthermore, in highlighting the importance of incorporating risk linkages in VaR, I proceed to provide further evidence through the application of the Absorption Ratio to the same data set. According to Kritzman et al (2010), it captures the extent to which markets are tightly linked and connected and, thereby indicates the more widespread implications of negative shocks to the markets.

A final objective is to identify an appropriate alternative approach to measuring VaR. Accordingly, through the literature review, I initially identify key factors in relation to their impact on risk spreading. Furthermore, according to certain themes and approaches discussed in relation to measurement of systemic risk, the application of network analysis is discussed. I thereby construct a Bayesian Network, comprised of two factors and model their impact on the returns of three UK banking stocks and related portfolio. The specification allows the production of simulated returns and subsequent estimation of quantiles relevant to VaR. In comparing such quantiles to those relating to the actual time series of returns, I assess the viability of application of the network model in practice. The subsequent contribution of the Bayesian Network is to produce a workable method that could be used in industry and which could also be altered to incorporate different factors.

1.6 Thesis Structure

Chapter 2 presents the literature relevant to the pre-defined research objectives and subsequent empirical analysis. The application of the Delta Co-VaR model to a given data set is presented in chapter 3 and the use of the Absorption Ratio is subsequently reflected in chapter 4 – the latter deemed to support the importance of considering financial interlinkages and coupling between financial institutions. Finally, a viable alternative modelling approach to VaR is presented in chapter 5, along with the empirical application of the model to a given data set.

Chapter 2:

Measuring Systemic Risk

Relevant Literature

2 Measuring Systemic Risk – Relevant Literature

The need to determine a suitable and practical measure of systemic risk, which can subsequently be applied in regulating financial institutions, is clearly defined in chapter 1. Should the latter become overly exposed and take on excessive risks, their failure can lead to expensive losses for creditors and the taxpayer through bailouts. Furthermore, the losses may not be isolated to the financials' sector but spread across many sectors as the wider economy begins to suffer. Theoretically, several concepts are suggested - some providing a means to simply monitor systemic risk and signal pending crises, others providing means to substantively measure exposures to it. This section presents a review of relevant literature in this area, with more specific focus provided in chapters 3, 4 and 5.

2.1 Monitoring Systemic Risk

2.1.1 Early Warning Mechanisms

Certain studies refer to "early warning" mechanisms – whereby, following imbalances in factors assumed within the model, the subsequent stability of the financial system is questioned. If such imbalances are deemed to be significant in the run up to a crisis, they can be used to signal the need for increased regulatory capital in the intervening period. Factors can relate to macro-economic indicators, such as growth in GDP, market liquidity indicators or, for example, rising and unsustainable levels of consumer debt, house price bubbles and rising levels of mortgage delinquencies.

For instance, Borio and Drehmann (2009b) incorporate property and equity prices from North America to provide evidence that unusually rapid growth in credit and asset prices can be early warning signals of the occurrence of imminent financial distress. Consistent with this is the work of Alessi and Detken (2009), who combine both economic data, such as GDP and the CPI, with financial variables, such as house price growth, to predict boom and boost cycles in the housing market as opposed to the financial system per se. Contrary to this, Alfaro and Drehmann (2009), illustrate the use of macro-economic indicators as being less useful. Indeed, in their investigations of historical banking crises, they find that a large proportion of them are not actually preceded by weak domestic macroeconomic conditions in relation to actual and forecast GDP figures.

The impact of the housing market in propagating the wider financial crisis is further explored by Khandani et al (2009), who illustrate that the boom in housing prices, very low interest rates and high levels of remortgaging lead to an untenable pressure on the lending institutions in the event of a small drop in house prices or rising mortgage delinquencies. Indeed, with regards consumer debt and related delinquencies, Khandani et al (2010) use credit bureau data for a sample of US commercial banking customers to generate out-of-sample forecasts of consumer delinquencies and defaults. They identify declining creditworthiness factors as having useful applications in relation to forecasting financial crises. Lastly, from a market perspective, given the suggested importance of liquidity, Hu et al (2010) examine the "noise" in US Treasury Yield curves and find that increased noise is indicative of capital being in short supply, signaling a liquidity crisis and possible broader financial crisis

Aside from early warning mechanisms linked to economic or financial data sets, there are those that focus on financial firm characteristics or on certain asset classes within the broader financial markets. For instance, Huang et al (2009b) present the Distressed Insurance Premium (DIP), where the latter refers to a risk metric denoted by a bank's defaulted debt as a proportion of its total liabilities. Using a hypothetical debt portfolio for a selection of banks, they illustrate a sharp rise in the DIP from early summer of 2007 and then a subsequent decline following a series of bank bailouts in the following year, consistent with the ideal of a pre-emptive indicator of systemic risk. With regards specific asset classes, certain empiricists focus on the impact of hedge funds on systemic risk. For example, Chan et al (2005) highlight that, given the higher degrees of illiquidity in their chosen investment portfolios, an increase in that exposure can be used as an indicator of increasing systemic risk in the wider market. Subsequently, Bisias et al (2012) suggest application of this approach to data pre and post financial crisis.

2.1.2 Simulation and Stress Testing

Rather than providing evidence of early warning indicators, factors identified as being systemically important can be applied to model potential losses resulting from a worsening in such factors but also respective resilience to them. Consequently, information can then assist in the setting of regulatory capital requirements. For instance, network analysis can be applied to identify a network of institutions and their linkages within the interbank markets whereby the consequences of a failing institution within that environment can be very serious and lead to transmissions of liquidity issues across the wider network (see Chan-Lau et al 2009). In essence, certain credit scenarios are being simulated, in particular, those relating to the inability to replace or raise funding through the inter-bank markets and specific research in this area is highlighted in chapter 5.

2.1.3 Measuring Interlinkages and Coupling Between Financial Institutions

Principal Components Analysis (PCA) and Granger Causality tests can be applied to assess the degrees of interconnectedness and interlinkages between financial institutions. The consensus is that increases in systemic risk are a consequence of those connections. In relation to PCA, which applies correlations between asset returns, Billio et al (2010) indicate that the first principal component explains over 90% of the variability in the returns across all of their selected assets during times of financial distress. Thereby illustrating how closely they are connected if influenced by the same component - further detailed analysis is provided in chapter 5. With regards Granger Causality (1969), Billio et al (2012, pp.66) indicate that "a variable X is said to cause Y if past values of X contain information that helps predict Y above and beyond the information contained in past values of Y alone." The variables in this instance refer to returns' time series of 25 financial institutions and the authors assess the number of them that are deemed to "Granger-Cause" or directly influence the returns of another financial institution. The higher the number of causal relationships, indicates a greater degree of interconnection within the financial system.

2.2 Measurement through Value-at-Risk

Aside from the monitoring process, when measuring exposure to systemic risk, there are a number of methods presented in the literature for quantifying Value-at-Risk. More recently, Kritzman and Li (2010) apply Mahalanobis distance[5] in the calculation of an institution's VaR. By considering only those returns above a certain value for the statistic, the subsequent VaR is deemed more realistic in quantifying maximum losses – essentially, days of low market volatility, represented by the smallest values for the statistic, are not considered. In relation to the RiskMetrics approach some question the accuracy of this variance-covariance method. Amongst others, Yu et al (2010) are critical of the assumed properties of the asset returns – that they follow a conditional normal distribution with a zero mean and a variance expressed as an exponentially weighted moving average (EWMA) of historical squared returns. Historical observations are assigned a weight, where such weights decrease exponentially as we move back through time and, subsequently, the

[5] Measures the distance of each return in a distribution of returns from the average of the distribution and, in this application, extracts the data points with a distance over the 75th percentile.

more recent observations carry a higher weighting. Such properties amount to linearity in the asset returns and, in reality, given the asymmetric characteristic, volatility structures actually change through time and there is clustering. Sollis (2009) consequently suggests that VaR is underestimated with the approach – clearly more of an issue during times of crisis. Indeed, Oanea and Anghelache (2015) provide evidence from the Romanian capital markets of the failure of the RiskMetrics tool in providing accurate VaR measures relating to the period of the 2008 financial crisis.

Alternatively, ARCH and GARCH models proposed by Engle (1982), Bollerslev (1986) and Nelson (1990), indicate ways to estimate volatility, where the deficiencies of EWMA are addressed somewhat through assuming changing volatility structures. For instance, with regards the asymmetric GARCH (EGARCH) model, it seeks to allow for the differing impacts on asset volatility of positive and negative shocks and good and bad news in the markets. Through inclusion of a leverage term, EGARCH captures the more pronounced effect of negative asset returns on volatility. However, in comparing the volatility outputs using an EWMA approach versus those adopting the ARCH / GARCH framework, the conclusions are relatively mixed. For example, Hammoudeh et al (2011) find that the GARCH-t model, when applied to commodities markets, outperforms EWMA and Degiannakis et al (2011) conclude the same when applying the ARCH framework to data before and after the 2008 crisis. Conversely, Ding and Meade (2010) illustrate that EWMA volatility forecasts are reliably accurate across a range of volatility scenarios from low to high, when applied to data before 2007. It appears that the relative accuracy of RiskMetrics' model is directly related to the degree of volatility during the data period under review.

When comparing RiskMetrics and the ARCH / GARCH techniques the former is intuitive and easily applied in practice. Meanwhile, the latter address certain distributional issues but are not readily applied in industry. Certainly, each of the methods has its advantages but, an obvious flaw in each of them is the lack of consideration relating to connections between institutions and how risk duly spreads when single entities fall into distress. VaRs at an institutional level do need to be measured but, the current outputs per say lead to insufficient regulatory capital being set aside because they do not incorporate the impact of the individual institution on the VaR of the entire financial system. However, progressing from the CAViaR model of Engle and Manganelli (1999), Adrian and Brunnermeier (2011) do go some way to addressing that issue in suggesting a model known as CoVaR (Conditional-Value-at-Risk). It is conditional because it measures the VaR of the financial system conditional on individual institutions being in a state of distress. Whereby, the latter is deemed in distress upon reaching its own 1% or 5% VaR. The premise behind this approach is, indeed, the capturing of those all-important risk spillovers and contagion as alluded to in chapter 1. An adaptation of this model is further illustrated by Girardi and Ergun (2013), who apply multivariate GARCH models to historical returns' distributions to derive CoVaR. I suggest that this model is somewhat of a workable compromise – individual 1% and 5% quantiles can be produced from it but also an indication of how systemically important an institution is. Thereby, improvements can be made to regulatory capital provisions. A direct assessment of the application of CoVaR to European financial institutions is presented in chapter 3.

Chapter 3:

Assessing the Impact of Interlinkages on Value-at-Risk

3 Assessing the Impact of Interlinkages on Value-at-Risk

3.1 Introduction

The application of Value-at-Risk (VaR) in industry is fundamental to the prevention of excessive risk taking and systemic financial failure. However, given the recent high profile institutional failures and bank rescue packages, questions have to be asked about the ongoing viability of the current VaR methodologies. Those used in practice tend not to incorporate any risk spillovers or related linkages and are contemporaneous in nature. One example is as follows:

95% VaR for a **1-day** time horizon = value of financial position $\times$ $(1.65 \times \sqrt{\sigma_{t+1}^2})$[6]

where: σ_{t+1}^2 represents the conditional variance of returns measured at time t+1 and derived on an EWMA basis.

The distribution of returns is assumed to be normal and according to Jorian (1996, p.47), the VaR in this case is said to be the expected maximum loss over a 1-day time horizon at a 95% confidence level. A more general probabilistic representation of VaR can be defined as:

$$P(L > VaR) \leq 1 - \beta$$

Where: L is the loss within a specified time horizon, VaR is the value-at-risk figure, β is the confidence level (eg. 95% or 0.95). This implies that the probability that the loss will exceed the VaR level is less than or equal to 1 minus the confidence level. At a confidence level of 0.95, the probability that the loss will exceed the VaR level is less than or equal to 0.05.

[6] Source: RiskMetrics

Furthermore, VaR for a single asset can be expressed as:

$$VaR = -NV \times \sigma \times \sqrt{\delta t} \times \alpha(1-\beta)$$

Where: NV refers to the notional value of the asset, σ refers to the standard deviation of the asset's daily returns, δt refers to the time horizon and $\alpha(1-\beta)$ refers to the number of standard deviations that a given quantile is below a mean value. For example, at a confidence level of beta = 95% or 0.95 and $(1-\beta) = 0.05$, alpha would be -1.65. The simplicity of such models facilitates their widespread implementation and comprehension – thereby enabling transparency in financial risk management. Indeed, a major objective of regulatory control is the achievement of transparency across the whole financial system. However, this approach is, perhaps, at the expense of accuracy and foresight.

This chapter attempts to assess and illustrate the importance of considering risk spreading across financial institutions in times of crisis. In isolation, an institution may have a low VaR measurement for its exposure to systemic risk but a significant negative shock suffered by another entity can ultimately have an impact. Should an institution fail, it can amplify the underlying fear and panic in the whole financial system and subsequently lead to increases in individual VaR levels and further insolvencies. This point is illustrated by a quote from Adam Applegarth, former Chief Executive of Northern Rock:

> "The world stopped on August 9th. It's been astonishing, gob smacking. Look across a full range of financial products, across the full geography of the world, the entire system has frozen."[7]

For each institution within the data set, I attempt to indicate the relationship between their VaR in

[7] The Telegraph, 16th September 2007

isolation and their contribution to the VaR of the whole financial system, where the latter is defined by a market index (MSCI Europe Financials Sector Index). This is done for the European financials' sector - a selection of 29 banks and insurance companies across Europe, including the UK. Specifically, this is achieved using the methodology proposed by Adrian and Brunnermeier (2011) and subsequently by Castro et al (2014), whereby they refer to such an individual contribution to systemic risk as Delta-CoVaR. Intuitively, one might suggest that small individual VaRs result in small contributions to the VaR of the whole financial system and that the largest figures indicate the greatest contribution. Such a relationship is not so clear-cut and I present the various anomalies. In addition, as noted by Castro et al. (2014), one institution may actually be more systemically important than another.

The aim of this chapter is not to isolate certain factors relating to any given organization that may lead it to be more systemically influential than another. For example, Adrian and Brunnermeier (2011) do not simply use the daily percentage change in security price but rather consideration is given to how the markets perceive the changes in value in financial assets over time. More specifically, they quantify the daily % change in market valued total financial assets for each institution over time – represented by market capitalization multiplied by a leverage ratio (Book valued assets: Book valued equity). They argue that focusing on the risk associated with growth in market valued total financial assets is directly relevant to risk spillovers. This is because the core business of financial institutions is the supply of credit and money supply to the economy. If balance sheet assets are not growing or, indeed, shrinking, it signals a stagnation in that supply and negative signals with regards economic growth to the markets and, in particular, to the financials' sector. The diminishing balance sheets impact the financial institution but the subsequent negative signals impact the wider financial environment. Furthermore, factors such as short-term funding balances are also considered given the liquidity issues faced by banks during the financial crisis due to the need to refinance large amounts of money market issues, such as commercial paper.

As explained in chapter 1, the latter points are clearly fundamental in understanding impacts on systemic risk. Indeed, the 2011 paper is of great importance, having been produced within the remits of the Federal Reserve Bank. It is subsequently cited on numerous occasions in empirical studies in this area. However, the capture of relevant data is a major issue. I consider that, if a VaR measure is to be useful to any organization and regulatory body, it must be capable of measuring and reacting on a short-term basis i.e. daily, weekly and monthly VaR estimates. At best, financial institutions collate balance sheet data on a monthly basis but more commonly every quarter. In addition, substantive information on short term funding balances and refinancing requirements is certainly not publicly available. Therefore, this chapter adds to the existing literature that applies CoVaR methods to market based data. An extension is the inclusion of insurance companies in the analysis given their influence as one of the largest institutional investor groups in the financial system and their major representation at an individual level within the financials' sector index. Surprisingly, they are rarely considered as systemically important in their own right in existing research, with banks being the primary focus. They were also a major influence in the Credit Default Swap (CDS) market, a contributing factor to the spread of the 2008 crisis. Indeed, with the exception of Billio et al (2010), very few studies incorporate other large institutional investors such as insurance companies and pension funds.

This chapter is divided into several parts. Section 3.2 highlights the recent literature regarding risk spillovers in general and then the application of the CoVaR model in various empirical scenarios. In addition, I present the developments in regulation in the areas of regulatory capital requirements since the 2007-2009 financial crisis. Section 3.3 defines the CoVaR model and specifically how it is used to produce estimates of VaR and Delta-CoVaR. Section 3.4 elaborates on the Ordinary Least Squares (OLS) model specification used to generate the time series of returns for input into the quantile regression and the methodology for the latter. Section 3.5 describes the data set in this context. Section 3.6 presents the VaR and Delta-CoVaR estimations and analysis for the specific data set. Section 3.7 details the significance test used to analyse the robustness of the Beta estimates defined in section 3.6 for certain institutions of note. Finally, the chapter ends with concluding remarks and potential implications for regulatory policy in this area.

3.2 Relevant Literature

3.2.1 Risk Spillovers

The notion of risk spillovers and spreading is commonly referred to in many areas of finance and economics. Some of the evidence is at a country, market and asset class level (for example the Credit Default Swap and hedge fund markets) and does not necessarily relate to the transmission of systemic risk per say. However, the studies are still relevant when illustrating the existence of any financial linkages. For example, with regards the crude oil markets, Fan et al (2008) reveal a significant two-way risk spillover effect between the West Texas Intermediate (WTI) and Brent Crude Oil markets. More specifically, they state that historical negative returns and subsequent VaR measures in the WTI market can be used to predict those in the Brent market. At a country level, Asgharian and Nossman (2010) use a stochastic volatility model to analyse risk spillovers from the US markets to certain European Equity markets. By way of contrast and referring to specific asset classes, Klaus and Rzepkowski (2008) investigate the occurrence among hedge funds. They find a significant relationship between redemptions amongst funds and the likelihood of ultimate failure of other hedge funds classified within the same investment style. The use of hedge fund data is further illustrated by Adams, Fuss and Gropp (2010) who suggest that hedge funds play a major role in the transmission of negative shocks across asset classes.

At a financial institution level one particular study by Elyasiani et al (2007) focuses on return linkages in addition to risk linkages. They investigate data for US financial institutions over a 10-year period from 1991 to 2001. Their findings are such that risk and return linkages are significant and vary according to the size of the institution. Specifically, the transmission of risk is more prominent amongst the larger financial institutions whilst links in returns are found to be most prominent in the smaller firms. This large firm emphasis is consistent with Brunnermeier et al (2009) - who suggest that a valid measure of systemic risk can be associated with large and interconnected firms that have negative risk spillover effects on other firms.

Finally, Chan-Lau (2009) investigates risk contagion by measuring default risk co-dependence (Co-Risk). More specifically, an assessment is made of how default risk of a specific financial institution affects that of another using 25 financial institutions in Europe, Japan and the USA. Applying credit default swap data, it is suggested that such co-dependence is strong during times of distress in the markets. However, Reongpitya and Rungcharoenkitkul (2010) state that, given the underlying data, the latter study only captures credit risk and subsequently suggest the updated CoVaR model of Adrian and Brunnermeier (2011) as a more appropriate approach in assessing such financial linkages and measuring exposures to systemic risk. Consequently, this chapter depicts the time invariant version of the aforementioned model.

3.2.2 Applications of CoVaR

The CoVaR concept relates back to the CAViaR model proposed by Engle and Manganelli (1999). They are both conditional value-at-risk models, examining the behaviour of returns at quantiles and, subsequently, the application of quantile regressions in their analysis. However, the CAViaR approach is an autoregressive one and focuses more on how a quantile changes or updates itself over time given a particular set of parameters in the updating process. Unlike the CoVaR, it does not consider the risk spillover effects from one institution to the whole financial system whereby the "conditional" element refers to the impact on the VaR of the whole system conditional on an individual institution being in distress. Indeed, more recently, Castro and Ferrari (2014) apply Delta-CoVaR to compare 26 large European banks in relation to their relative importance with regards contributions to systemic risk. In terms of reviewing recent applications of conditional VaR models, I focus more on the CoVaR and not the CAViaR concept.

Rungporn and Rungcharoenkitkul (2010) apply the earlier Brunnermeier (2008) CoVaR model to the Thailand Banking system. Specifically, they quantify systemic risk among six Commercial Banks for the period 1996 quarter 2 to 2009 quarter 1. Their findings highlight the viability of CoVaR during periods of increased and sustained market turbulence, in particular during the 1998 Asian crisis. During this difficult time, the larger banks are found to contribute more to systemic risk. Such results are further evidenced by Arias et al (2010) who confirm that risk co-dependencies are highlighted by the CoVaR model also during distress periods but, this time, among Colombian financial institutions. Similar to the Thailand and Colombian cases, Fong et al (2009) illustrate that there is significant risk interdependence among banks in Hong Kong. However, in the latter case, the smaller local banks are found to *match* their larger international counterparts in terms of impacts on systemic risk. Their study ultimately confirms the application of CoVaR as a useful tool for analyzing risk interdependencies among financial institutions, albeit with reduced emphasis on the previously mentioned size factor in relation to systemic risk contributions.

An interesting application of the model is offered by Lopez-Espinosa et al (2012) at the IMF

Institute. They illustrate the impact of over-reliance on short term funding on systemic risk contribution. As mentioned in the introductory chapter, such funding sources are deemed to increase interconnectedness between banks and therefore exacerbate financial crises. Specifically, for 18 of the largest global banks, their results identify wholesale short term funding as the most relevant factor affecting systemic risk. Such a finding warrants further investigation across European data sets. However, it is somewhat restricted by the availability of data in relation to a financial institution's ongoing outstanding issues of money market issues and their rollover and refinancing dates. The latter are generally refined to an annual record per the published financial statements. Despite such limitations, a proxy for the market liquidity factor is considered in chapter 5 of this thesis.

3.2.3 Regulatory Requirements and the Capital Base

Given the core product offered by banks and the risk of default attached to said loans, it is imperative that they have a large enough buffer of capital to absorb losses. Indeed, the worst-case scenario is the risk that the bank's capital is completely eroded by such losses and it becomes insolvent. Should the business activities incorporate exposures to complex credit derivatives or securtised products and subsequent underestimated default by the underlying borrowers, tighter restriction on the capital requirements becomes a necessity. The inevitable fallout from the global financial crisis put intense pressure on the regulators and banking authorities to devise more rigid risk assessments and capital requirements for banks and financial institutions. In conjunction with the Basel III Accord, the most recent directive in this area is the Capital Requirements Directive IV. It represents an initial package of legislation developed and designated by the EU, and applicable from January 2014 but with ongoing and evolving reforms and enhancements following industry consultations. It has the express intention of stating the legal requirements of banks, building societies and investment firms in relation to the quality and quantity of their capital base, liquidity and leverage requirements, measurement of counterparty risk and additional capital buffers. With regards this chapter, the most relevant requirements relate to the capital base and additional buffering capital conditional upon the systemic importance of certain institutions (as identified by the directive itself).

The Bank of England (2015) sets out the framework for capital requirements to be in place by 2019. Some of the detail is already in effect, for example the current minimum equity requirements, whereas other parts are being phased in. The minimum equity requirement for all banks is 6% of the balance of risk-weighted assets per the balance sheet,[8] otherwise referred to as Pillar 1 of Tier 1 capital. There are also buffers of extra capital that increase the overall Tier 1 capital base to 11%. The latter are intended to provide additional protection against bank failure and are an initiative in response to the failings encountered in 2008 and 2009. Specifically, according to the Bank of England (2015) framework, those buffers are defined in table 3.2.3.1.

[8] Source: Bank of England Supplement to the December 2015 Financial Stability Report

Table 3.2.3.1: Explanation of Additional Capital Requirement Buffers as specified by the Capital Requirement IV Directive[9]

Additional Capital Requirement (Buffer)	**Reason for the Buffer**	**% of Risk Weighted Assets**	**To be In Effect from:**
Capital conservation buffer	The buffer to be used to absorb losses while keeping the 6% minimum intact	2.5%	phased in between 2016 – 2019
Countercyclical capital buffer	A time varying buffer to be applied at different points in the financial cycle depending upon the scale of risk faced by the entire financial system	Time-varying and dependent upon the scale of the risk faced	2017
Global systemic importance buffer	Buffer set for those banks identified as being globally systemic - to reduce their probability of failure or distress commensurate with the greater cost their failure or distress would have for the **global financial system and economy**	0% to 2.5% for UK institutions (average of 1.5%)	phased in between 2016 – 2019
Systemic risk buffer	Buffer set for ring-fenced banks and large building societies to reduce their probability of failure or distress commensurate with the greater cost their failure or distress would have for the **UK economy**	0% to 3% (average of 0.5%)	2019

Interestingly, the authorities do recognize the relevance and impact of systemically important banks both to the global financial system and the UK in isolation. Indeed, as at December 2015, the Capital Requirement Directive IV identifies those institutions falling within the remit of the Global buffer and the Systemic Risk buffer. In terms of the methodology that is applied to identify the said institutions, the Delta-CoVaR approach is not used. Following the empirical analysis in

[9] Source: Bank of England Supplement to the December 2015 Financial Stability Report

this chapter, I compare those institutions from the UK that the analysis identifies as being systemically important with those listed in table 3.2.3.2 below.

Table 3.2.3.2: List of Global and UK systemic risk firms according to the Capital Requirement IV Directive.[10]

Globally Systemic Firms (UK) – Relevant to the Global Systemic Importance Buffer	**UK based Systemic Firms – Relevant to the Systemic Risk Buffer**
HSBC Holdings	**Barclays Plc**
Barclays Plc	Citigroup Global Markets Limited
Royal Bank of Scotland Group Plc	Credit Suisse International
Standard Chartered Plc	Credit Suisse Investments (UK)
	Goldman Sachs Group UK Limited
	HSBC Holdings
	JP Morgan Capital Holdings Limited
	Lloyds Banking Group Plc
	Merrill Lynch International
	Morgan Stanley International Limited
	Nationwide Building Society
	Nomura Europe Holdings Plc
	Royal Bank of Scotland Group Plc
	Santander UK Plc
	Standard Chartered Plc
	UBS Limited

3.3 The Time Invariant CoVaR Approach to Measuring Systemic Risk

For the purposes of this chapter, we interpret CoVaR as being the measure of the value-at- risk of the whole financial system. In line with the concept of contagion, such a VaR is actually conditional on the distress of individual institutions – hence the term “conditional value-at-risk.” Furthermore, the latter are deemed in distress when they reach and / or breach their own 5% or 1% VaR. A further term, Delta-CoVaR, is defined as the marginal contribution of an individual institution to the overall system’s VaR. That **marginal contribution** is deemed to be the difference

[10] Source: CRD IV updates, Bank of England.

between the VaR of the whole financial system when an institution breaches its own 5% or 1% VaR and the median state of that institution (i.e. the 50% quantile). That impact on the whole financial system for each institution is what is measured and evaluated in this chapter. The quantile regression is specified as follows:

$$\widehat{R_t} = \hat{\alpha}_\tau^i + \hat{\beta}_\tau^i \hat{r}_t^i + \hat{\varepsilon} \qquad (3.1)$$

where: "R" refers to the daily returns of the specified market index;

"r" refers to the daily returns of the financial institution, 'i' (denoted by the residuals in each case generated by the OLS regression specified in section 3.4.1).

τ is specified as 0.95 or 0.99 in the quantile regression and relates to the said quantiles of the market index. In specifying "tau", we generate the estimated alpha and beta coefficients corresponding to the 95% or 99% quantile of the returns distribution of the market index.

The aforementioned alpha and beta coefficients are required to determine the systemic risk contribution of each financial institution to the overall market and the following specification is applied:

$$\Delta CoVaR_\tau^{Index|i} = \left(\alpha_\tau^i + \beta_\tau^i VaR_{q\%}^i\right) - \left(\alpha_\tau^i + \beta_\tau^i VaR_{50\%}^i\right) \qquad (3.2)$$

where: $VaR_{q\%}^i$ refers to the actual observed 1% or 5% quantile of the time series of returns of the financial institution, 'i';

$VaR_{50\%}^i$ refers to the median state of the individual institution (i.e. the actual observed 50% quantile).

When tau = 0.95, the Delta-CoVaR measures the % point change in the financial system's 5% VaR when a particular institution reaches its own 1% or 5% VaR[11] .When tau = 0.99, the Delta-CoVaR measures the % point change in the financial system's 1% VaR when a particular institution reaches its own 1% or 5% VaR. It is clearly dependent on both the institution's q% VaR and the beta coefficient and, consequently, I report them both in the results. Interestingly, a large individual institution VaR does not necessarily imply the largest Delta-CoVaR – therefore the requirement to identify beta coefficients.

Equations (3.1) and (3.2) present a methodology for estimating CoVaR and Delta-CoVaR that is constant over time and merely applies the historical distributions of the daily returns of the whole financial system and each individual financial institution (as represented by the residuals from the OLS regression). The financial system returns are simply the daily percentage change in the chosen market index.

3.4 Methodologies

3.4.1 OLS Model Specification

Being consistent with Adrian and Brunnermeier (2011) and Castro et al (2014), the objective is to identify the impact, if any, of a given financial institution on the wider market. Therefore, a control is required for the impact of other variables on each time series. I run a series of OLS regressions that provide a control mechanism for possible external factors. Each regression generates a time series of residuals and it is those that are applied in the quantile regressions. The OLS model specification is as follows:

$$y_t = \alpha + \beta_1 X_{1_{t-1}} + \beta_2 X_{2_{t-1}} + \beta_3 X_{3_{t-1}} + \varepsilon_t \tag{3.3}$$

[11] Adrian and Brunnermeier (2011)

where:

y_t refers to the time series of daily returns for each Financial Institution

X_{1t-1} refers to the lagged time series of daily returns for the MSCI Europe Industrials Sector Index (where the lagging period is 1 day).

X_{2t-1} refers to the lagged time series of daily returns for the MSCI Europe Materials Sector Index (where the lagging period is 1 day).

X_{3t-1} refers to the lagged time series of daily returns for the Stoxx 50 volatility index (where the lagging period is 1 day).

A further two controls are run for potential external factors, denoted by running OLS regressions based on t-2 and t-3 lags. If the dependent variable reacts instantaneously to changes in the independent variables then the OLS model is relatively static and measures a contemporaneous relationship between the returns of the financial institution and the control variables. However, if the dependent variable does not react fully and immediately to a change in the independent variables, then a lagged rather than a wholly contemporaneous relationship may exist, as depicted by Sclove (2013, p.178).

$$y_t = \alpha + \beta_1 X_{1_{t-2}} + \beta_2 X_{2_{t-2}} + \beta_3 X_{3_{t-2}} + \varepsilon_t \quad (3.4)$$

$$y_t = \alpha + \beta_1 X_{1_{t-3}} + \beta_2 X_{2_{t-3}} + \beta_3 X_{3_{t-3}} + \varepsilon_t \quad (3.5)$$

Assessing degrees of significance in the output coefficients in both the contemporaneous and lagged cases determines the need to run subsequent quantile regressions using the related residuals. If significance is absent or minimal, there is deemed no need to produce Delta-CoVaR figures from data sourced at greater lags.

There is, of course, a potential issue with omitting an unknown but important independent variable. While estimating OLS regressions, the error term must be uncorrelated with the explanatory variables and, should there be omitted variable bias, the omitted variable would impact the error term. The resulting OLS estimators are, themselves, biased and unreliable. Ordinarily, in the absence of running the subsequent quantile regressions, dummy variables could be used to assist with this issue.

3.4.2 Quantile Regression

In evaluating the relationship between two or more variables through ordinary least squares regression techniques, an assumption is that any such relation is the same across the entire distribution of data – whereas, the effect of one variable on another could actually differ across the observed distribution. Quantile regression seeks to overcome this assumption by specifying a model that estimates the relation between "X" and "Y" but conditional on quantiles or percentiles of Y. As introduced by Koenker and Bassett (1978), it evaluates how the relationship changes depending on a particular quantile or percentile of the dependent variable. In particular, the slope coefficient represents the incremental change in the dependent variable for a one-unit change in the independent variable at the predefined quantile of the dependent variable (tau = 0.95 or 0.99 in this case).

Any quantile regression can be represented by the following equation:

$$y_i = x_i\beta_q + e_i \quad (3.6)$$[12]

where: β_q is the vector of unknown parameters associated with the qth quantile.

Accordingly, for different values of "q", different values for beta are generated.

[12] Source: Koenker (2005)

The OLS regression process minimizes the sum of the squares of the model prediction error i.e. $\Sigma_i e_i^2$. Furthermore, the median regression minimizes $\Sigma_i |e_i|$. Subsequently, a quantile regression at a particular quantile, q, minimizes the expression in equation (3.7) and thereby accounts for the under ($q|e_i|$) and over-predictions ($(1-q)|e_i|$) of the model in equation (3.6) for values of the dependent variable, y.

$$\Sigma_i q|e_i| + \Sigma_i (1-q)|e_i| \tag{3.7}$$

Using equation (3.6) and substituting in for the error term, we generate the following:

$$Q(\beta_q) = \Sigma_{i:y_i \geq x_i \beta}^{N} q\left|y_i - x_i \beta_q\right| + \Sigma_{i:y_i < x_i \beta}^{N} (1-q)\left|y_i - x_i \beta_q\right| \tag{3.8}$$

where: $0 < q < 1$ and y_i is the actual value of y.

Equation (3.8) is the basis for finding the Beta coefficients at each specified value of q. Essentially, they estimate the change in a specified quantile q of the dependent variable y produced by a one-unit change in the independent variable. In this chapter, the former is specified as the impact on the 5% or 1% VaR of the whole financial system. In the empirical analysis, quantile regressions are run for the entire sample period, based on residuals generated in the OLS estimations and then for two sub-samples – January 1999 to December 2007 and January 2008 to May 2015, thereby capturing the market environment pre and post financial crisis.

3.5 Data Set

3.5.1 Time frames and Data Source

The data used for the estimations are daily stock returns for 29 large European Banks and Insurance

Companies – 16 banks and 13 insurance companies. The full sample covers the period from 4th January 1999 to 11th May 2015 and therefore, for each time series there are 4264 observations. The two sub-samples cover the periods from January 1999 to December 2007 and January 2008 to May 2015. All data is taken from Bloomberg and the full sample extends across several periods of extended market volatility, the most obvious being between 2007 and 2009.

3.5.2 Control Variables and Stock Selection

In contrast to Castro et al (2014), in defining the market index proxy for the financial system and the control variables, I make use of major benchmark indices provided by MSCI as opposed to those provided by STOXX. They are the MSCI Europe Financials Sector Index, the MSCI Europe Industrials Sector Index and the MSCI Europe Materials Sector Index. In assessing the reliability of the data, MSCI are market leaders in the provision of international equity benchmarks to both active and passive managers in the asset management industry. A further motive for the use of MSCI data is that it does not appear in existing empirical research in this area. However, I do use the conventional and widely accepted indicator of volatility in the European markets, namely the Euro STOXX 50 Volatility index (VSTOXX).

Euro STOXX 50 Volatility Index

In North America, there are a number of indices published by the Chicago Board Options Exchange (CBOE) that are subsequently used by investors to gauge the market's expectation of future volatility. For example, the CBOE Volatility Index (VIX), the CBOE Nasdaq Volatility

Index (VXN) and the CBOE S&P 100 Volatility Index (VXO). [13]The VIX is the pioneer volatility index and measures market expectations of short-term volatility (30-day) as conveyed by the implied volatilities of near-dated listed option prices. The relevant listed options are those based on the underlying index, the S&P 500.

A number of volatility indices have developed subsequent to the VIX. The comparatives in Europe are VDAX-NEW, VFTSE, VSMI and the VSTOXX. The three former indices reflect the implied volatility in the German, UK and Swiss markets as measured by options on the DAX, FTSE100 and SMI indices. [14]With regards the VSTOXX, it measures the market expectations of short-term volatility in the European markets in general as indicated by the implied volatility on listed options where the underlying is the Euro Stoxx 50 index. The latter index covers 50 stocks from 12 Eurozone countries, namely, Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. Despite the underlying index excluding UK stocks, the VSTOXX is appropriate in this context as it covers the broadest representation of European markets, compared with the other available volatility indices.

Choice of Financial Institutions

The MSCI Europe Financials Sector Index is comprised of 98 stocks from 15 countries within Europe and with diversity in market capitalization from large to medium cap. The top 10 weighted institutions in the index are presented in table 3.5.2.1.

[13] Source: http://www.cboe.com/micro/vix-and-volatility.aspx
[14] Source: https://www.stoxx.com/index-details?symbol=sx5e

Table 3.5.2.1: Stock weightings within the Index

Company	Country	Weighting in the Index
HSBC Holdings	UK	9.6%
Banco Santander	ES	5.2%
BNP Paribas	FR	4.0%
Allianz	DE	4.0%
UBS	CHF	3.8%
BBVA	ES	3.5%
Lloyds	UK	3.4%
Barclays	UK	3.2%
Prudential	UK	2.8%
ING Groep	NL	2.7%
	Total	42.2%

Source: msci.com

The data set, comprising 29 stocks, contains all of the top 10 constituents of the market index to ensure that the largest weighted stocks in the index are represented. Given that my sample contains just 29 stocks of the 98 in the index, at the very least, I have chosen the top 10 weights and then spread the remaining 57.8% across a broad representation of European countries and their respective financial stocks. With regards the sample of stocks selected by Castro et al (2014), they include only banks, and exclude three insurance companies (Allianz, Prudential and AXA) that actually have large weightings in the STOXX Europe 600 Financials Index. Furthermore, that index contains 139 stocks and their sample comprises just 26. In using the MSCI index as a proxy for the financial system and my associated stock selection, it could be argued that my sample is a fairer representation of the underlying constituents and also respective impacts on the financial system.

3.5.3 Data Trends and Visual Description

Summary statistics for the control variables and the financial institutions are provided in tables

3.5.3.1 and 3.5.3.2. What is clear is that, whilst the mean returns are near zero in each case, the maxima and minima indicate large swings in both directions around the mean return. The latter is evidenced by the graphs, illustrating the stationarity in each time series and the clustering in volatility. Figures 3.5.3.1 to 3.5.3.6 are presented after the summary statistics, with the remainder in the appendices – A3.5.3.7 to A3.5.3.29. For all institutions, the largest spikes appear in the 2007-2009 time-frame – consistent with the most severe period of the recent financial crisis. Following 2010, volatility appears to stabilise for the UK, Switzerland, Ireland and Belgium. Commerzbank and ING Groep exhibit sustained volatility until 2012, along with the French and Spanish banks, exhibiting large swings between 2008 and 2012. Furthermore, the Italian, Austrian and Greek Banks remain in a volatile state, with no sustained periods of stability since 2008.

With regards the entire sample period from 1999 to present, the UK institutions exhibit far less volatility than the other European markets – perhaps with the exceptions of HSBC and Prudential. This is particularly evident during the period from 1999 to 2002, where the UK markets are stable relative to their counterparts. However, on the whole, between 2002 and 2007, volatility is fairly stable for most of the countries – a time of global prosperity and bullish markets. Across the whole sample period, the insurance sector appears to follow the pattern of the respective peaks and troughs of the banking sector, with variations in the magnitudes of those peaks and troughs. For example, pre-2008, the UK insurance companies appear to have greater peaks and troughs than their UK banking counterparts.

In order to assess dependencies in the returns' data, autocorrelation functions are produced for each data set. A sample of the plots are presented in figures 3.5.3.7 to 3.5.3.11 – on the whole, correlations are found not to be an issue and not affecting chosen bootstrapping methodologies.

Table 3.5.3.1: Summary statistics – financial institutions – whole sample.

Company	Sector	Country	No. of Obs.	Minimum	Maximum	Mean
Aegon	Insurance	NL	4264	-24.18211	35.27697	-0.00062
Ageas	Insurance	BE	4264	-77.57285	29.54545	0.00591
Allianz	Insurance	DE	4264	-14.51067	19.49208	0.01005
Axa	Insurance	FR	4264	-18.41312	21.86971	0.02959
Banco Santander	Bank	ESP	4264	-14.08932	23.21606	0.03018
Bank of Ireland	Bank	IRE	4264	-54.75687	48.10127	0.02075
Barclays	Bank	UK	4264	-24.84642	48.10127	0.02075
BBV	Bank	ESP	4264	-13.53532	22.02591	0.01858
BCO Pop	Bank	ITL	4264	-16.36472	18.94400	-0.00165
Commerzbank	Bank	DE	4264	-24.60901	21.47925	-0.01974
Credit Agricole	Bank	FR	4264	-13.36634	26.31549	0.02715
Erste Group	Bank	AUT	4264	-18.10237	18.54032	0.05536
Generali	Insurance	ITL	4264	-8.817635	13.10295	0.00131
Hannover	Insurance	DE	4264	-18.03541	16.63064	0.04777
HSBC	Bank	UK	4264	-18.77876	15.51481	0.02209
ING Groep	Bank	NL	4264	-27.48387	29.24331	0.03708
KBC Group	Bank	BE	4264	-24.92147	49.90664	0.04316
Legal & General	Insurance	UK	4264	-28.87701	27.50716	0.04056
Lloyds	Bank	UK	4264	-33.94800	50.34540	0.00770
Mapfre	Insurance	ESP	4264	-12.58046	17.56744	0.04135
Natl Bk of Greece	Bank	GRE	4264	-26.77665	29.15473	-0.02967

Old Mutual	Insurance	UK	4264	-21.64203	30.25274	0.04674
Paribas	Bank	FR	4264	-17.24304	20.89688	0.04174
Prudential	Insurance	UK	4264	-20.00000	23.45679	0.04953
RBS	Bank	UK	4264	-66.57061	35.66878	0.01033
SCOR	Insurance	FR	4264	-30.39216	20.99976	-0.00463
Swiss Life	Insurance	CHF	4264	-20.07416	20.65115	0.00978
UBS	Bank	CHF	4264	-17.21393	31.66144	0.01745
Vienna	Insurance	AUT	4264	-17.91405	16.47919	0.03898

Table 3.5.3.2: Summary statistics – Market Index and Control Variables – whole sample.

Variable	No. of Obs.	Minimum	Maximum	Mean Return
MSCI Europe Financials Sector Index	4264	-9.844642	16.039919	0.007582
MSCI Europe Materials Sector Index	4264	-11.95772	13.44137	0.03426
MSCI Europe Industrials Sector Index	4264	-9.27486	10.74250	0.02750
Euro Stoxx 50 Volatility Index (VSTOXX)	4264	-22.0524	63.1319	0.16850

Figure 3.5.3.1: Time Series of Allianz Returns

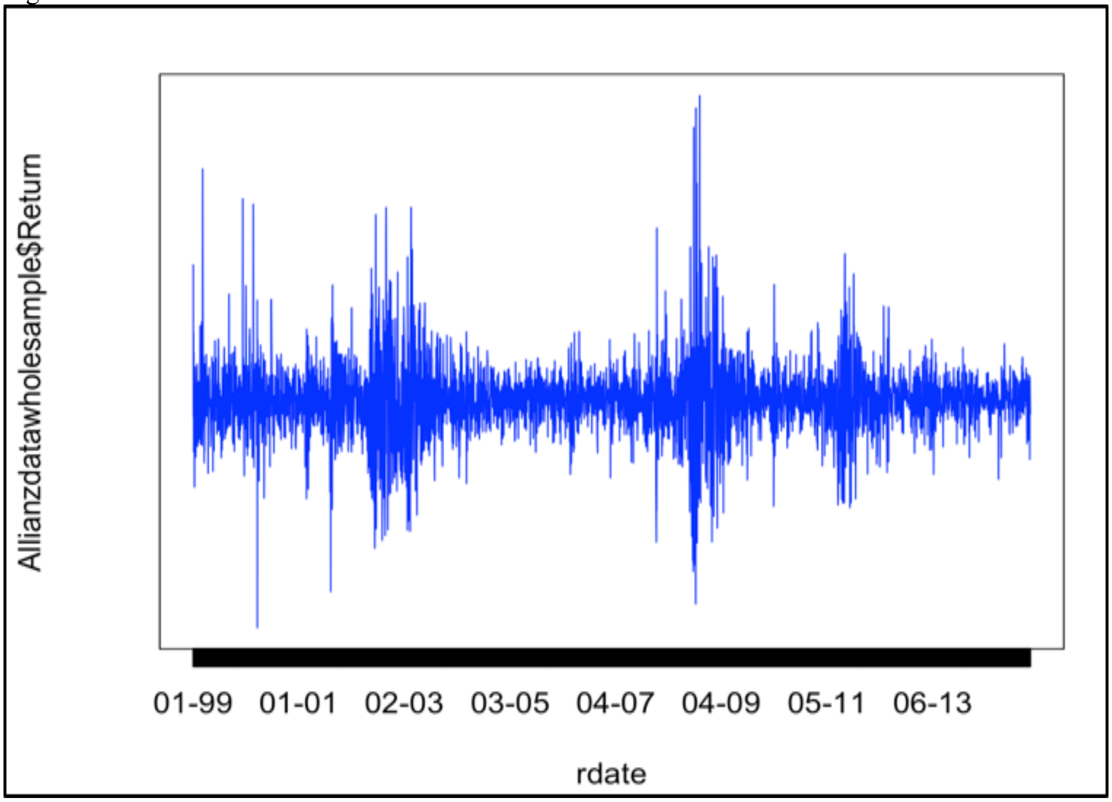


Figure 3.5.3.2: Time Series of Commerzbank Returns

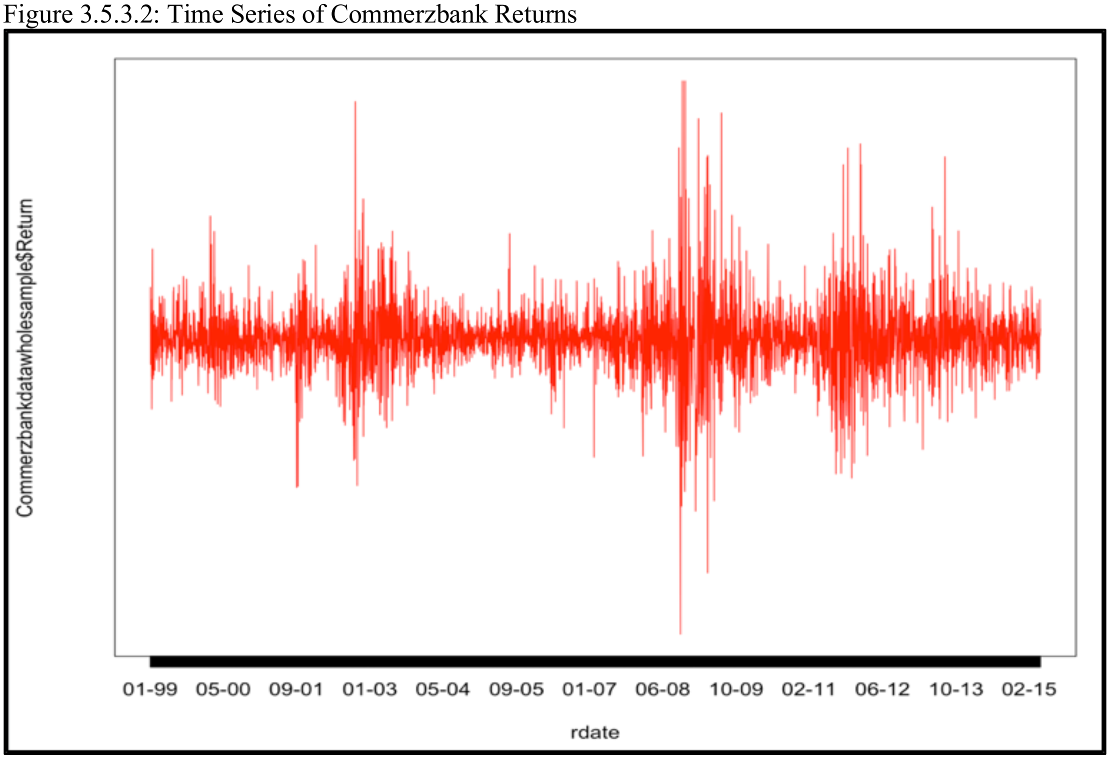


Figure 3.5.3.3: Time Series of Hannover Returns

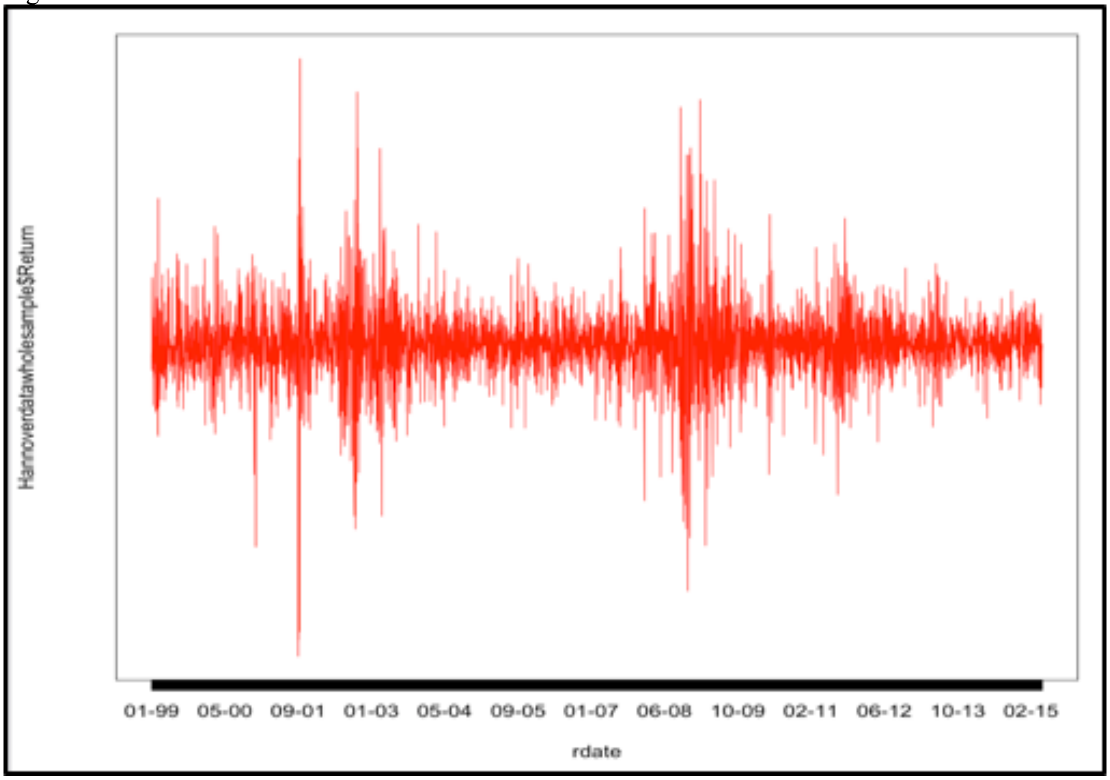


Figure 3.5.3.4: Time Series of Aegon Returns

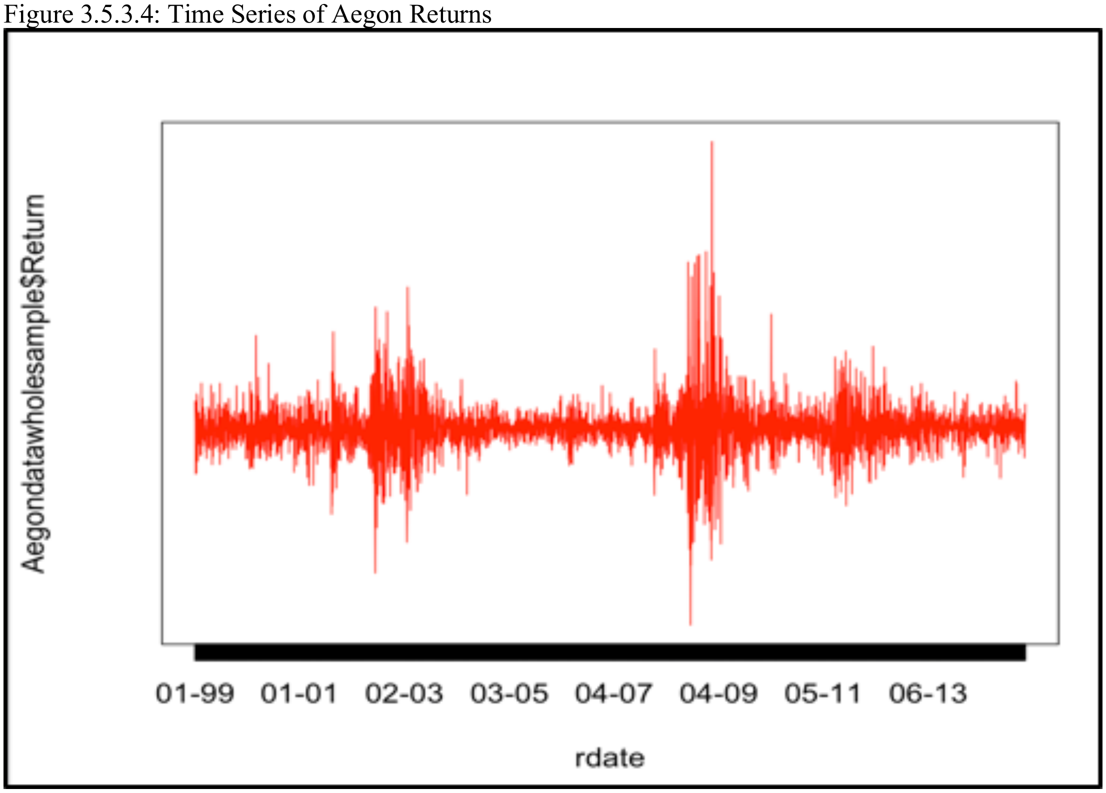


Figure 3.5.3.5: Time Series of ING Groep Returns

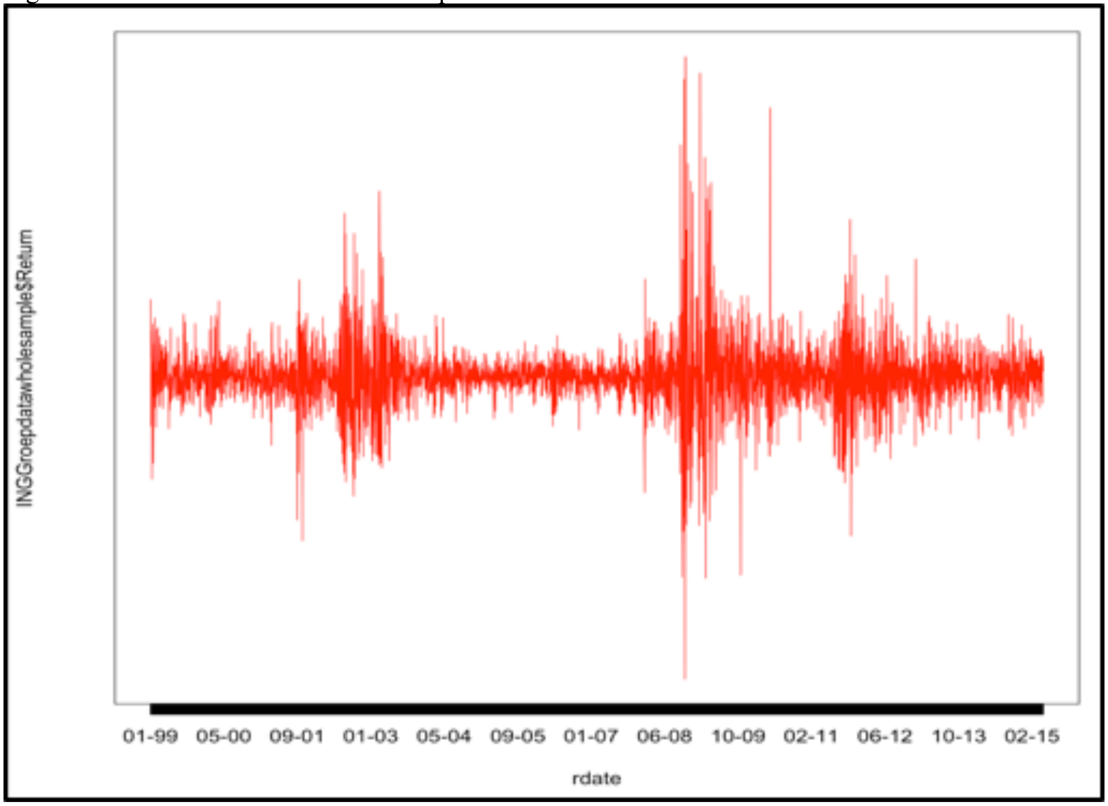


Figure 3.5.3.6: Time Series of Barclays Returns

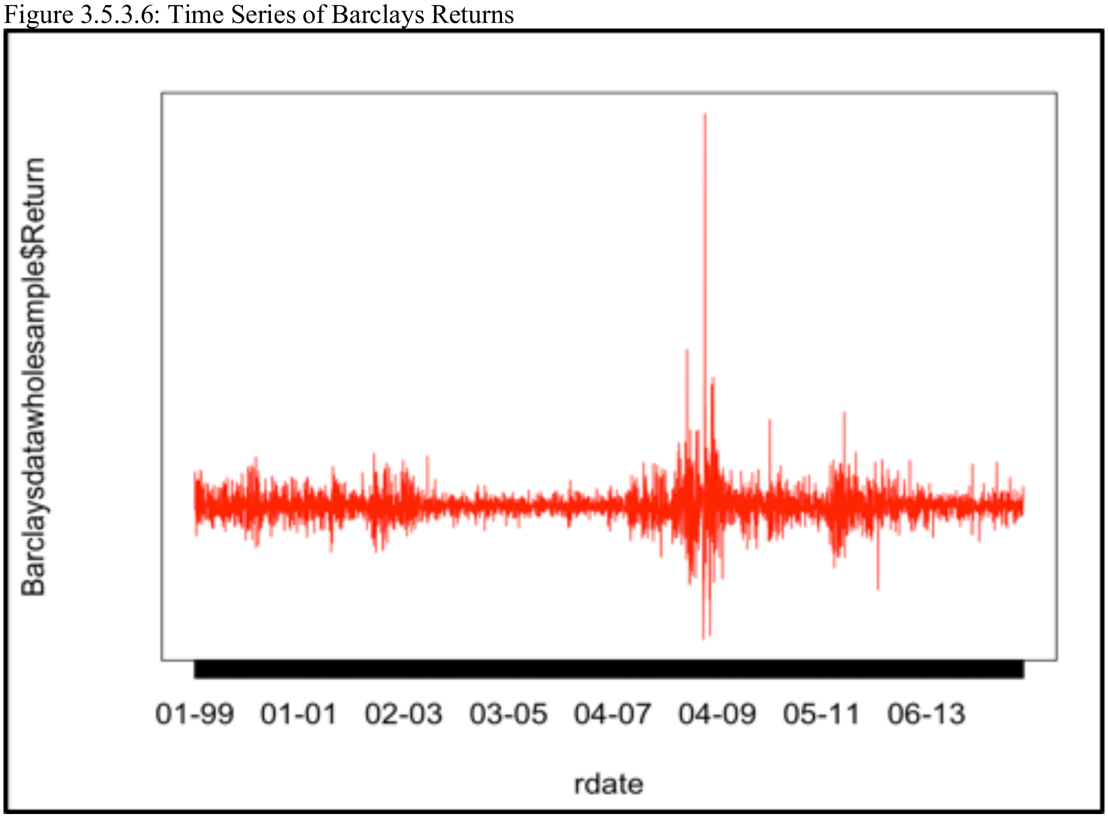


Figure 3.5.3.7: Autocorrelation function for MSCI Europe Financials Sector Index Returns.

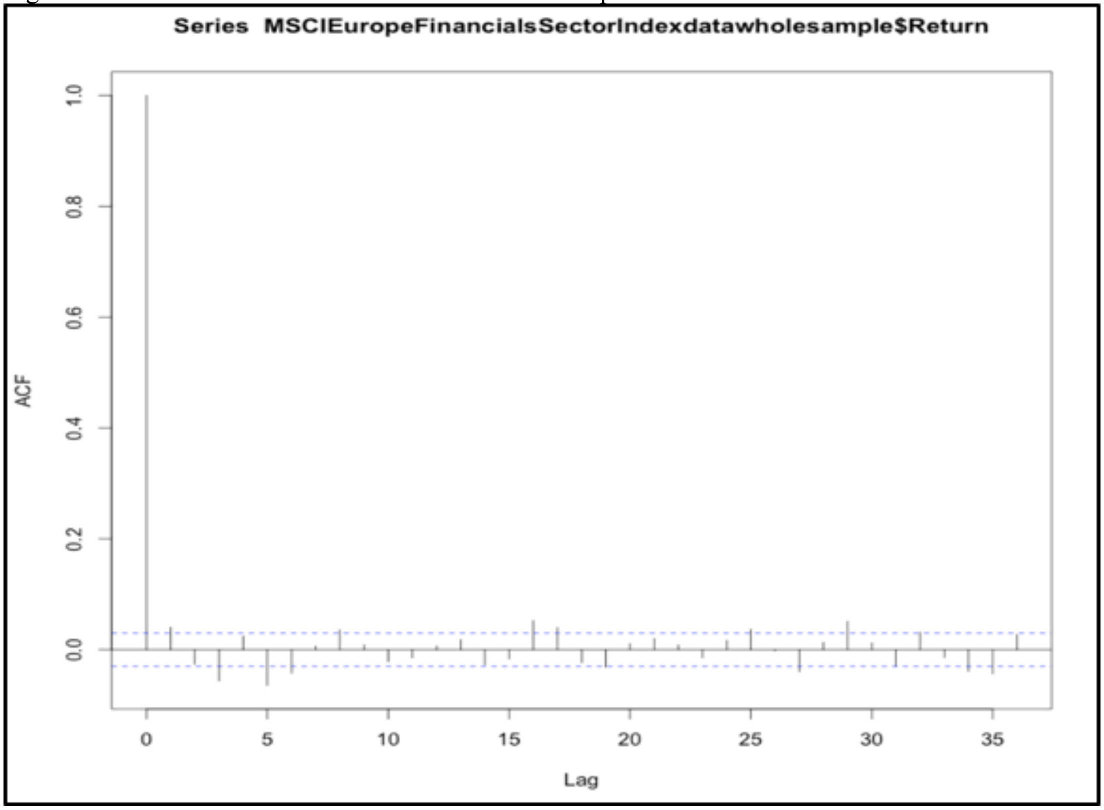


Figure 3.5.3.8: Autocorrelation function for Aegon Returns.

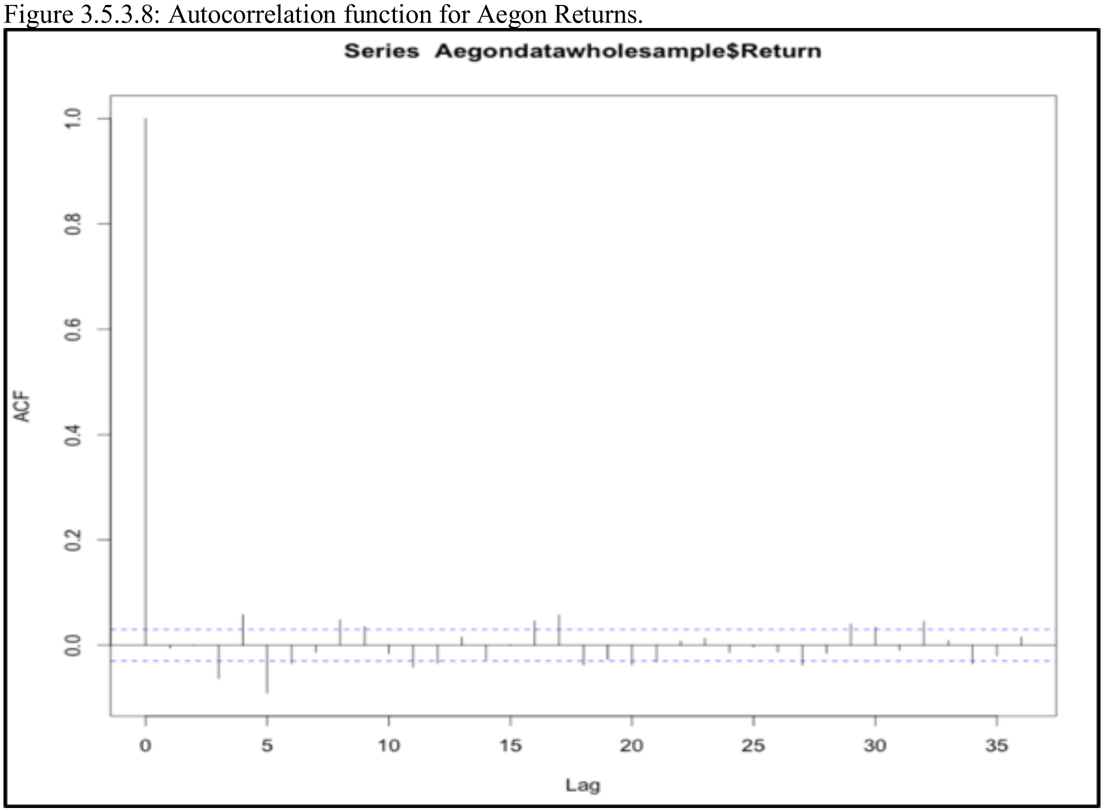


Figure 3.5.3.9: Autocorrelation function for ING Groep Returns.

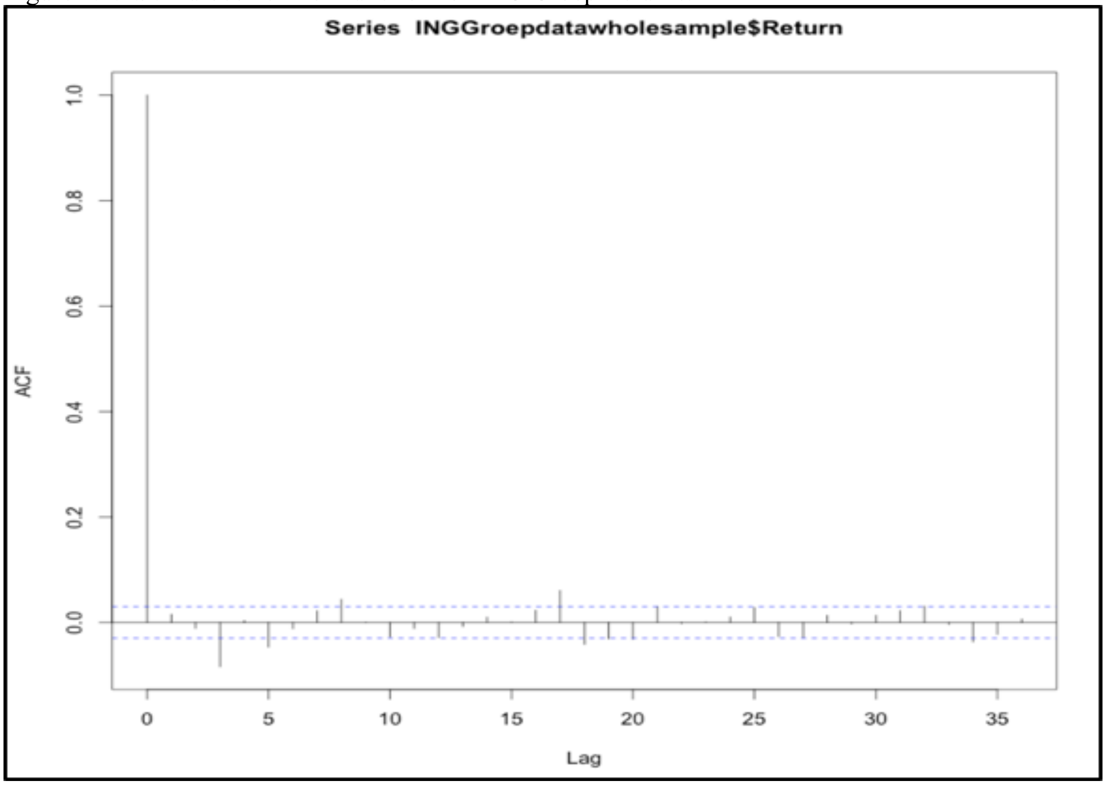


Figure 3.5.3.10: Autocorrelation function for BBVA Returns.

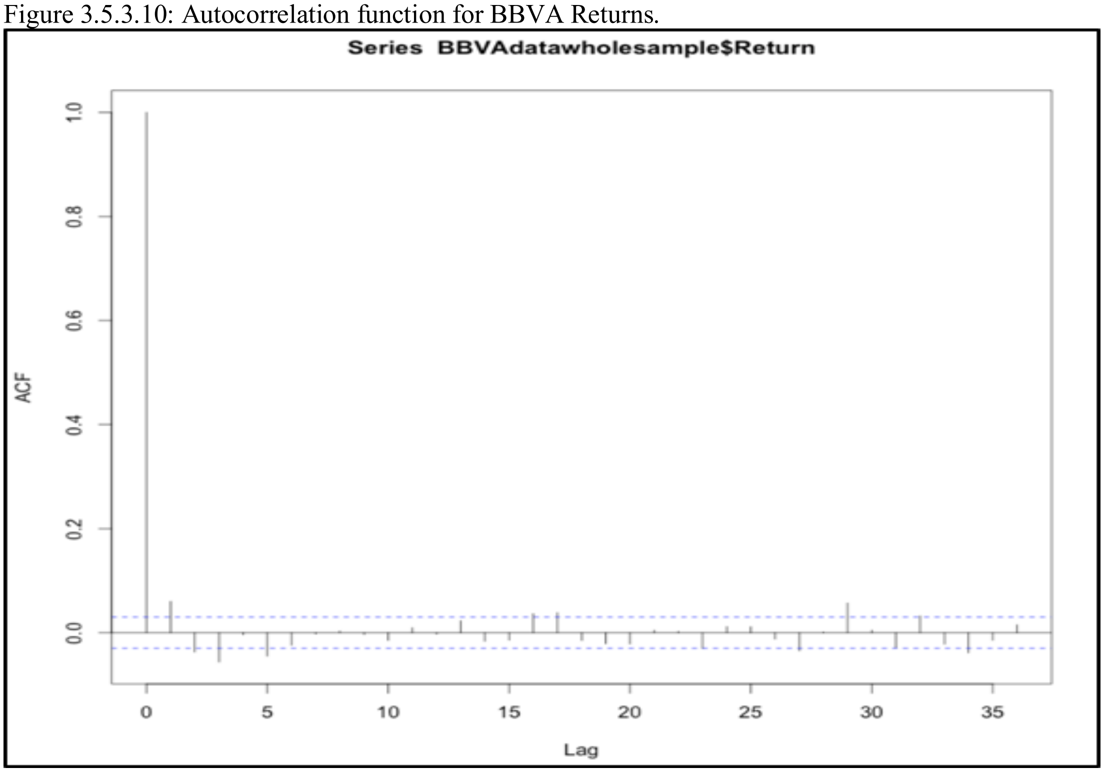
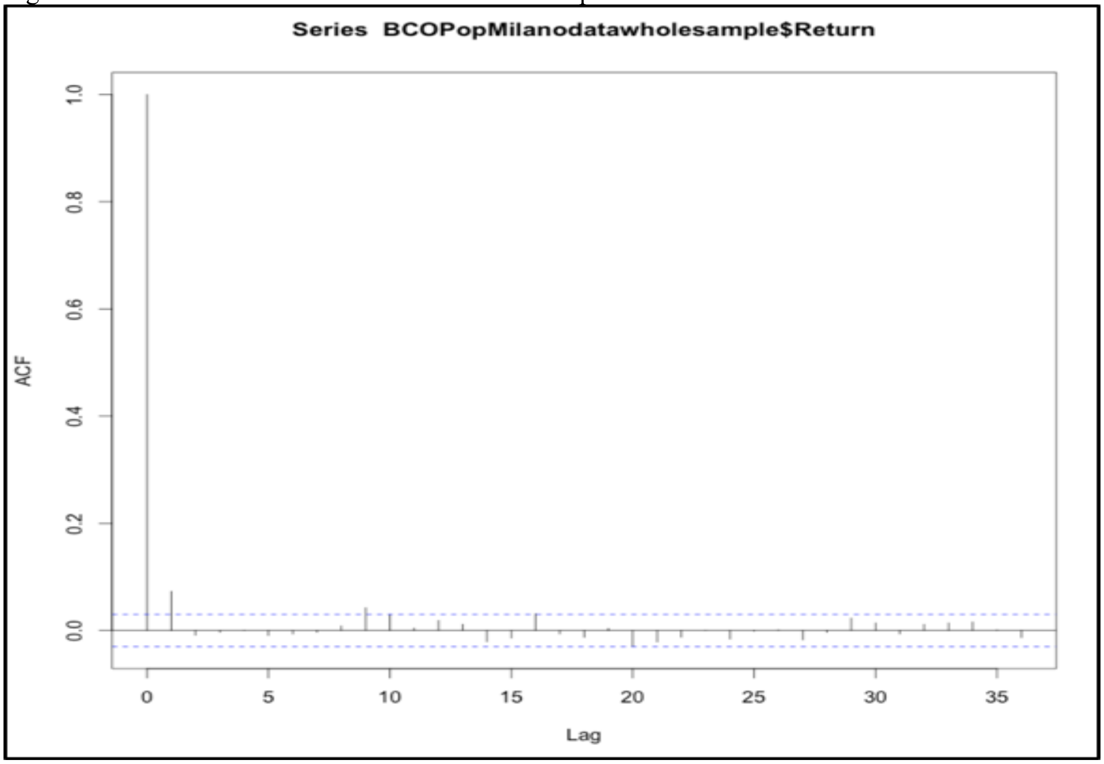


Figure 3.5.3.11: Autocorrelation function for BCO Pop Returns.



3.6 Results

3.6.1 OLS Regression Estimations

It is clear from the coefficient estimators and associated p-values in table 3.6.1.1, that their relative significance is sporadic at best. However, 16 out of 29 institutions do exhibit a degree of significance at the 1% or 5% level in relation to the control variables – for example, Allianz, AXA, Bank of Ireland and Barclays. For the most part, the significant estimators relate to the impact of the MSCI Europe Industrials Sector Index and the MSCI Europe Materials Sector Index (Beta 1 and Beta 2 in equation 3.3) on the returns of each Financial Institution. In just two instances, the impact of the Stoxx 50 volatility index is significant. In any event, it is deemed appropriate to continue with the quantile regressions based upon the residuals' time series generated in each OLS estimation.

Conversely, when running the OLS estimations for the control variables at 2 and 3 lags, per tables 3.6.1.2 and 3.6.1.3, there is very little evidence of any significance – only in 9 cases at 2 lags and mostly in relation to the impact of the Stoxx 50 Volatility Index. There are even fewer cases for the estimators produced at 3 lags. Consequently, all subsequent quantile regressions are based on the contemporaneous state.

3.6.2 Unconditional, Time Invariant CoVaR – Whole Sample

A tabulated summary of the results is presented in tables 3.6.2.1 and 3.6.2.2. The suggestion that the higher an institution's VaR the greater its contribution to systemic risk, is only partially evidenced in the results.

Table 3.6.1.1: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	β_1	β_2	β_3
Aegon	0.001391 (0.975)	0.114432 (0.12)	-0.093910 (0.113)	-0.011597 (0.269)
Ageas	0.01047 (0.8235)	-0.13752 (0.0736)	0.03553 (0.5657)	-0.01188 (0.2776)
Allianz	0.006777 (0.8428)	0.142025 (0.0112)*	-0.070529 (0.1176)	0.010651 (0.1813)
AXA	0.027426 (0.50385)	0.177687 (0.008)**	-0.094325 (0.08126)	0.002999 (0.75385)
Banco Santander	0.028385 (0.3994)	0.043560 (0.4297)	-0.047084 (0.2890)	0.013146 (0.0941)
Bank of Ireland	0.023181 (0.71706)	0.265249 (0.0114)*	-0.241359 (0.0042)**	-0.008783 (0.55586)
Barclays	0.038346 (0.4112)	0.189149 (0.0134)*	-0.080548 (0.1904)	0.005184 (0.6336)
BBVA	0.016216 (0.6212)	0.104552 (0.0518)	-0.053295 (0.2180)	0.007853 (0.3046)
Banca Pop	-0.011315 (0.76984)	0.131969 (0.0373)*	0.024907 0.625209	0.030947 (0.0006)**

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.1 cont'd: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	β_1	β_2	β_3
Commerzbank	-0.02671 (0.540297)	0.27286 (0.000)**	-0.11159 0.052388	0.01962 (0.053665)
Credit Agricole	0.027356 (0.46)	0.065336 (0.281)	-0.051205 (0.294)	-0.001489 (0.863)
Erste Group	0.047631 (0.23175)	0.186733 (0.004)**	0.003184 (0.95164)	0.014896 (0.10867)
Generali	0.000112 (0.997)	0.02408 (0.579)	0.00154 (0.965)	0.00287 (0.642)
Hannover	0.04594 (0.1604)	0.10301 (0.0547)	-0.0666 (0.1226)	0.007615 (0.3182)
HSBC	0.019704 (0.4623)	0.08682 (0.048)*	-0.07662 (0.0302)*	0.015633 (0.0124)*
ING	0.032431 (0.481)	0.105565 (0.162)	0.024067 (0.692)	0.005565 (0.604)
KBC Group	0.03399 (0.4697)	0.11808 (0.1252)	0.07283 (0.2400)	0.02054 (0.0609)
Legal & General	0.038113 (0.319)	0.094023 (0.134)	-0.043344 (0.390)	0.008039 (0.368)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.1 cont'd: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	β_1	β_2	β_3
Lloyds	0.009314	0.158067	-0.140506	-0.006919
	(0.8394)	(0.0358)*	(0.0204)*	(0.5184)
Mapfre	0.045239	0.101214	-0.137252	-0.011808
	(0.16826)	(0.05986)	(0.0015)**	(0.12292)
National Bk of	-0.03088	0.01965	0.10193	-0.01674
Greece	(0.588)	(0.833)	(0.175)	(0.208)
Old Mutual	0.0456461	0.0122964	0.00002	0.0045115
	(0.236)	(0.845)	(1.0000)	(0.615)
Paribas	0.039746	0.141191	-0.112949	0.011774
	(0.2885)	(0.0214)*	(0.0222)*	(0.1774)
Prudential	0.049165	0.045297	-0.015718	-0.00203
	(0.225)	(0.495)	(0.769)	(0.830)
RBS	0.007473	0.294157	-0.194083	0.008372
	(0.878244)	(0.000)**	(0.0026)**	(0.46156)
SCOR	-0.008024	0.257908	-0.130387	0.004583
	(0.8363)	(0.000)**	(0.0109)*	(0.6127)
Swiss Life	0.005222	0.192829	-0.033096	0.002386
	(0.88712)	(0.001)**	(0.49508)	(0.78089)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.1 cont'd: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	β_1	β_2	β_3
UBS	0.016565 (0.6458)	0.122407 (0.0382)*	-0.0617 (0.1942)	-0.002179 (0.7954)
Vienna	0.035286 (0.212)	0.1024928 (0.0269)*	0.0222565 (0.5504)	0.0007069 (0.9146)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.2 OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	β_1	β_2	β_3
Aegon	-0.0058 (0.8975)	-0.001517 (0.9836)	0.055813 (0.3468)	0.019701 (0.0604)
Ageas	0.006146 (0.896)	0.015646 (0.839)	0.029084 (0.638)	-0.009522 (0.384)
Allianz	0.011865 (0.729)	0.040725 (0.467)	-0.059167 (0.19)	-0.005486 (0.491)
AXA	0.000314 (0.444)	-0.000347 (0.605)	-0.00026 (0.630)	-0.000362 (0.997)
Banco Santander	0.028834 (0.392)	-0.028121 (0.610)	0.016244 (0.715)	0.009155 (0.244)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.2 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	β_1	β_2	β_3
Bank of Ireland	0.006348 (0.9208)	0.144857 (0.1662)	0.133726 (0.1124)	0.035529 (0.0171)*
Barclays	0.04061 (0.384)	0.08117 (0.289)	-0.07913 (0.199)	0.00884 (0.417)
BBVA	0.015892 (0.6281)	-0.020113 (0.7082)	0.026081 (0.5466)	0.013875 (0.0697)
Banca Pop	-0.010426 (0.78751)	0.079336 (0.21053)	0.067088 (0.18846)	0.025870 (0.0041)**
Commerzbank	-0.02589 (0.553)	0.16151 (0.024)*	-0.02889 (0.616)	0.01625 (0.111)
Credit Agricole	0.024815 (0.503)	0.072716 (0.230)	-0.057205 (0.241)	0.013434 (0.119)
Erste Group	0.050747 (0.2036)	0.083379 (0.2022)	-0.050698 (0.3355)	0.023865 (0.0104)*
Generali	-0.001570 (0.9527)	0.005717 (0.8952)	0.022481 (0.5198)	0.01160 (0.0603)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.2 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	β_1	β_2	β_3
Hannover	0.045525 (0.164)	0.083706 (0.118)	-0.045290 (0.294)	0.008832 (0.247)
HSBC	0.020705 (0.441)	-0.035964 (0.413)	0.038771 (0.273)	0.006245 (0.318)
ING	0.03232 (0.483)	0.08665 (0.251)	-0.03113 (0.609)	0.02038 (0.058)
KBC Group	0.036931 (0.4328)	0.055282 (0.4734)	-0.001824 (0.9766)	0.028218 (0.0102)*
Legal & General	0.040105 (0.295)	0.012202 (0.846)	-0.020411 (0.686)	0.004753 (0.594)
Lloyds	0.008774 (0.849)	-0.020566 (0.785)	-0.030749 (0.612)	0.002934 (0.784)
Mapfre	0.038547 (0.2405)	-0.071962 (0.1810)	0.070186 (0.1052)	0.014092 (0.0657)
National Bk of Greece	-0.03534 (0.5363)	0.10365 (0.2682)	-0.04838 (0.5209)	0.02641 (0.0475)*

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.2 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	β_1	β_2	β_3
Old Mutual	0.047401 (0.2179)	-0.125271 (0.0469)*	0.073184 (0.1492)	0.001577 (0.8604)
Paribas	0.039801 (0.288)	-0.012202 (0.842)	0.011889 (0.810)	0.010989 (0.208)
Prudential	0.048962 (0.227)	-0.006636 (0.920)	-0.017643 (0.741)	0.007840 (0.406)
RBS	0.010093 (0.836)	0.070283 (0.38)	-0.076828 (0.233)	0.005303 (0.641)
SCOR	-0.007814 (0.841)	0.080800 (0.205)	-0.034973 (0.496)	0.012799 (0.159)
Swiss Life	0.008338 (0.821)	0.088199 (0.145)	-0.036264 (0.456)	0.001677 (0.846)
UBS	0.01550 (0.6671)	0.07181 (0.2238)	-0.07725 (0.1041)	0.01524 (0.0696)
Vienna	0.039525 (0.16345)	0.117721 (0.01130)*	-0.102791 (0.00602)**	-0.001690 (0.79828)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.3 OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	β_1	β_2	β_3
Aegon	0.003464 (0.939)	-0.023433 (0.750)	-0.062042 (0.296)	-0.008030 (0.444)
Ageas	0.003816 (0.935)	-0.075981 (0.323)	0.038193 (0.537)	0.016739 (0.126)
Allianz	0.009768 (0.775)	0.058413 (0.297)	-0.062118 (0.168)	0.004626 (0.562)
AXA	0.034620 (0.399)	-0.052574 (0.434)	-0.066118 (0.222)	-0.008193 (0.392)
Banco Santander	0.032224 (0.339)	-0.025031 (0.650)	-0.036290 (0.414)	-0.000914 (0.907)
Bank of Ireland	0.01157 (0.8565)	0.02481 (0.8129)	0.10419 (0.2170)	0.02933 (0.0494)*
Barclays	0.041233 (0.377)	-0.030944 (0.686)	-0.002688 (0.965)	0.007876 (0.469)
BBVA	0.019326 (0.556)	-0.035498 (0.509)	-0.003251 (0.940)	0.001886 (0.805)
Banca Pop	-0.003283 (0.932)	-0.023918 (0.706)	0.032487 (0.525)	0.006938 (0.443)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.3 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	β_1	β_2	β_3
Commerzbank	-0.022570 (0.606)	0.014088 (0.844)	0.001468 (0.980)	0.014018 (0.169)
Credit Agricole	0.026073 (0.481)	0.044145 (0.466)	-0.066237 (0.175)	0.012307 (0.154)
Erste Group	0.054249 (0.174)	-0.062699 (0.338)	0.025913 (0.623)	0.011307 (0.225)
Generali	0.002233 (0.933)	-0.009121 (0.834)	-0.008669 (0.804)	-0.002269 (0.713)
Hannover	0.047030 (0.151)	-0.021721 (0.685)	0.002587 (0.952)	0.007236 (0.343)
HSBC	0.023617 (0.379)	0.002367 (0.957)	-0.035781 (0.312)	-0.002271 (0.717)
ING	0.0412868 (0.370)	-0.036706 (0.626)	-0.0965507 (0.112)	0.0001082 (0.992)
KBC Group	0.03540 (0.45211)	0.05473 (0.47781)	0.03486 (0.57449)	0.02992 (0.00643)**
Legal & General	0.040551 (0.2891)	0.074481 (0.2345)	-0.097108 (0.0543)	0.007334 (0.4109)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.3 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	β_1	β_2	β_3
Lloyds	0.006963 (0.880)	-0.070351 (0.350)	0.054875 (0.366)	0.004622 (0.666)
Mapfre	0.037971 (0.2478)	-0.038521 (0.4741)	0.088443 (0.0413)*	0.008509 (0.2667)
National Bk of Greece	-0.03358 (0.557)	-0.00964 (0.918)	0.03342 (0.658)	0.01781 (0.182)
Old Mutual	0.040551 (0.2891)	0.074481 (0.2345)	-0.097108 (0.0543)	0.007334 (0.4109)
Paribas	0.044147 (0.238)	-0.049804 (0.416)	-0.040260 (0.415)	0.001656 (0.849)
Prudential	0.053840 (0.183)	-0.091832 (0.166)	-0.036854 (0.490)	-0.003505 (0.710)
RBS	0.006961 (0.8867)	-0.090140 (0.2599)	0.113351 (0.0785)	0.011669 (0.3055)
SCOR	-0.008165 (0.8339)	0.106975 (0.0935)	-0.054262 (0.2906)	0.014438 (0.1118)
Swiss Life	0.007480 (0.839)	0.011589 (0.848)	0.004448 (0.927)	0.010773 (0.211)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.1.3 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	β_1	β_2	β_3
UBS	0.018396 (0.610)	0.013415 (0.82)	-0.060070 (0.206)	0.004131 (0.623)
Vienna	0.036151 (0.203)	-0.006219 (0.894)	0.040239 (0.282)	0.009621 (0.146)

Notes: * Denotes coefficient significance at 5% and ** at 1%

Table 3.6.2.1 Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Whole Sample and Contemporaneous Residuals

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
ING Groep	Bank	NL	-8.47	3	-4.103	1
Axa	Insurance	FR	-7.41	11	-3.923	2
Credit Agricole	Bank	FR	-7.03	14	-3.910	3
BBVA	Bank	ESP	-5.72	23	-3.839	4
Aegon	Insurance	NL	-8.37	4	-3.742	5
Paribas	Bank	FR	-6.76	18	-3.721	6
Generali	Insurance	ITL	-4.84	29	-3.689	7
Barclays	Bank	UK	-7.67	10	-3.631	8
HSBC	Bank	UK	-4.92	28	-3.567	9

Table 3.6.2.1 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Whole Sample and Contemporaneous Residuals

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
Banco Santander	Bank	ESP	-5.72	24	-3.565	10
UBS	Bank	CHF	-6.49	21	-3.559	11
Allianz	Insurance	DE	-6.31	22	-3.537	12
Swiss Life	Insurance	CHF	-7.03	15	-3.391	13
Prudential	Insurance	UK	-7.06	13	-3.359	14
Ageas	Insurance	BE	-7.99	6	-3.310	15
KBC Group	Bank	BE	-8.15	5	-3.273	16
Legal & General	Insurance	UK	-6.74	20	-3.219	17
Commerzbank	Bank	DE	-7.76	9	-3.196	18
RBS	Bank	UK	-7.77	8	-3.143	19
Erste Group	Bank	AUT	-7.41	12	-3.124	20
Lloyds	Bank	UK	-7.78	7	-3.091	21
Old Mutual	Insurance	UK	-6.76	19	-2.996	22

Table 3.6.2.1 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Whole Sample and Contemporaneous Residuals

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
Banca Pop Milano	Bank	ITL	-6.86	17	-2.882	23
Mapfre	Insurance	ESP	-5.46	26	-2.694	24
Vienna	Insurance	AUT	-5.32	27	-2.575	25
Hannover	Insurance	DE	-5.63	25	-2.509	26
Bank of Ireland	Bank	IRE	-11.56	1	-2.265	27
SCOR	Insurance	FR	-6.87	16	-1.854	28
Natl Bk of Greece	Bank	GRE	-10.86	2	-1.685	29

Notes: the Delta-CoVaR is the impact on the market index VaR in % terms, as measured by $\Delta CoVaR_{\tau}^{index|i} = \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}\right) - \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i}\right)$, where tau = 0.95 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the entire sample period of data and daily returns are used. Although small in % terms, the impact on the net worth of a multi-billion-dollar financial system as a whole would not be insignificant. A figure of 4.103% for ING Groep would infer the respective % increase in the 5% VaR of the whole financial system when a particular institution reaches its own 1% VaR

Table 3.6.2.2 Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Whole Sample and Contemporaneous Residuals

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
Credit Agricole	Bank	FR	-7.03	14	-4.269	1
Banca Pop Milano	Bank	ITL	-6.86	17	-4.144	2
Allianz	Insurance	DE	-6.31	22	-4.049	3
BBVA	Bank	ESP	-5.72	23	-4.000	4
Generali	Insurance	ITL	-4.84	29	-3.907	5
ING Groep	Bank	NL	-8.47	3	-3.850	6
Aegon	Insurance	NL	-8.37	4	-3.794	7
Banco Santander	Bank	ESP	-5.72	24	-3.770	8
Paribas	Bank	FR	-6.76	18	-3.694	9
Mapfre	Insurance	ESP	-5.46	26	-3.641	10
UBS	Bank	CHF	-6.49	21	-3.640	11
Axa	Insurance	FR	-7.41	11	-3.617	12
HSBC	Bank	UK	-4.92	28	-3.578	13

Table 3.6.2.2 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Whole Sample and Contemporaneous Residuals

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
Legal and General	Insurance	UK	-6.74	20	-3.526	14
Barclays	Bank	UK	-7.67	10	-3.426	15
Commerzbank	Bank	UK	-7.76	9	-3.413	16
KBC Group	Bank	BE	-8.15	5	-3.388	17
Erste Group	Bank	AUT	-7.41	12	-3.382	18
Prudential	Insurance	UK	-7.06	13	-3.330	19
Old Mutual	Insurance	UK	-6.76	19	-2.985	20
RBS	Bank	UK	-7.77	8	-2.938	21
Ageas	Insurance	BE	-7.99	6	-2.914	22
Vienna	Insurance	AUT	-5.32	27	-2.899	23
Swiss Life	Insurance	CHF	-7.03	15	-2.885	24
Hannover	Insurance	DE	-5.63	25	-2.689	25
Bank of Ireland	Bank	IRE	-11.56	1	-2.644	26

Table 3.6.2.2 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Whole Sample and Contemporaneous Residuals

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
Natl Bk of Greece	Bank	GRE	-10.86	2	-2.506	27
Lloyds	Bank	UK	-7.78	7	-2.391	28
SCOR	Insurance	FR	-6.87	16	-2.031	29

Notes: the Delta-CoVaR is the impact on the market index VaR in % terms, as measured by $\Delta CoVaR_{\tau}^{index|i} = (\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}) - (\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i})$, where tau = 0.99 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the entire sample period of data and daily returns are used. Although small in % terms, the impact on the net worth of a multi-billion-dollar financial system as a whole would not be insignificant. A figure of 4.27% for Credit Agricole would infer the respective % increase in the 1% VaR of the whole financial system when a particular institution reaches its own 1% VaR.

For example, National Bank of Greece has the highest 1% VaR but ranks as one of the lowest in terms of its Delta-CoVaR at both tau = 0.95 and 0.99. This observation is further evidenced in appendices A3.6.2.1 and A3.6.2.2. At tau = 0.95, only Barclays, ING Groep and Aegon rank in the top 10 according to **both** Delta-CoVaR and the institution's 1% VaR. Bank of Ireland and National Bank of Greece have the top two highest 1% VaRs but rank at the bottom in terms of Delta-CoVaR. At tau = 0.99, only Aegon and ING Groep rank in the top 10 according to **both** Delta-CoVaR and the institution's 1% VaR. Once again, Bank of Ireland and National Bank of Greece rank close to the bottom despite having the highest 1% VaR figures.

The actual values of the systemic risk contributions for each institution range from -4.103% to -1.685% (the impact on the market index VaR in % terms) at tau = 0.95 and from -4.269 to -2.031 at tau = 0.99. Compared with Castro et al (2014), certain consistencies are evident. Clearly, the sample sizes, data periods and constituent companies do differ. In addition, they split the sample into three sub-periods. However, the top 10 contributors in my data for the banks at tau = 0.95 are, ING Groep, Credit Agricole, BBVA, Paribas, Barclays, HSBC and Banco Santander. In relation to Castro et al (2014), ING Groep, Banco Santander, Paribas and BBVA are also ranked in their top 10 in terms of their systemic risk contributions on the full data sample. Neither Barclays or HSBC fall within their top 10, being 20th and 15th respectively and they do not include Credit Agricole in their sample. Likewise, the insurance sector is not evaluated in their paper but clearly does have an impact as evidenced by the presence of AXA, Aegon and Generali in my top 10. In terms of an overall country presence, France, the UK, Italy, Spain and the Netherlands are prominent.

Castro et al (2014) do not evaluate their data set at tau = 0.99. However, with regards my data set there appears to be a partial shift in the top 10 rankings. Indeed, AXA, Barclays and HSBC drop out of the top 10 and Banca Pop Milano, Allianz and Mapfre move into it. One insurance company and two banks are replaced by two insurance companies and one bank. Further highlighting the need to consider the systemic impact of the insurance sector. With regards Banca Pop Milano and Credit Agricole, they are both cooperative, mutual style banks whose activities were curtailed more by the subsequent global economic crisis as opposed to initial exposures to toxic debt. Indeed, aside from Unicredito, Italian banks managed to circumvent the huge write-downs on toxic assets but post 2010, the country was plunged into recession[15]. Their lending is driven by the members of the cooperative and in times of economic crisis and recession, deposits and lending in the credit markets fall. In terms of country representation, the top 10 rankings are once again dominated by Spain, France, Italy and the Netherlands, with BBVA, Aegon, Banco Santander, ING Groep and Paribas retaining their positions in the top 10 at both tau = 0.95 and 0.99.

When comparing the top 10 ranked institutions at both levels of tau with table 3.2.3.2, section 3.2.3, HSBC and Barclays are consistent with the Capital Requirement Directive IV. Clearly, the non-UK based institutions will not be listed in the table. With regards RBS and Lloyds, in my data analysis, they do not rank in the top 10 at either levels of tau. Indeed, their rankings are 19 and 21 and 21 and 28 respectively at tau = 0.95 and tau = 0.99. However, RBS is deemed as systemically significant at both the global and UK level and Lloyds at the UK level only, according to the Directive. There is not an equivalent table for the insurance sector, but as already alluded to, my results do indicate their systemic importance, at least at the European and UK level.

[15] Source: Moody's press release May 2012.

3.6.3 Unconditional, Time Invariant CoVaR – Sub-Samples

3.6.3.1 Pre-2008 Sample

With reference to table 3.6.3.1, at tau = 0.95, the range of Delta-CoVaR values is from -3.57% to -0.49%, smaller than those for the whole sample. This is consistent with the exclusion of the majority of the most volatile period in the markets from the summer of 2007 to the end of 2009. As with the full data sample, in terms of the individual institution VaRs, the same conclusion can be drawn in so far as a large individual 1% VaR does not imply large systemic contribution to risk. For example, BBVA, Generali and UBS are ranked at numbers 20, 21 and 23 for their individual 1% VaRs but are all ranked in the top 10 in terms of their Delta-CoVaRs. In terms of the top 10 ranked institutions, there are similarities with the full data set. ING Groep is once again ranked at no. 1 and AXA, BBVA, Generali, Aegon and HSBC are ranked at 3, 4, 5, 6 and 10 respectively. Credit Agricole, Paribas, Barclays and Banco Santander do not feature in the top 10 in this sub-sample. There is a greater presence from insurance stocks than banks.

With reference to table 3.6.3.2, at tau = 0.99, the range of Delta-CoVaR values is from -3.43% to -0.39. There is some comparison with the rankings for the sub-sample at tau = 0.95. For instance, ING Groep is still ranked first and Generali, Aegon, AXA, HSBC and BBVA remain in the top 10. However, Barclays, Commerzbank, RBS and Legal and General now move into the top 10. There is certainly a greater UK presence than in any of the previous samples at both levels of tau.

3.6.3.2 Post 2007 Sample

The average 1% VaR for the data set pre-2008 is -5.427% whereas the corresponding figure for the post 2007 data set is -8.644%. This clearly has an impact on the magnitude of the subsequent Delta-CoVaR figures when compared to those of the full sample and the pre-2008 sub-sample.

This indicates a need for regular reflections upon systemic risk contributions given changes in volatility in the underlying markets. With reference to table 3.6.3.3, at tau = 0.95, the range in the Delta-CoVaRs is from -5.01% to -2.33% and, once again, having a large institution VaR does not imply a top 10 ranking in terms of systemic contribution. There remain consistencies in the top 10 rankings with the full sample, with Banco Santander, ING Groep, HSBC, BBVA, AXA, Aegon, Barclays, and Credit Agricole forming part of the top 10. The exceptions are the German stock, Allianz and the UK insurance stock, Legal and General. As with the pre-2008 sample, there is a greater representation of UK stocks.

With reference to table 3.6.3.4, at tau = 0.99, the range of Delta-CoVaRs is from -5.87% to -2.68%. Thereby, when a financial institution reaches its own 1% VaR it has a larger % impact on the 1% VaR of the financial system than on the corresponding 5% VaR. There are some new entrants to the top 10 rankings, for example, Banca Pop Milano is ranked first, and KBC Group is ranked at number 10. On the whole, though, the same stocks at tau = 0.95 for this sub-sample also form the top 10 at tau = 0.99.

Table 3.6.3.1 Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Pre-2008 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
ING Groep	Bank	NL	-7.17	4	-3.57	1
Swiss Life	Insurance	CHF	-7.79	1	-3.08	2
Axa	Insurance	FR	-6.67	5	-2.98	3
BBVA	Bank	ESP	-4.93	20	-2.96	4
Generali	Insurance	ITL	-4.79	21	-2.94	5
Aegon	Insurance	NL	-7.51	3	-2.91	6
Ageas	Insurance	BE	-6.23	6	-2.89	7
UBS	Bank	CHF	-4.51	23	-2.83	8
Allianz	Insurance	DE	-5.94	8	-2.69	9
HSBC	Bank	UK	-4.31	26	-2.67	10
Banco Santander	Bank	ESP	-5.26	15	-2.67	11
Commerzbank	Bank	DE	-5.79	9	-2.66	12
Barclays	Bank	UK	-5.26	14	-2.64	13

Table 3.6.3.1 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Pre-2008 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
Paribas	Bank	FR	-5.09	19	-2.63	14
RBS	Bank	UK	-5.53	11	-2.55	15
Prudential	Insurance	UK	-6.16	7	-2.53	16
Lloyds	Bank	UK	-5.22	17	-2.41	17
Credit Agricole	Bank	FR	-4.34	24	-2.39	18
Legal & General	Insurance	UK	-5.38	12	-2.34	19
Old Mutual	Insurance	UK	-5.71	10	-2.32	20
KBC Group	Bank	BE	-4.77	22	-2.31	21
Hannover	Insurance	DE	-5.28	13	-1.73	22
Bank of Ireland	Bank	IRE	-5.21	18	-1.61	23
Banca Pop	Bank	ITL	-4.25	27	-1.49	24
Bank of Greece	Bank	GRE	-5.26	16	-1.31	25
SCOR	Insurance	FR	-7.75	2	-1.24	26

Table 3.6.3.1 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Pre-2008 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
Mapfre	Insurance	ESP	-4.34	25	-1.22	27
Erste Group	Bank	AUT	-4.03	28	-1.21	28
Vienna	Insurance	AUT	-2.93	29	-0.49	29

Notes: Notes: the Delta-CoVaR is the impact on the market index VaR in % terms, as measured by $\Delta CoVaR_{\tau}^{index|i} = (\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}) - (\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i})$, where tau = 0.95 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the pre-2008 sample period of data and daily returns are used. Although small in % terms, the impact on the net worth of a multi-billion-dollar financial system as a whole would not be insignificant. A figure of 3.57% for ING Groep would infer the respective % increase in the 5% VaR of the whole financial system when a particular institution reaches its own 1% VaR.

Table 3.6.3.2 Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Pre-2008 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
ING Groep	Bank	NL	-7.17	4	-3.43	1
Barclays	Bank	UK	-5.26	14	-3.39	2
Generali	Insurance	ITL	-4.79	21	-3.34	3
Commerzbank	Bank	DE	-5.79	9	-3.31	4
Aegon	Insurance	NL	-7.51	3	-3.18	5
Axa	Insurance	FR	-6.67	5	-3.01	6
HSBC	Bank	UK	-4.31	26	-2.97	7
RBS	Bank	UK	-5.53	11	-2.75	8
BBVA	Bank	ESP	-4.93	20	-2.74	9
Legal & General	Insurance	UK	-5.38	12	-2.71	10
UBS	Bank	CHF	-4.51	23	-2.71	11
Ageas	Insurance	BE	-6.23	6	-2.69	12
Old Mutual	Insurance	UK	-5.71	10	-2.69	13

Table 3.6.3.2 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Pre-2008 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
Banco Santander	Bank	ESP	-5.26	15	-2.67	14
Allianz	Insurance	DE	-5.94	8	-2.58	15
Lloyds	Bank	UK	-5.22	17	-2.57	16
Swiss Life	Insurance	CHF	-7.79	1	-2.55	17
Paribas	Bank	FR	-5.09	19	-2.53	18
KBC Group	Bank	BE	-4.77	22	-2.44	19
Prudential	Insurance	UK	-6.16	7	-2.38	20
Credit Agricole	Bank	FR	-4.34	24	-2.23	21
Banca Pop	Bank	ITL	-4.25	27	-2.15	22
Bank of Ireland	Bank	IRE	-5.21	18	-2.12	23
Bank of Greece	Bank	GRE	-5.26	16	-1.82	24
Hannover	Insurance	DE	-5.28	13	-1.74	25
Erste Group	Bank	AUT	-4.03	28	-1.66	26

Table 3.6.3.2 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Pre-2008 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
SCOR	Insurance	FR	-7.75	2	-1.20	27
Mapfre	Insurance	ESP	-4.34	25	-1.20	28
Vienna	Insurance	AUT	-2.93	29	-0.39	29

Notes: the Delta-CoVaR is the impact on the market index VaR in % terms, as measured by $\Delta CoVaR_{\tau}^{index|i} = \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}\right) - \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i}\right)$, where tau = 0.99 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the pre-2008 sample period of data and daily returns are used. Although small in % terms, the impact on the net worth of a multi-billion-dollar financial system as a whole would not be insignificant. A figure of 3.43% for ING Groep would infer the respective % increase in the 1% VaR of the whole financial system when a particular institution reaches its own 1% VaR.

Table 3.6.3.3 Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Post-2007 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
Banco Santander	Bank	ESP	-6.86	20	-5.01	1
ING Groep	Bank	NL	-10.79	5	-5.00	2
HSBC	Bank	UK	-5.74	27	-4.84	3
Allianz	Insurance	DE	-6.65	22	-4.73	4
BBVA	Bank	ESP	-6.42	25	-4.71	5
AXA	Insurance	FR	-8.10	17	-4.68	6
Aegon	Insurance	NL	-9.51	11	-4.56	7
Legal & General	Insurance	UK	-8.57	14	-4.53	8
Barclays	Bank	UK	-10.19	7	-4.51	9
Credit Agricole	Bank	FR	-8.20	16	-4.47	10
UBS	Bank	CHF	-8.34	15	-4.45	11
KBC Group	Bank	BE	-12.16	3	-4.44	12
Erste Group	Bank	AUT	-9.78	8	-4.36	13

Table 3.6.3.3 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Post-2007 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
Prudential	Insurance	UK	-8.03	18	-4.32	14
Paribas	Bank	FR	-7.62	19	-4.29	15
Old Mutual	Insurance	UK	-9.05	12	-4.28	16
Generali	Insurance	ITL	-4.84	29	-4.21	17
Swiss Life	Insurance	CHF	-6.64	23	-4.09	18
Mapfre	Insurance	ESP	-6.26	26	-4.02	19
RBS	Bank	UK	-11.06	4	-3.90	20
Banca Pop Milano	Bank	ITL	-8.61	13	-3.84	21
Lloyds	Bank	UK	-10.50	6	-3.80	22
Commerzbank	Bank	DE	-9.64	10	-3.79	23
Hannover	Insurance	DE	-6.48	24	-3.63	24
Vienna	Insurance	AUT	-6.68	21	-3.60	25
Ageas	Insurance	BE	-9.72	9	-3.57	26

Table 3.6.3.3 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.95 – Post 2007 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.95	Ranking According to Delta-CoVaR
SCOR	Insurance	FR	-5.10	28	-2.99	27
Bank of Ireland	Bank	IRE	-15.83	1	-2.88	28
National Bank of Greece	Bank	GRE	-13.29	2	-2.33	29

Notes: the Delta-CoVaR is the impact on the market index VaR in % terms, as measured by $\Delta CoVaR_{\tau}^{index|i} = (\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}) - (\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i})$, where tau = 0.95 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the post-2007 sample period of data and daily returns are used. Although small in % terms, the impact on the net worth of a multi-billion-dollar financial system as a whole would not be insignificant. A figure of 5.01% for Banco Santander would infer the respective % increase in the 5% VaR of the whole financial system when a particular institution reaches its own 1% VaR.

Table 3.6.3.4 Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Post-2007 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
Banca Pop Milano	Bank	ITL	-8.61	13	-5.87	1
Banco Santander	Bank	ESP	-6.86	20	-5.32	2
BBVA	Bank	ESP	-6.42	25	-5.21	3
Credit Agricole	Bank	FR	-8.20	16	-5.16	4
Allianz	Insurance	DE	-6.65	22	-5.15	5
Generali	Insurance	ITL	-4.84	29	-4.84	6
ING Groep	Bank	NL	-10.79	5	-4.81	7
Aegon	Insurance	NL	-9.51	11	-4.75	8
UBS	Bank	CHF	-8.34	15	-4.73	9
KBC Group	Bank	BE	-12.16	3	-4.70	10
Mapfre	Insurance	ESP	-6.26	26	-4.61	11
Commerzbank	Bank	DE	-9.64	10	-4.59	12
Erste Group	Bank	AUT	-9.78	8	-4.54	13

Table 3.6.3.4 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Post-2007 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
HSBC	Bank	UK	-5.74	27	-4.49	14
Legal & General	Insurance	UK	-8.57	14	-4.43	15
Hannover	Insurance	DE	-6.48	24	-4.40	16
Paribas	Bank	FR	-7.62	19	-4.28	17
Prudential	Insurance	UK	-8.03	18	-4.24	18
AXA	Insurance	FR	-8.10	17	-4.14	19
Vienna	Insurance	AUT	-6.68	21	-3.94	20
National Bank of Greece	Bank	GRE	-13.29	2	-3.94	21
SCOR	Insurance	FR	-5.10	28	-3.84	22
Barclays	Bank	UK	-10.19	7	-3.82	23
Old Mutual	Insurance	UK	-9.05	12	-3.82	24
Bank of Ireland	Bank	IRE	-15.83	1	-3.75	25
Swiss Life	Insurance	CHF	-6.64	23	-3.74	26

Table 3.6.3.4 cont'd Institution 1% VaR and Delta-CoVaR at Tau = 0.99 – Post-2007 Sub-Sample

Company	Sector	Country	Company VaR at q = 1%	Ranking According to VaR	Delta-CoVaR at tau = 0.99	Ranking According to Delta-CoVaR
RBS	Bank	UK	-11.06	4	-3.40	27
Lloyds	Bank	UK	-10.50	6	-3.37	28
Ageas	Insurance	BE	-9.72	9	-2.68	29

Notes: the Delta-CoVaR is the impact on the market index VaR in % terms, as measured by $\Delta CoVaR_{\tau}^{index|i} = \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}\right) - \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i}\right)$, where tau = 0.99 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the post 2007 sample period of data and daily returns are used. Although small in % terms, the impact on the net worth of a multi-billion-dollar financial system as a whole would not be insignificant. A figure of 5.87% for Banca Pop Milano would infer the respective % increase in the 1% VaR of the whole financial system when a particular institution reaches its own 1% VaR.

3.7 Significance of Estimations

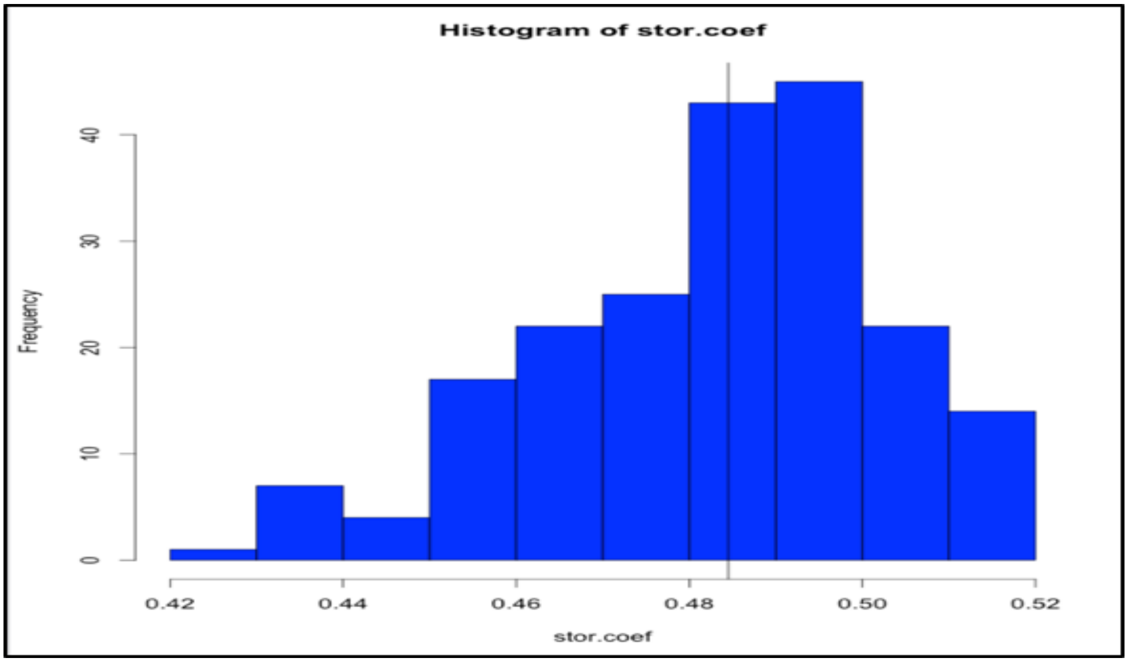
3.7.1 Specification of Significance Tests on the Delta-CoVaR Estimations

The bootstrapping method is applied to assess the significance of the slope coefficients produced in the quantile regression specified in equation (3.1). Its aim is to recreate the population distribution of estimators by sampling with replacement from the data sets specified in section 3.5 above. In this case the sampling process is repeated 200 times in order to create the bootstrap distribution of the slope coefficient estimators for both the 5% and 1% cases and this is done for each financial institution. P-values are then calculated for each set of bootstrapped output and inferences made regarding the significance of the original beta coefficients.

3.7.2 Results of Significance Tests

A selection of the graphical distributions of the beta coefficients generated by the resampling bootstrap technique are presented in figures 3.7.2.1 and 3.7.2.2. Six institutions having a large Delta-CoVaR relative to the entire population of financial institutions are shown – ING Groep, AXA, Credit Agricole, BBVA, Aegon, and Paribas. In each chart, the original beta coefficient estimate is highlighted. The corresponding P-values of each bootstrapped distribution are presented in tables 3.7.2.1 and 3.7.2.2. The latter suggest a lack of significance in the beta coefficients across the board. However, given the number of financial institutions within the European financials' sector, you would expect fairly small contributions from each towards the VaR of the entire system. That is not to say that they would not be considered as important, given that a small shift in that VaR in a multi-billion-dollar industry is significant in financial terms.

Figure 3.7.2.1: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.95) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
ING Groep



Credit Agricole

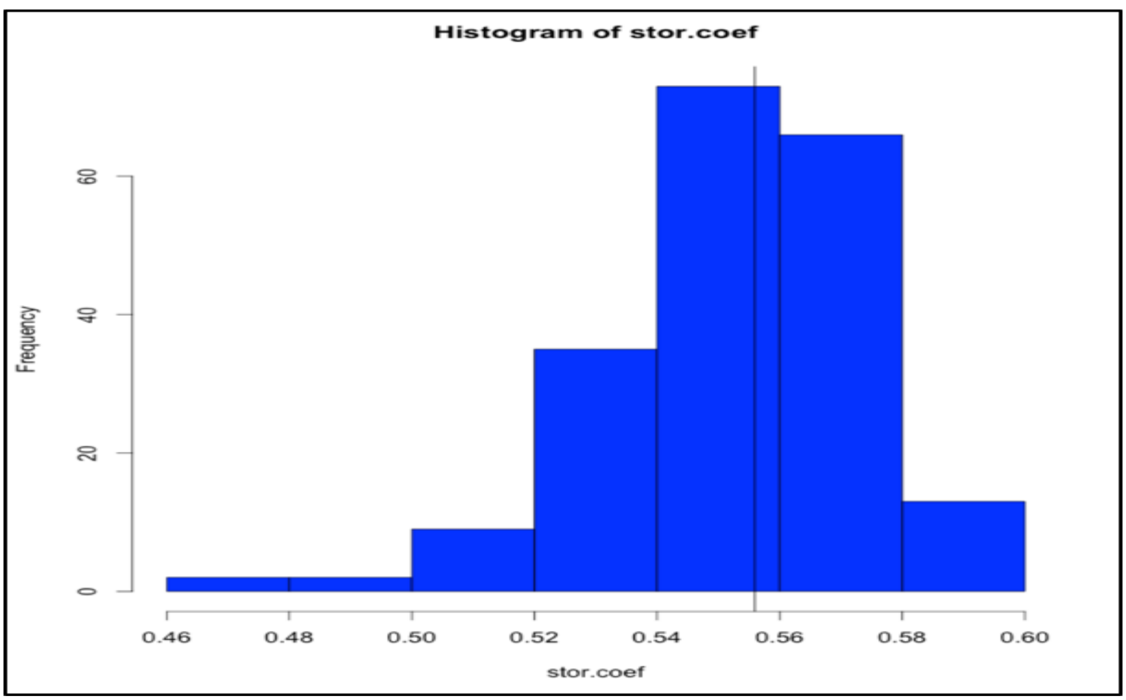
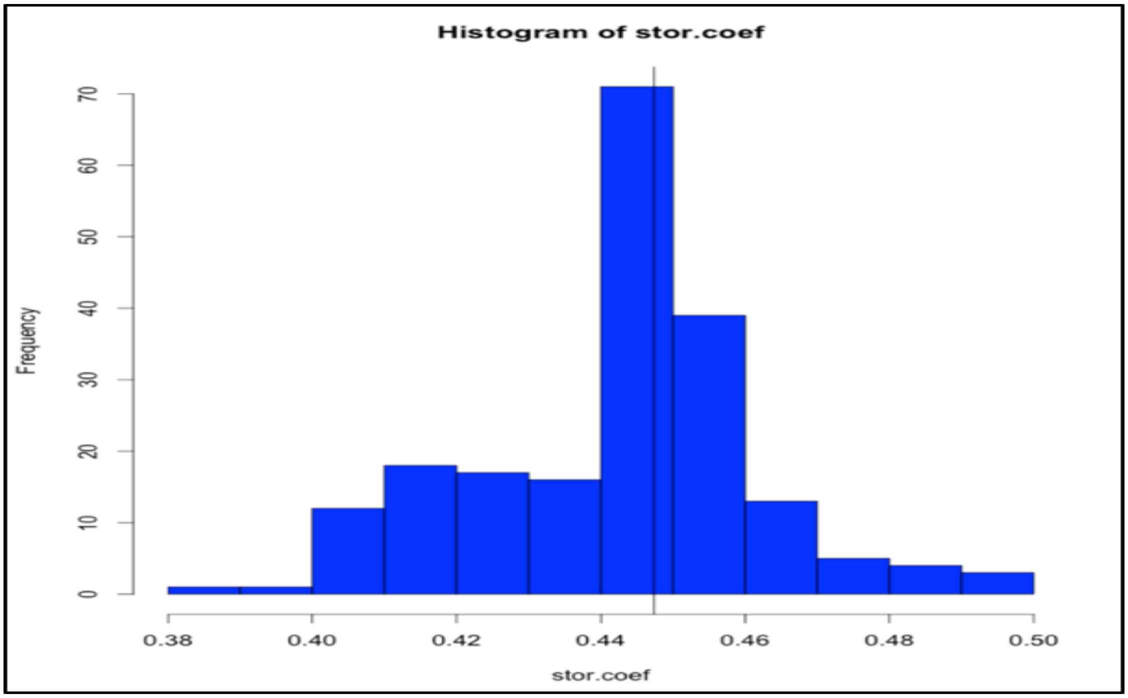


Figure 3.7.2.1: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.95) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
Aegon



AXA

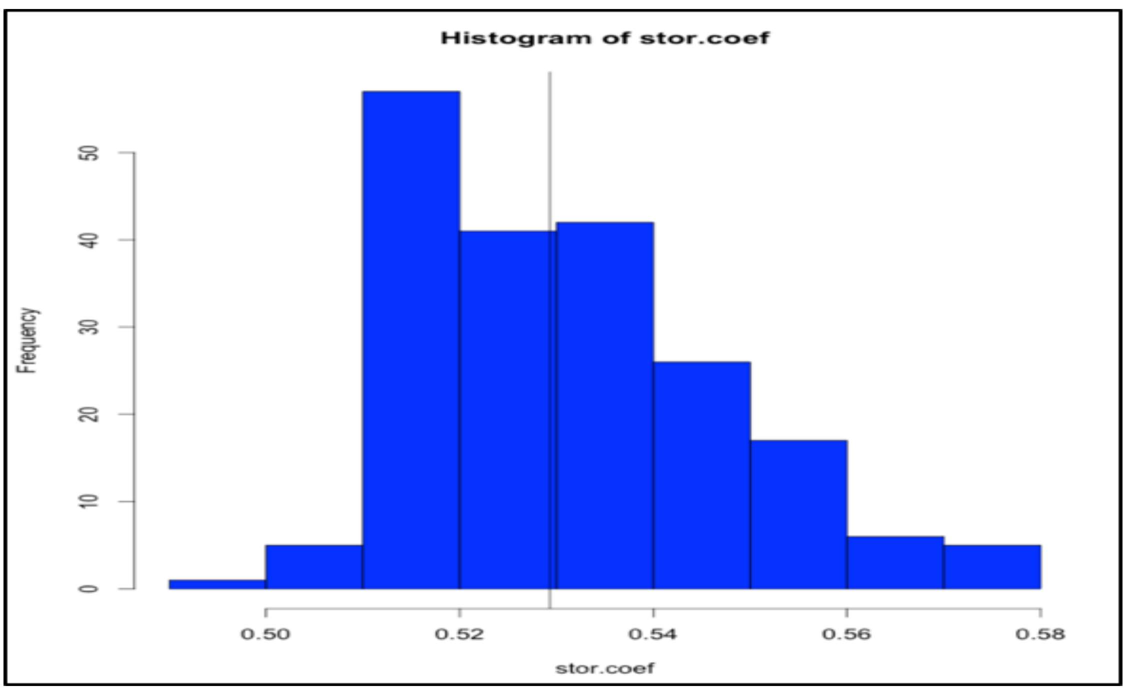
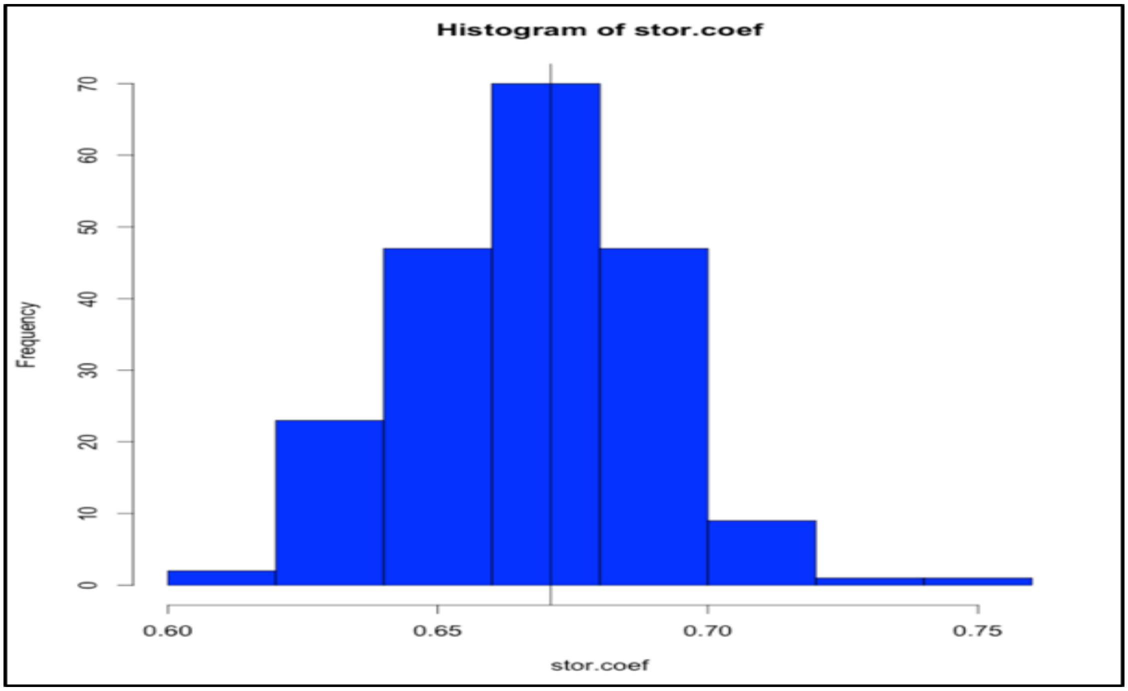


Figure 3.7.2.1: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.95) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
BBVA



Paribas

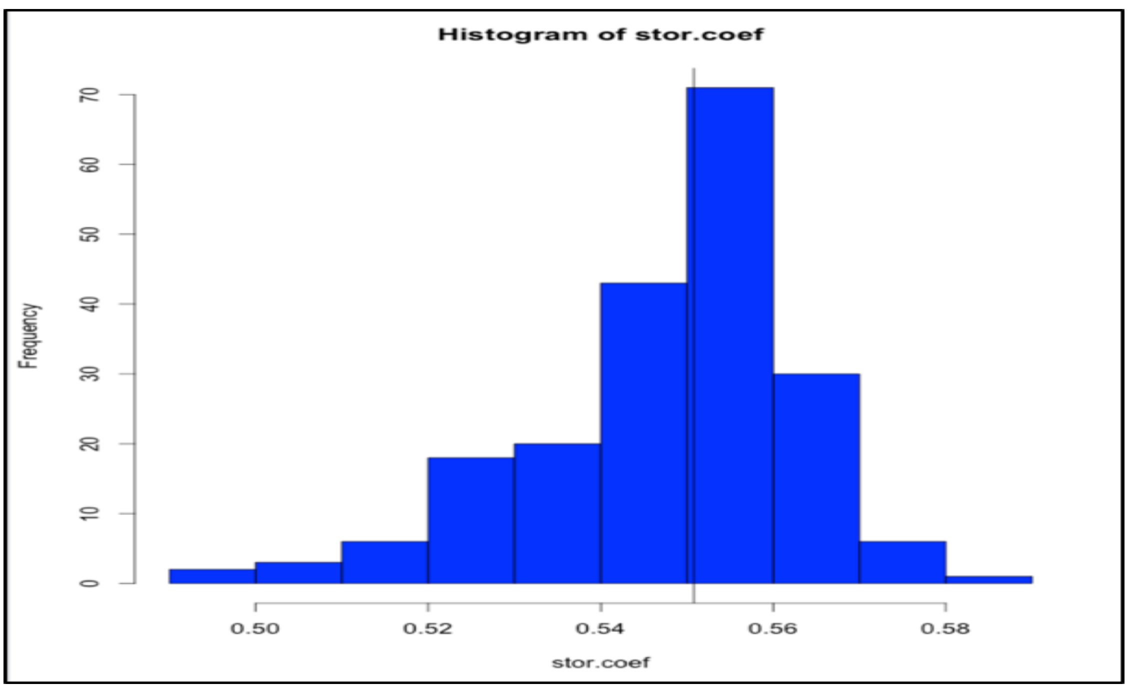
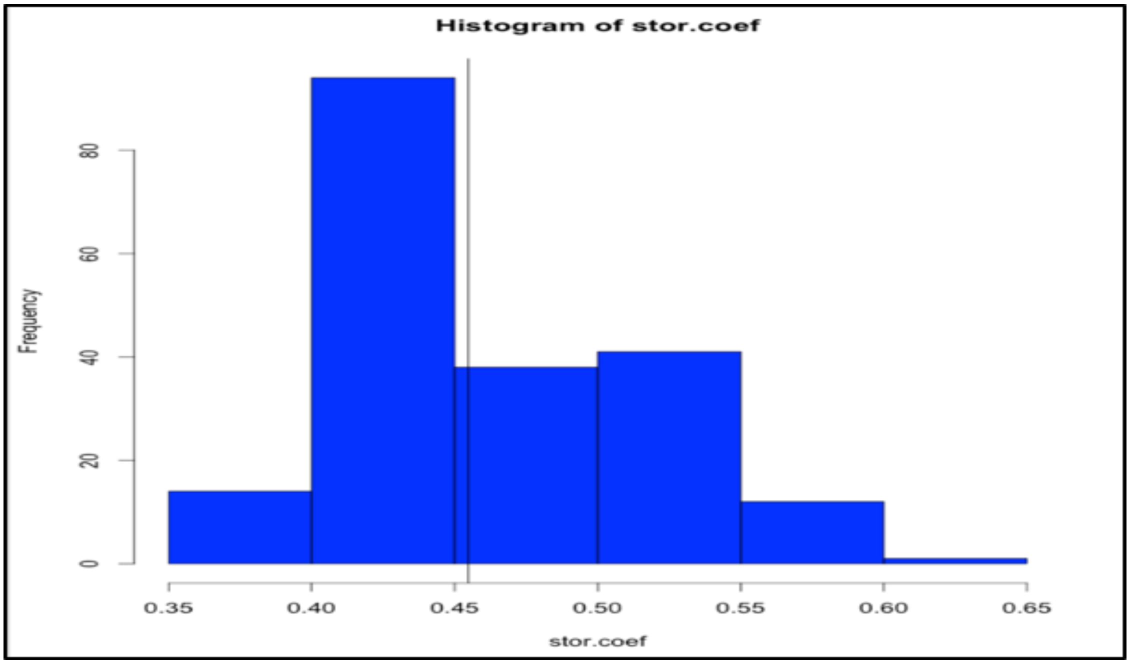


Figure 3.7.2.2: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.99) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
ING Groep



Credit Agricole

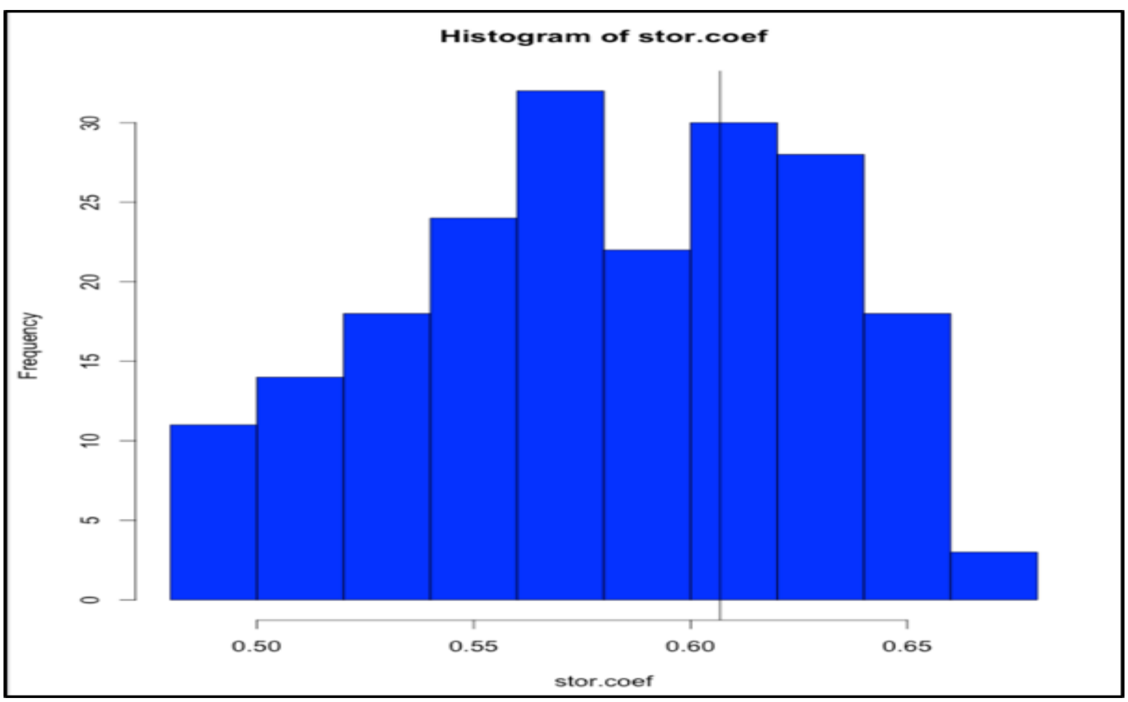
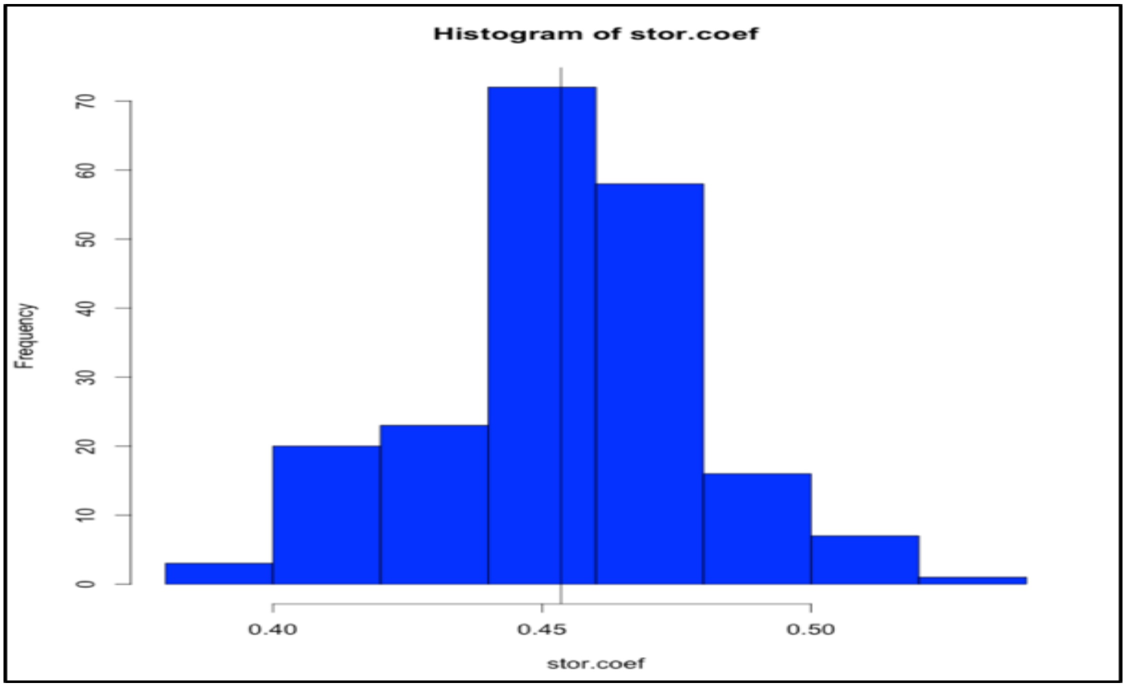


Figure 3.7.2.2: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.99) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
Aegon



AXA

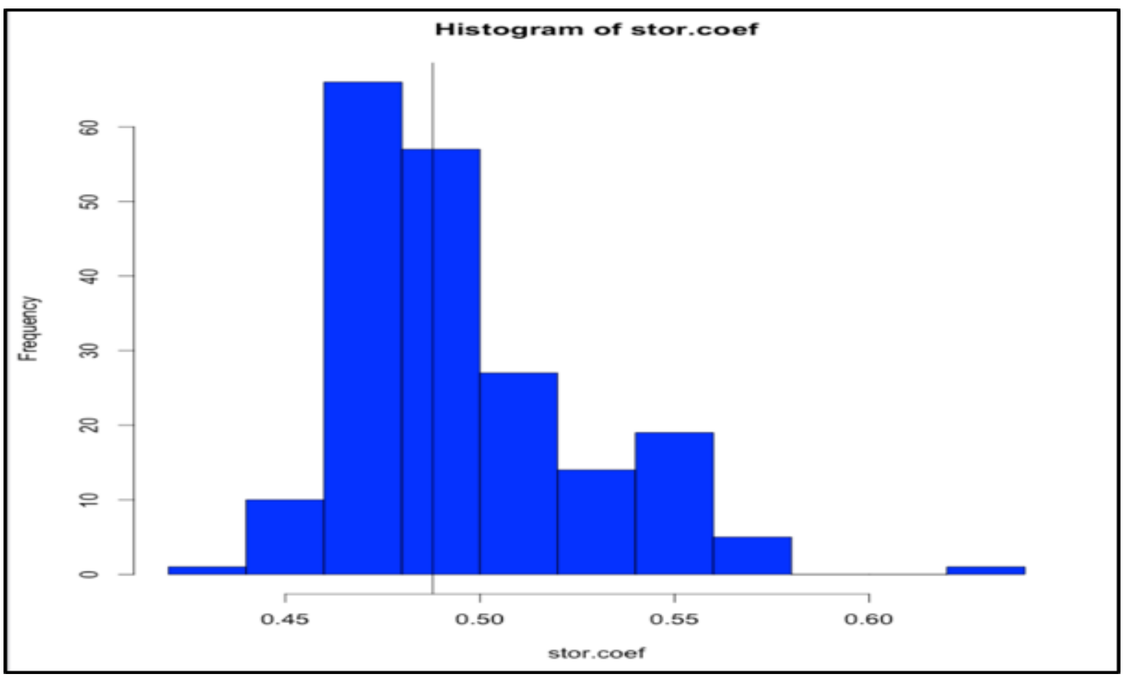
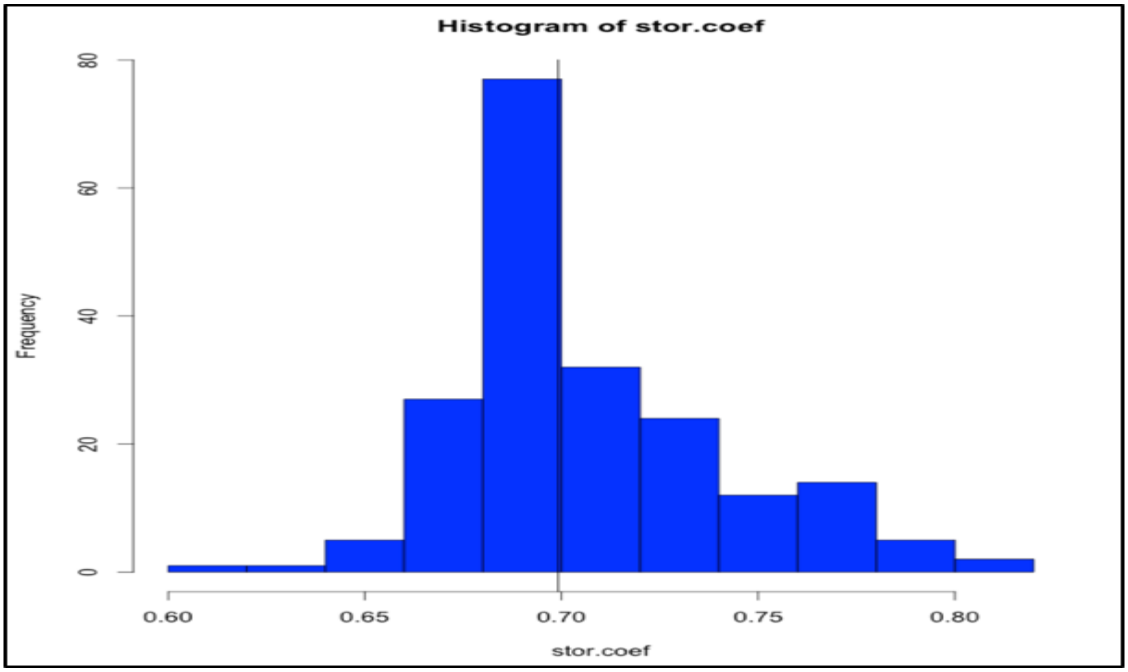


Figure 3.7.2.2: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.99) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
BBVA



Paribas

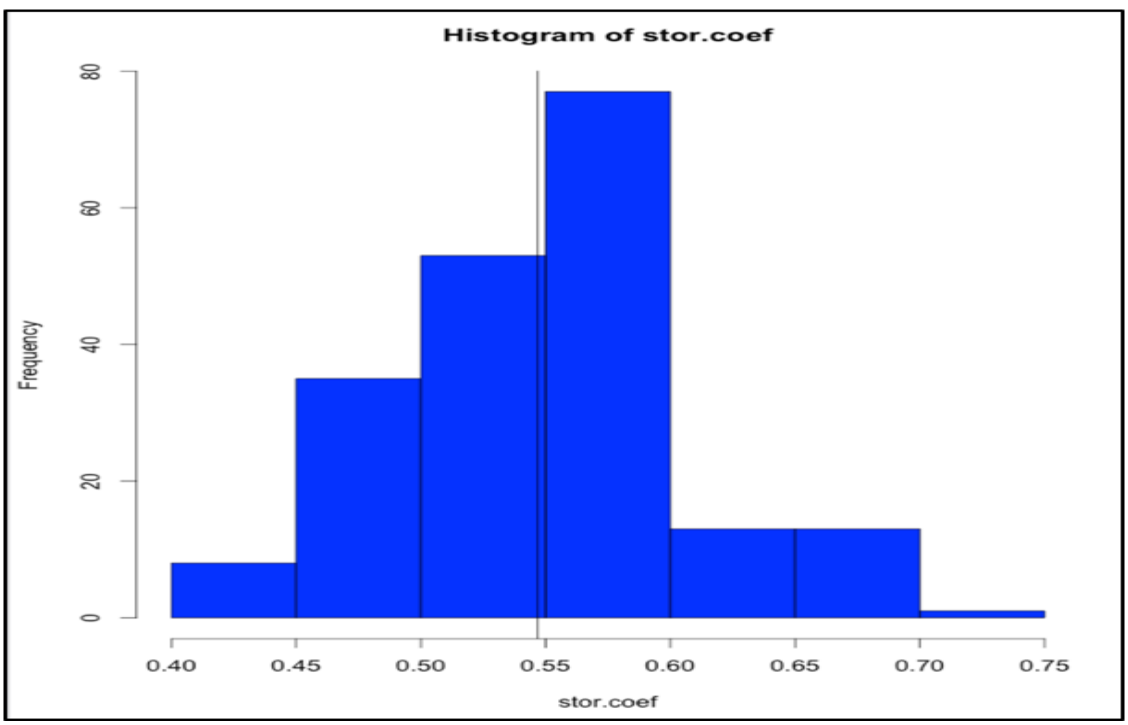


Table 3.7.2.1: P-Values of the Bootstrapped Distributions at tau = 0.95.

Company	P-Value
ING Groep	0.52
AXA	0.50
Credit Agricole	0.48
BBVA	0.43
Aegon	0.44
Paribas	0.52

Table 3.7.2.2: P-Values of the Bootstrapped Distributions at tau = 0.99.

Company	P-Value
ING Groep	0.45
AXA	0.51
Credit Agricole	0.37
BBVA	0.45
Aegon	0.58
Paribas	0.54

3.8 Concluding Remarks

At the very least, it is encouraging that some of the findings of this investigation are consistent with those of the published paper by Castro and Ferrari (2014). That is, despite the use of a mostly different data set and time frame, some of the institutions identified as major contributors are consistent in both papers. In the absence of more substantive data in relation to company size and regular, informative, balance sheet categories, inferences and implications for regulatory capital can still be made. The model itself is intuitive and in this case highlights the importance of considering both country of origin and the financial sector in which the financial institution is based. Furthermore, consideration should be given to the differing degrees of impact when referring to a 1% or 5% financial system VaR – individual institutions ranked outside of the top 10 at tau of 0.95, fall into it at tau of 0.99. Add to that the need to regularly reflect on systemic risk contributions given the changing conditions in the underlying markets – evidenced by the change in magnitude in the Delta-CoVaR figures during the 2008 to 2015 data period.

In recent studies, most do highlight the overall systemic importance of banks and both Adrian and Brunnermeier (2011) and Castro and Ferrari (2014) attempt to rank them relative to each other.

However, in both cases, the ranking process does not provide particularly useful information, indeed, very few banks can actually be ranked according to their systemic risk contribution on the basis of Delta-CoVaR at a particular point in time. This paper does not attempt any kind of “modelled” ranking process other than ranking on the basis of the size of the Delta-CoVaR figure, but, nevertheless, it does yield important observations in relation to non-bank financial institutions and country impacts – neither of which are highlighted by the previously mentioned authors. Given the impact of the AIG failure on the financial system, this paper subsequently suggests that greater emphasis should be placed on the role of insurance companies in any financial crisis. They are a significant institutional player in the markets and I suggest that stricter rules in relation to regulatory capital should not appear to be biased towards the banks. Insurance companies generally have significant weightings within financial indices and exposures to them should be more carefully managed. Perhaps the insurance companies themselves could have a weighting applied to their regulatory capital base consistent with their weighting in the primary financial market index. The latter could also be considered on a country basis given that the research highlights that only a few countries monopolise the top ten Delta-CoVaR figures at *both* the 5% and 1% levels based on the entire sample – France, Italy, Spain and the Netherlands, with 2 representatives from the UK in the top 10 at tau = 0.95. Furthermore, the Delta-CoVaR comparative method for highlighting systemic significance is a statistical tool that regulatory bodies could apply in conjunction with their existing scoring methods. The data in this chapter highlights certain consistencies in the UK banks deemed to be systemically significant at the global and UK level, perhaps, therefore, Delta-CoVaR could be applied as an alternative measure. Although ex-ante, it can be applied to data sets with regular updates, unlike the current scoring methods applied in CRD IV.

Chapter 4:

Application of the Absorption Ratio to Illustrate Connectedness and Interlinkages

4 Application of the Absorption Ratio to Illustrate Connectedness and Interlinkages

4.1 Introduction

Chapter 3 illustrates the importance of considering the impact of risk contagion and interlinkages when measuring exposures to systemic risk through VaR. If a financial institution falls into a state of distress, Delta-CoVaR identifies the subsequent impact on the whole financial system. Given that the distress of a single institution does appear to affect the wider financial system, this is an example of risk contagion and spreading. As previously indicated in chapter 1, the latter occurs due to interlinkages or interconnectedness within the system. Therefore, in order to substantiate the findings in chapter 3, I seek to provide evidence of the connections that exist between financial institutions leading to the propagation or spreading in a crisis. This is done through application of the Absorption Ratio (AR), as proposed by Kritzman et al (2010). They suggest that this ratio captures the existence and extent of any financial linkages and highlight the greater severity of the "spreading" effect when the links are strong. Furthermore, a low AR suggests markets are less tightly coupled whereas a high ratio suggests the opposite – in the latter case a greater proportion of the assets' returns are explained by a certain number of key components. The analysis is performed using ten UK and European stocks, from the banking and insurance sub-sectors and constituents of the MSCI financials' sector index. The data is applied to assess how closely the AR follows the path of the relevant market index and whether there is a discernable pattern or relationship between the two. Rather than investigating the linkages between all industries within a given market index, I am exploring the fragility just of the financials' sector and thereby focus only on the asset returns of financial firms.

The chapter is structured as follows. Section 4.2 presents relevant literature in relation to factor analysis and, in particular, Principal Components Analysis (PCA), a strand of research incorporating the AR. In addition, I discuss instances of the application of the AR. Within section 4.3, the data and its characteristics are discussed. The concepts of Eigenvalues and Eigenvectors are presented in section 4.4, along with their application in deriving the AR. I present the results and inferences in section 4.5 and end with concluding remarks in section 4.6.

4.2 Relevant Literature

4.2.1 Factor and Principal Components Analysis

When explaining variations in asset returns or, indeed, economic data sets, factor or Principal Component models can be utilised. In either case, ascertaining an appropriate number of factors or components is presented in the literature. For example, Connor and Korajczyk (1993), present evidence of one to six factors through interpretation of non-zero eigenvalues relating to a sample covariance matrix. Most recently, Ivanov et al (2017) identify two factors as capturing 95.4% of the variability in a specified set of US stock returns, with 80 to 90% generated from a single factor. Likewise, Bai and Ng (2007) suggest the presence of two factors when investigating the variation in monthly returns of 8,436 stocks traded on the NYSE, AMEX and NASDAQ. Interestingly, Hallin and Liska (2007) split their US economic data set into two sub-samples – 1960 to 1982 and 1983 to 2003. In the former case, three factors are identified and one factor in the later sub-sample – both indicating a low number of factors driving the US economy. Consistently, low numbers of factors are identified as the key drivers (see Ahn and Horenstein (2013)), perhaps due to the tight coupling that exists between markets as a whole and within sectors and perceived increased correlations.

In relation to PCA, it can be described as a method used to identify sets of correlated variables that can subsequently be combined linearly into a set of components. In essence, it provides a means to explain correlations between variables (asset returns) through some linear combinations of the variables where the latter capture the variability in the original data set. A key objective of the technique is to identify as small a set of components as possible, where the latter also account for as much of the variation in the correlated variables as possible. Of all of the components, the first one accounts for the most variation in the original variables, the second accounts for the next largest amount of variation but which is also uncorrelated with the first component. Subsequent components account for less and less variation in a descending manner and none of them correlate with any of the preceding components. It is a non-parametric type of analysis where each component is assigned an eigenvalue. The largest eigenvalues are attached to those components that explain the greatest proportion of the variation in the original variables and they are presented in descending order (the largest eigenvalue being associated with principal component number 1).

4.2.1.1 Applications of PCA

The use of PCA techniques can be found in several areas outside of finance. For instance, within genetics they are applied to determine the existence of genetically distinct sub-groups within a population set (see Patterson, Price and Reich 2006). Applications in scientific spheres are very common, particularly within physics specialisms and medical research. For example, understanding the surface properties of asteroids and variations in the degrees of weathering amongst asteroids of different size (see Koga et al 2018) or within medical research in understanding variations in success rates in lung cancer patients undergoing radiotherapy treatments (see Ellsworth et al 2017). Clearly, PCA is applied in a very diverse range of contexts, where a recognised advantage is in its ability to analyse large data sets.

With regards finance, a common application relates to the financial markets. Some research relates to specific asset classes and instruments, for example, applications to yield curves and resulting forward curves and variations in their movement through ascertaining components. According to Laurini and Ohashi (2015), the application of PCA in this context yields mixed results and is deemed to perform more effectively when the correlation matrices are based upon longer term data sets. Contrary to this, Barber and Copper (2010) indicate with greater success that PCA isolates more than 90% of the total variation in the yield curve for US Treasury Securities. They also indicate the ease of application of the technique - the components are "observable" given that they are constructed from linear combinations of data, which in itself is observable and clearly defined. From a risk management perspective, it is clearly useful to understand the dynamics in the shifts and variations of a yield curve.

When discussing financial crises, the application of PCA is widespread. In several instances, it is used to investigate spreading across markets. Upon identifying a prominent component in relation to a given region's returns, it can be applied in a Dynamic Conditional Correlation (DCC) model to estimate the impact of the dominant component on the returns of a different region. For example, Yiu et al (2010) present a finding of spreading from the US to the Asian markets following a shift in the DCC just prior to the start of the 2008 crisis. Similarly, Martinez and Ramirez (2010), apply PCA to assess the extent of market reactions across certain Latin American countries. Having identified the first principal component, it is then applied in ARCH-GARCH volatility models to analyse volatility across markets in the region – in this instance there is only a mild increase in market sensitivities to shocks as opposed to an extreme reaction. In terms of markets as a whole, Pukthuanthong and Roll (2009) isolate principal components and apply them in regressions on various country index returns to assess the degree of integration across international markets. The indicator used for inference on this occasion is the R-squared from the regression.

It appears that the PCA is applied in many cases to first isolate the principal components underlying the correlations in returns. Subsequently, the latter are applied in further modelling processes to understand the extent and / or existence of risk contagion. However, PCA can also be used in simply assessing how well the components explain variation in asset returns during times of financial crisis. Billio et al (2012) illustrate that a single component explains a greater proportion of the total variation in returns during such crises because firms are tightly coupled during such periods. This is consistent with Kritzman et al (2010) in relation to the Absorption Ratio and the next section presents relevant literature in the area of PCA and the AR.

4.2.2 Literature in Relation to the Absorption Ratio

The AR is a relatively recent advancement in approach relating to investigation of interlinkages. However, certain studies do apply or extend upon Kritzman et al (2010). An extension is provided by Reyngold et al (2015). The latter only include financial firms in their data set and their subsequent Credit Absorption Ratio (CAR) incorporates an additional component to reflect the risk of failure of the said firms within their data. Their results are broadly consistent in so far as the individual financial firm returns tend to be closely linked during times of distress and reflected in the higher values of the CAR at such times. Preparation of this ratio is rather data intensive and reliant upon accurate measures or proxies for monthly book values of both debt and equity. Furthermore, it assumes that debt levels are relatively stable over medium term horizons, when, in fact, a characteristic of certain financial institutions prior to the financial crisis was the use of short term debt requiring regular refinancing.

Dumitrescu (2015) applies the ratio in a predictive capacity in relation to an early warning indicator of forthcoming turbulence in the markets of the European Union. Indeed, it is suggested that its predictive capacities are actually applied within industry in relation to rebalancing portfolios - if the ratio suggests tight coupling amongst assets and increased susceptibility to bad news in the broader markets, then rebalance to more defensive asset classes (see Goyal 2014). The latter findings are also promoted by the Portfolio Management industry professional body, the CFA, in their recent publications (see Kritzman 2014). However, given that individual asset management strategies are not a matter of public record, it is difficult to assess the actual extent of its use. In applying it to the data in this chapter, at the very least, further evidence is provided in relation to its validity in signaling linkages.

4.3 The Data

As mentioned in section 4.1, in exploring the fragility of the financials' sector, the focus is just on financial stocks across the banking and insurance sub-sectors within Europe. Therefore, the data set differs from that of Kritzman et al (2010). The latter apply a market wide index incorporating 632 stocks across a variety of large and mid-cap US stocks and 51 sub-industries. I incorporate 10 stocks from within the MSCI Europe Financials' Sector index where the stocks chosen account for over 40% of the weightings of all stocks in the index. There are 900 daily return observations for each stock - HSBC Holdings, Banco Santander, Paribas, Allianz, UBS, BBVA, Lloyds, Barclays, Prudential, and ING. The market index is the MSCI Europe Financials' Sector Index and all of the daily observations are collected for the period 30th December 2005 to 12th June 2009. This allows for incorporating sufficient time periods pre-financial crisis and also the time-frame following the crisis when the underlying market index starts to recover – from March 2009. In relation to the daily observations for return, it is derived as follows:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{4.1}$$

Where: p_t refers to the closing price of the stock or index at time t.
p_{t-1} refers to the closing price of the stock or index at time t-1.
r_t refers to the daily return of the stock or index at time t.

All data is sourced from Bloomberg and the summary statistics for the stocks and index are presented in table 4.3.1. The mean daily return in each case is close to zero and the impact of the 2008 crisis is reflected in the minimum return values for each variable. Augmented Dickey-Fuller tests are produced, for 1 to 10 lags in table 4.3.2 and all of the time series indicate stationarity.

Table 4.3.1: Summary Statistics for Stock Variables and Nominated Market Index.

	HSBC	Santander	Paribas	Allianz	UBS
Mean	-0.01085	-0.00308	-0.00434	-0.00650	-0.0541
Median	0.0000	0.0000	0.0000	0.0000	0.0000
Max	15.5148	23.2161	20.8968	19.4921	31.6614
Min	-18.7788	-11.9418	-17.2430	-12.9928	-17.2139

Table 4.3.1 cont’d: Summary Statistics for Stock Variables and Nominated Market Index.

	BBVA	Lloyds	Barclays	Prudential	ING	Market
Mean	-0.01773	-0.0561	0.00397	0.0633	-0.01614	-0.04067
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	22.0259	30.3454	25.2347	23.4568	29.2433	16.0399
Min	-12.7795	-33.9480	-24.8464	-20.0000	-27.4839	-9.8446

Table 4.3.2: ADF tests for Stock Variables and Nominated Market Index at 1 to 10 lags

	HSBC	Santander	Paribas	Allianz	UBS
1 lag	-29.6375*	-28.7452*	-27.0368*	-29.7439*	-29.4869*
2 lags	-25.0955*	-24.4628*	-24.8896*	-23.9711*	-25.6528*
3 lags	-20.8081*	-20.5336*	-20.6317*	-18.9890*	-22.1427*
4 lags	-18.4708*	-19.0587*	-19.0020*	-18.9318*	-19.8048*
5 lags	-18.3841*	-17.0540*	-17.8355*	-17.1769*	-18.9323*
6 lags	-16.3363*	-15.8188*	-17.3884*	-15.9228*	-18.1326*
7 lags	-14.8635*	-15.1684*	-15.8632*	-14.3038*	-16.3678*
8 lags	-14.0897*	-14.5235*	-15.2712*	-13.8153*	-14.2962*
9 lags	-13.5885*	-13.9113*	-14.2249*	-13.4396*	-13.1934*
10 lags	-13.5424*	-13.2921*	-13.7288*	-12.7183*	-13.2103*

Note: Critical values of -3.43, -2.86, -2.57. * denotes test statistic < critical values at all levels.

Table 4.3.2 cont'd: ADF tests for Stock Variables and Nominated Market Index at 1 to 10 lags

	BBVA	Lloyds	Barclays	Prudential	ING	Market
1 lag	-28.2832*	-26.5454*	-26.3700*	-31.1088*	-28.2755*	-28.4825*
2 lags	-23.4308*	-22.4408*	-22.6686*	-27.1607*	-24.8617*	-24.3880*
3 lags	-20.0129*	-18.9723*	-19.3143*	-21.0917*	-20.8565*	-19.8685*
4 lags	-18.5631*	-18.7637*	-18.2028*	-20.9042*	-18.9262*	-18.8846*
5 lags	-17.0573*	-18.4707*	-18.0698*	-20.2356*	-17.4280*	-17.7456*
6 lags	-15.9146*	-17.9940*	-17.3072*	-16.8913*	-15.3486*	-16.2391*
7 lags	-15.3991*	-17.5633*	-16.7939*	-15.3235*	-13.9018*	-15.0126*
8 lags	-14.7386*	-16.1846*	-14.4821*	-14.0162*	-13.2297*	-14.0283*
9 lags	-13.9369*	-14.3095*	-13.6645*	-13.2138*	-12.9712*	-13.3302*
10 lags	-12.7559*	-13.2877*	-13.1145*	-13.0608*	-12.4902*	-12.9091*

Note: Critical values of -3.43, -2.86, -2.57. * denotes test statistic < critical values at all levels.

4.4 Methodology

4.4.1 The Absorption Ratio

The AR is defined as the proportion of the total variation in the returns of a set of assets explained by a finite set of non-zero eigenvectors. According to Kritzman et al (2010), it is represented by the following expression:

$$AR_t = \frac{\sum_{i=1}^{n} \sigma_{Ei}^2}{\sum_{j=1}^{N} \sigma_{Aj}^2} \tag{4.2}$$

Where: AR_t refers to the absorption ratio at time t;
N = number of assets;
n = number of "non-zero" eigenvectors;
σ_{Ei}^2= variance of the i^{th} non-zero eigenvector;
σ_{Aj}^2= variance of the j^{th} asset.

The eigenvectors are derived specifically in relation to a covariance or correlation matrix of returns of a set of assets. The first eigenvector represents a particular linear combination of weights of each asset's return. Subsequent eigenvectors depict linear combinations of the weights orthogonal to the preceding eigenvector and the proportions of the variation in the asset returns that they represent or explain reduce in value for each subsequent eigenvector. Furthermore, each subsequent eigenvector seeks to explain the variation in the asset returns not explained by the preceding eigenvectors. For this data set daily absorption ratios are estimated for the entire data set where the associated correlation matrices and eigenvectors are derived on an EWMA[16] basis from a rolling window of returns of 365 days.

4.4.2 Eigenvectors and Eigenvalues

According to Tsay (2010), in applying PCA to identify the sources of variations in the returns of ten assets, we have a k-dimensional vector of asset returns denoted by R_A:

$$R_A = (r_1, r_2, r_{3,} \dots \dots \dots .. r_k)' \qquad where\ k = 10, \tag{4.3}$$

which, for this data set, is equivalent to:

$$R_A = (r_{HSBC}, r_{Sant}, r_{Paribas,} r_{Allianz}, r_{UBS}, r_{BBVA}, r_{Lloyds}, r_{Barc}, r_{Pru}, r_{ING})' \tag{4.4}$$

A given portfolio of assets incorporates linear combinations of the asset weights and we can depict the weights as the following vector for assets 1 to k, where:

$$W_i = (w_{i1,} w_{i2}, w_{i3}, \dots \dots .. w_{ik})' \tag{4.5}$$

$and\ w_{i1}$ refers to the weight attached to asset 1

Furthermore, the return of a multi-stock portfolio, "i", containing k stocks and where each stock is assigned a weight w_i, can be depicted as:

$$y_i = W_i R_A \equiv \sum_{j=1}^{k} w_{ij} r_j \tag{4.6}$$

where: w_{i1} refers to the weight attached to the 1st stock in portfolio "i", r_1 is the return associated with stock 1 in portfolio "i", w_{ik} is the weight attached to stock k in portfolio "i" and r_k is the return associated with stock k in portfolio "i".

[16] EWMA – Exponentially Weighted Moving Average – giving more weight to the more recent return observations in each 365-day window versus that given to the older return observations.

According to section 4.2.1, an objective of PCA in this context is to provide a means to explain correlations between stock returns through some linear combinations of the said returns, where the latter capture the variability in the original data set. Therefore, if we refer to principal component 1 (PCA1) of R_A as being associated with a particular linear combination of the stock returns, then:

$$y_1 = W_1 R_A \equiv \sum_{j=1}^{k} w_{1j} r_j \tag{4.7}$$

Furthermore, PCA1 is intended to identify the particular linear combination of the stock returns that represents the maximum variability in such returns i.e. Var (y_1) is maximised.

The second principle component (PCA2) of R_A, is denoted by the following linear combination:

$$y_2 = W_2 R_A \equiv \sum_{j=1}^{k} w_{2j} r_j \tag{4.8}$$

where: $Var(y_1) > Var(y_2)$ and $\mathrm{Cor}(y_2, y_1) = 0$

The vector of the linear combination of weights associated with a principal component is otherwise referred to as an eigenvector, E. Therefore, for the i^{th} component:

$$W_i \equiv E_i = (e_{i1,} e_{i2}, e_{i3}, \ldots \ldots . . e_{ik})' \tag{4.9}$$

$$y_i = E_i R_A \equiv \sum_{j=1}^{k} e_{ij} r_j \tag{4.10}$$

For PCA1:

$$W_1 \equiv E_1 = (e_{1,1,} e_{1,2}, e_{1,3}, \ldots \ldots . . e_{1,k})' \tag{4.11}$$

and, $$y_1 = E_1 R_A \equiv \sum_{j=1}^{k} e_{1j} r_j \tag{4.12}$$

An eigenvalue is associated with each principle component and eigenvector and denoted by λ_i (i^{th} component), λ_1 (1st component), λ_2 (2nd component). The eigenvalue / eigenvector pairs are as follows:

i^{th} component: (λ_i, E_i), 1st component: (λ_1, E_1), 2nd component: (λ_2, E_2)

and: $\lambda_1 > \lambda_2 > \lambda_3 > \lambda_4 \dots\dots\dots\dots\dots. > \lambda_i > 0$

The proportion of the total variation in the stock returns explained by each component is the ratio of the individual eigenvalue divided by the sum of all of the eigenvalues for all of the identified components. Furthermore, only non-zero eigenvalues and vectors are considered. The larger the eigenvalue for PCA1, the greater the proportion of the variability in the asset returns that is being explained by it. Larger values for λ_1 indicate that a single component is impacting asset returns collectively, more than any others. As the influence of a single component increases, the implication is that all stocks are being impacted by it and this is because the stocks are tightly coupled. If this was not the case, then one component would not have such a significant influence across the board.

4.4.3 Evaluating the Absorption Ratio

Periods of tighter coupling are measured by significant changes in the absorption ratio over time. Such shifts can indicate market fragility and returns across institutions moving together. If they are moving in a unified manner, any negative shocks can impact institutions in the same way. I calculate a moving average of the daily AR on a two-week basis and subtract the moving average of the AR over one year – then I divide by the standard deviation of the moving average of the AR over one year.

$$\Delta AR = \frac{(AR_{2-week} - AR_{1-year})}{\sigma AR_{1-year}} \tag{4.13}$$

The shift is then compared with the percentage price movements in the market index to identify any indications of spikes in the AR being followed by a significant downturn in the market.

4.5 Results and Inferences

4.5.1 Movement in the AR versus the Market Index

Figure 4.5.1.1 illustrates the movements in the underlying market index for the time-frame 30th December 2005 to 30th December 2011. There appears to be a period of sustained recovery in the index from March 2009 to February 2011. Accordingly, movement in the AR is observed from 30th December to June 2009 to identify how closely the AR tracks the index and to identify any potential early-warning indications of market downturns.

In generating the Absorption Ratios, there appear to be four key components identified as explaining the variability in the returns of the four stocks, with, as expected, principal component 1 (PCA1) explaining the greatest proportion of that variability. Furthermore, PCA1 > PCA2 > PCA3 > PCA4. Summary statistics relating to the explanatory proportions assigned to each component are presented in table 4.5.1.1.

Figure 4.5.1.1: Graph of Price Movements in the MSCI Financials Sector Index

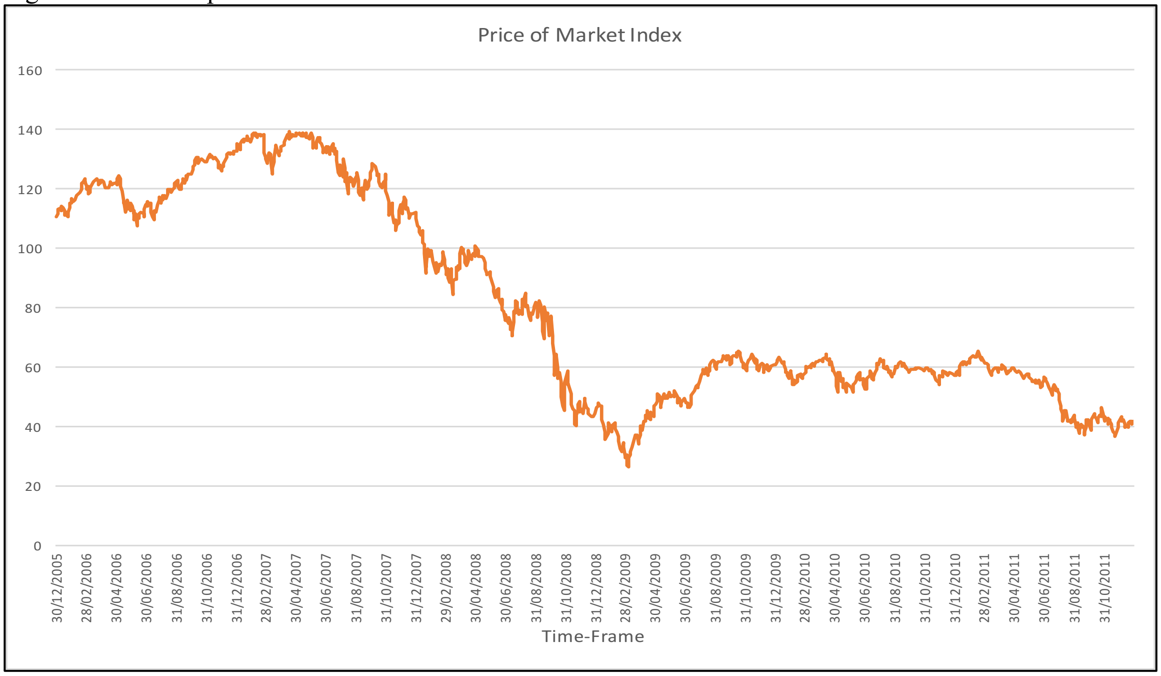


Table 4.5.1.1: Summary Statistics for Each Principal Component – Assigned Explanatory Proportions

	Principal Component 1	Principal Component 2	Principal Component 3	Principal Component 4	Total Proportion Across Top 4 Components
Maximum	0.7931	0.09385	0.0703	0.0742	0.9068
Minimum	0.5252	0.0451	0.0245	0.0288	0.7464
Standard Deviation	0.06472	0.008826	0.007764	0.00859	0.04191
Mean	0.67246	0.07051	0.05013	0.04336	0.83646

The maximum variation explained by four key components is almost 91%, with 80% being attributed to PCA1 i.e. 80% of the variation in all of the stock returns is explained by PCA1. The minimum variation explained by four components is 75% with 52.5% relating to the first component. Given the explanatory provided in section 4.2.1, this result in itself is not surprising – markets in general now appear tightly coupled, and, subsequently, a very small number of risk factors can be found to drive variations in asset returns. Furthermore, one factor alone can conceivably explain 70 to 80 percent of that variation in a single sector.

In terms of further analysis, PCA1 is used when considering the movement of the AR in relation to the underlying market index. A comparison of the movement through time in the proportions attributed to PCA1 and to all four components is depicted in figure 4.5.1.2. It reflects a steady increase in the AR to a peak in the period July 2007 to September 2008 – coincidental with the building financial crisis.

Figure 4.5.1.2: Proportion of the Variability in the Stock Returns Explained by PCA1 and All Four Components

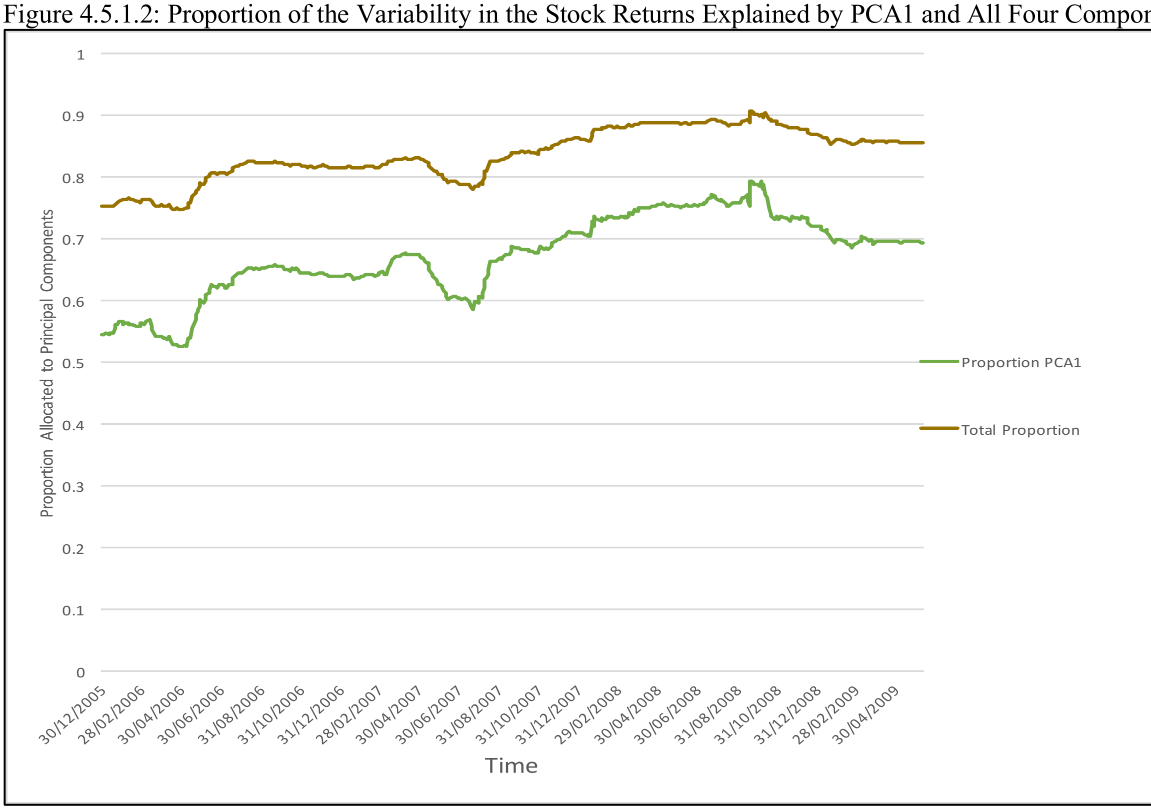
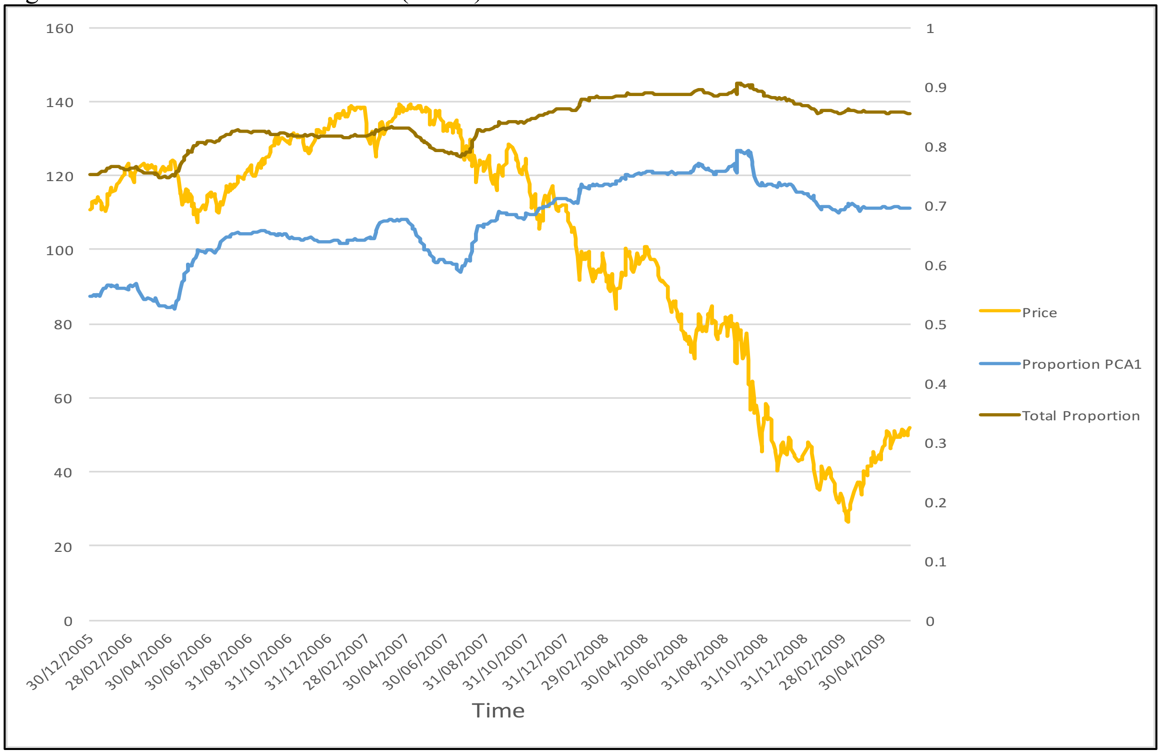


Figure 4.5.1.3 depicts the movement in the AR versus that of the underlying market index. In the earlier years, there does appear to be an inverse relationship between the level of the AR and the level of the underlying market index. It also presents that the AR increases quite significantly to its highest level during the financial crisis and fairly consistent with the fall in the price of the market index. However, it does not appear to be a pre-emptive or early-warning relationship and

in some instances seems to be lagging the index – for example the incline in the AR in 2007 is not exactly coincidental with the drop in the index, which begins in May 2007. A further contraindication occurs from October 2008, when the AR actually starts to reduce but the market index continues to fall quite significantly. This anomaly could be indicative of the sample size and applying just ten stocks in the analysis – future research could incorporate all stocks within a given market index, consistent with Kritzman (2010). Furthermore, as the market begins to recover in March 2009, the AR levels off and does not reduce significantly from its highest point. As indicated by Kritzman at al (2010), this could imply remaining fragility within the sector – in remaining quite high the AR reflects that the same component is explaining a large proportion of the movement in all ten stocks. Therefore, it can be argued that the stocks are still tightly coupled in their behaviour.

Figure 4.5.1.3: Movement in the AR (PCA1) versus the Price Level of the MSCI Financials' Sector Index



4.5.2 Inferences from Shifts in the AR

The graphs are not indicative of the AR being useful as an early warning indicator of pending turmoil in the markets. However, certain inferences can be made through a comparison of shifts in the AR with the largest daily movements in the market index. For the worst percentage downturns in the market index, Table 4.5.2.1 presents the proportion of those occasions when there is a corresponding 1-sigma increase in the AR.

Table 4.5.2.1: Number of times a % Drop in the Index is Accompanied by a 1-sigma increase in the AR

	>1% drop in the index	>1.5% drop in the index	>2.0% drop in the index	>2.5% drop in the index	>3.0% drop in the index	>3.5% drop in the index
% of cases with at least a 1-sigma increase in the AR	54%	55%	51%	47%	40%	39%

The figures in table 4.5.2.1 are further evidence of the AR not being an early warning indicator of pending turmoil. In addition, it appears that the more severe the drop in the index, the lower the likelihood of an accompanying significant shift in the AR. However, at the very least, the shifts are consistent with figure 4.5.1.3. Some of the largest downturns in the market occur from October 2008, when, intuitively, you would expect a corresponding increase in the AR – what actually occurs is a reduction and levelling off in the AR, thereby explaining the low number of occurrences of at least a 1-sigma shift.

4.6 Concluding Remarks

For the given data set, this empirical analysis is consistent with Kritzman et al (2010) in so far as the graphs themselves do not provide clear evidence of the AR acting as any kind of early warning indicator of market turmoil. Indeed, there appears a satisfactory inverse relationship with the market index but, at times, it appears to be lagging in nature. Furthermore, during the most significant period of the financial crisis, the AR eventually decreases and levels off. What Kritzman et al (2010) do provide is evidence that the majority of the worst market downturns are preceded by at least a 1-simga upward shift in the AR. They argue that the latter can then be used in day to day portfolio management to signal the need to switch between asset classes or reduce weightings in sectors that are deemed to be tightly coupled. For the data analysed in this chapter, the shifts in the AR do not infer similar findings – only half of the worst market downturns are preceded by at least a 1-sigma shift in the AR. However, the objective of this chapter was to substantiate the findings in chapter 3, through seeking to provide evidence of the connections that exist between financial institutions leading to the propagation or spreading in a crisis. In applying the Absorption Ratio, its consistently high level indicates the existence and extent of financial linkages and highlights the greater severity of the "spreading" effect when the links are strong.

Furthermore, a high AR suggests the stocks are more tightly coupled whereby a large proportion of the assets' returns are explained by a single key component, PCA1. In this case, the proportion of the variation in the assets' returns explained by one principal component remained between 0.70 and 0.80 for much of the time. Such findings are important because the underlying data set encompasses financial institutions across two subsectors and a number of countries within Europe – thereby illustrating the extent of financial linkages.

Chapter 5: Applying a Bayesian Network to VaR Calculations

5 Applying a Bayesian Network to VaR Calculations

5.1 Introduction

In their survey of 31 quantitative measures of systemic risk, Bisias et al (2012) identify a research method in relation to Network Analysis in general. Specifically, a small network of factors is defined as being systemically important in relation to their impact on the returns of a set of financial entities. Where each factor is regarded as commonly significant to each entity. Existing research tends to focus on applying such networks in the assessment of how events spread through a financial system and interconnectedness in general. For example, simulating how the failure of one bank can trigger the domino effects across many and whether certain ones are more resilient to the default than others. Indeed, Chan-Lau et al (2009) and the IMF (2009a) use network models to assess the impact of a failing bank on others given respective exposures between them. While the specified networks *can* be used to quantify VaR losses at the bank level following the original default and subsequent domino effect, this is rarely discussed. This chapter thereby attempts to contribute to existing literature by applying a Bayesian Network of two factors to determine their impact on the returns of three UK banking stocks and their three-stock portfolio in terms of VaR.
Identification of the factors isn't necessarily intuitive but existing literature in relation to financial linkages and reasons for the spread in financial crises, can be drawn upon. For example, in chapters 1 and 2, issues around market liquidity are raised and I suggest that the latter is an important factor when assessing impacts on stock returns. There are certain market indicators of the overall health and strength of liquidity among financial institutions, such as the LIBOR-OIS spread in the UK and the TED-spread in the US. Indeed, Hull and White (2013) suggest that, despite both spreads being stable and largely ignored pre-financial crisis, both are now used as the summary indicators of liquidity following their extreme movements in 2007 and 2008. Subsequently, in order to define

a workable network, I begin with just two factors – firstly the aforementioned liquidity factor and secondly, the influence of the wider financials' sector on each stock. In terms of visualising the network, there are a series of nodes connected to each other by edges – where the latter represent the relationship between the nodes. Thereafter, the resulting model is used to simulate returns' data for each bank and their three-stock portfolio and quantify their respective 5% and 1% quantiles - where the latter can be used in a VaR calculation and be reasonably applied as an alternative to the RiskMetrics approach. The network itself is specified using Bayesian techniques as presented by Scutari and Denis (2015) and Shonoy and Shonoy (2000).

This chapter is divided into several parts. Section 5.2 highlights the recent literature in relation to Network Analysis and measuring systemic risk but also general applications of Bayesian Networks (BN). Section 5.3 presents the data, identifying each time series and summary statistics. Application of the BN to this data set in modelling stock returns is presented in section 5.4 – including specification of the network, the underlying probability distributions and tests of conditional independence and model specifications. The process for simulating stock returns is also discussed. Results are detailed in section 5.5 – specifically the respective significance of the partial correlations, the parameters of the BN model specifications and the comparisons of the simulated summary statistics and quantiles versus those of the actual returns. The chapter ends with concluding remarks.

5.2 Relevant Literature

A network rationale has been applied in a diverse range of social and behavioural science contexts. For example, considering how large corporations differ in the extent to which they offer support or assistance to local communities in which they have a presence. Corporate and social responsibility dictates that they should be actively involved in their communities but how much of that is influenced by the activities of other corporations? A network can be used to model how such community involvement is influenced by their interactions and relationships with other corporations. Likewise, in any decision-making process involving several individuals or groups, a network approach can be used to understand how individuals within a group influence each other in the decision-making process. A common underlying theme is how the units within the network interact – they are not viewed in isolation. According to Faust and Wasserman (1994, pp. 7):

> "The network perspective differs in fundamental ways from standard social and behavioural science research methods. Rather than focus on attributes of autonomous individual units, the associations among these attributes, or the usefulness of one or more attributes for predicting the level of another attribute are theorised and modelled through a network."

Such associations and relationships can be witnessed in many other contexts, certainly within science, finance and economics. Indeed, the interlinkages and interconnectedness between financial institutions and within financial systems, as presented in chapter 1, are directly relevant. From a scientific perspective, networks are used in a variety of contexts – engineering, biology, ecology, medicine. For example, they are used to analyse ecological systems and specifically how the food chains and ecosystems are connected. In relation to public health, Luke and Harris (2007) present their use in the study of how diseases are transmitted, specifically HIV and AIDS. Applications in medical and microbiology contexts are popular – for instance, Barabasi et al (2011) use network-based methods in genetics to identify molecular linkages and subsequent gene mutations.

Of course, this thesis is interested in their application in finance and economics, specifically in relation to systemic risk. Given the focus on liquidity issues, particularly in the interbank markets in chapter 1, the work of Chan-Lau et al (2009), as previously mentioned, is particularly relevant. In using network models, they highlight the impact of institutional failure when there are exposures within such markets – where the network illustrates the domino effect between connected banks when exposed to a failing institution. Furthermore, Bilio et al (2010) go beyond the inter-bank markets in their application of Granger-causality networks to the study of interconnectedness between a variety of investor sub-groups, specifically hedge funds, banks, brokers and insurance companies. Likewise, the IMF (2012) assess linkages within the global OTC derivative markets and the identification of systemically important financial intermediaries. In each case, as suggested by Battiston et al (2012), there is no widely accepted, single methodology to determine the systemically important nodes or factors within the network – it is very much linked to interpretation and the underlying data set (financial instrument, market, sub-sector, region). The latter indicates the degree of qualitative judgement required in defining the network in the first instance. Nevertheless, Allen and Babus (2009, pp. 367) argue that network analysis can assist our understanding of financial systems and specifically risk contagion, given the interconnections revealed by the 2008 financial crisis. Furthermore, aside from defining the network itself, they suggest that it can then be usefully applied in formulating a regulatory framework for supervising financial institutions, an objective entwined within this thesis. Consistent with Allen and Babus (2009), Hu at al (2012) allude to the deficiencies of pre-existing methods in measuring exposures to systemic risk, given the significant widespread losses post 2008. Accordingly, they too suggest a network-based approach as a more appropriate and accurate measurement and monitoring process.

Unsurprisingly, there has been an upsurge in interest in research in this area - several empiricists more recently identify the importance of the use of network analysis. For example, Markose et al (2012) apply a network to investigate the connections between banks in the Credit Default Swap market – the latter market being identified as a key determinant of substantial losses in 2008. In some cases, there is the final realisation that, given their widespread application in science and medicine, surely analogies can be drawn in finance. For instance, Haldane and May (2011) apply the dynamics of food webs in an ecological context to modelling the stability of a given financial system. A leading empiriscist in relation to network theory, Kimmo Soramaki, has several publications focusing on applications in finance. For instance, Soramaki et al (2016) simplify complex network structures in order to filter or highlight the most important determinants of correlations between returns of European stocks. Earlier studies focus on the interbank payment systems and, specifically, the creation of a network representing how payments are transferred between financial institutions (see Soramaki et al (2007)). The latter highlights the key players in such markets and the degrees of connectedness between them but also makes the point that the "minor" players in the market are also connected to the tightly connected core of major players. Given the financial linkages, the network illustrates the severe impact of any subsequent disruption to it and the issues arising in transferring and accessing capital through the interbank markets. This is further explored by Soramaki and Cook (2013) and Soramaki and Langfield (2016), whereby, following a bank's failure, the disruption to the payment network is identified along with systemically important institutions and resulting impacts on individual network participants. A common theme, once again, is the interbank markets. It is clear that, whether referring to literature immediately following the crisis or more recently, that theme remains - the liquidity issues generating from within the inter-bank markets. Similar to Chan-Lau et al (2009), Krause and Giansante (2012) also focus on the exposures within those markets and use a network of connected banks to model how failure of one spreads through the network. Subsequently, a factor encompassed within the BN defined in section 5.4, relates to liquidity – denoted by a particular spread quoted in the inter-bank markets.

Bayesian Networks are encompassed within the framework of network analysis and incorporate graphical theories and conditional dependencies between variables in the graphical network. Within the literature there are several instances of the application of BNs to data sets, not necessarily from a finance perspective. Indeed, almost any event conditional on the probability of a prior event can be analysed using this concept. In geographical and environmental studies, for example, a BN is used to evaluate flood plains and the extent of flooding given certain extreme prior events such as changes in sea level and improvements in coastal defenses (see Narayan et al 2018). They are also applied within the context of Social Corporate Responsibility in assessing a corporation's likely compliance with child labour regulations across their supply chain network. The BN is used to determine the likelihood of breaches to such regulations using available data on suppliers, their employee demographics and the frequency of child labour incidents (see Thoni et al 2018). From a medical research perspective, BNs are also readily applied. For instance, in assessing links between patients diagnosed with clinical depression and variability in their heart rates and also in identifying important factors in relation to survival rates from lung cancer (see

Anisa and Lin 2017).

From a risk management perspective, there is ample literature relevant to their application, particularly in relation to operational risk. Essentially, various factors are identified and inserted into the BN with estimates made of associated loss distributions resulting from the various risk factors. According to Cowell et al (2007), such techniques can be applied in insurance settings when assessing the financial impact of cases of fraud upon the insuring company and thereby in the setting aside of adequate regulatory capital in relation to such cases. From a banking perspective, Aquaro et al (2010) present their application in relation to losses sustained through cases of failed internal processes, human error, IT failures and certain litigation cases. The factors leading to the losses in each situation become part of the BN and the associated loss distributions are generated. Clearly, there is some degree of subjectivity in identifying the break-downs in the internal processes or human interventions leading to loss making errors but, this is a commonality across all BNs, regardless of the arena in which they are being applied. In all cases, analogies can certainly be drawn with VaR and the need to ascertain the loss quantiles from subsequent returns' distributions. Indeed, Martin et al (2005) apply BNs to specifically model the severest loss inducing events, referred to as the long tails or unexpected losses from an operational loss perspective – similar of course to the 1% and 5% VaR scenarios. Of direct relevance to this chapter is the research of Hager and Andersen (2010) who seek to model loss severity across all activities of a financial institution and not just from an operational perspective. This is done through the identification of influencing factors – which I argue can be liquidity and market based.

Consistent with chapters 3 and 4, other literature identifies the importance of contagion through BN modelling of default probabilities resulting from financial linkages – for example Giudici and Spelta (2016) and Chong and Kluppelberg (2017). Furthermore, interconnectedness is also examined through the effect of exposures within the interbank markets. A BN is applied to model individual institutional liabilities within that market and the subsequent impact on other banks in the event that a participant in the network defaults. Gandy and Veraart (2016) illustrate that the BN can be used to stress test differing assumed levels of inter-bank liabilities and likelihood of default conditional on another bank defaulting. At the very least it indicates the importance of the inter-bank markets once more, if not specifically assessing the impact on bank returns' distributions. Despite all of the literature under review, there appears to be a lack of focus on application of BNs specifically in modelling stock returns and losses applied in VaR estimations. This chapter seeks to provide a workable alternative approach to modelling both, whilst also considering the importance of the entire financials' sector and the reducing liquidity within the inter-bank markets.

5.3 The Data

In order to produce the appropriate network, and specifically assess the impact of the chosen factors, the data is gathered for the period 14th December 2000 to 29th June 2012 – implying 2,914 daily observations for each variable. This timeframe incorporates the financial crisis but also adequate periods pre and post crisis. The data is sourced from Bloomberg (excluding the portfolio) and the variables are as follows, where the daily return and the daily percentage change ensure stationarity:

- Daily returns for Barclays Bank stock;
- Daily returns for Lloyds Bank stock;
- Daily returns for HSBC stock;
- Daily percentage change in the 3-month Sterling LIBOR vs. 3-month sterling

overnight index swap spread (OIS);

- Daily returns for the MSCI Financials' Sector Index:
- Daily returns for the three-stock portfolio.

The data set representing the impact of the market on each stock is the MSCI Financials Sector Index, within which all three banking stocks have a percentage weighting. The chosen liquidity factor represents the daily percentage change in the difference between the 3-month sterling LIBOR rate and the 3-month sterling overnight indexed swap rate. Overnight indexed swaps are interest rate swaps whereby a fixed rate of interest is exchanged for floating and the latter is the average of a daily overnight rate. In deriving the floating rate payment, the intention is to replicate the aggregate amount of interest that would be earned from rolling over a sequence of daily loans at an appropriate overnight rate. Given that we are applying a 3-month time-frame, it implies rolling over a sequence of daily loans, for 90 days at an overnight rate – where that rate is determined in the UK by the Bank of England and referred to as SONIA (sterling overnight index average). The 3-month sterling libor rate is the average interest rate at which a selection of banks lend British pounds to one another for a period of 3 months.

In deriving the daily returns for each bank and the nominated market index, the following is applied:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{5.1}$$

Where: p_t refers to the closing price of the stock or index at time t.
p_{t-1} refers to the closing price of the stock or index at time t-1.
r_t refers to the daily return of the stock or index at time t.

With regards the three-stock portfolio, we begin with a total initial investment of £30,000,000, split equally between the stocks – representing an equal weighting of 33.33% and £10,000,000 invested in each stock in the portfolio. As the prices of the component stocks change in value, their weights in the portfolio change, as does the notional value of the portfolio. The daily return on the portfolio is derived as follows:

$$r_{port,t} = \frac{Notional\ Value_{port,t} - Notional\ Value_{port,t-1}}{Notional\ Value_{port,t-1}} \tag{5.2}$$

The notional value of the portfolio each day is derived as follows:

$$NV_{port,t} = \left[(1 + r_{t,B}) \times NV_{t-1,B}\right] + \left[(1 + r_{t,H}) \times NV_{t-1,H}\right] + \left[(1 + r_{t,L}) \times NV_{t-1,L}\right] \tag{5.3}$$

Where: $NV_{port,t}$ refers to the notional value of the 3-stock portfolio at time t.
$r_{t,B}$ refers to the daily return of Barclays at time t;
$NV_{t-1,B}$ refers to the notional value of investment in Barclays at time t-1;
$r_{t,H}$ refers to the daily return of HSBC at time t;
$NV_{t-1,H}$ refers to the notional value of investment in HSBC at time t-1;
$r_{t,L}$ refers to the daily return of Lloyds at time t;
$NV_{t-1,L}$ refers to the notional value of investment in Lloyds at time t-1.

The graphs are presented for each time series of returns' data in figures 5.3.1 to 5.3.5 plus an indication of how the LIBOR-OIS spread moved in the period under review in figure 5.3.6. The former illustrate stationarity in the time series and significant volatility in the 2007-2008 time-frame of the financial crisis. In relation to the LIBOR-OIS spread, there are noticeable peaks associated with certain key events. For instance, in September 2007, the spread reached 85 basis points in response to the Bank of England announcing emergency funding to rescue Northern Rock and, three months later as the crisis began to unfold, reached an all-time high of 108 basis points.

At its worst, following the insolvency of Lehman Brothers in the autumn of 2008, the spread was around 300 basis points. The Augmented Dickey Fuller tests at various lags in table 5.3.1, indicate the stationarity in the time series of returns for each variable:

Table 5.3.1: Augmented Dickey Fuller tests for each variable

	LIBOROIS	Market	Barclays	HSBC	Lloyds
1 Lag	-47.0068*	-38.5601*	-36.5903*	-41.127*	-38.3401*
2 lags	-40.925*	-33.0937*	-30.3896*	-33.8231*	-31.5608*
3 lags	-33.7785*	-27.1927*	-25.4275*	-28.0044*	-27.0613*
4 lags	-29.4624*	-26.0475*	-23.5451*	-25.5346*	-26.8292*
5 lags	-24.4209*	-24.5432*	-21.8710*	-24.7745*	-25.0340*
6 lags	-22.0149*	-22.1618*	-20.8262*	-21.6686*	-23.5661*
7 lags	-20.7559*	-19.8397*	-19.6280*	-19.5955*	-21.9056
8 lags	-18.6174*	-18.4505*	-17.2105*	-18.2352*	-20.2806*
9 lags	-17.3829*	-17.9787*	-17.1425*	-17.7670*	-18.0233*
10 lags	-16.8473*	-17.4447*	-16.3418*	-17.9372*	-16.7871*

Note: Critical values of -3.43, -2.86, -2.57. * denotes test statistic < critical values at all levels.

Figure 5.3.1: Time Series of Barclays Daily Returns.

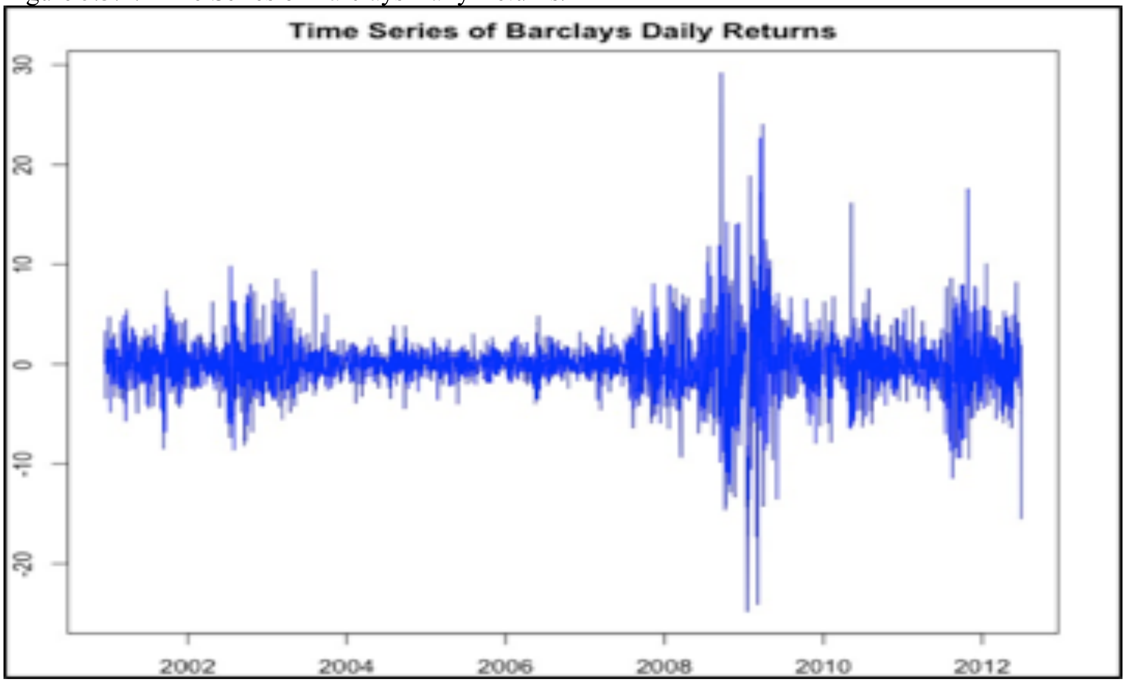


Figure 5.3.2: Time Series of HSBC Daily Returns.

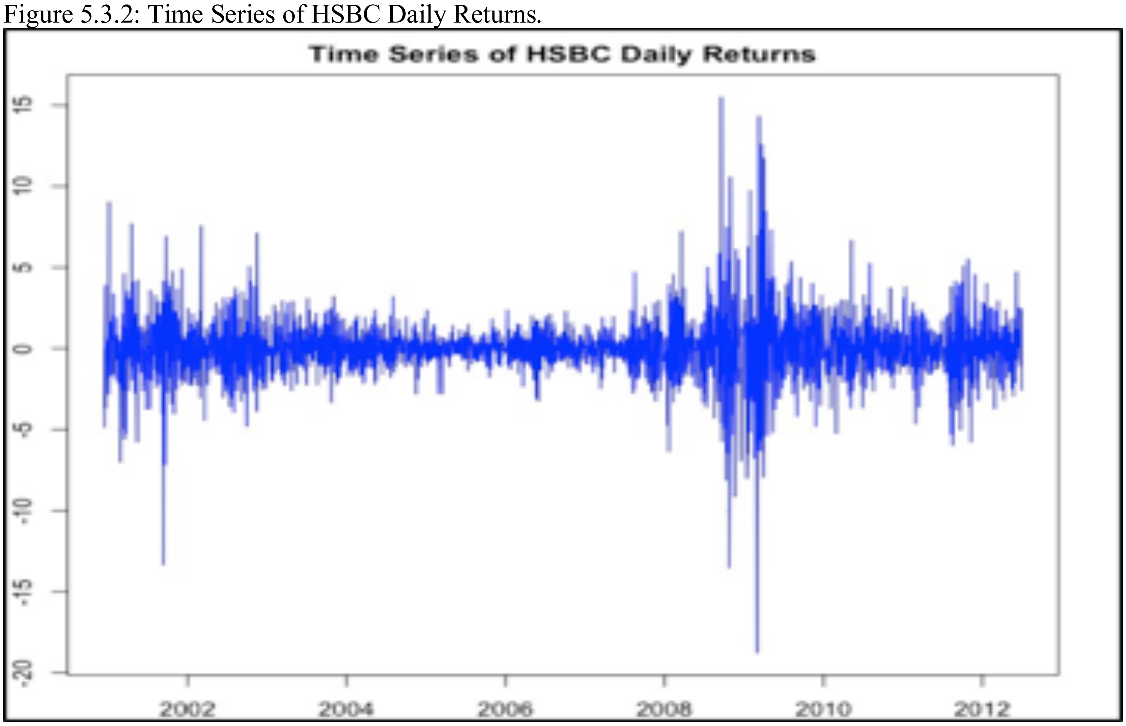


Figure 5.3.3: Time Series of Lloyds Daily Returns.

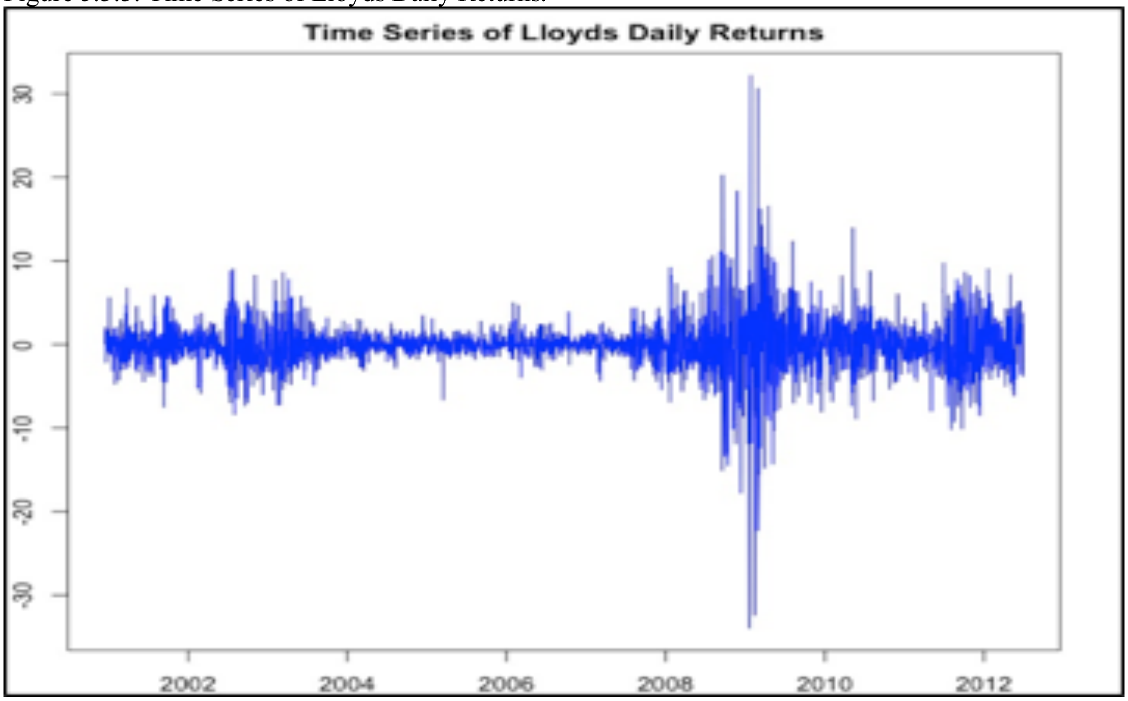


Figure 5.3.4: Time Series of Market Daily Returns.

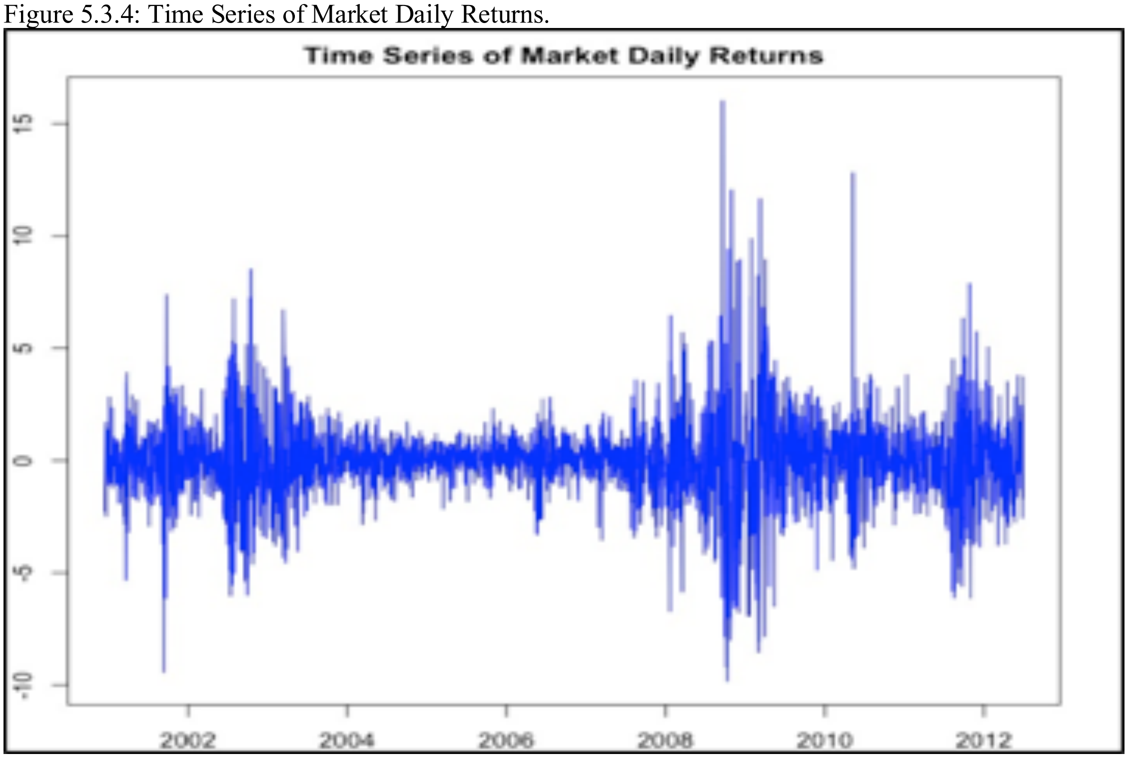


Figure 5.3.5: Time Series of Portfolio Daily Returns.

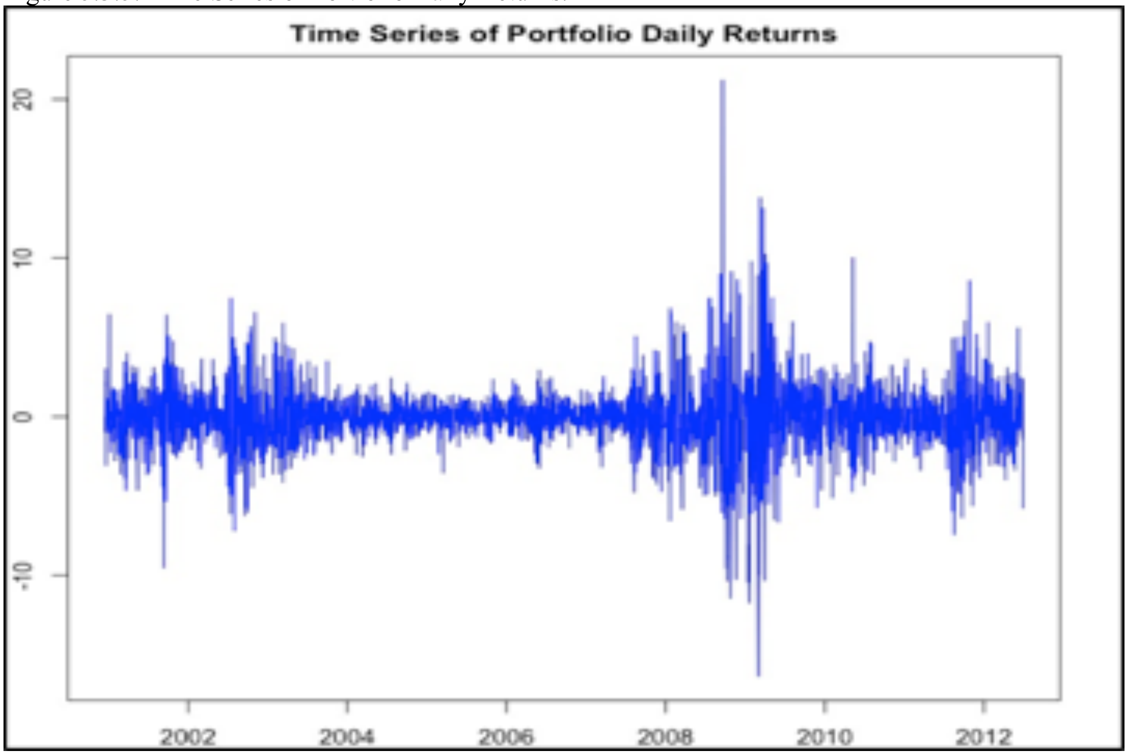


Figure 5.3.6: Graph of the LIBOR-OIS spread.

In relation to the summary statistics presented in table 5.3.2, the mean daily returns appear close to zero and the minimum returns reflect the substantial losses during the financial crisis.

Table 5.3.2: Summary Statistics for LIBOROIS % change, Market, Stock and Portfolio Daily Returns.

	LIBOROIS	Market	Barclays	HSBC	Lloyds	Portfolio
Max	141.6667	16.0399	29.2357	15.5148	32.2159	21.2197
Min	-67.6692	-9.8446	-24.8464	-18.7788	-33.9479	-16.3841
Median	0.0000	0.0000	-0.0501	0.0000	-0.0504	-0.0076
Mean	0.7612	-0.0223	-0.0076	0.0024	-0.0429	-0.0183

5.4 Application of a Gaussian Bayesian Network to Continuous Data

5.4.1 Proposed Network Structure

In applying Bayesian Networks to modelling data, they are useful in the situation where information is incomplete and uncertainty exists over the key determinants of the dependent variable. According to Shenoy and Shenoy (2000), there is initially a degree of qualitative judgement and subjectivity in specifying the factors to include in the graphical representation of the network. However, in subsequently applying quantitative tests of the model and simulating posterior data distributions, certain inferences can be made about its validity. In this instance the proposed network is being applied to model portfolio returns based on certain inputs or factors added to it. Furthermore, given the simulated posterior return distribution of the portfolio, a cut-off return is derived for use in a VaR calculation, where the cut-offs refer to the 1% and 5% quantiles of the said distribution.

In specifying a Gaussian Bayesian Network, I am modelling continuous data sets with the underlying assumption of multivariate normality. With regards the variables defined in section 5.3, I denote them with the following abbreviations:

- Daily returns for Barclays Bank stock→B

- Daily returns for Lloyds Bank stock→L
- Daily returns for HSBC stock→H
- Daily percentage change in the 3-month Sterling LIBOR vs. 3-month sterling overnight index swap spread (OIS) →S
- Daily returns for the MSCI Financials' Sector Index→M
- Daily returns for the three-stock portfolio→P

Prior to tests of conditional independence, the suggested relationships between variables are as follows:

B is directly influenced by S and M, L is directly influenced by S and M, H is directly influenced by S and M and P is directly influenced by B, L and H. Consequently, the proposed relationships are defined as follows:

$$\{S, M\} \rightarrow B, \ \{S, M\} \rightarrow L, \quad \{S, M\} \rightarrow H, \ \{B, L, H\} \rightarrow P \tag{5.4}$$

5.4.2 Proposed Network Graph and Probability Distribution

Based upon the above suggested relationships between the variables a graphical representation can be defined – as presented in figure 5.4.2.1. It is referred to as a directed acyclic graph (DAG) and contains a series of arcs and nodes. The former reflect the direct dependencies between variables and the latter reflect the variables within the network. Each variable or node has its own distribution – for example, 'B" has a distribution or time series of daily returns. If an arc exists from one variable to another, the latter variable is dependent upon the former, otherwise known as the parent. The overall distribution, encompassing all variables and suggested dependencies, can be depicted as follows:

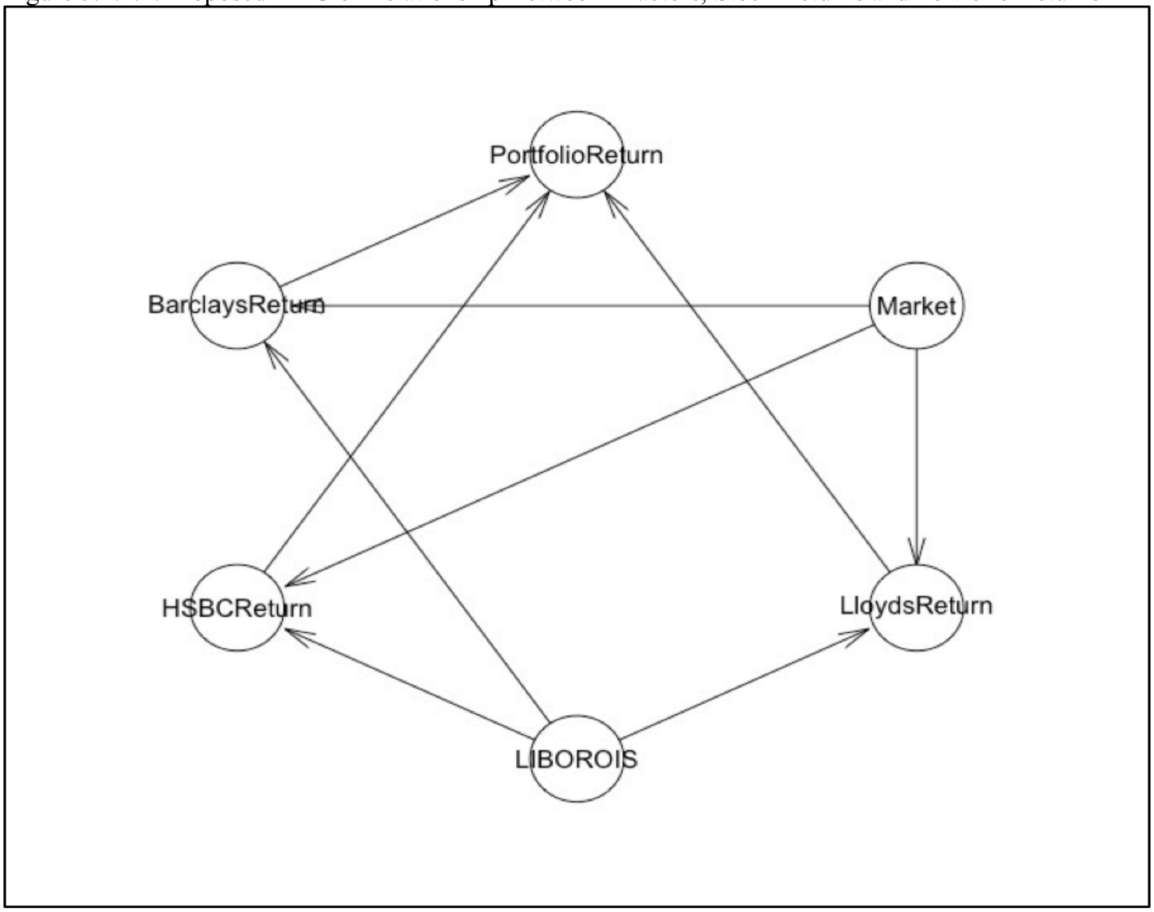
$$\Pr(S, M, B, L, H, P) = \Pr(S)\Pr(M)\Pr(B|S, M)\Pr(H|S, M)\Pr(L|S, M)\Pr(P|B, H, L)$$

Furthermore, the distributions at each node can be expressed as:

$$B|S = s, M = m \qquad H|S = s, M = m \qquad L|S = s, M = m \qquad P|B = b, H = h, L = l$$

where, the distribution at each node is conditional on the values of its parents. Rather than determining the overall joint probability distribution encompassing all variables from the outset, the Bayesian Network (BN) approach breaks the distribution into sub-groups and derives the local distributions at each node. Scutari and Denis (2015) present that specifying a joint probability distribution is rather difficult and complex given the numbers of variables and correlations requiring estimation. Therefore, the BN overcomes this modelling issue through specifying the local distribution at each node conditional on the values of the parents.

Figure 5.4.2.1: Proposed DAG of Relationship Between 2 factors, Stock Returns and Portfolio Returns



5.4.3 Algebraic Representation of the DAG

The conditional relationships for each of the nodes of the three stocks may be specified as an equation, consistent with the assumptions that 1) every node follows a normal distribution and 2) the equations represent a Gaussian linear model incorporating an intercept, with the node's parents as the explanatory variables. The specifications in this case, for each factor and stock are as follows:

$$S \sim N(\mu_S, \sigma_S^2) \qquad M \sim N(\mu_M, \sigma_M^2) \tag{5.5}$$

$$B \big| S = s, M = m \sim N(\alpha_B + \beta_{1,B} s + \beta_{2,B} m,\ \varepsilon_B^2) \tag{5.6}$$

$$H \big| S = s, M = m \sim N(\alpha_H + \beta_{1,H} s + \beta_{2,H} m,\ \varepsilon_H^2) \tag{5.7}$$

$$L|S = s, M = m \sim N(\alpha_L + \beta_{1,L}s + \beta_{2,L}m,\ \varepsilon_L^2) \quad (5.8)$$

Where: α refers to the intercepts, β refers to the regression coefficients for the parents, S and M and ε represents the standard deviation of the residuals.

There is no specification for the three-stock portfolio because its subsequent simulated returns are derived using equations (5.2) and (5.3).

5.4.4 Testing for Conditional Independence

As each arc in the DAG encompasses a probabilistic dependence, conditional independence tests can be used to assess whether the data actually supports it. In terms of hypotheses, for each variable, the following conditional dependencies are being tested:

$H_0: B\ is\ independent\ from\ M|S$ versus $H_1: B\ is\ not\ independent\ from\ M|S$

$H_0: B\ is\ independent\ from\ S|M$ versus $H_1: B\ is\ not\ independent\ from\ S|M$

$H_0: H\ is\ independent\ from\ M|S$ versus $H_1: H\ is\ not\ independent\ from\ M|S$

$H_0: H\ is\ independent\ from\ S|M$ versus $H_1: H\ is\ not\ independent\ from\ S|M$

$H_0: L\ is\ independent\ from\ M|S$ versus $H_1: L\ is\ not\ independent\ from\ M|S$

$H_0: L\ is\ independent\ from\ S|M$ versus $H_1: L\ is\ not\ independent\ from\ S|M$

The null hypothesis depicts that B, H or L may be independent from M given S or S given M. If the null is proven, the Beta coefficients in equations 5.6 to 5.8 are equal to zero. Using "B" as an example, through the hypotheses, the partial correlation between B and M given S or S given M, is being tested – denoted by $\rho_{B,M|S}$ or $\rho_{B,S|M}$. The null holds if $\rho_{B,M|S}$ or $\rho_{B,S|M}$ is not statistically different from zero. In the test, the appropriate distribution is a student's t distribution with n – 3 degrees of freedom (where n refers to the total number of observations in each time series of B, H and L and 3 refers to the number of variables in the test e.g. B, S and M).

$$t(\rho_{B,M|S}) = \rho_{B,M|S}\sqrt{\frac{2911}{1-\rho_{B,M|S}^{2}}} \qquad (5.9)$$

The null hypothesis of independence is rejected if the corresponding p-value is less than the 10%, 5% and 1% degrees of significance.

5.4.5 Simulating the Returns' Distributions

Following the independence tests in section 5.4.4, the parameters of equations 5.6 to 5.8 are estimated using the maximum likelihood estimator. Each time-series of bank returns, as the response variables, are regressed on the time-series of the daily percentage change in the LIBOROIS spread and the daily returns in the market index. Having determined the parameters of the models proposed by the DAG in section 5.4.3, they are then used to simulate sets of random variables for each node, B, H and L. Simulation is performed from the BN by generating a sample of random values from the joint distribution of the specified nodes. It is performed following the order implied by the arcs in the DAG – from the parents first, followed by the children (LIBOROIS and the Market being the parents, the 3 banks being the children). For each node, 2,914 random values are generated – depicting estimates of the daily returns for each stock. In each case, the simulation is performed on the basis of both a normal distribution and a student's t-distribution, using the "rnorm" and "rt" functions in R-studio.

5.5 Results

5.5.1 Tests of Conditional Independence

For each of the banks, inverse correlation matrices are produced, which are required for the significance tests and generation of p-values. The resulting correlations are presented in tables 5.5.1.1 to 5.5.1.3.

Table 5.5.1.1: Correlation Matrix for Barclays versus 2 parent nodes

	Barclays Returns	LIBOROIS	Market
Barclays Returns	1.0000	0.0332	0.7818
LIBOROIS	0.0332	1.0000	-0.0827
Market	0.78718	-0.0827	1.0000

Table 5.5.1.2: Correlation Matrix for HSBC versus 2 parent nodes

	HSBC Returns	LIBOROIS	Market
HSBC Returns	1.0000	0.0306	0.7828
LIBOROIS	0.0306	1.0000	-0.0805
Market	0.7828	-0.0805	1.0000

Table 5.5.1.3: Correlation Matrix for Lloyds versus 2 parent nodes

	Lloyds Returns	LIBOROIS	Market
Lloyds Returns	1.0000	0.0192	0.6953
LIBOROIS	0.0192	1.0000	-0.0787
Market	0.6953	-0.0787	1.0000

The respective significance tests for the partial correlations are presented in table 5.5.1.4 In all cases, the bank returns have a significant positive correlation with the market (M) given the daily percentage change in the LIBOROIS spread (S) and we can thereby reject the null hypothesis of independence given the extremely small p-values at all levels of significance. In relation to the conditional dependence between the bank returns and the LIBOROIS variable, given the market returns, there is positive correlation but at a low level. Furthermore, the p-values only indicate significance at the 10% level. However, at that level of significance the null hypothesis of independence is rejected and we can surmise that there is a degree of conditional dependence between daily bank returns and the chosen indicator of liquidity in the financial markets. Thereby, both factors, deemed to be the parents in the DAG, can subsequently be applied in the modelling of the bank returns.

Table 5.5.1.4: Significance Tests of Partial Correlations

	$B \sim S \mid M$	$B \sim M \mid S$	$H \sim S \mid M$	$H \sim M \mid S$	$L \sim S \mid M$	$L \sim M \mid S$
Pearson's Correlation	0.0332	0.7818	0.0306	0.7828	0.0192	0.6953
Degrees of Freedom	2911	2911	2911	2911	2911	2911
P-Value	0.0729*	0.0000***	0.0991*	0.0000***	0.0990*	0.0000***

Note: * denotes significance at 10%, ** significance at 5%, * significance at 10%.

5.5.2 Parameters of the BN Model Specification

Following the Gaussian linear regression for each bank, the respective maximum likelihood estimators are produced and presented in table 5.5.2.1. Values for the intercepts ($\alpha_B, \alpha_H and\ \alpha_L$) and contributions of the parents, as depicted by the Beta coefficients, are provided.

Table 5.5.2.1: Parameters of the BN Model for the returns of each bank

α_B	α_H	α_L	$\beta_{1,B}$	$\beta_{2,B}$	$\beta_{1,H}$	$\beta_{2,H}$	$\beta_{1,L}$	$\beta_{2,L}$	ε_B^2	ε_H^2	ε_L^2
0.0175	0.0174	-0.019	0.0053	1.304	0.0028	0.769	0.0036	1.197	1.95^2	1.15^2	2.32^2

The contributions from the LIBOROIS variable are small but the value of the spread itself is also and percentage changes in the daily returns of any stock are rarely sizeable.

Referring back to equations 5.6 to 5.8, the BN model specifications, following the linear regression, are as follows:

$$B \mid S = s, M = m \sim N(0.0175 + 0.0053s + 1.304m,\ 1.95^2) \quad (5.10)$$

$$H \mid S = s, M = m \sim N(0.0174 + 0.0028s + 0.769m,\ 1.15^2) \quad (5.11)$$

$$L \mid S = s, M = m \sim N(-0.019 + 0.0036s + 1.197m,\ 2.32^2) \quad (5.12)$$

$$S \sim N(0.76, 12.39^2) \qquad M \sim N(-0.0223, 1.88^2)$$

Equations 5.10, 5.11 and 5.12 are then applied in simulating sets of returns for the three bank stocks.

5.5.3 Simulated Data

Following the simulation of time series of returns for each of the three bank stocks and subsequent three-stock portfolio, a comparison is made between the summary statistics of the original, actual data sets and the simulations, applying both a normal and student's t-distribution. Both are presented in tables 5.5.3.1 to 5.5.3.4.

Table 5.5.3.1: Comparison of Summary Statistics – Actual versus Simulated Returns - Barclays

	Barclays Actual Returns	Simulated Returns (Normal Dist'n)	Simulated Returns (t-distribution)
Mean	-0.00759%	-0.02102%	0.06029%
Max	29.2357%	10.45150%	11.02510%
Min	-24.8464%	-9.75948%	-10.64131%
Median	-0.05013%	0.01165%	0.06097%
Stdev	3.13367%	3.14959%	3.25881%

Table 5.5.3.2: Comparison of Summary Statistics – Actual versus Simulated Returns - HSBC

	HSBC Actual Returns	Simulated Returns (Normal Dist'n)	Simulated Returns (t-distribution)
Mean	0.002432%	-0.008251%	0.03320%
Max	15.51481%	6.407118%	7.63505%
Min	-18.77880%	-6.580565%	-7.42987%
Median	-0.00000%	0.038593%	0.07663%
Stdev	1.84544%	1.82093%	2.13113%

Table 5.5.3.3: Comparison of Summary Statistics – Actual versus Simulated Returns - Lloyds

	Lloyds Actual Returns	Simulated Returns (Normal Dist'n)	Simulated Returns (t-distribution)
Mean	-0.04285%	-0.09143%	-0.07486%
Max	32.21586%	10.26661%	10.93075%
Min	-33.94790%	-11.76306%	-11.21700%
Median	-0.007604%	-0.02116%	0.000267%
Stdev	2.13653%	1.61464%	1.802019%

Table 5.5.3.4: Comparison of Summary Statistics – Actual versus Simulated Returns - Portfolio

	Portfolio Actual Returns	Simulated Returns (Normal Dist'n)	Simulated Returns (t-distribution)
Mean	-0.018333%	-0.04074%	0.011784%
Max	21.21970%	6.19230%	6.413994%
Min	-16.38410%	-5.72795%	-5.939262%
Median	-0.007604%	-0.021160%	0.000267%
Stdev	2.13653%	1.61464%	1.802019%

Given that the mean return is expected to be close to zero, in all cases the simulated values are consistent. Furthermore, the simulated standard deviations match the actuals with reasonable accuracy. Of greater relevance is the model's ability to derive meaningful estimates of minimum returns, given the implications for VaR. For each bank and the portfolio, the estimated minimum returns are significantly different from the actual values. However, given the underlying assumption of a Gaussian BN and normality, it will not necessarily correctly evaluate the tails of the distribution. It is encouraging that, when applying a t-distribution, the resulting minima are larger than in the normal case for three of the four data series – consistent with its ability to model tails more effectively. Despite the clear differences in summary statistics, it is important to consider the relative accuracy of the model in relation to quantiles. After all, they are used as the cut-off points in relation to VaR calculations. Given that the most severe maxima or minima values for daily returns occur so infrequently, they are not necessarily an accurate indicator of the most likely maximum daily loss. Thereby, a comparison of the quantiles from the actual returns and the simulated cases are presented in tables 5.5.3.5 to 5.5.3.8.

Table 5.5.3.5: Comparison of Quantiles – Actual versus Simulated - Barclays

Quantile	Barclays Actual	Simulated (Normal Dist'n)	Over / Under Estimates	Simulated (t-distribution)	Over / Under Estimates1
1%	-8.786%	-7.782%	Under	-7.479%	Under
5%	-4.372%	-5.174%	Over	-5.288%	Over
10%	-3.069%	-3.976%	Over	-4.123%	Over
90%	2.939%	3.854%	Over	4.287%	Over
95%	4.785%	5.035%	Over	5.482%	Over
99%	8.641%	7.322%	Under	7.708%	Under

Table 5.5.3.6: Comparison of Quantiles – Actual versus Simulated - HSBC

Quantile	HSBC Actual	Simulated (Normal Dist'n)	Over / Under Estimates	Simulated (t-distribution)	Over / Under Estimates1
1%	-5.279%	-4.215%	Under	-4.718%	Under
5%	-2.546%	-3.065%	Over	-3.529%	Over
10%	-1.835%	-2.382%	Over	-2.774%	Over
90%	1.849%	2.289%	Over	2.752%	Over
95%	2.689%	3.008%	Over	3.615%	Over
99%	5.107%	4.154%	Under	5.035%	Under

Table 5.5.3.7: Comparison of Quantiles – Actual versus Simulated - Lloyds

Quantile	Lloyds Actual	Simulated (Normal Dist'n)	Over / Under Estimates	Simulated (t-distribution)	Over / Under Estimates1
1%	-8.893%	-7.859%	Under	-7.809%	Under
5%	-4.408%	-5.390%	Over	-5.523%	Over
10%	-3.051%	-4.204%	Over	-4.394%	Over
90%	2.920%	3.927%	Over	4.210%	Over
95%	4.468%	5.268%	Over	5.318%	Over
99%	9.079%	7.487%	Under	8.264%	Under

Table 5.5.3.8: Comparison of Quantiles – Actual versus Simulated - Portfolio

Quantile	Portfolio Actual	Simulated (Normal Dist'n)	Over / Under Estimates	Simulated (t-distribution)	Over / Under Estimates1
1%	-5.874%	-3.881%	Under	-4.236%	Under
5%	-3.099%	-2.766%	Under	-2.997%	Under
10%	-2.187%	-2.106%	Under	-2.312%	Over
90%	2.079%	2.027%	Under	2.300%	Over
95%	3.163%	2.641%	Under	2.938%	Under
99%	6.423%	3.582%	Under	4.318%	Under

In all cases, the simulated 1% quantiles from the simulated returns, are less than those based upon the actual time series of returns. Perhaps not surprising given the underlying normal distribution assumption. However, the related simulated 5% and 10% quantiles are larger than those on an actual basis. This implies greater prudence in subsequent VaR estimates due to the left tail being larger in the simulated cases if the quantiles are used as the appropriate cut-off. Despite the under-estimations at the 1% level, the simulated results are still of use in a practical context due to the industry convention of reporting VaRs at the 5% level for individual stocks. The simulated portfolio quantiles are slightly misleading given that they are impacted by the respective weights of the component stocks. They are, nevertheless, comparable to the portfolio actual quantiles at both the 5% and 10% levels.

Application of the t-distribution, allows for a more realistic modelling of the tails. Consequently, in the simulations, the resulting 1% and 5% quantiles for all stocks are even more prudent than in the normal case.

Table 5.5.3.9 illustrates the absolute percentage increases in the 5% and 10% quantiles offered by the simulated results. At the 5% level, the increases in the quantile range from 0.5% to just over 1%. From a regulatory perspective, and the setting aside of regulatory capital based on VaR assessments, an additional 1% would be significant – if we consider the notional values of stocks and equity portfolios.

Table 5.5.3.9: Absolute % increase in 5% and 10% quantiles offered by Simulated Data

	Barclays Normal Dist'n	HSBC Normal Dist'n	Lloyds Normal Dist'n	Barclays t-dist'n	HSBC t-dist'n	Lloyds t-dist'n
5%	0.802%	0.519%	0.982%	0.916%	0.983%	1.115%
10%	0.907%	0.547%	1.153%	1.054%	0.939%	1.343%

Finally, figures 5.5.3.1 to 5.5.3.3 reflect the fitted distributions of the simulated stock returns according to the underlying assumption of normality.

Figure 5.5.3.1: Barclays Fitted Simulated Returns

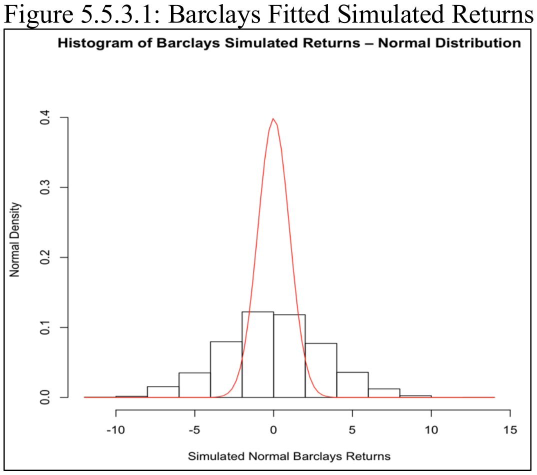


Figure 5.5.3.2: HSBC Fitted Simulated Returns

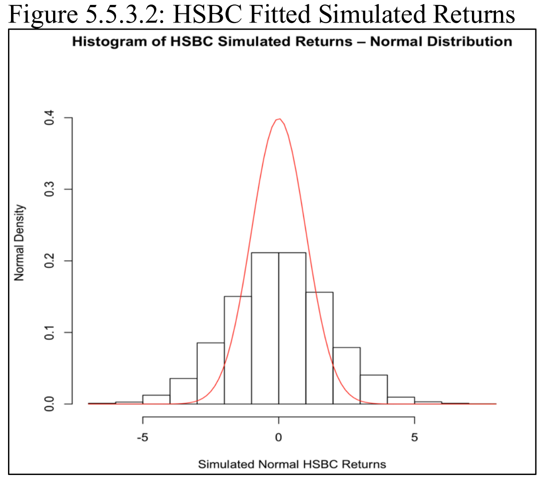
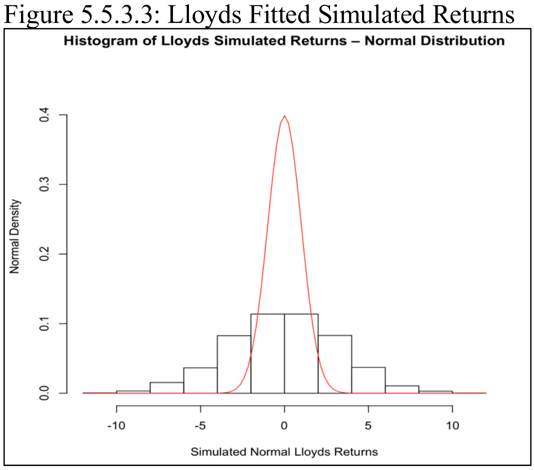
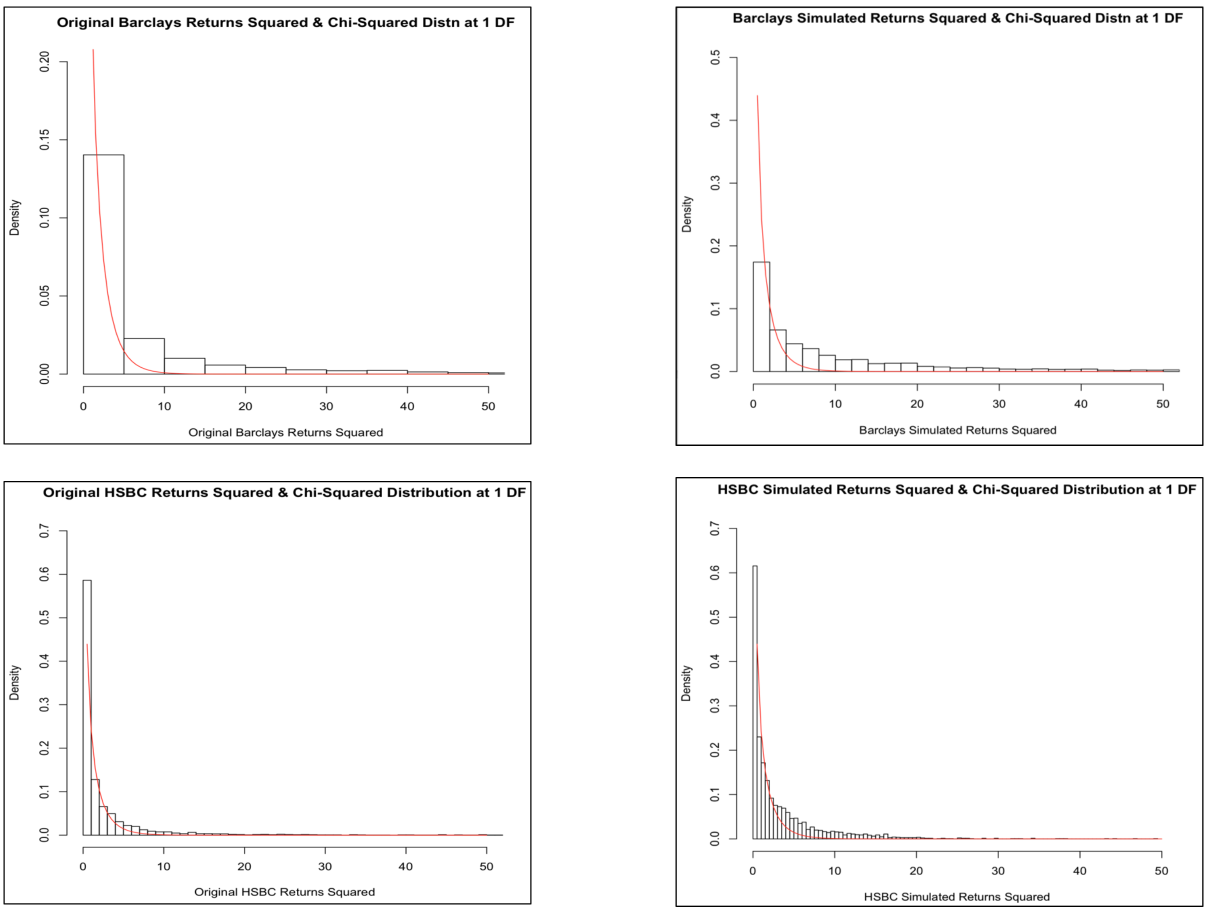


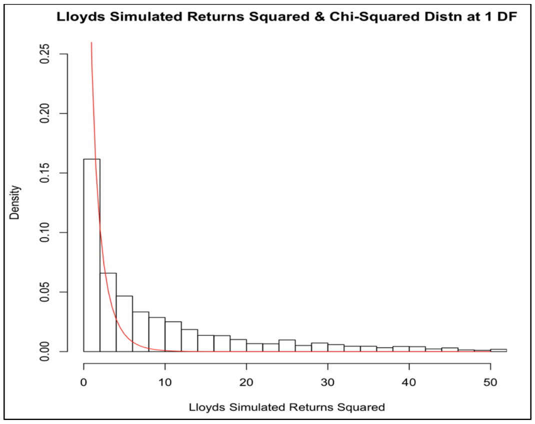
Figure 5.5.3.3: Lloyds Fitted Simulated Returns

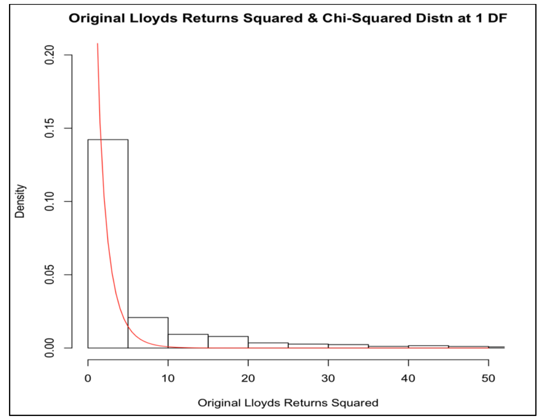


Consistent with the quantiles reflected in tables 5.5.3.5 to 5.5.3.7, the left tails in the fitted distributions reflect the 10%, 5% and 1% levels. For example, the 1% quantile for Lloyds being -7.859% and reflected in the spread of the left-hand side of figure 5.5.3.3. Figure 5.5.3.4 reflects comparisons between the original and simulated returns for each stock on the basis of an assumed Chi-Squared Distribution. In each case, the outcomes are similar.

Figure 5.5.3.4: Comparative Graphs of Original versus Simulated Squared Returns and Chi-Squared Distribution:







5.6 Concluding Remarks

This chapter provided a BN approach to modelling stock returns. The data was sourced from Bloomberg and included time series of daily returns for three UK banks, namely, Barclays, HSBC and Lloyds. A subsequent portfolio was constructed from the three stocks. Using a degree of qualitative judgement, a DAG was constructed using the evidence presented in chapter two with regards factors being important in relation to their impact on stock returns. In this instance, the market and the liquidity factors were selected with the latter being represented by the 3-month LIBOR versus OIS spread.

The DAG suggested conditional dependencies between the factors and stock returns, subsequently verified by conditional independence tests and partial correlations. Whilst low levels of significance were indicated for the liquidity factor, it did still exist and the linear regression models were specified for the returns of each stock. The latter were subsequently used to simulate time series of returns. Summary statistics and quantiles were compared for the actual returns and the simulated returns. Whilst the simulated returns underestimated minimum values, the quantiles were comparable at the 5% and 10% levels. The latter suggests that the underlying Gaussian BN (GBN) could be applied in modelling stock returns and could be further used to estimate quantiles and VaR cut offs. Although it does assume normality, and may be regarded as over-simplifying the modelling issues, its comparable estimations are a positive. An objective in this instance was to suggest a workable alternative to the RiskMetrics approach in deriving VaR. As suggested by Scutari and Denis (2015), a more complex specification may be preferred but relatively simple models often perform better. Indeed, the widely used RiskMetrics approach is convenient to apply and well understood but, I suggest that the GBN is as intuitive and, furthermore, appears to provide prudent estimates for the quantiles used as the cut-offs in VaR calculations. Given that losses were underestimated in the 2008 financial crisis applying VaR techniques of the time, a model resulting in a potential 1% increase in regulatory capital would be an improvement. Based on a portfolio with a notional value of £1 billion, it would result in at least an additional £10 million in regulatory capital.

There are, of course, certain limitations with this technique, not least of which is determining the DAG structure in the first instance. Subsequently, if the structure is ascertained, there may be issues with data being readily available representing the components of the DAG – for example sourcing regular data in relation to balance sheet indicators such as levels of indebtedness or rising levels of delinquencies amongst bank customers. Furthermore, although the network can be altered or updated for new components, as the number of variables grows, the simulation methods may produce less reliable estimations.

Bibliography

Adams, Z., Fuss, R., and Gropp, R (2010), "Modeling Spillover Effects Among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk (SDSVaR) Approach." European Business Research Paper No. 10-12.

Adrian, T., and Shin, H., (2010), "Liquidity and Leverage," Journal of Financial Intermediation, 19(3), 418-437.

Ahn, S.C., and Horenstein, A.R., (2013), "Eigenvalue Ratio Test for the Number of Factors." Econometrica,Vol. 83, Issue No. 3, pp. 1203-1227.

Alessi, L and Detken, C., (2009), "Real Time Early Warning Indicators for Costly Asset Price Boom/Bust Cycles: A Role for Global Liquidity." ECB Working Paper 1039, European Central Bank.

Alfaro, R., and Drehmann, M., (2009), "Macro Stress Tests and Crises: What Can We Learn?" BIS Quarterly Review, pp. 29.41.

Allen, F., and Gale, D., (2007), "Understanding Financial Crises." Clarendon Lectures in Finance, Oxford University Press, pp. 14-18.

Anisa, K.N., and Lin, S.W., (2017), "Effect of Socioeconomic Status on Lung Cancer Survival: A Mediation Analysis Based on Bayesian Network Approach." 2017 IEEE International Conference on Industrial Engineering and Engineering Management.

Aquaro, V., Bardoscia, M., Belotti, R., Consiglio, A., De Carlo, F., and Ferri, G., (2010), "A Bayesian Networks Approach to Operational Risk." Physica A: Statistical Mechanics and its Applications, Volume 389, Issue No. 8, pp. 1721-1728.

Arias, M., Mendoza, J.C., Perez-Reyna, D., (2010), "Applying CoVaR to Measure Systemic Market Risk: the Colombian Case." Temas De Estabilidad Financiera, Banco de la Republica de Colombia.

Asgharian, H., and Nossman, M., (2011), "Risk Contagion Among International Stock Markets." Journal of International Money and Finance, Volume 30, Issue 1, pp. 22-38.

Bai, J., and Ng, S., (2002), "Determining the Number of Factors in Approximate Factor Models." Econometrica, Vol. 70, Issue No. 1, ISSN: 0012-9682.

Bank of England., (2015), "Supplement to the December 2015 Financial Stability Report: The Framework of capital requirements for UK banks."

Barabasi, A.l., Gulbahce, N., and Loscalzo, J., (2011), "Network Medicine: a network-based approach to human disease." Nature Reviews Genetics, Vol. 12, pp. 56-68.

Barber, J., and Copper, M., (2012), "Principal Component Analysis of Yield Curve Movements."

Journal of Economics and Finance, Vol. 36, Issue No. 3, pp. 750-765.

Battiston, S., Puliga, M., Kaushik, R., Tasca, P., and Caldarelli, G., (2012), "DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk." Scientific Reports, Vol. 2, Article number: 541.

Billio, M., Getmansky, M., Lo, A.W., and Pelizzon, L., (2010), "Econometric Measures of Systemic Risk in the Finance and Insurance Sectors." NBER Working Paper 16223, NBER.

Billio, M., Getmansky, M., Lo, A.W., and Pelizzon, L., (2012), "Econometric Measures of Systemic Risk in the Finance and Insurance Sectors." Journal of Financial Economics, 104, pp. 535-559. (originally the working paper specified above).

Bisias, D., Flood, M., and Lo, A.W., (2012). "A Survey of Systemic Risk Analytics." Annual Review of Financial Economics, Volume 4, pp. 255-296.

Bollerslev, T., (1986), "Generalised Autoregressive Conditional Heteroscedasticity." Journal of Econometrics, Vol. 31, Issue No. 3, pp. 307-327.

Borio, C., and Drehmann, M., (2009b). "Towards an Operational Framework for Financial Stability: 'fuzzy' measurement and its consequences," BIS Working Papers 284, Bank for International Settlements.

Brunnermeier, M. (2009). "Deciphering the Liquidity and Credit Crunch, 2007-2008." The Journal of Economic Perspectives, Volume 23, Issue 1, pp. 77-100.

Brunnermeier, M., and Adrian, T., (2011), "CoVaR." Federal Reserve Bank of New York Staff Report No. 348

Brunnermeier, M., Crocket, A., Goodhart, C., Perssaud, A., and Shin, H (2009), "The Fundamental Principles of Financial Regulation: 11th Geneva Report on the World Economy."

Brunnermeier, M. K., and Pedersen, L.H., (2009), "Market Liquidity and Funding Liquidity," Review of Financial Studies, 22, 2201-2238

Caruana, J., (2010), "Systemic Risk: how to deal with it?" Bank for International Settlements, Research and Publications.

Castro, C., and Ferrari, S., (2014), "Measuring and Testing for the Systemically Important Financial Institutions." Journal of Empirical Finance, Vol. 25, issue C, pp. 1 – 14.

Chan-Lau, J., (2009), "Co-risk measures to assess systemic financial linkages." IMF Working Paper.

Chan-Lau, J., Espinosa, M., and Sole, J., (2009), "On the Use of Network Analysis to Assess Systemic Financial Linkages." Working Paper. International Monetary Fund. (Forthcoming)

Chan, N., Getmansky, M., Haas, S.H., and Lo, A.W., (2005), "Systemic Risk and Hedge Funds." NBER Working Paper No. 11200, March 2005.

Chong, C., and Kluppelberg, C., (2017), "Contagion in Financial Systems." Working Paper, Cornell University Library.

Cowell, R.G., Verrall, R.J and Yoon, Y.K., (2007), "Modelling Operational Risk with Bayesian Networks." Journal of Risk and Insurance, December 2007, Vol. 74, Issue. No. 4, pp. 795-827.

Connor, G., and Korajczyk, R.A., (1993), "A Test for the Number of Factors in an Approximate Factor Model." The Journal of Finance, Volume 48, Issue No. 4, pp. 1263-1291.

Degiannakis, S., Christos, F., and Alexandra, L., (2011), "Evaluating value-at-risk models before and after the financial crisis of 2008: International evidence." Managerial Finance. Vol. 38, Issue No. 4, pp. 436-452.

Diao, X., Li, W., and Yeldan, E., (2000), "How the Asian Crisis Affected the World Economy: A General Equilibrium Perspective." Federal Reserve Bank of Richmond, Economic Quarterly Volume 86/2 Spring 2000, pp. 37-38.

Ding, J., and Meade, L., (2010), "Forecasting accuracy of stochastic volatility, GARCH and EWMA models under different volatility scenarios." Applied Financial Economics, Vol. 20, Issue

No. 10, pp. 771-783.

Duarte, F., and Eisenbach, T.M., (2015), "Fire-Sale Spillovers and Systemic Risk." Federal Reserve Bank of New York, Staff Report No.645, February 2015.

Dumitrescu, S., (2015), "Turbulence and Systemic Risk in the European Union Financial System." Financial Studies, 2015, v. 19, iss. 2, pp. 41-71.

Ellsworth, S.G., Rabatic, B.M., Chen, J., Zhao, J., Campbell, J., Wang, W., Pi, W., Stanton, P., Matuszak, M., Jolly, S., Miller, A., Kong, F.M., (2017), "Principal Component Analysis Identifies Patrens of Cytokine Expression in Non-Small Cell Lung Cancer Patients Undergoing Definitive Radiation Therapy." Plos One, Vol. 12 (9), pp. e0183239, Public Library of Science.

Elyasiani, E., Mansur, I., and Pagano, M (2007), "Convergence and risk-return linkages across financial service firms." Journal of Banking and Finance, Volume 31, Issue 4, pp. 1167-1190.

Engle, R., (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." Econometrica, Vol.50, Issue No. 4, pp. 987-1008.

Engle, R. F., Manganelli, E., (1999), "CAViaR: Conditional Value at Risk by Quantile Regression", NBER Working Paper No. 7341, September 1999.

Fan, Y, et al. (2008), "Estimating Value-at-Risk of Crude Oil Price and its spillover effect using the GED-GARCH approach." Energy Economics, Volume 30, Issue 6, pp. 3156-3171.

Faust, K., and Wasserman, S., (1994, pp. 7), "Social Network Analysis: Methods and Applications." Cambridge University Press. ISBN: 0521387078.

Fong, T., Fung, L., Lam, L., and Yu, I., (2009), "Measuring the Interdependence of Banks in Hong Kong." No 0919, Working Papers, Hong Kong Monetary Authority.

Forbes, K.J., and Rigobon, R., (2002), "No Contagion, Only Interdependence: Measuring Stock Market Comovements." The Journal of Finance, Volume 57, Issue No. 5.

Gandy, A., and Veraart, L.A.M., (2017), "A Bayesian Methodology for Systemic Risk Assessment in Financial Networks." Management Science, Volume 63, Issue No. 12, pp. 4428-4446.

Girardi, G., and Ergun, A., (2013), "Systemic Risk Measurement: Multivariate GARCH estimation of CoVaR." Journal of Banking and Finance, Volume 37, pp. 3169-3180.

Giudici, P., and Spelta, A., (2016), "Graphical Network Models for International Financila Flows." Journal of Business and Economic Statistics, Volume 34, Issue No. 1, pp. 128-138.

Goyal, G., (2014), "Practical Applications of Risk Disparity." Journal of Portfolio Management, Spring 2014, pp. 14-16.

Hager, D., and Andersen, L.B., (2010), "A Knowledge Based Approach to Loss Severity Assessment in Financial Institutions Using Bayesian Networks and Loss Determinants." European Journal of Operational Research, Volume 207, Issue No. 3, pp. 1635-1644.

Haldane, A.G., and May, R.M., (2011), "Systemic risk in banking ecosystems." Nature, International Journal of Science, Issue 469, pp. 351-355.

Hallin, M., and Liska, R., (2007), "Determining the Number of Factors in the General Dynamic Factor Model." Journal of the American Statistical Association, Vol. 102, Issue No. 478.

Hammoudeh, S.M., McAleer, M.J., and Malik, F., (2011), "Risk Management of Precious Metals." The Quarterly Review of Economics and Finance, Volume 51 (4).

Hanse, L.P., (2012), "Challenges in Identifying and Measuring Systemic Risk." NBER Working Paper No. 18505, December 2012.

Hoshi, T., and Kashyap, A.K., (2004), "Japan's Financial Crisis and Economic Stagnation." Journal of Economic Perspectives, Volume 18, No. 1, pp. 3-26

Hu, D., Zhao, J.L., Hua, Z., and Wong, M.C.S., (2012), "Network-Based Modelling and Analysis of Systemic Risk in Banking Systems." MIS Quarterly, Vol. 36, No. 4, pp. 1269-1291.

Hu, X., Pan, J., and Wang, J., (2010), "Noise as Information for Illiquidity," working paper, Massachusetts Institute of Technology.

Huang, X., Zhou, H., and Zhu, H., (2009b), “A Framework for Assessing the Systemic Risk of Major Financial Institutions,” working paper, University of Oklahoma.

Hull, J., and White, A., (2013), “LIBOR vs. OIS: The Derivatives Discounting Dilemma.” The Journal of Investment Management, Vol. 11, No. 3, pp. 14-27.

International Monetary Fund (2009a), “Assessing the Systemic Implications of Financial Linkages,” Global Financial Stability Review, pp. 73-110.

International Monetary Fund (2012), “Systemic Risk from Global Financial Derivatives: A Network Analysis of Contagion and its Mitigation with Super-Spreader Tax.” IMF Working Paper, (2012).

Ivanov, E., Min, A., and Ramsauer, F., (2017), “Copula-Based Factor Models for Multivariate Asset Returns.” Econometrics, Vol. 5, Issue No. 2. ISSN: 2225-1146

Jorion, P., (1996), “Measuring the Risk in Value at Risk.” Financial Analysts Journal, CFA Institute, Vol. 52, No. 6, pp. 47-56.

Kaufman, G., and Scott, K.E., (2003), “What is Systemic Risk, and Do Bank Regulators Retard or Contribute to It?” The Independent Review, Vol. 7, No. 3 (Winter 2003), pp. 371 – 391.

Keys, B.J., Mukherjee, T.K., Seru, A., and Vig, V., (2008), "Did Securitisation Lead to Lax Screening?" Evidence from Sub-Prime Loans. Available at SSNR: http//papers.ssrn.com/sol3/papers.cfm?abstract_id=1093137&rec=1&srcabs=1027475

Khandani, A.E., Lo, A.W., and Merton, R.C., (2009), "Systemic Risk and the Refinancing Ratchet Effect," MIT Sloan School Working Paper 4750-09, MIT.

Khandani, A.E., Kim, A.J., and Lo A.W., (2010), "Consumer Credit Risk Models via Machine-Learning Algorithms," Journal of Banking and Finance, Vol. 34, Issue 11, pp. 2767-2787.

Klaus, B., and Rzepkowski, B., (2009), "Risk Spillover among Hedge Funds: The Role of Redemptions and Fund Failures." ECB Working Paper No. 1112.

Koenker, R., (2005),"Quantile Regression," Econometric Society Monographs, Cambridge University Press.

Koga, S.C., Sugita, S., Kamata, S., Ishiguro, M., Hiroi, T., Tatsumi, E., Sasaki, S., (2018), "Spectral Decomposition of Asteroid Itokawa based on Principal Component Analysis." Icarus, January 01 2018, Vol. 299, pp. 386-395.

Krause, A., and Giansante, S., (2012), "Interbank Lending and the spread of bank failures: A network model of systemic risk." Journal of Economic Behaviour and Organisation, Vol. 83, Issue

No. 3, pp. 583 – 608.

Kritzman, M., and Li, Y., (2010), “Skulls, Financial Turbulence and Risk Management.” Financial Analysts Journal, Vol. 66, Issue No. 5, pp. 30-41.

Kritzman, M., Li, Y., Page, S., and Rigobon, R., (2010), “Principal Components as a Measure of Systemic Risk,” MIT Sloan Research Paper No. 4785 – 10.

Kritzman, K., (2014)., “Risk Disparity.” Journal of Portfolio Management, Vol. 40, Issue. No. 1, pp.40-48.

Laurini, M.P., and Ohashi, A., (2015), “A Noisy Principal Component Analysis for Forward Rate Curves.” European Journal of Operational Research, Vol. 246, Issue No. 1, pp. 140-153.

Luke, D.A., and Harris, J.K., (2007), “Network Analysis in Public Health: History, Methods and Applications.” Annual Review of Public Health, Vol. 28, pp. 69-93.

Lopez-Espinosa, G., Moreno, A., Rubia, A., and Valderrama, L., (2012), “Short-term Wholesale Funding and Systemic Risk: A Global CoVaR Approach.” IMF Working Paper.

Markose, S., Giansante, S., and Shaghaghi, A.R., (2012), “Too Interconnected to fail financial network of US CDS Market: Topological fragility and systemic risk.” Journal of Economic Behaviour and Organisation, Vol. 83, Issue 3, pp. 627-646.

Martin, N., Fenton N., and Tailor, M., (2005), "Using Bayesian Networks to Model Expected and Unexpected Operational Losses." Risk Analysis, Volume 25, Issue No. 4, pp. 963-972.

Martinez, C., and Ramirez, M., (2010), "International Propagation of Shocks: an Evaluation of Contagion Effects for Some Latin American Countries." Macroeconomics and Finance in Emerging Market Economies." Vol. 4, Issue No. 2

Narayan, S., Nicholls, R.J., Clarke, D., and Simmonds, D., (2018), "A Bayesian Network Model for Assessments of Coastal Inundation Pathways and Probabilities." Journal of Flood Risk Management, January 2018, 11:S233-S250.

Oanea, D. C., and Anghelache, G., (2015), "Value-at-Risk Prediction: The Failure of RiskMetrics in Preventing Financial Crisis. Evidence from Romanian Capital Market." Procedia Economics and Finance, Volume 20, 2015, pp. 433-442.

Patterson, N., Price, A.L., Reich, D., (2006), "Population Structure and Eigenanalysis." PLOS Genetics, December 2006.

Reongpitya, R., and Rungcharoenkitkul, P., (2011), "Measuring Systemic Risk and Financial Linkages in the Thai Banking System." Systemic Risk, Basel III, Financial Stability and Regulation 2011.

Reyngold, A., Shnyra, K., and Stein, R.M., (2015), “Aggregate and Firm-Level Measures of Systemic Risk from a Structural Model of Default.” Journal of Alternative Investments, Vol. 17, Issue No. 4, pp. 58 – 78.

Schwarcz, S., (2008), “Systemic Risk.” *97* Georgetown Law Journal pp.193-249, October 2008.

Sclove, S.L, (2013), “A Course on Statistics for Finance.” pp. 178 CRC Press, Taylor and Francis Group

Scutari, M., and Denis, J.B., (2015), “Bayesian Networks With Examples in R.” CRC Press, Taylor and Francis Group, ISBN: 9781482225600.

Shenoy, C. and Shenoy, P.P., (2000), “Bayesian Network Models of Portfolio Risk and Return.” Computational Finance, pp. 87-106, The MIT Press, Cambridge, MA.

Shleifer, A. and R. Vishny., (2011), “Fire Sales in Finance and Macroeconomics.” Journal of Economic Perspectives 25 (1), pp. 29–48

Sollis, R., (2009), “Value-at-Risk: a critical overview.” Journal of Financial Regulation and Compliance, Vol. 17, Issue No. 4, pp. 398-414.

Soramaki, K., Bech, M.L., Arnold, J., Glass,R.J., and Beyeler, W.E., (2007), “The Topology of Interbank Payment Flows.” Physica A:Statistical Mechanics and its Applications, Volume 379, Issue 1, pp. 317-333.

Soramaki, K., Birch, J., and Pantelous, A.A., (2016), "Analysis of Correlation Based Networks Representing DAX 30 Stock Price Returns." Volume 47, Issue No. 4, pp. 501-525.

Soramaki, K., and Cook, S., (2013), "SinkRank: An Algorithm for Identifying Systemically Important Banks in Payment Systems." Economics, The Open-Access, Open-Assessment E-Journal, Vol. 7, 2013-28.

Soramaki, K., and Langfield, S., (2016), "Interbank Exposure Networks." Computational Economics, Vol. 47, Issue No. 1, pp. 3-17.

Thoni, A., Tjoa., A.M., and Taudes, Q., (2018), "An Information System for Assessing the Likelihood of Child Labour in Supplier Locations Leveraging Bayesian Networks and Text Mining." Journal of Information Systems and e-Business Management, 7th February 2018, pp. 1-34.

Tsay, R.S., (2010), "Analysis of Financial Time Series." Chapter 9, pp. 483-489. John Wiley and Sons Inc. eISBN-13: 9780470644553.

Walker, W.C., (1998), "Contagion: How the Asian Crisis Spread." Asian Development Bank, EDRC Briefing Notes No. 3, October 1998.

Yiu, M.S., Ho, W.Y.A., and Choi, D.F., (2010), "Dynamic Correlation Analysis of Financial

Contagion in Asian Markets in Global Financial Turmoil." Applied Financial Economics, Vol. 20, pp. 345-354.

Yu, P. L. H., Li, W. K., and Shusong, J., (2010), "Some Models for Value-at-Risk." Econometric Reviews, Vol. 29 (5-6), pp. 622.641.

https://www.stoxx.com/index-details?symbol=V2TX

http://www.cboe.com/micro/vix/vixintro.aspx

http://www.bankofengland.co.uk/pra/Pages/crdiv/updates.aspx

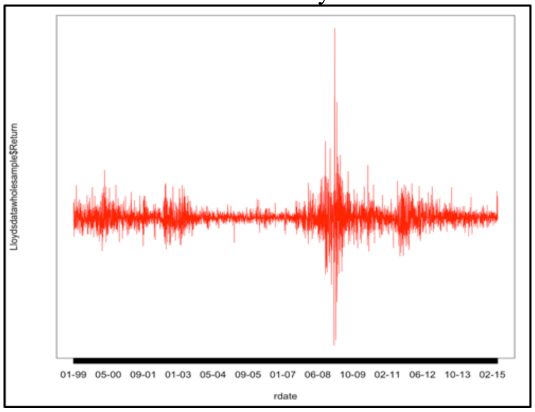
http://www.bankofengland.co.uk/pra/Documents/crdiv/2015osiilist.pdf

https://www.moodys.com/research/Moodys-downgrades-Italian-banks-outlooks-remain-negative--PR_244732

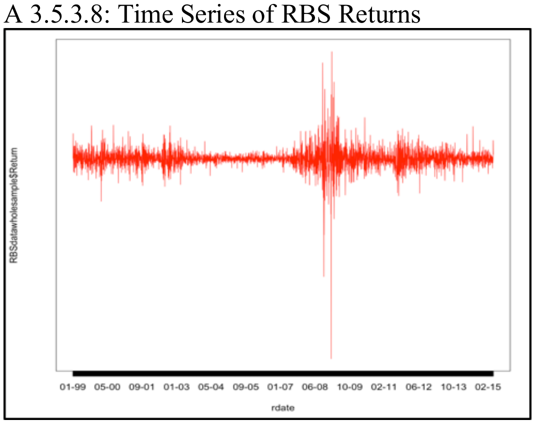
Oxford English Dictionary (2017)

Appendices

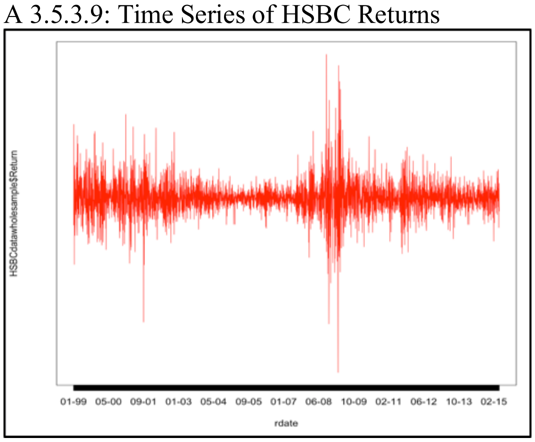
A 3.5.3.7: Time Series of Lloyds Bank Returns



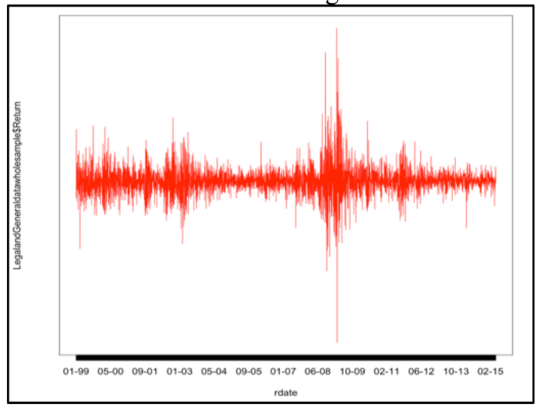
A 3.5.3.8: Time Series of RBS Returns



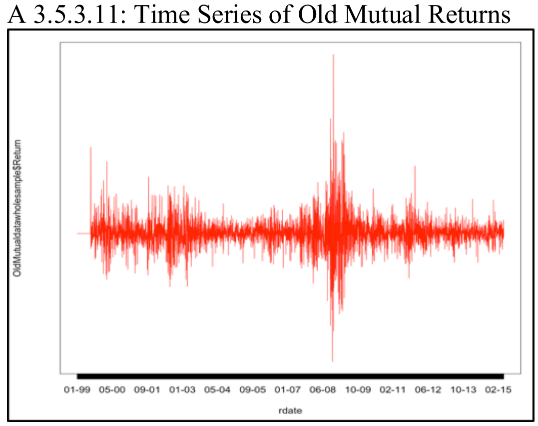
A 3.5.3.9: Time Series of HSBC Returns



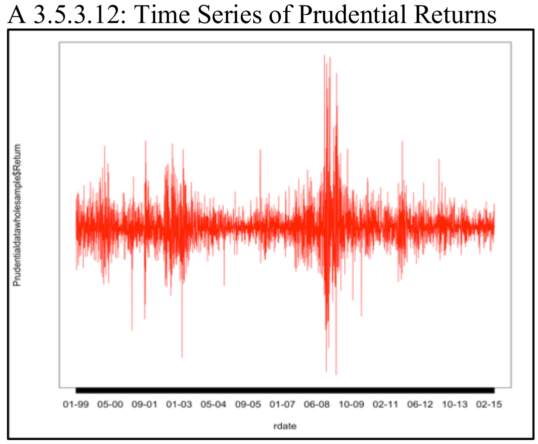
A 3.5.3.10: Time Series of Legal & General Returns



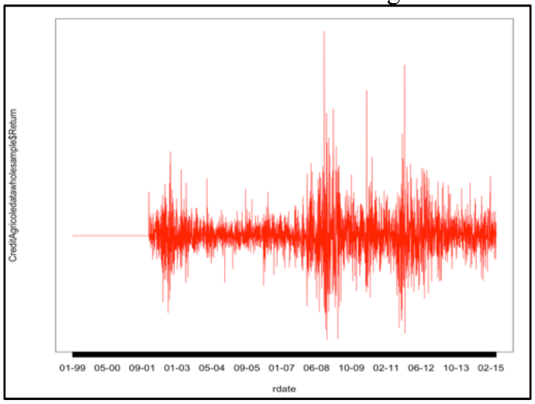
A 3.5.3.11: Time Series of Old Mutual Returns



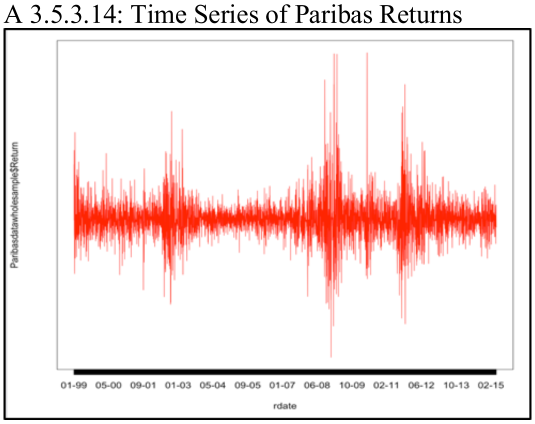
A 3.5.3.12: Time Series of Prudential Returns



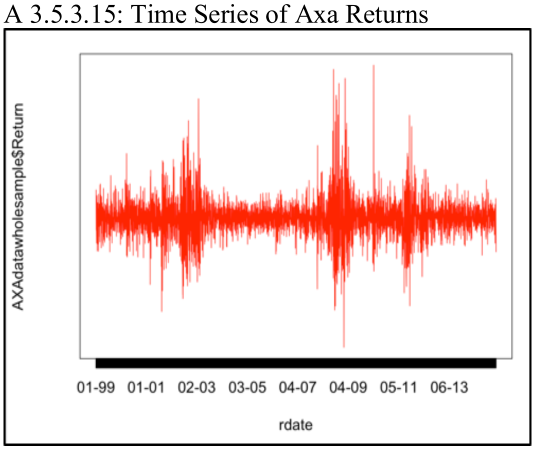
A 3.5.3.13: Time Series of Credit Agricole Returns



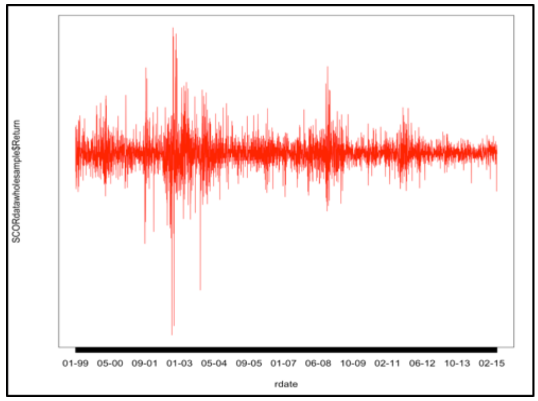
A 3.5.3.14: Time Series of Paribas Returns



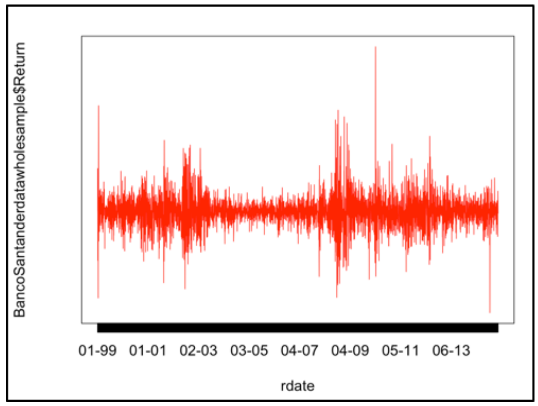
A 3.5.3.15: Time Series of Axa Returns



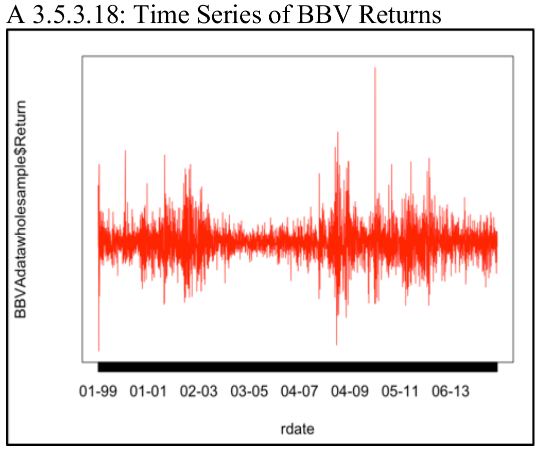
A 3.5.3.16: Time Series of SCOR Returns



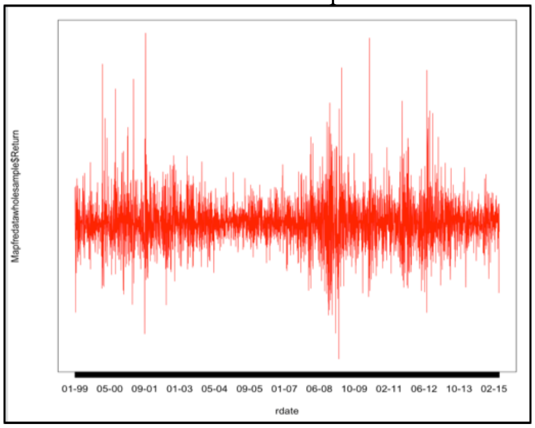
A 3.5.3.17: Time Series of Banco Santander Returns



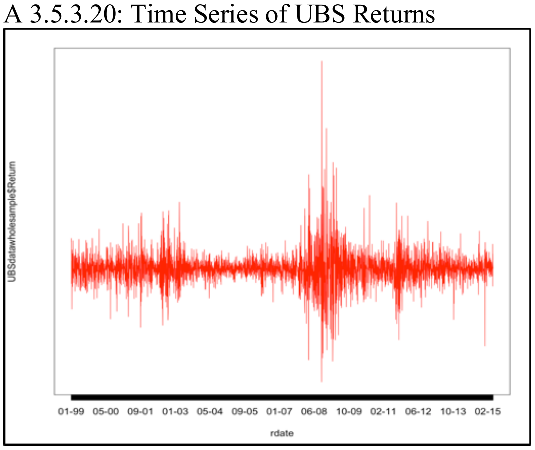
A 3.5.3.18: Time Series of BBV Returns



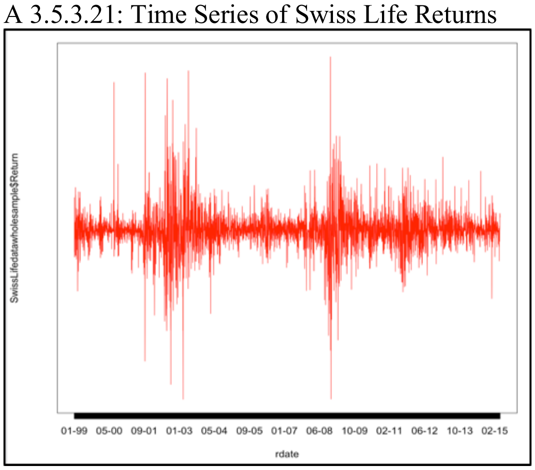
A 3.5.3.19: Time Series of Mapfre Returns



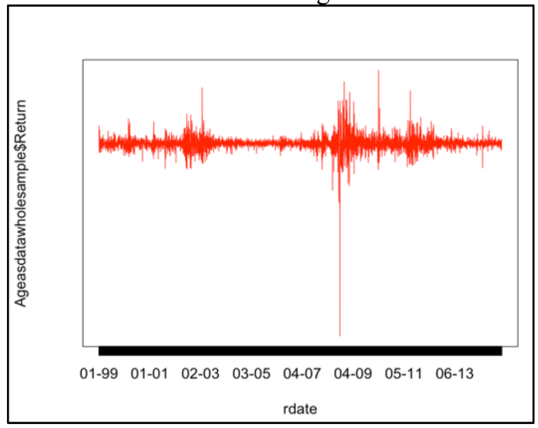
A 3.5.3.20: Time Series of UBS Returns



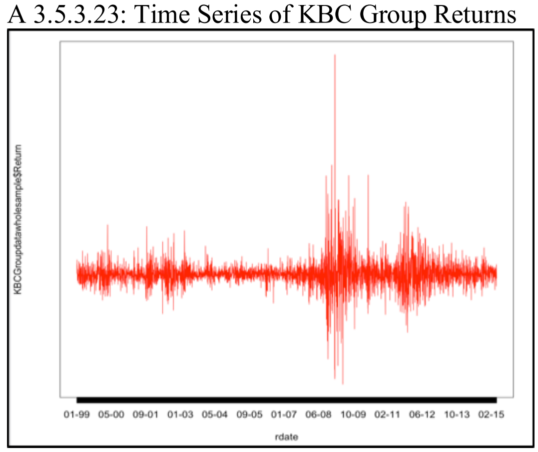
A 3.5.3.21: Time Series of Swiss Life Returns



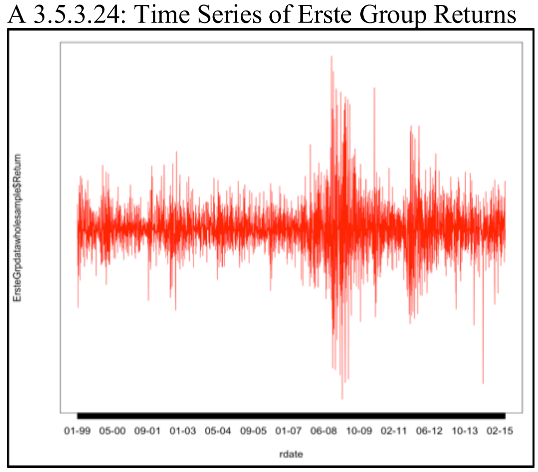
A 3.5.3.22: Time Series of Ageas Returns



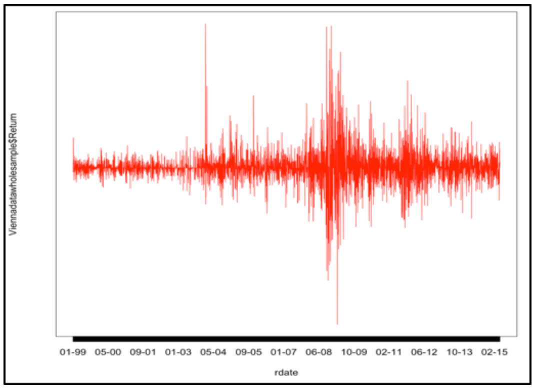
A 3.5.3.23: Time Series of KBC Group Returns



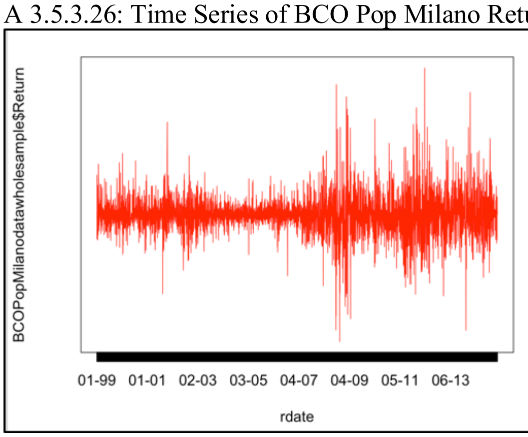
A 3.5.3.24: Time Series of Erste Group Returns



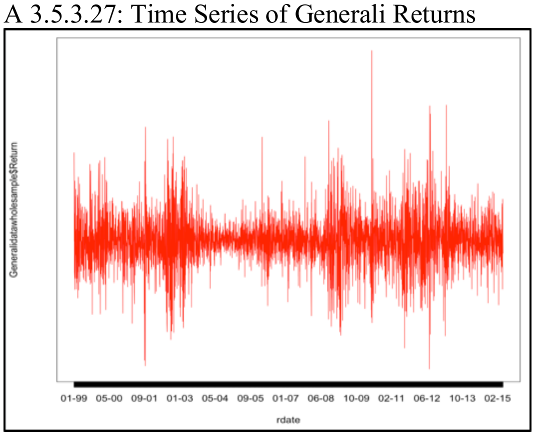
A 3.5.3.25: Time Series of Vienna Insurance Returns



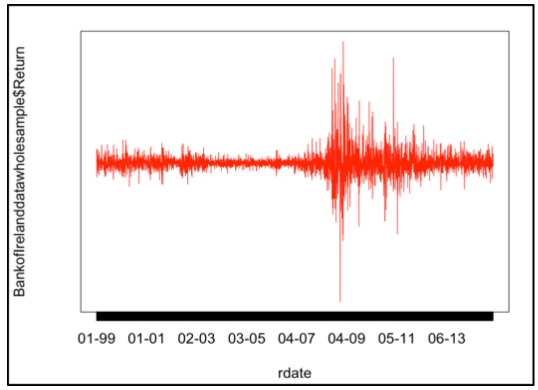
A 3.5.3.26: Time Series of BCO Pop Milano Returns



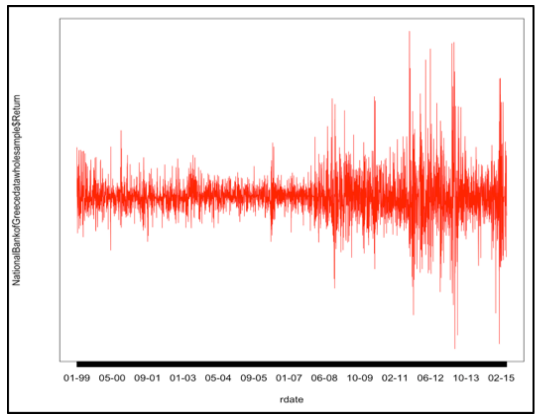
A 3.5.3.27: Time Series of Generali Returns



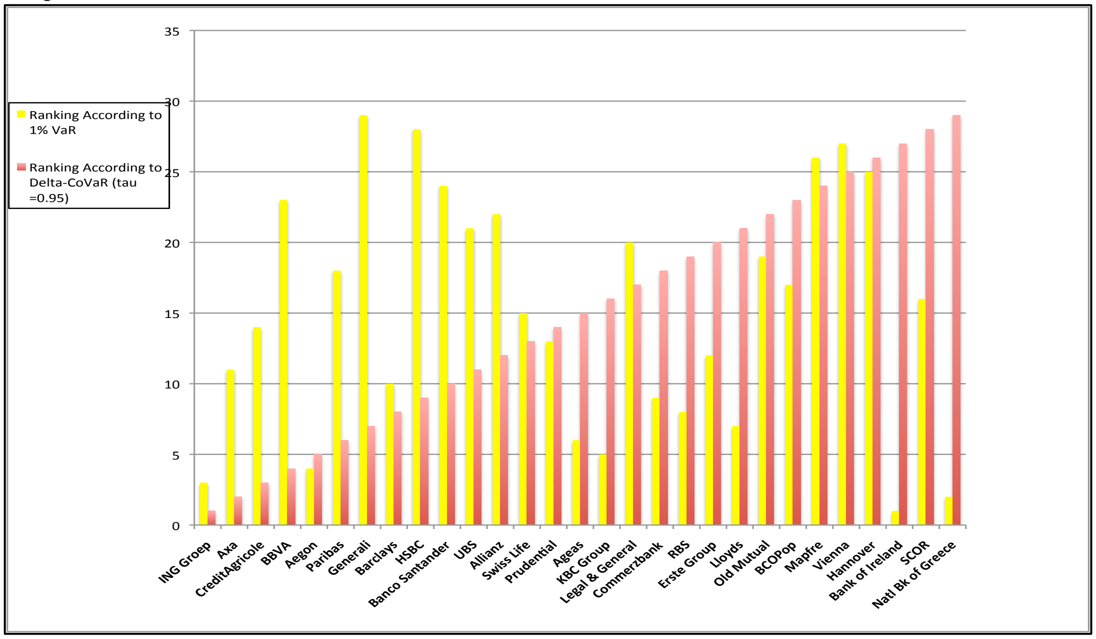
A 3.5.3.28: Time Series of Bank Of Ireland Returns



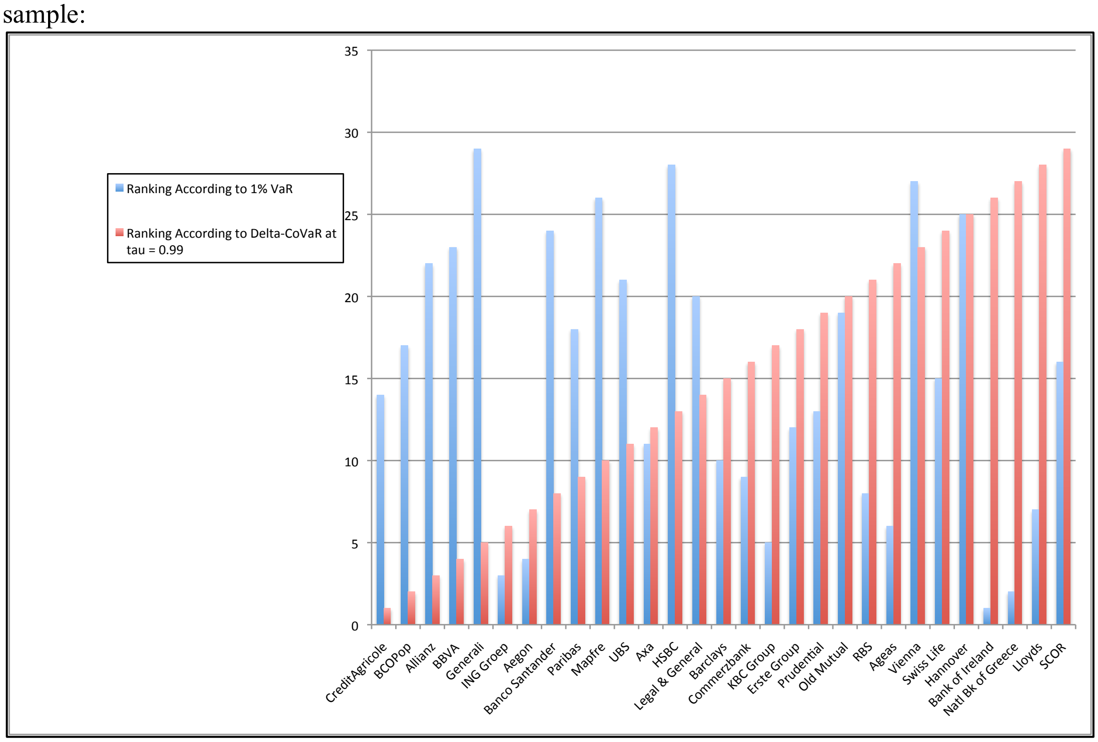
A 3.5.3.29: Time Series of Nat'l Bk of Greece Returns



A 3.6.2.1: Graph of rankings per financial institution for their 1% VaR and Delta-CoVaR (at tau = 0.95) and whole sample:



A 3.6.2.2: Graph of rankings per financial institution for their 1% VaR and Delta-CoVaR (at tau = 0.99) and whole sample:



Both graphs illustrate that an institution with the largest 1% individual VaR does not necessarily have the largest Delta-CoVaR. In many cases, an institution is ranked highly for individual VaR but not for Delta-CoVaR.