UNIVERSITY OF LIVERPOOL Management School

Working Paper in Economics

 # 202023

July 2020

Assessing the Impact of Interlinkages on Value-at-Risk

Emma Apps

https://www.liverpool.ac.uk/management/people/economics/
© authors

Assessing the Impact of Interlinkages on Value-at-Risk

Abstract

This paper 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.

Assessing the Impact of Interlinkages on Value-at-Risk

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 past 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 $\times$ $(1.65 \times \sqrt{\sigma_{t+1}^2})$[1]

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

[1] Source: RiskMetrics

confidence level of 0.95, the probability that the loss will exceed the VaR level is less than or equal to 0.05. 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 paper 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.”[2]

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

[2] The Telegraph, 16th September 2007

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.

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 paper 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 paper is divided into several parts. Section 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 defines the CoVaR model and specifically how it is used to produce estimates of VaR and Delta-CoVaR. Section 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 5 describes the data set in this context. Section 6 presents the VaR and Delta-CoVaR estimations and analysis for the specific data set. Section 7 details the significance test used to analyse the robustness of the Beta estimates defined in section 6 for certain institutions of note. Finally, the paper ends with concluding remarks and potential implications for regulatory policy in this area.

2 Relevant Literature

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 paper depicts the time invariant version of the aforementioned model.

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 and the subsequent systemic risk contribution. Such funding sources are deemed to increase interconnectedness between banks and can exacerbate crises. Financial institutions reliant on commercial paper issues and borrowing through the money markets will impact investors and lenders if they fall into financial distress and become unable to redeem paper issues or repay short-term debt. Likewise, if they cannot access funding in the first instance through the money markets or roll over commercial paper, financial distress is once again the outcome and can subsequently have widespread consequences. In the IMF study, for 18 of the largest global banks, the 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 confined to an annual record per the published financial statements. Despite such limitations, a proxy for the market liquidity factor is a consideration for further research.

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 paper and VaR, 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) set out the framework for capital requirements to be in place by 2019. The minimum equity requirement for all banks is 6% of the balance of risk-weighted assets per the balance sheet,[3] 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 2.3.1.

Table 2.3.1: Explanation of Additional Capital Requirement Buffers as specified by the Capital Requirement IV Directive[4]

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

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

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 this paper, I compare those institutions from the UK that the analysis identifies as being systemically important with those listed in table 2.3.2 below.

Table 2.3.2: List of Global and UK systemic risk firms according to the Capital Requirement IV Directive.[5]

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

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

	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. The Time Invariant CoVaR Approach to Measuring Systemic Risk

For the purposes of this paper, we interpret CoVaR as being the measure of the value-at-risk of the whole financial system. In line with the concept of risk 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 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 paper. The quantile regression is specified as follows:

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

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 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:

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

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[6] .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

[6] Adrian and Brunnermeier (2011)

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.

4 Methodologies

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:

$$y_t = \alpha + \beta_1 X_{1_{t-1}} + \beta_2 X_{2_{t-1}} + \beta_3 X_{3_{t-1}} + \varepsilon_t \qquad (4.1)$$

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).

$$y_t = \alpha + \beta_1 X_{1_{t-2}} + \beta_2 X_{2_{t-2}} + \beta_3 X_{3_{t-2}} + \varepsilon_t \tag{4.2}$$

$$y_t = \alpha + \beta_1 X_{1_{t-3}} + \beta_2 X_{2_{t-3}} + \beta_3 X_{3_{t-3}} + \varepsilon_t \tag{4.3}$$

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.

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:

$$y_i = x_i\beta_q + e_i \quad (4.4)$$

[7]

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.

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 (4.5) and thereby accounts for the under $(q|e_i|)$ and over-predictions ($(1-q)|e_i|$) of

[7] Source: Koenker (2005)

the model in equation (4.4) for values of the dependent variable, y.

$$\Sigma_i q|e_i| + \Sigma_i (1-q)|e_i| \tag{4.5}$$

Using equation (4.4) and substituting in for the error term, we generate the following:

$$Q(\beta_q) = \Sigma^N_{i:y_i \geq x_i\beta} q\left|y_i - x_i\beta_q\right| + \Sigma^N_{i:y_i < x_i\beta}(1-q)\left|y_i - x_i\beta_q\right| \tag{4.6}$$

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

Equation (4.6) is the basis for finding the Beta coefficients at each specified value of q. Essentially, they estimate the change at a specified quantile 'q' of the dependent variable y produced by a one-unit change in the independent variable. In this paper, 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.

5 Data Set

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.

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). [8]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

[8] Source: http://www.cboe.com/micro/vix-and-volatility.aspx

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. [9]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 5.2.1.

Table 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%

[9] Source: https://www.stoxx.com/index-details?symbol=sx5e

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.

5.3 Data Trends and Visual Description

Summary statistics for the control variables and the financial institutions are provided in tables 5.3.1 and 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 5.3.1 to 5.3.6 are presented after the summary statistics, with the remainder in the appendices – A5.3.7 to A5.3.29. 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 5.3.7 to 5.3.11 – on the whole, correlations are found not to be an issue and not affecting chosen bootstrapping methodologies.

Table 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 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 5.3.1: Time Series of Allianz Returns

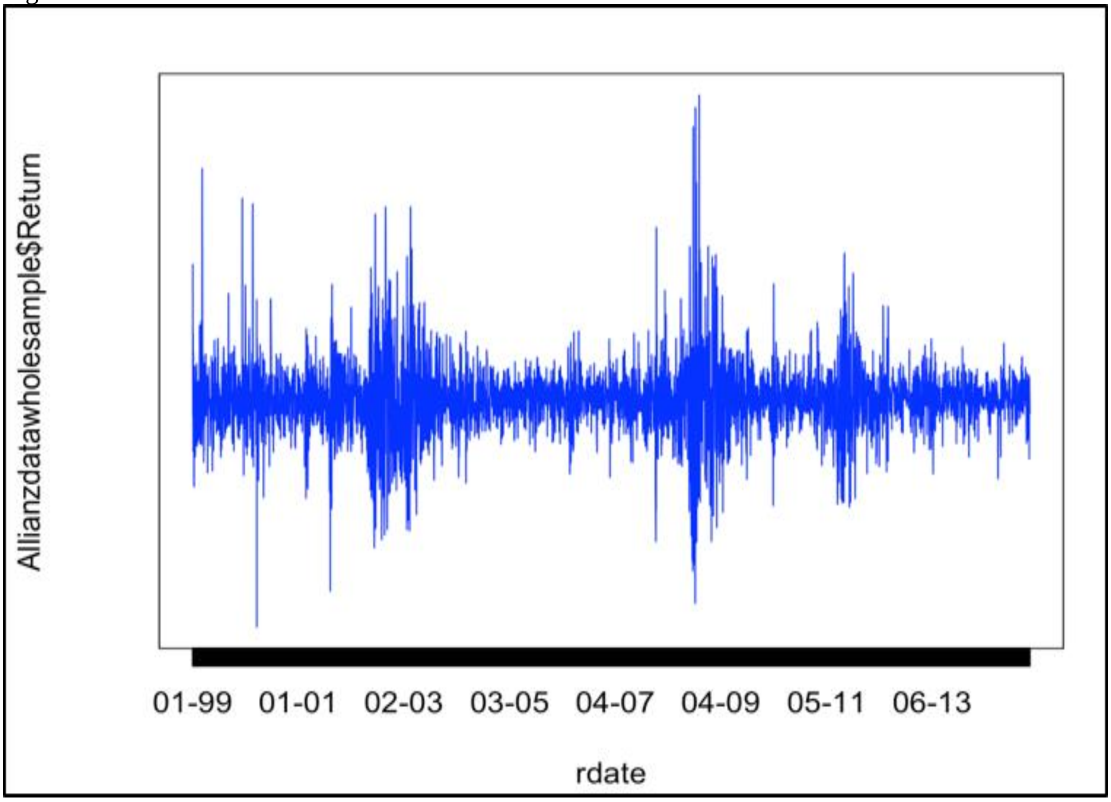


Figure 5.3.2: Time Series of Commerzbank Returns

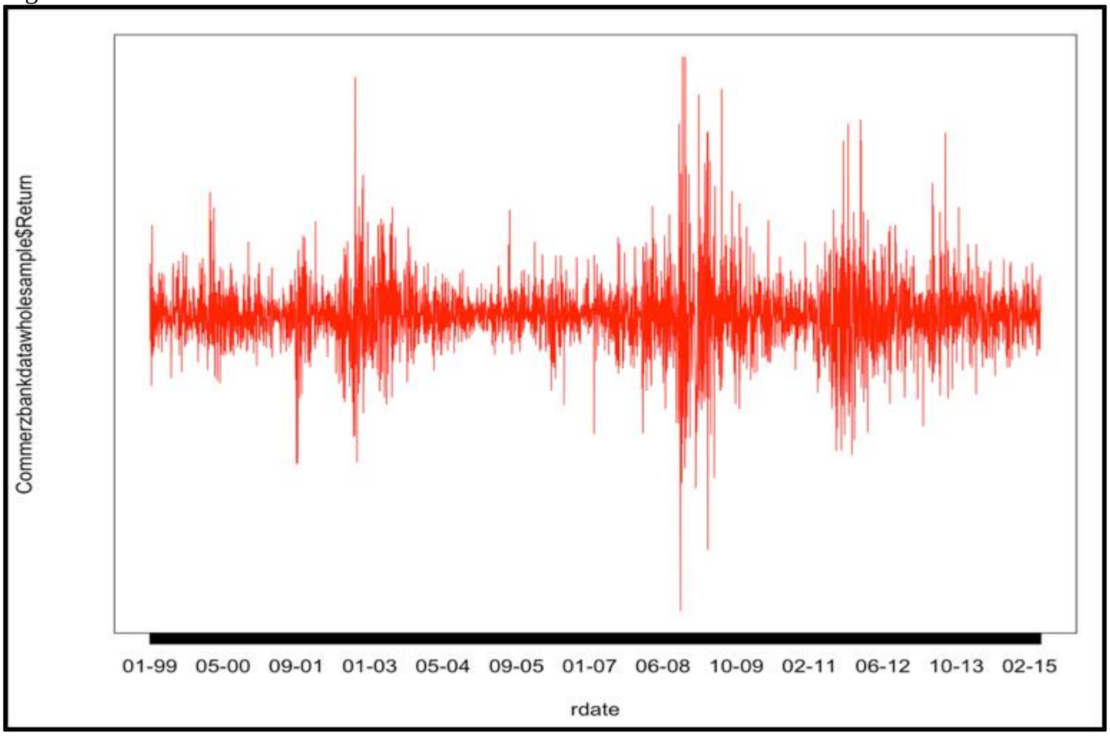


Figure 5.3.3: Time Series of Hannover Returns

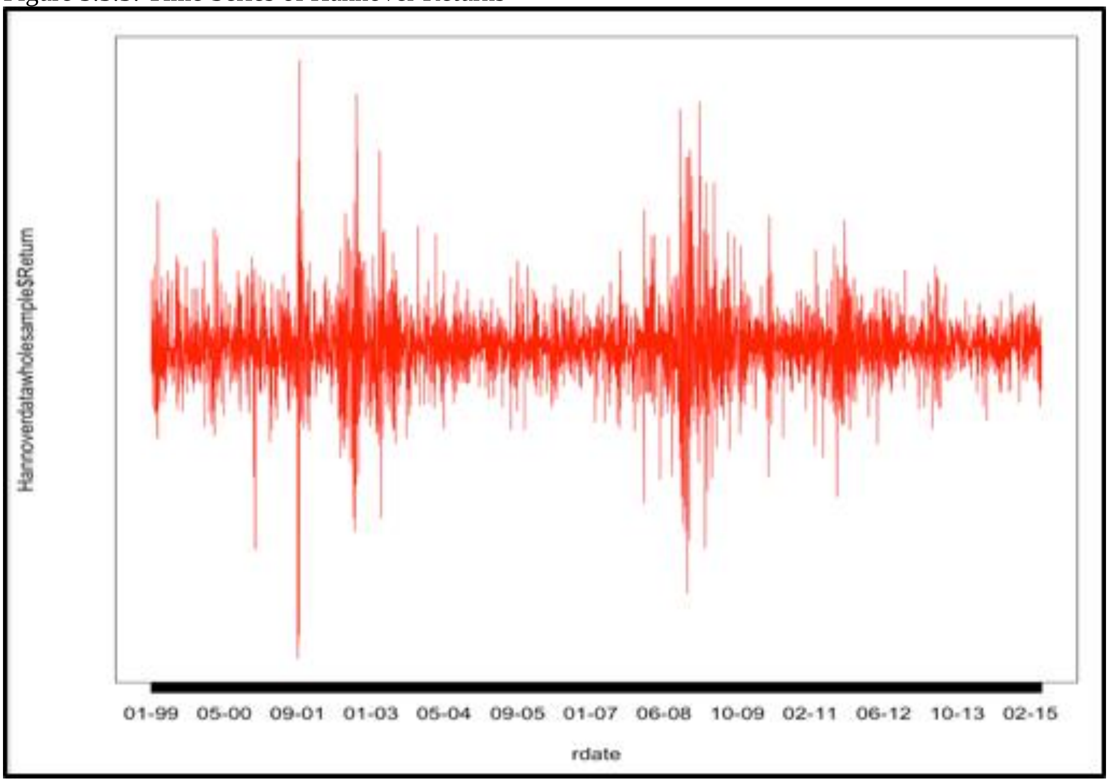


Figure 5.3.4: Time Series of Aegon Returns

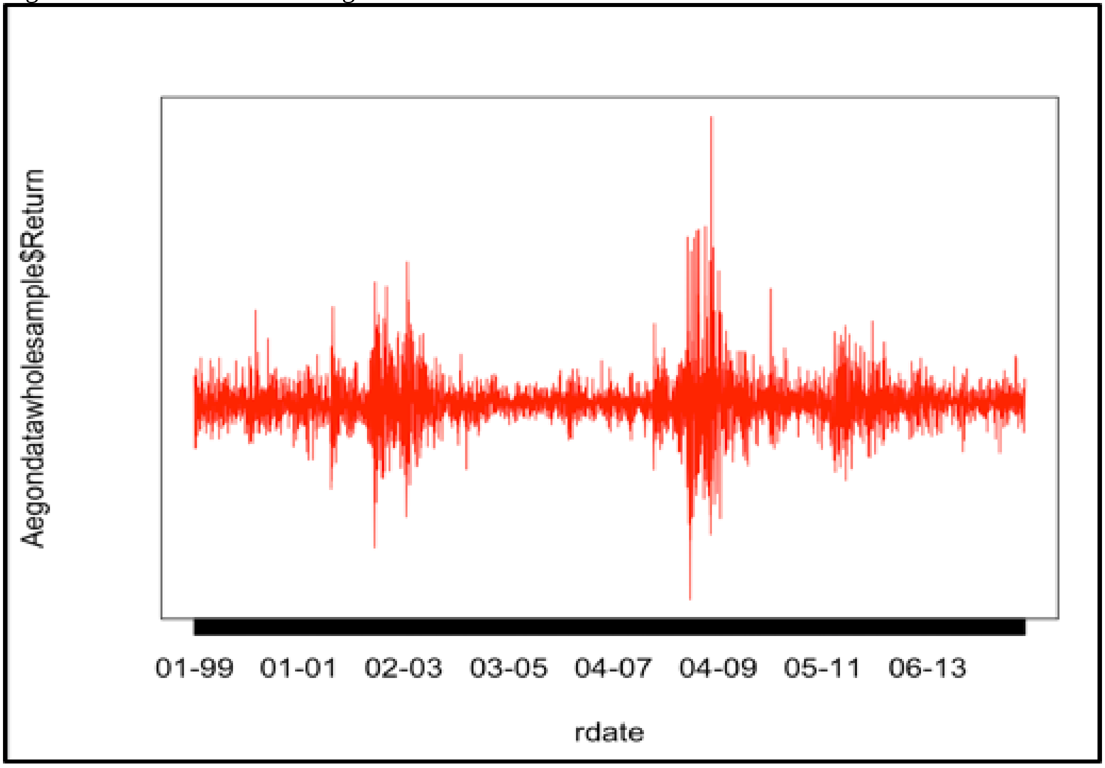


Figure 5.3.5: Time Series of ING Groep Returns

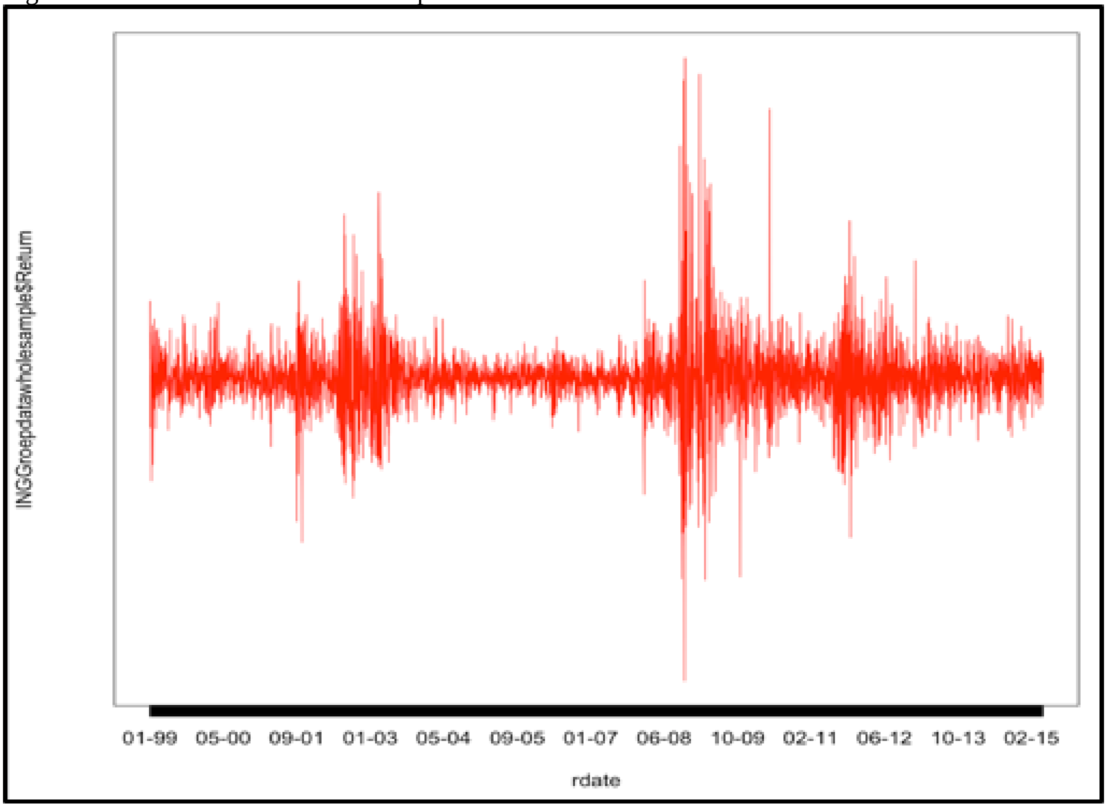


Figure 5.3.6: Time Series of Barclays Returns

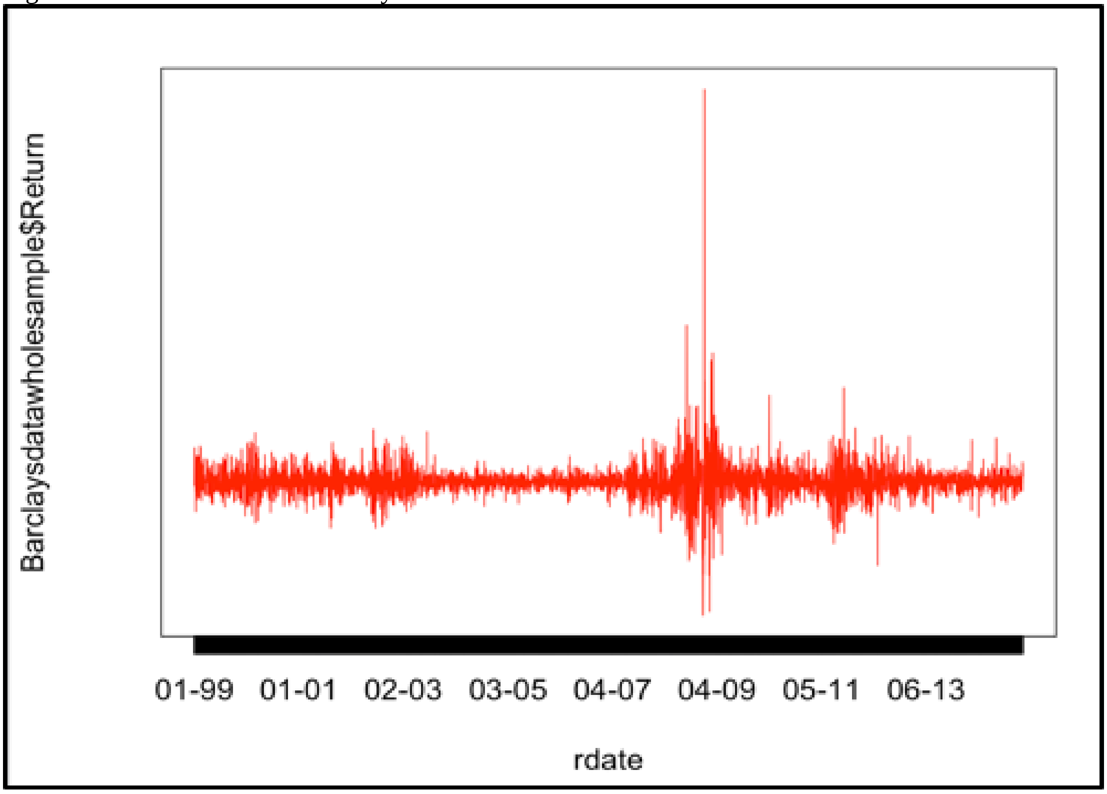


Figure 5.3.7: Autocorrelation function for MSCI Europe Financials Sector Index Returns.

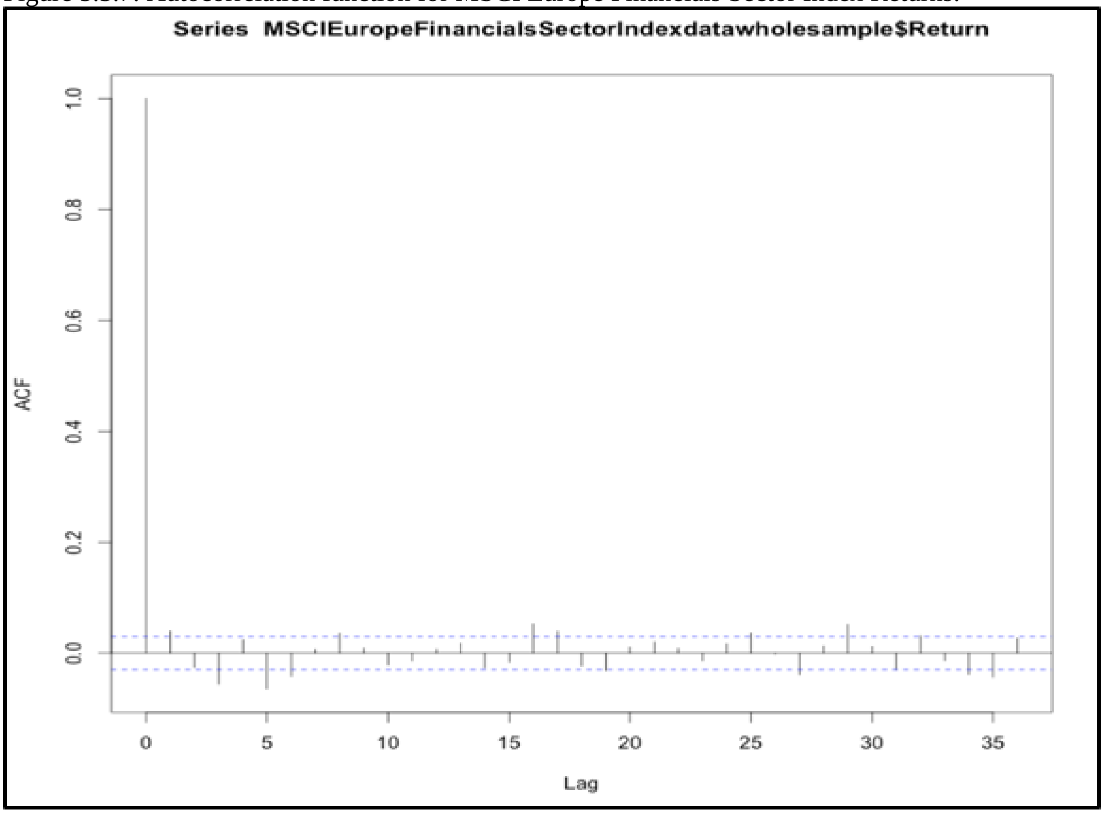


Figure 5.3.8: Autocorrelation function for Aegon Returns.

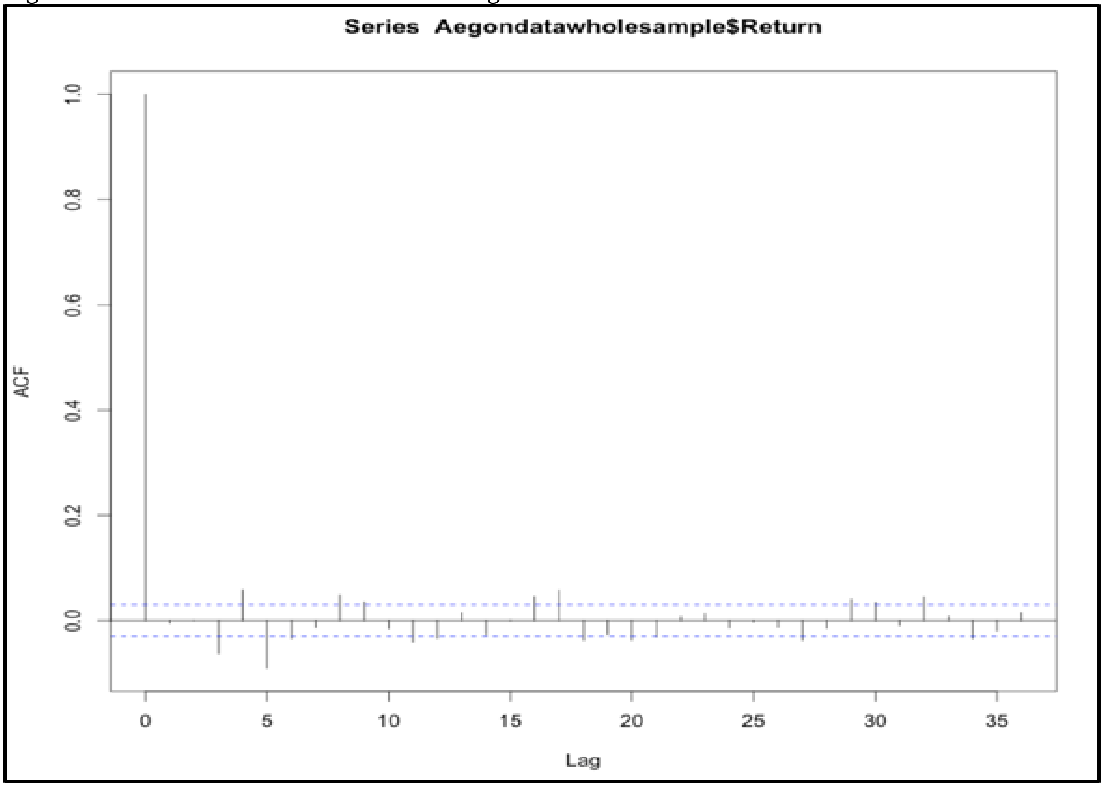


Figure 5.3.9: Autocorrelation function for ING Groep Returns.

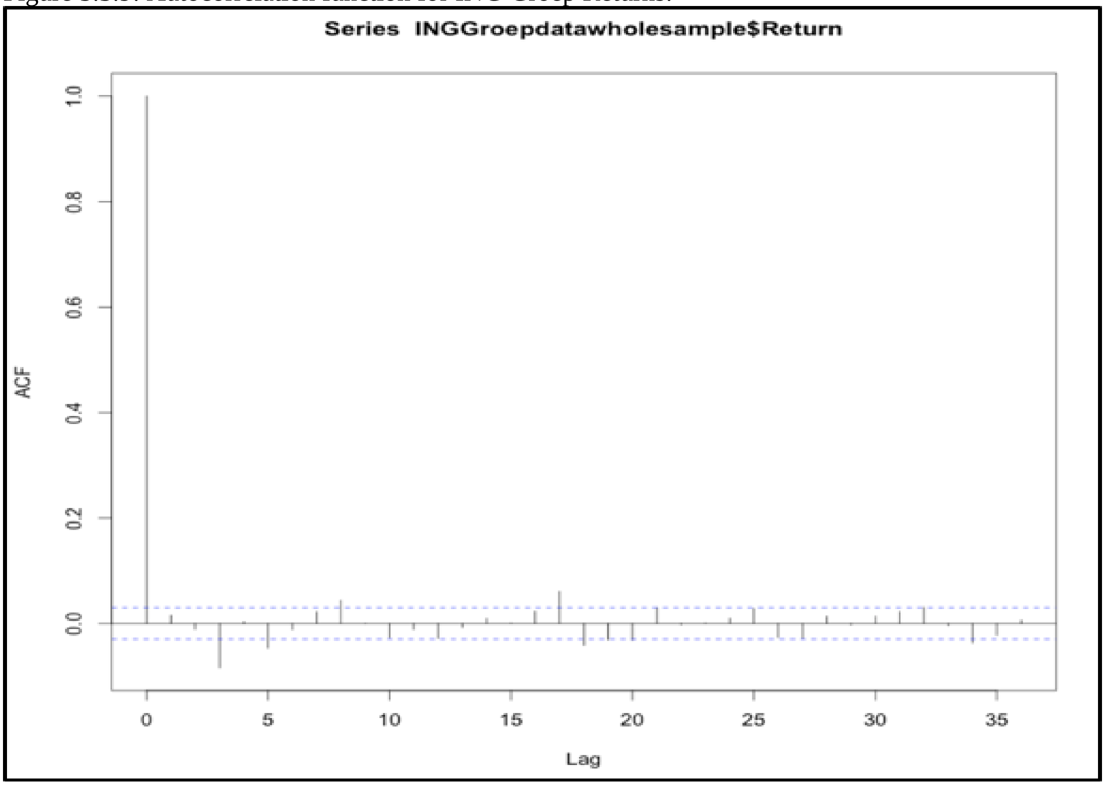


Figure 5.3.10: Autocorrelation function for BBVA Returns.

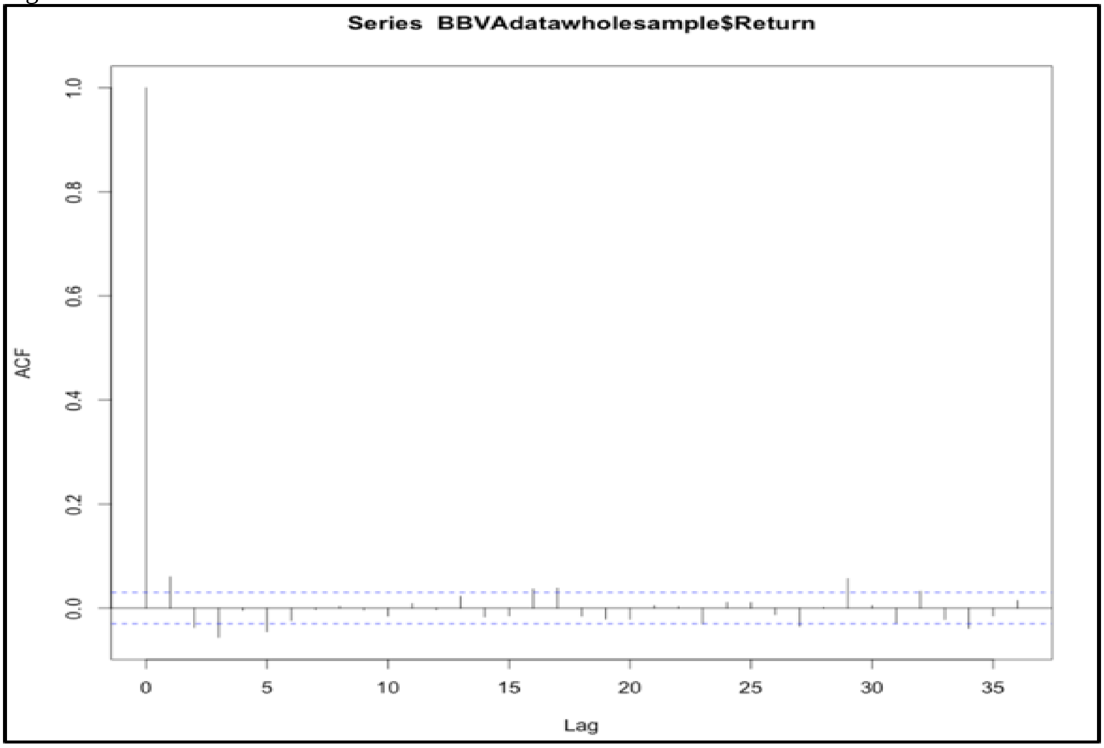
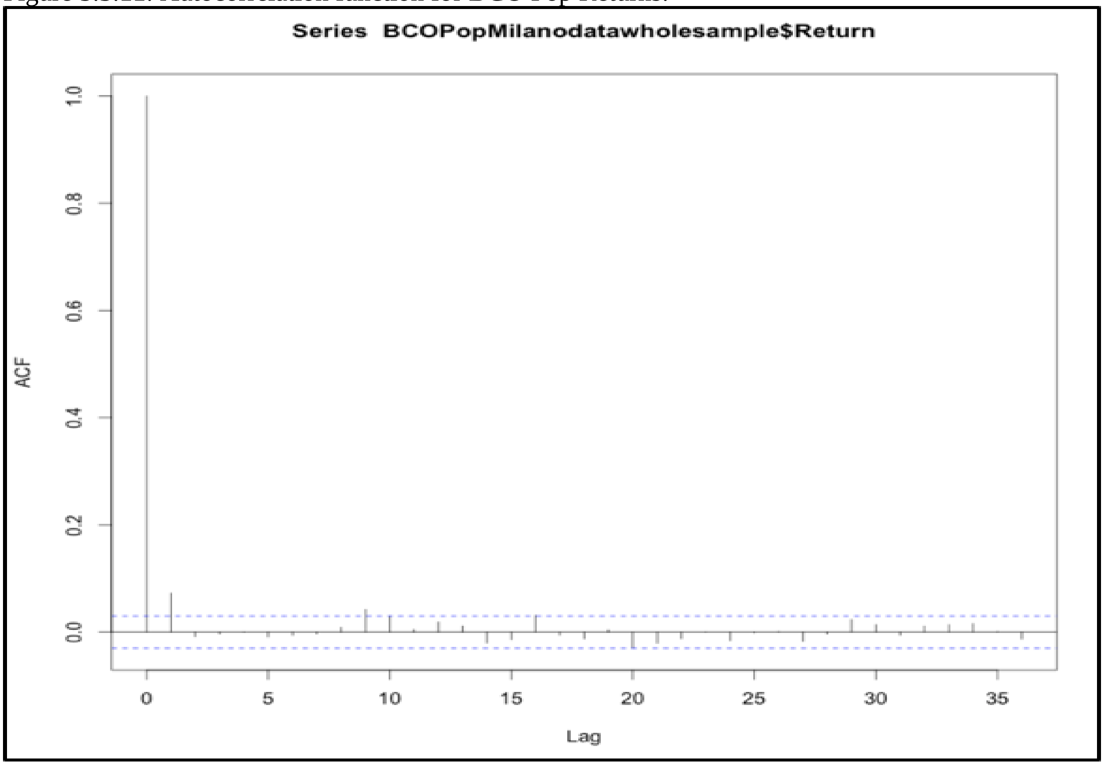


Figure 5.3.11: Autocorrelation function for BCO Pop Returns.



6 Results

6.1 OLS Regression Estimations

It is clear from the coefficient estimators and associated p-values in table 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 4.1) on the returns of each Financial Institution. In just two instances, the impact of the Stoxx 50 volatility index is significant. 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 6.1.2 and 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.

6.2 Unconditional, Time Invariant CoVaR – Whole Sample

A tabulated summary of the results is presented in tables 6.2.1 and 6.2.2. The suggestion that the higher an institution's individual VaR the greater its contribution to systemic risk, is only partially evidenced in the results.

Table 6.1.1: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	b_1	b_2	b_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 6.1.1 cont'd: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	b_1	b_2	b_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 6.1.1 cont'd: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	b_1	b_2	b_3
Lloyds	0.009314 (0.8394)	0.158067 (0.0358)*	-0.140506 (0.0204)*	-0.006919 (0.5184)
Mapfre	0.045239 (0.16826)	0.101214 (0.05986)	-0.137252 (0.0015)**	-0.011808 (0.12292)
National Bk of Greece	-0.03088 (0.588)	0.01965 (0.833)	0.10193 (0.175)	-0.01674 (0.208)
Old Mutual	0.0456461 (0.236)	0.0122964 (0.845)	0.00002 (1.0000)	0.0045115 (0.615)
Paribas	0.039746 (0.2885)	0.141191 (0.0214)*	-0.112949 (0.0222)*	0.011774 (0.1774)
Prudential	0.049165 (0.225)	0.045297 (0.495)	-0.015718 (0.769)	-0.00203 (0.830)
RBS	0.007473 (0.878244)	0.294157 (0.000)**	-0.194083 (0.0026)**	0.008372 (0.46156)
SCOR	-0.008024 (0.8363)	0.257908 (0.000)**	-0.130387 (0.0109)*	0.004583 (0.6127)
Swiss Life	0.005222 (0.88712)	0.192829 (0.001)**	-0.033096 (0.49508)	0.002386 (0.78089)

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

Table 6.1.1 cont'd: OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables

Company	Alpha	b_1	b_2	b_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 6.1.2 OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	b_1	b_2	b_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 6.1.2 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	b_1	b_2	b_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 6.1.2 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	b_1	b_2	b_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 6.1.2 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at two lags

Company	Alpha	b_1	b_2	b_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 6.1.3 OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	b_1	b_2	b_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 6.1.3 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	b_1	b_2	b_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 6.1.3 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	b_1	b_2	b_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 6.1.3 cont'd OLS Regression Parameters by Financial Institution – Whole Sample and Contemporaneous Control Variables at three lags

Company	Alpha	b_1	b_2	b_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 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 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 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 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 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 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 $\Delta CoVaR_{\tau}^{index|i} = \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}\right) - \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i}\right)$, where tau = 0.99 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the 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 A6.2.1 and A6.2.2. 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[10]. 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 2.3.2, section 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

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

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.

6.3 Unconditional, Time Invariant CoVaR – Sub-Samples

6.3.1 Pre-2008 Sample

With reference to table 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 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.

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 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 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 versus the impact on the 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 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 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 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 $\Delta CoVaR_{\tau}^{index|i} = \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}\right) - \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i}\right)$, where tau = 0.95 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the 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 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 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 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 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 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 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 $\Delta CoVaR_{\tau}^{index|i} = \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{q\%}^{i}\right) - \left(\alpha_{\tau}^{i} + \beta_{\tau}^{i} VaR_{50\%}^{i}\right)$, where tau = 0.95 and q is the 1% VaR of the financial institution in this instance. The measures are taken using the 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 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 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 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.

7 Significance of Estimations

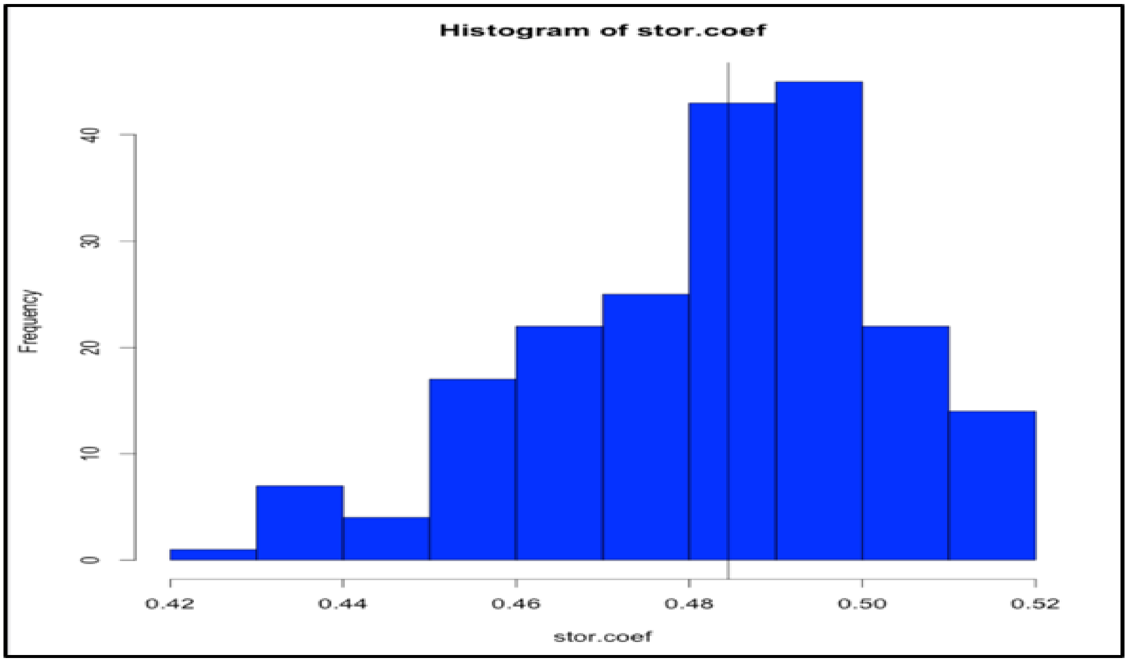
7.1 Specification of Significance Tests on the Delta-CoVaR Estimations

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 5.3 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.

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 7.2.1 and 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 7.2.1 and 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 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

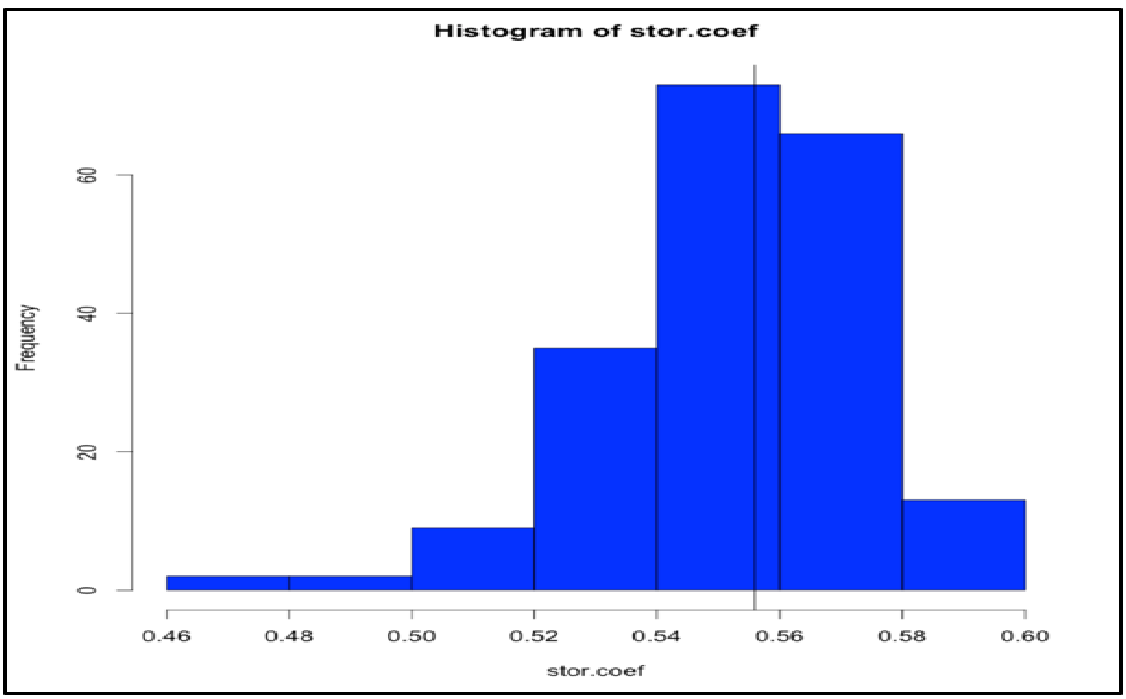
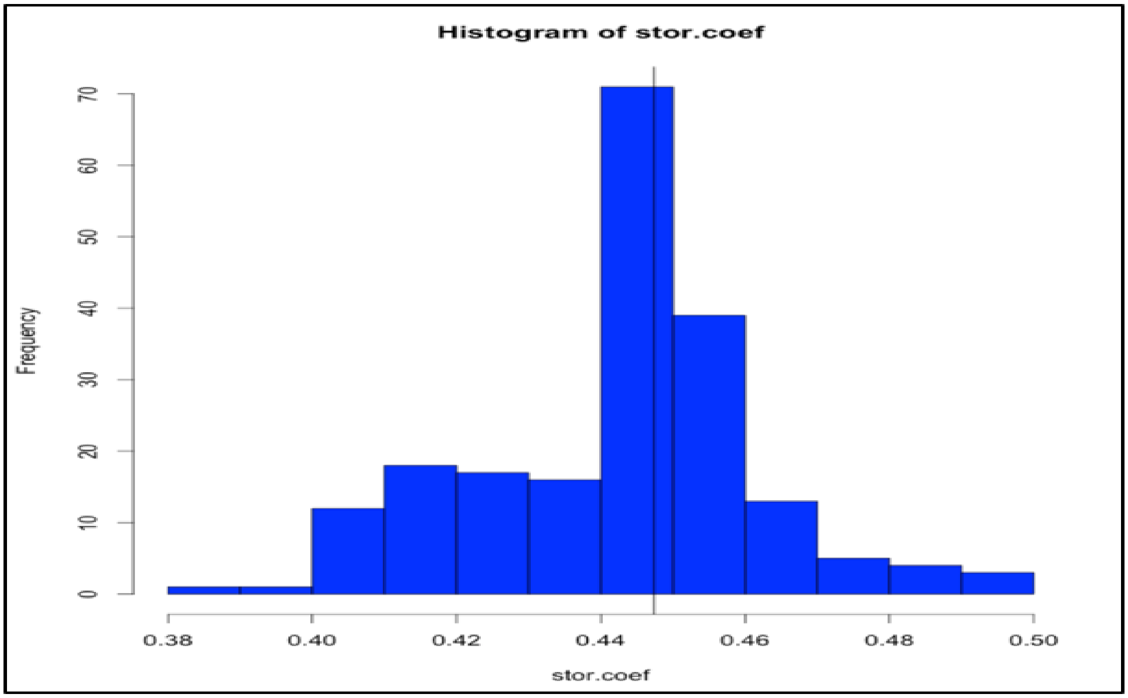


Figure 7.2.1: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.95) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
Aegon



AXA

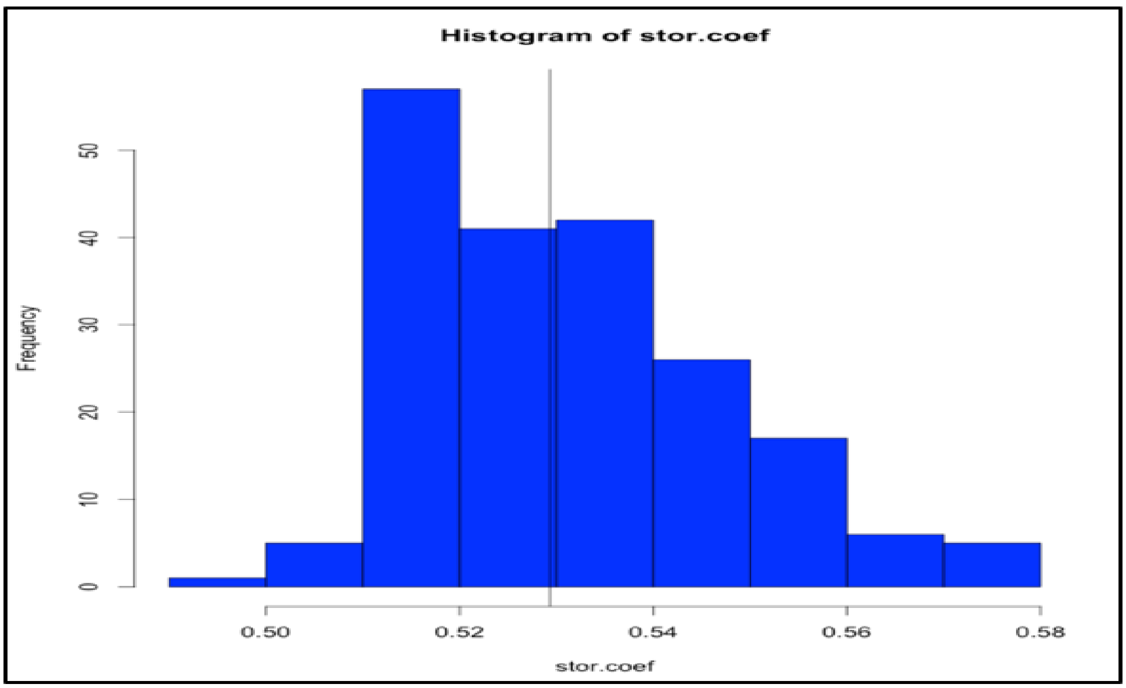
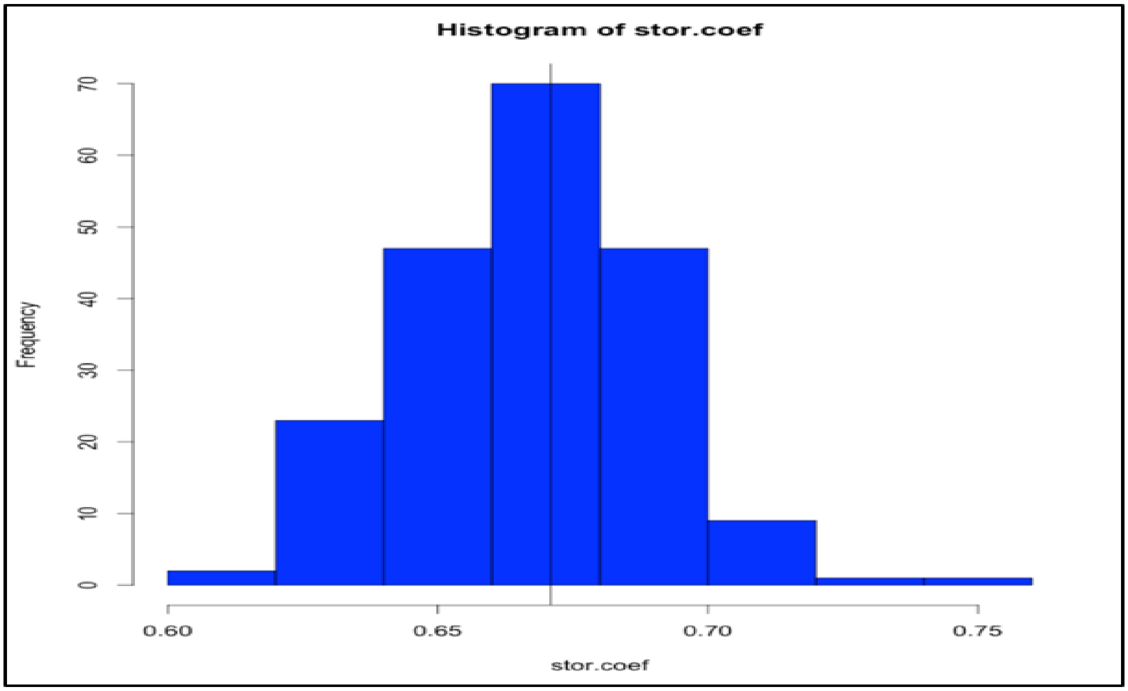


Figure 7.2.1: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.95) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
BBVA



Paribas

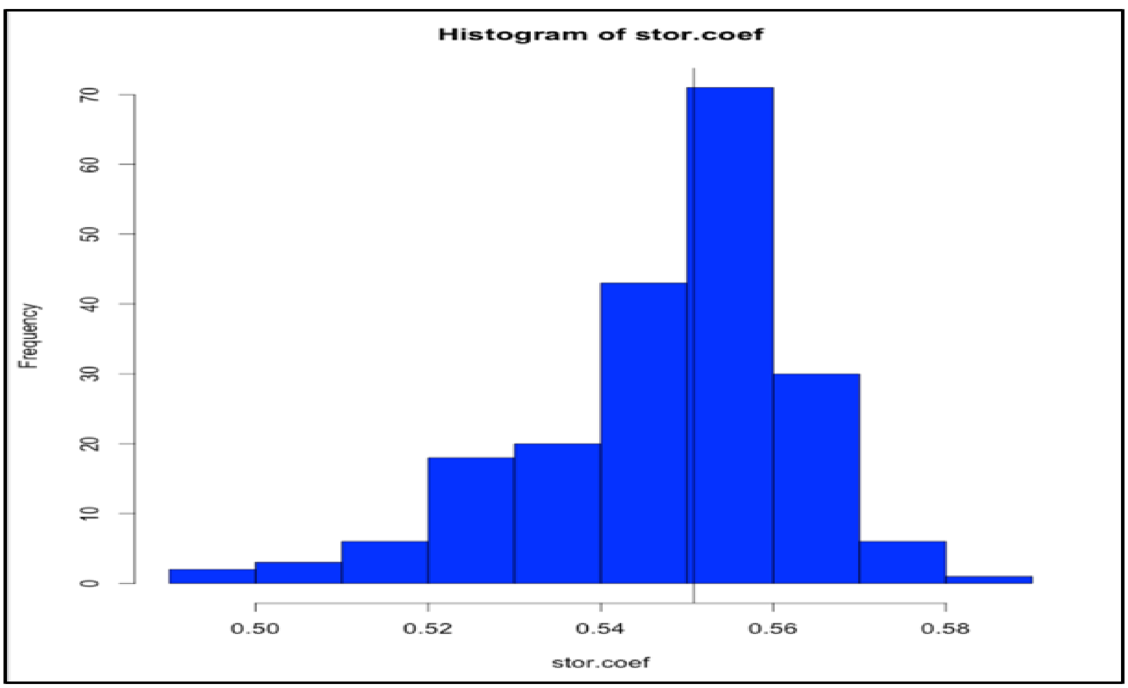
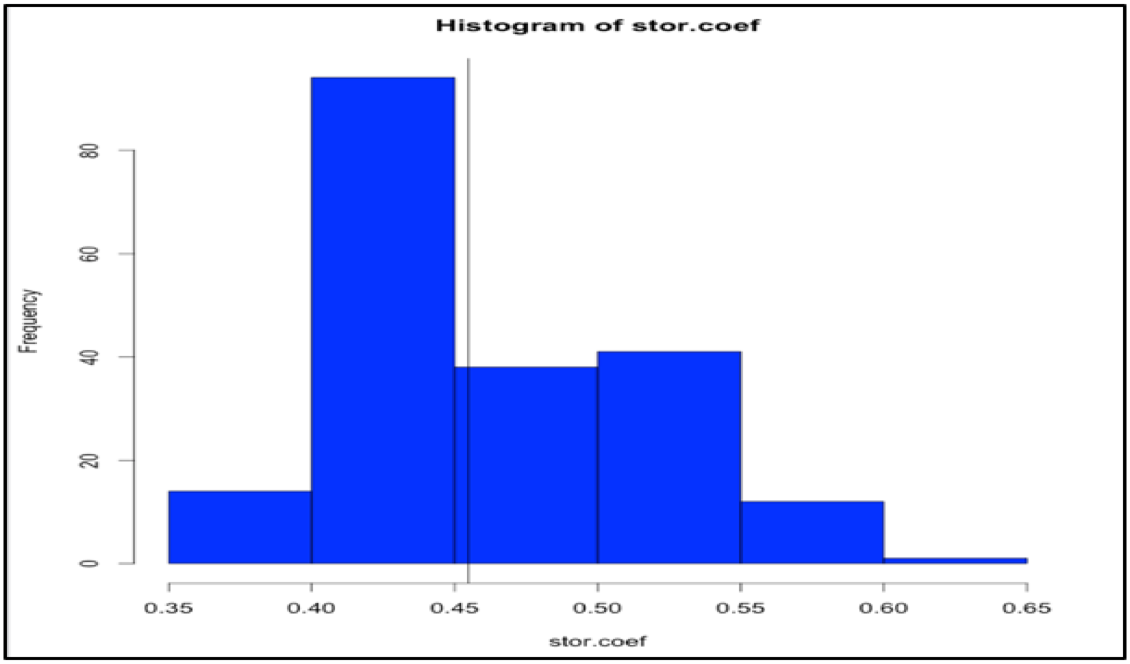


Figure 7.2.2: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.99) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.

ING Groep



Credit Agricole

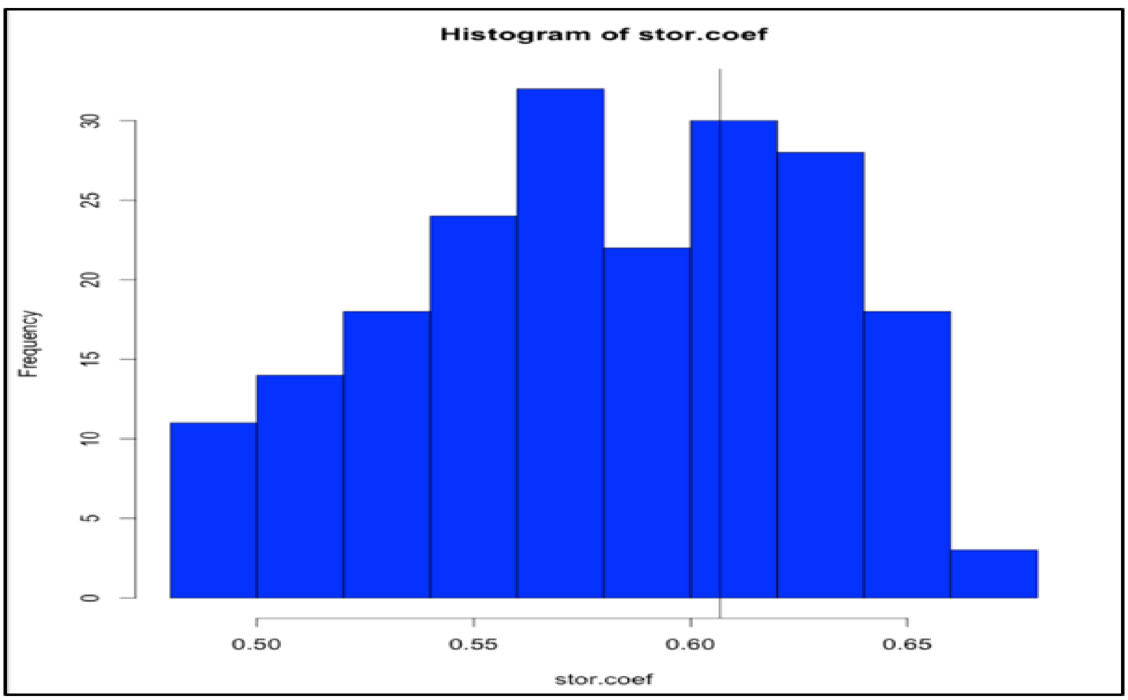
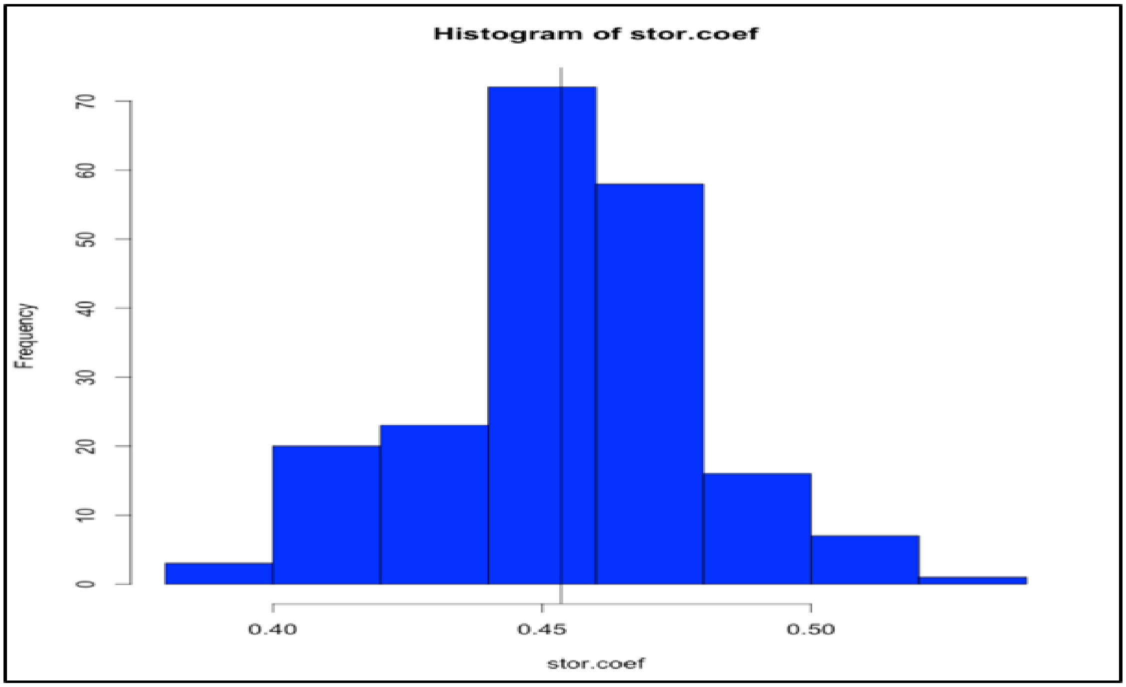


Figure 7.2.2: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.99) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
Aegon



AXA

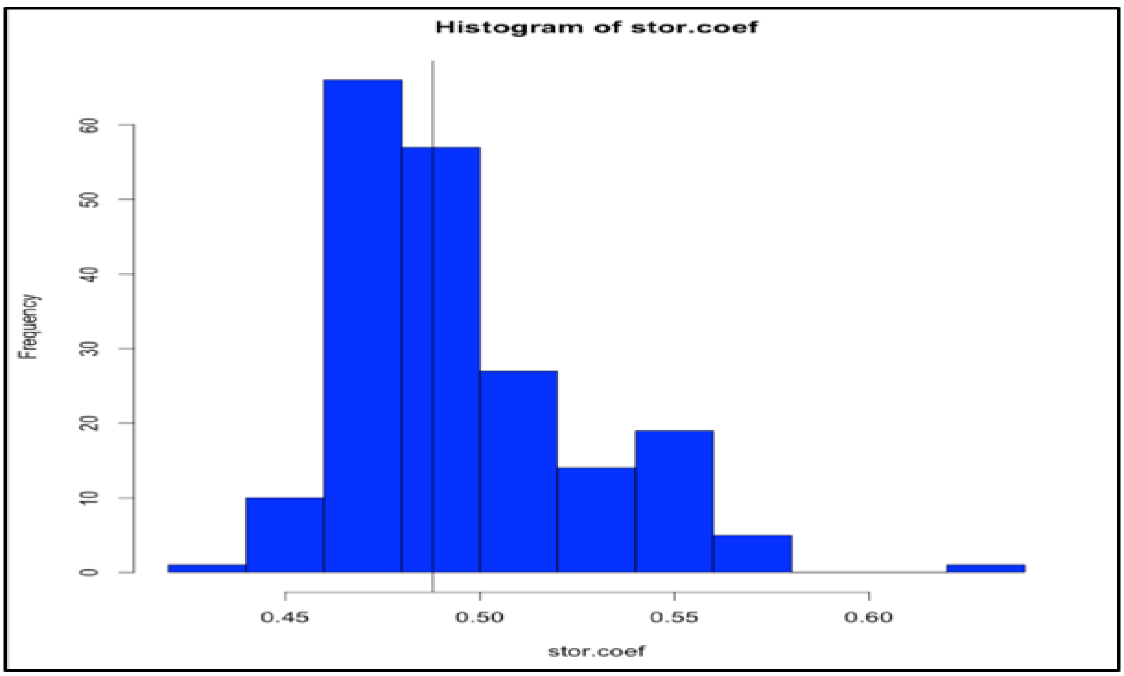
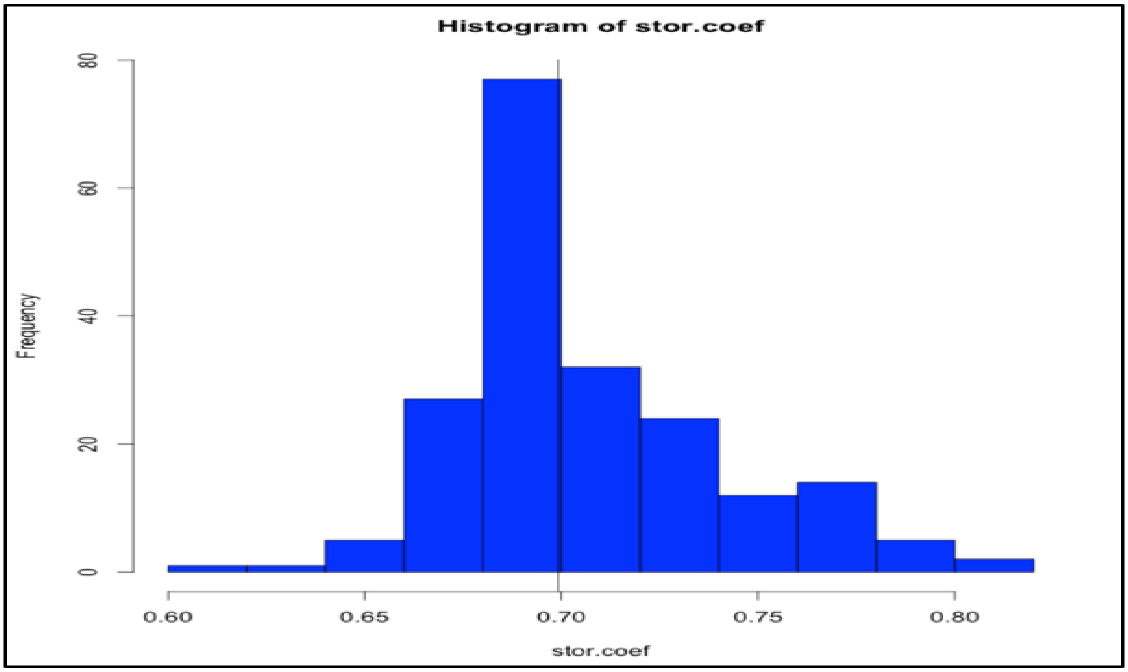


Figure 7.2.2: Histograms of resampled bootstrapped distributions of beta coefficients (where VaR is 1% and tau = 0.99) – entire sample. The original beta coefficients are denoted by the vertical black line in each case.
BBVA



Paribas

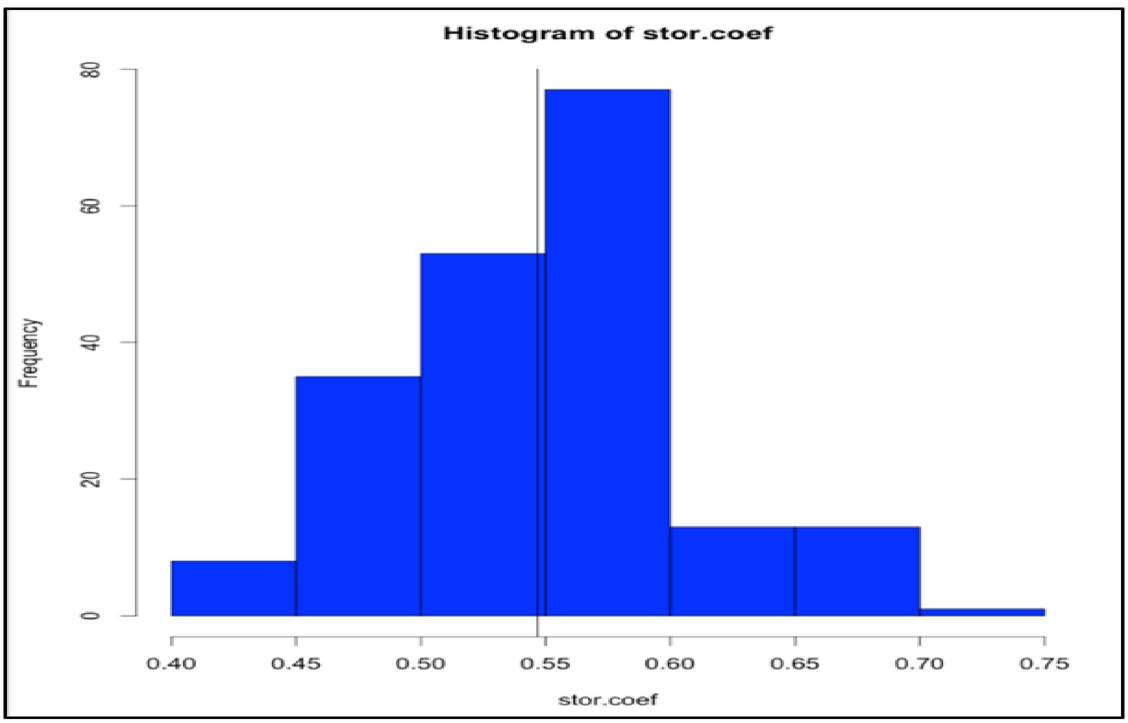


Table 7.2.1: P-Values of the Bootstrapped Distributions at tau = 0.95.

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

Table 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

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.

References

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.

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."

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).

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."

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.

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.

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.

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

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

Klaus, B., and Rzepkowski, B., (2008), “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.

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.

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.

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

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

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

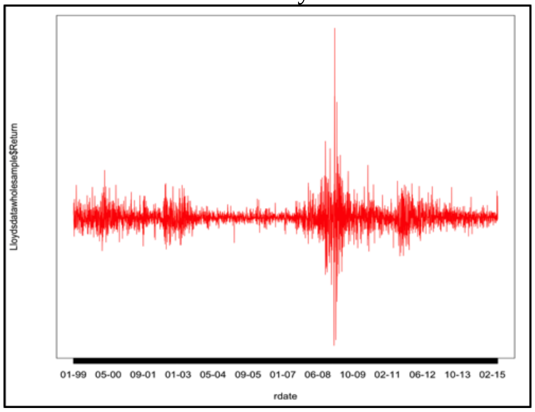
http://www.bankofengland.co.uk/pra/Pages/crdiv/updates.aspx

http://www.bankofengland.co.uk/pra/Documents/crdiv/2015osiilist.pdf https://www.moodys.com/research/Moodys-downgrades-Italian-banks-outlooks-remain-negative--PR_244732

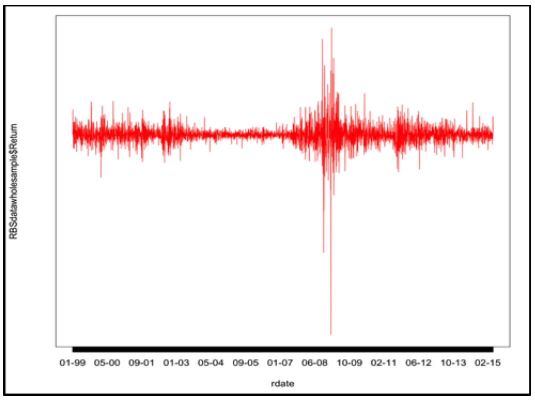
Oxford English Dictionary (2017)

Appendices

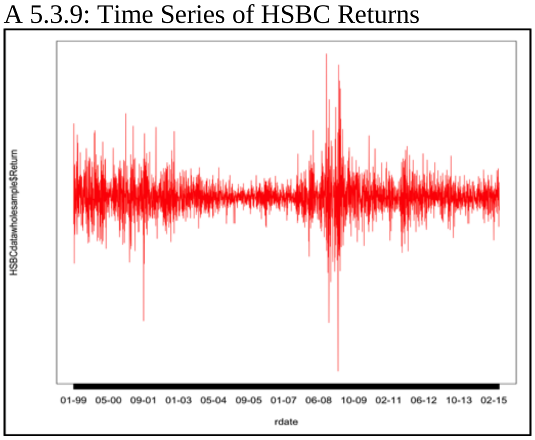
A 5.3.7: Time Series of Lloyds Bank Returns



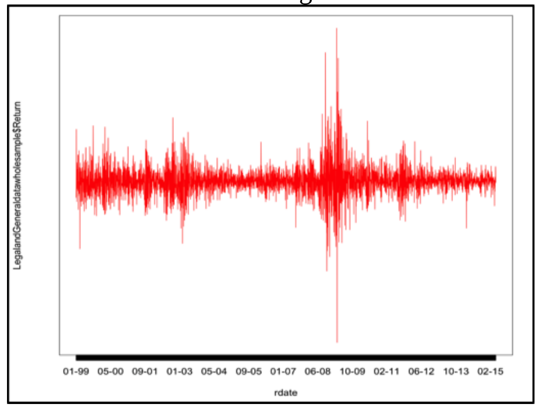
A 5.3.8: Time Series of RBS Returns



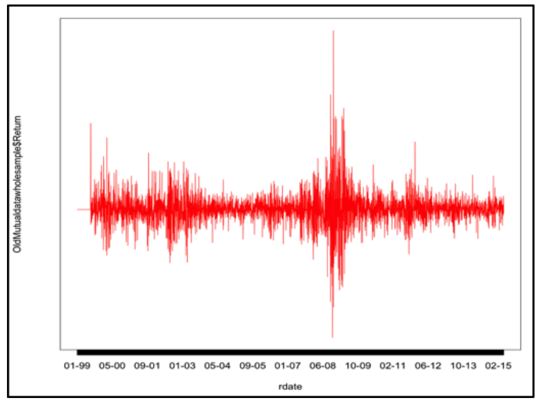
A 5.3.9: Time Series of HSBC Returns



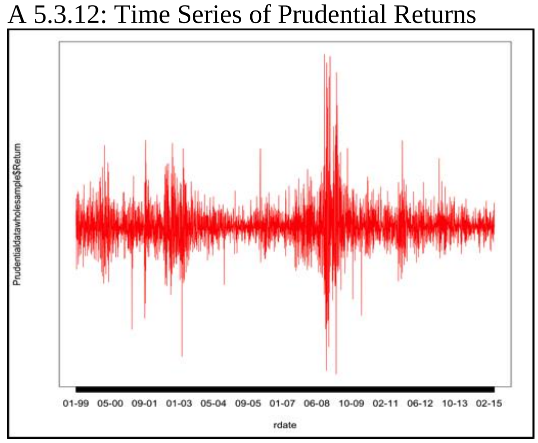
A 5.3.10: Time Series of Legal & General Returns



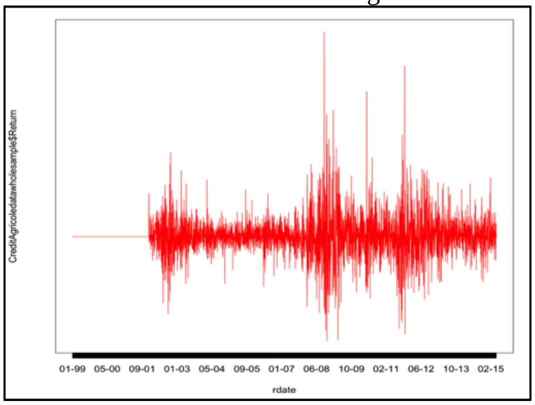
A 5.3.11: Time Series of Old Mutual Returns



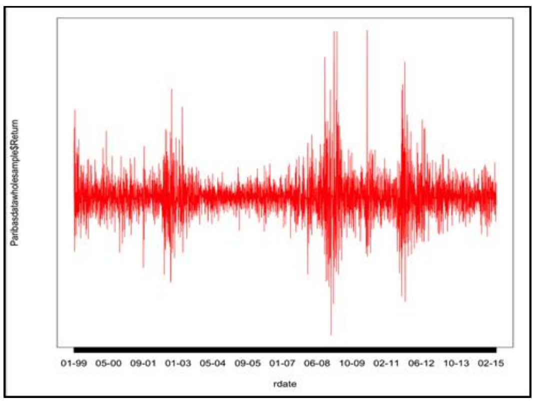
A 5.3.12: Time Series of Prudential Returns



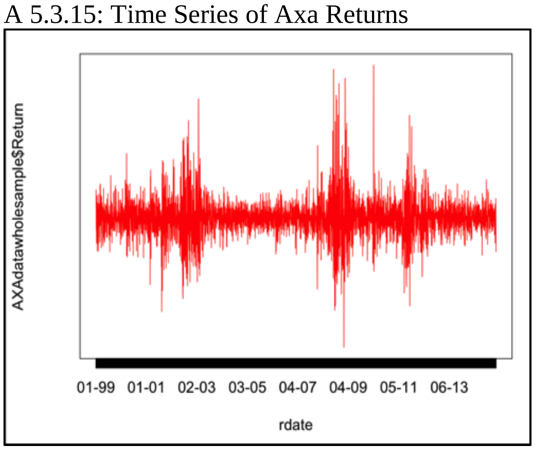
A 5.3.13: Time Series of Credit Agricole Returns



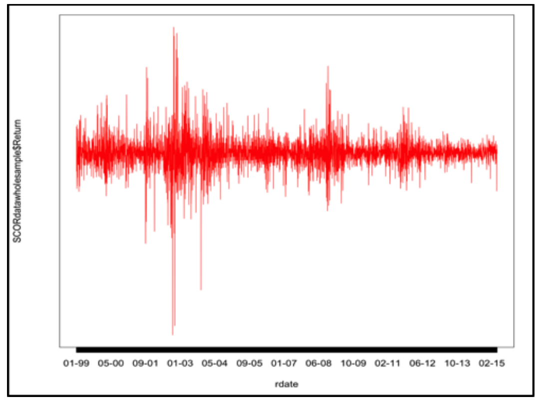
A 5.3.14: Time Series of Paribas Returns



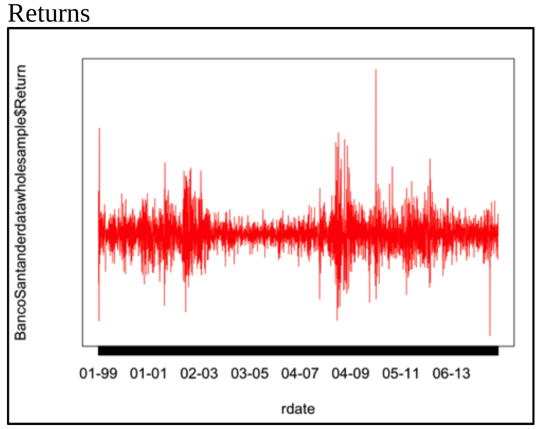
A 5.3.15: Time Series of Axa Returns



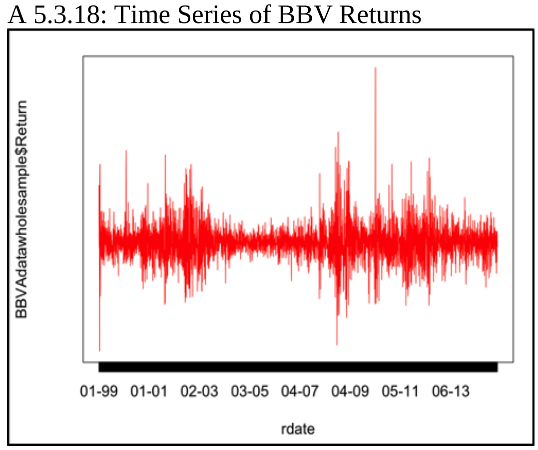
A 5.3.16: Time Series of SCOR Returns



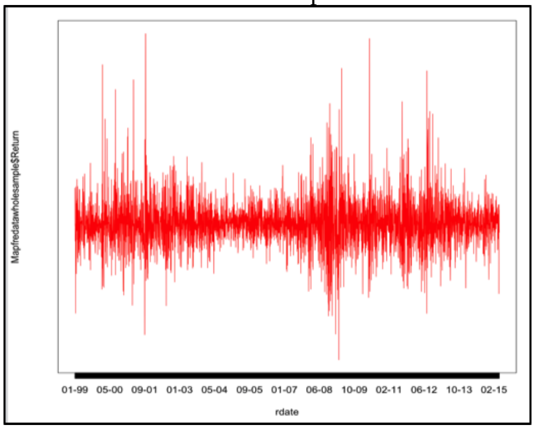
A 5.3.17: Time Series of Banco Santander Returns



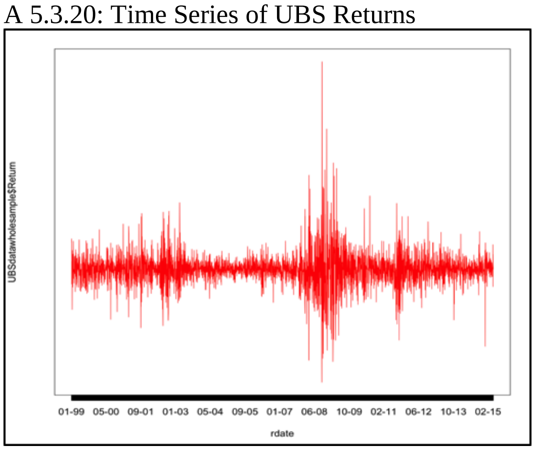
A 5.3.18: Time Series of BBV Returns



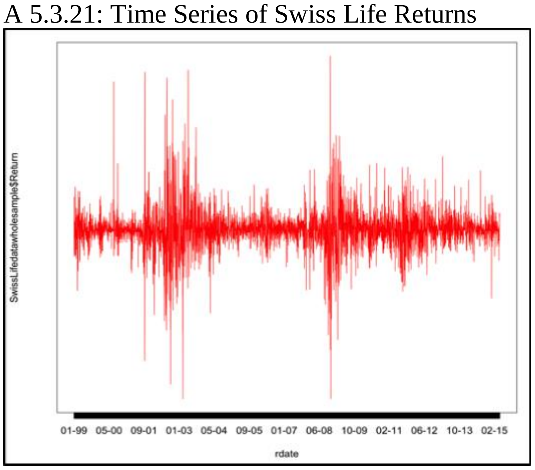
A 5.3.19: Time Series of Mapfre Returns



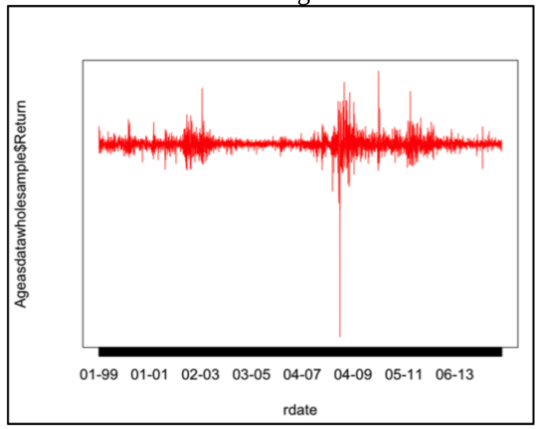
A 5.3.20: Time Series of UBS Returns



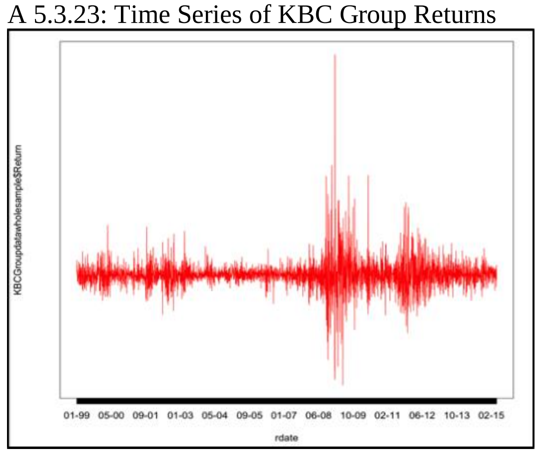
A 5.3.21: Time Series of Swiss Life Returns



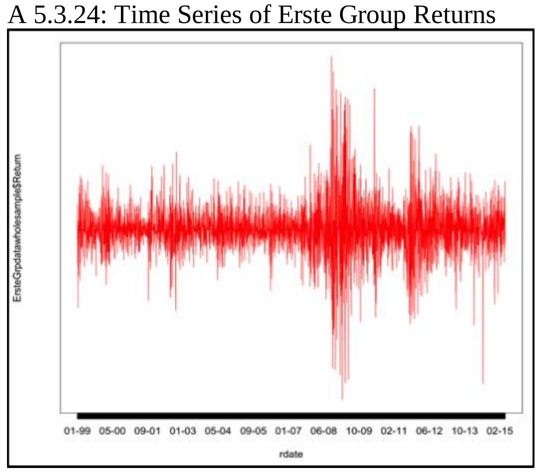
A 5.3.22: Time Series of Ageas Returns



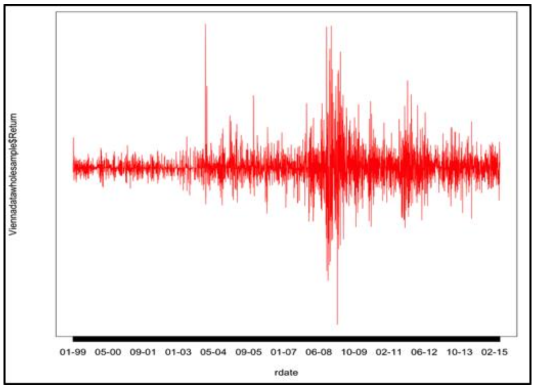
A 5.3.23: Time Series of KBC Group Returns



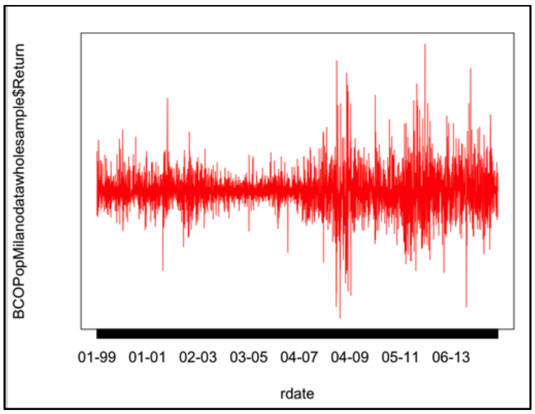
A 5.3.24: Time Series of Erste Group Returns



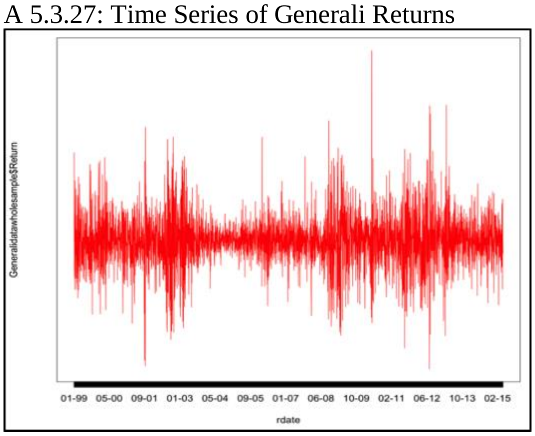
A 5.3.25: Time Series of Vienna Insurance Returns



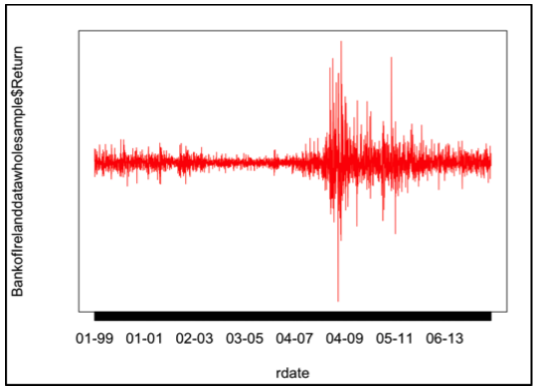
A 5.3.26: Time Series of BCO Pop Milano Returns



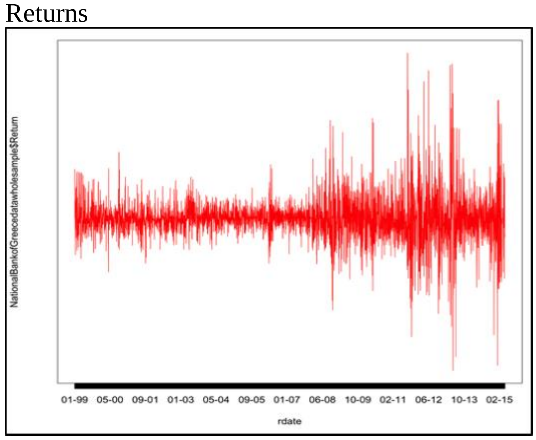
A 5.3.27: Time Series of Generali Returns



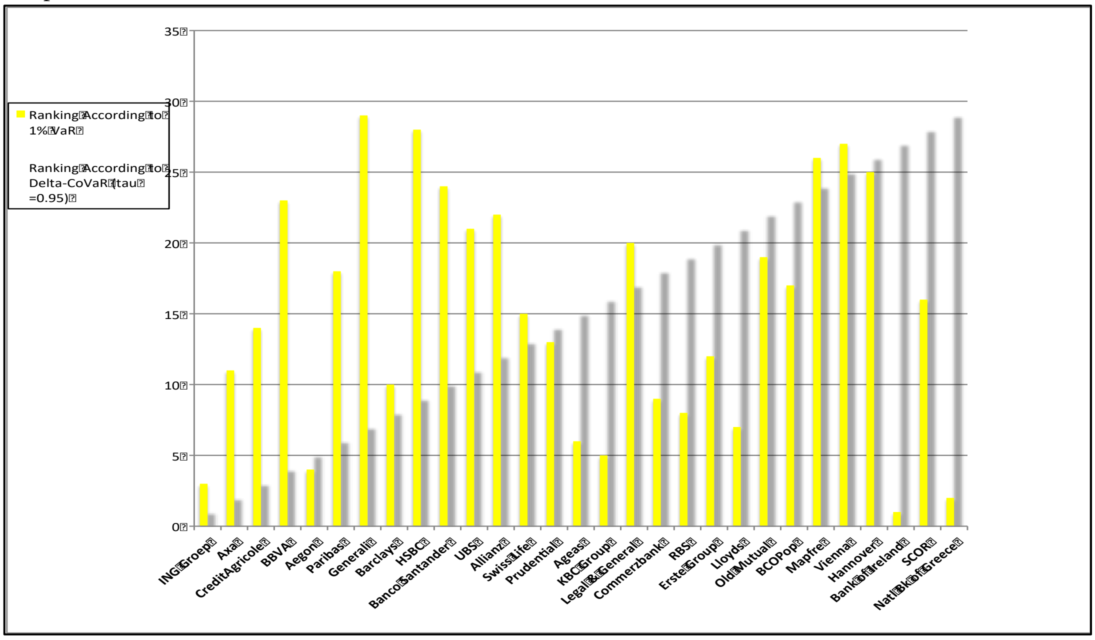
A 5.3.28: Time Series of Bank Of Ireland Returns



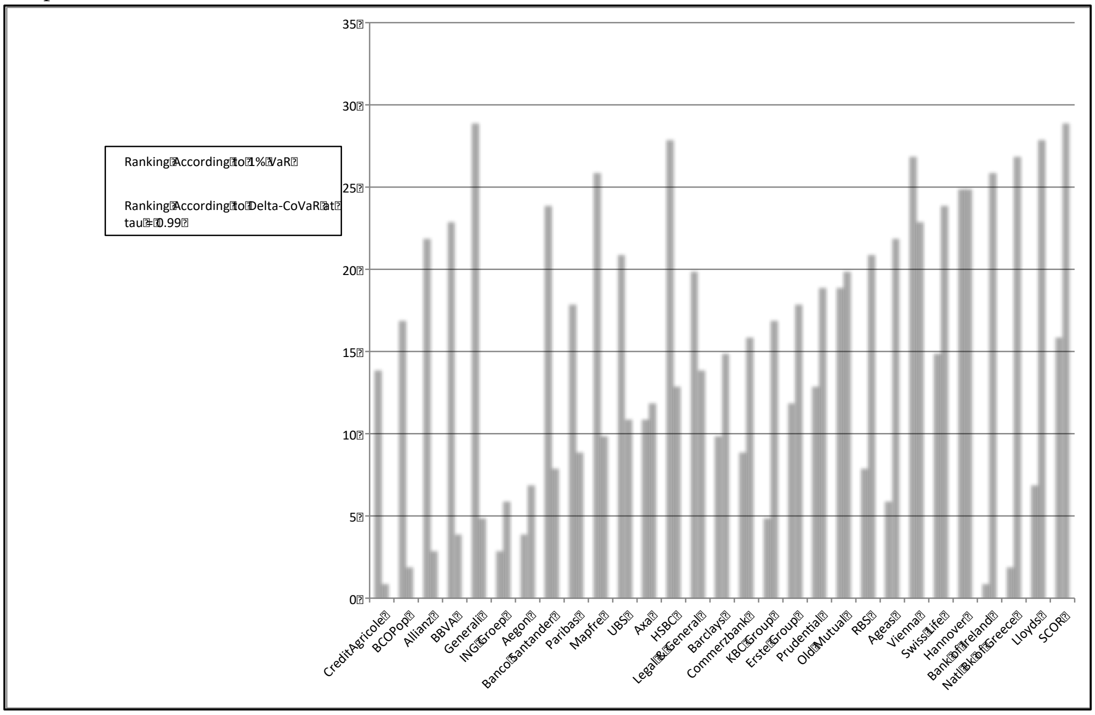
A 5.3.29: Time Series of National Bank of Greece Returns



A 6.2.1: Graph of rankings per financial institution for their 1% VaR and Delta-CoVaR (at tau = 0.95) and whole sample:



A 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.