Stockholm School of Economics

Master Thesis in Finance

Managing Market Risk in Europe:

The Performance of Value-at-Risk Models in Different Economic Conditions and the Impact of Basel II.5 on Financial Stability

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Abstract

Major regulatory standards, like the Basel II.5 accord, refer to a bank's internal Value-at-Risk model for determining its respective amount of market risk and for imposing adequate capital charges on the bank. This demonstrates the importance of a high quality of disclosed VaR figures – not only during non-crisis periods, but also especially during crisis periods when market risk increases. The purpose of this paper is to empirically test the disclosed VaR figures of a sample of six large European banks between 2004/2005-2013 by analyzing the VaR performance over the whole sample period, comparing the performance during non-crisis and crisis periods, and testing for a possible improvement effect after the crisis. We furthermore analyze the impact of the Basel II.5 standards of 2011 on required market risk charges and test for systemic risk in Europe as a possible obstacle to financial stability. The necessary daily P&L and VaR data for our analysis is obtained from graphs published in the banks' annual reports by applying a Matlab-based data extraction approach. Even though we find a non-uniform VaR performance over the whole sample period and in the non-crisis period, there exists a strong evidence of VaR understatement during the financial crisis in our sample and no significant performance improvement of the disclosed VaR figures in the aftermath of the crisis, compared to the pre-crisis period. Furthermore, despite the fact that the Basel II.5 accord increases the imposed market risk charges by a factor of two to three, we find a significant existence of systemic risk in the sample of the six European banks.

Key words
Value-at-Risk (VaR), Backtesting, Basel II.5, Market Risk Charges, Financial Crisis

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Glossary

BCBS – Basel Committee on Banking Supervision

BIS – Bank for International Settlements

DVaR – Disclosed Value-at-Risk

EBA – European Banking Authority

FSB – Financial Stability Board

MRC – Market Risk Charge

RWA – Risk Weighted Assets

P&L – Profit and Loss

QIS – Quantitative Impact Assessment

SVaR – Stressed Value-at-Risk

VaR – Value at Risk

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1. Introduction

During the past few years, the area of risk management in banks has raised a high amount of public as well as regulatory attention. Before the financial crisis in 2007, the rise in size and complexity of trading accounts at large commercial banks, driven to a large extent by a sharp growth in the over-the-counter derivatives markets (Berkowitz & O'Brien, 2002), made an effective management of market risk very important. Therefore, numerous regulatory advances have been targeting this area, attempting to ensure solvency and economic stability of the banking industry.

One primary example are the Basel standards issued by the Basel Committee on Banking Supervision. The 1996 Market Risk Amendment to the Basel Accord as well as its revision in the form of the Basel II standards that was initially published in 2004, focus on imposing minimal regulatory capital requirements on banks, depending on their respective amount of risk. The standards refer to the commonly used market risk measure Value-at-Risk (VaR) as the basis for determining market risk capital charges, more precisely to the obtained VaR output of a bank's internal model. It is notable that the definition of the regulations was accompanied by lobbying effort of banks towards the VaR approach instead of more static/non-mathematical risk measuring approaches, even though it relies on certain flawed assumptions, like the possibility to instantly liquidate positions.

Despite the regulatory requirements, the global financial crisis of 2007/2008 hit even major financial institutions severely, questioning the effectiveness of the previously implemented Basel II regulations. Although it can be argued that these requirements were officially established only shortly before the crisis – in January 2007 in Europe, and even later in the US – and might not have been able to prevent the crisis starting in August 2007 due to not being fully effective yet, many authors take the view that the crisis revealed limitations of the established risk management framework.

One point of criticism was the use of the VaR as a sole measure of market risk. As the trading book losses of many banks significantly exceeded their minimum capital requirements under the Pillar 1 market risk rules during the crisis, a demand for tighter regulatory standards with the purpose of capturing more extreme and tail conditions when determining the capital requirements of a bank, emerged. The Basel Committee responded to those claims by introducing the revised Basel II.5 standards in 2011, which base the determination of the market risk charges not only on the VaR, but also on the Stressed VaR, a measure that takes into account a one-year observation period relating to significant losses. This additional requirement is also intended to reduce the criticized procyclicality of minimum capital requirements for market risk (BIS), meaning that in recessions, when losses erode banks' capital, risk-based capital requirements become higher. If banks are not able to quickly raise sufficient new capital, their lending capacity falls, and this can possibly induce a credit crunch. Besides the introduction of the Stressed VaR, the new regulation also includes an Incremental Risk Charge (ICR), the Comprehensive Risk Measure (CRM) and a standard charge for securitization.

In the context of the new regulatory advances, another highly debated point remains however unaddressed: The fact that under the Basel system banks are allowed to use their own internal VaR estimates as a basis for their regulatory required capital, meaning that regulatory capital requirements for banks' market risk exposures are explicitly a function of the banks' own Value-at-Risk estimates. This fact demonstrates the importance of the quality of a bank's internal model for effective regulation (Berkowitz et al., 2011). However, it also shows a potential conflict of interest because the stated VaR directly influences the amount of required regulatory capital a bank has to hold leading to the consideration, that banks could deliberately influence their models to obtain preferable capital requirements. It can be questioned whether the added sophistication of supervision through the new standards truly increases security or whether it is substantially jeopardized by modeling benefits of the banks through the use of their own internal models.

The crucial accuracy of the internal models can, in theory, be evaluated through an adequate backtesting analysis. However, due to a lack of disclosure of the required daily P&L and VaR data by banks, there exist not many academic papers that conduct such an analysis. An important objective of this thesis is to innovatively circumvent the lack-of-data problem by applying a Matlab-based data extraction method on publicly available graphs, developed by Pérignon et al. (2008). This approach will enable testing the quality of internal VaR used in practice and therefore allow valuable conclusions on the effectiveness of regulation.

More precisely, as Pérignon et al. (2008) only analyzed a sample of Canadian banks before the financial crisis (1999-2005), our study intends to increase the geographical scope of the analysis to Europe by analyzing the internal models of a sample of large six European banks. We furthermore intend to analyze the period from 2004/2005 until 2013 in order to compare the performance of the internal models in crisis vs. non-crisis periods, and to study a potential learning effect of banks after the crisis. Lastly, a "what-if-analysis" that addresses the question whether an implementation of Basel II.5 before the financial crisis could have significantly improved the banks performance and weakened the severity of the crisis on the banks' performance will complement our analysis and enable drawing conclusions about a possible higher safety within the banking industry through the new regulation.

The thesis is structured as follows. Firstly, a detailed thesis statement covering our research question and the tested hypotheses enables a clear understanding of the objectives and the structure of our analysis. In the following section, the literature review provides an overview of academic insights into the banks' internal VaR models in practice and into the effectiveness of the Basel standards. Moreover, our extension to existing insights is outlined. In the Theoretical Background section, important information about the risk measure VaR and the regulatory development within the European banking sector is discussed. After describing the underlying data and the methodology of our analysis, our results are explained and interpreted. Lastly, the Conclusion contains our most relevant findings, while outlining certain limitations of our approach and suggesting interesting areas for further research.

2. Thesis Statement

The purpose of this paper is to address the following research question:

"How accurate are internal models used by European banks regarding the estimation of market risk quantified in terms of the VaR – in general as well as in different economic conditions – and has there been a learning effect in the aftermath of the financial crisis? In line with that, how effective are regulatory revisions in improving solvency and financial stability of the banking system?"

This multifaceted research question is split into four hypotheses containing specific subparts to assure detailed and structured insights. The first sub-question refers to the quality of internal VaR models in practice. Previous studies focusing on banks outside of Europe found evidence that the banks surprisingly do not have a disposition to underestimate their market risk, but rather tend to overestimate their VaR (see Pérignon et al., 2008; Berkowitz and O'Brien, 2002). A possible reason could be reputation issues in line with a substantial number of outliers – events when a trading loss exceeds the VaR. Therefore, we will test the following hypothesis for our European sample banks:

Hypothesis 1 – Overall performance of VaR Models

European banks generally tend to overstate their VaR by using a too conservative model.

Previous studies refer however only to sample periods that can be classified as non-crisis periods. It is important that a bank's model is highly responsive to different market conditions in order to constantly obtain an accurate output over time. Nevertheless, unlike in the pre-crisis period, banks experienced many outliers during the financial crisis. Therefore, the following hypothesis will be tested:

Hypothesis 2 – Comparative analysis of VaR performance: non-crisis vs. crisis

Regardless of the overall performance, the banks' internal models tend to deliver a significantly too low VaR estimate of market risk during the financial crisis and they generally perform better in non-crisis periods.

The severe impact of the financial crisis not only led to the bankruptcy of some, even major financial institutions like Lehman Brothers in September 2008, it endangered the bankruptcy of many other banks, which finally had to be bailed out by governments in order to prevent an even more severe impact on the financial markets. In the aftermath, it is therefore not only in the interest of regulators to ensure solvency and economic stability of the banking system, but also in the banks' interest to improve their risk management practices to prevent similar scenarios that endanger their future existence. This leads to the third hypothesis:

Hypothesis 3 – Improvement in VaR determination after the financial crisis

In the aftermath of the financial crisis, European banks have significantly improved the quality of their internal models, leading to a better performance of the disclosed VaRs in the post-crisis period than in the pre-crisis period.

Looking at the regulatory advances in Europe, the revised Basel II.5 standards added several specifications regarding the determination of regulatory capital requirements, like the calculation of a Stressed VaR. As a consequence, the Basel Committee estimates market risk charges to increase by a factor of three on average (see BCBS 2010, 2012a, 2012b, 2013). The question can be asked how the financial crisis would have been affected if the new standards had already been implemented. Would the banks' market risk charges have been more sufficient to cover their trading losses?

In order to answer the question whether the new standards actually increase the safety within the banking industry, it is however not sufficient to look at the solvency of individual banks. It is important to additionally understand the potential of systemic risk – "the probability of breakdowns in an entire system as opposed to breakdowns in individual parts or components" (Kaufman and Scott, 2000). If the banks' P&Ls are highly correlated, even higher market risk charges might not be able to prevent a scenario similar to the crisis in 2007/2008 due to the simultaneous impact of the downturn on all the banks. Therefore, the forth hypothesis is the following:

Hypothesis 4 – Sufficiency of Basel II.5 MRCs and systemic risk in Europe

The revised capital market charges of the Basel II.5 framework would have significantly increased the banks' possibility to cover their trading losses during the financial crisis if already implemented before the crisis. However, the existence of a significant amount of systemic risk in Europe is still potentially jeopardizing the safety of the European banking system.

3. Literature Review

After outlining and specifying the content of the paper in the preceding thesis statement, the Literature Review section provides deeper insights into existing literature about both, studies of internal VaR models in use as well as the effectiveness of the Basel standards. It furthermore intends to outline the scope in which the thesis will add to the previous research.

3.1 Studies of Internal VaR Models

Even though a large body of literature discussing theoretical concepts of VaR-models for managing market risk and different backtesting approaches exists, not many academic insights can be found when it comes to the performance of the risk models that banks apply in practice. A probable reason is the insufficient disclosure of the banks' internal models as well as their daily P&L and VaR data – information that is necessary to backtest the models in use. When, for example, Pérignon and Smith (2010) analyzed the VaR disclosure of a sample consisting of the ten largest US banks from 1996 until 2005, they found that its level highly varied for their sample banks. Greenspan (1996) outlined that quantitative measures of market risk, such as the VaR, are however only expressive when they are accompanied by sufficient information on their calculation and their actual performance. The insufficiency of information restricts many analyses of the banks' internal models in the public domain by the use of illustrative portfolios[1] for their comparisons of modeling approaches and implementation procedures (Berkowitz & O'Brien, 2002). This leads to the question how the "limited-public-disclosure problem" can be circumvented and the performance of the banks' models in use can be tested.

There exist two academic papers that tackle this issue in different ways: Berkowitz and O'Brien (2002) use anonymous data for their analysis of the internal risk management models of six US commercial banks from 1998 until 2000. In contrast to that, Pérignon et al. (2008) extract the necessary daily P&L and VaR data from graphs published in annual reports for their empirical study of six Canadian banks for the period 1999-2005. They use a Matlab-based method that will also be the fundament of our thesis and that will be explained in more detail in the Data and Methodology section.

[1] An illustrative portfolio is a created portfolio that mimics the actual portfolio of a tested bank.

Looking at the findings, Berkowitz and O'Brien (2002) detect significant risk overstatement of their sample banks. However, despite the conservatism, there exist losses that substantially exceed the VaR and those events tend to be clustered, suggesting that the internal models have difficulties to forecast changes in the volatility of the P&L. Furthermore, the internal models of the examined US banks do not lead to more accurate VaR estimates than simple ARMA(1,1)-GARCH(1,1) models.

Pérignon et al. (2008) quantify the banks' conservatism into a risk-overstatement coefficient, which ranges from 19% to 79% for the banks of their Canadian sample. The findings are therefore qualitatively in line with the results of Berkowitz and O'Brien. Pérignon et al. (2008) find however, that the large commercial banks have not been overstating their VaRs over the entire post 1996 Basel Accord amendment period. One example for that, noted by Jorion (2006), is J.P. Morgan, which experienced 20 exceptions in 1998 and therefore significantly more than the 13 exceptions that would have been expected with a 95% confidence level. Pérignon et al. (2008) explain the VaR overstatement not through an inaccurate risk assessment of banks, but rather through an incorrect measurement of market risk due to an overcautious VaR determination and an underestimation of the diversification effect when aggregating VaRs across different business lines and/or risk categories. They conclude however that banks exhibit learning effects in their VaR setting over the sample period.

3.2 Effectiveness of the Basel standards

As already mentioned, the accuracy of banks' internal risk management models is especially important, because their output constitutes the regulatory foundation for the determination of individual market risk capital charges in the Basel regulation framework. The Basel Committee states its mandate as the strengthening of "the regulation, supervision and practices of banks worldwide with the purpose of enhancing financial stability" (see www.bis.org). However, numerous lobbying effects of banks over the years arose suspicions regarding the compliance of regulatory revisions with the interests of the banks and thus, their effectiveness and impact on the stability of the financial system is highly discussed in academic research.

One study that supports the regulatory framework referring to the VaR approach is an analysis of the trading VaRs disclosed by a sample of eight major U.S. commercial banks (Jorion, 2002). He finds that these VaRs are related to the subsequent variability of trading revenues over a period of almost six years commencing in 1994 and therefore he argues that the trading VaR is a proper measure to compare risk profiles of trading portfolios. Also Hendricks (1996) finds, when applying value-at-risk models to 1,000 randomly chosen foreign exchange portfolios over the period 1983-1994, that virtually all of twelve defined subcategories of the three major classes of value-at-risk models — equally weighted moving average, exponentially weighted moving average, and historical simulation approaches – produced accurate 95th percentile risk measures. Remarkable findings were however, that extreme outcomes occurred more often and were larger than predicted by the normal distribution (fat tails) and that the size of market movements was not constant over time (conditional volatility). As both of these characteristics are not captured by the VaR approach (Hendricks, 1996), they are also not addressed by a VaR-based regulation. Also Alexander et al. (2014) claim that the regulatory standards are not totally effective in controlling tail risk.

In addition to the limitations of the VaR, Breuer et al. (2010) criticize the regulatory standards' division of risk into market risk and credit risk and their independent treatment in the calculation of risk capital. As many financial positions depend simultaneously on both types of risk, an approximation of the portfolio value function with a separation of value changes into a pure market risk plus pure credit risk components can therefore result in an overestimation, but also in an underestimation of risk (Breuer et al., 2010).

Danielsson et al. (2001) point out that the underestimation of the joint downside risk of different assets by statistical measures used for forecasting within the VaR framework additionally constitutes a potential regulatory threat: The endogeneity of risk can possibly destabilize an economy and due to the inherent procyclicality VaR – based financial regulations can induce crashes that would otherwise not occur. O'Brien and Berkowitz argue, however, that a risk-modeling framework is not destabilizing the financial markets, because banks have significantly heterogeneous exposures to market factors (O'Brien and Berkowitz, 2006). And also Jorion (2007) opposes this view, supported by finding only a moderate correlation among quarterly trading revenues of banks in the US. Looking at Europe, Schüler (2003) found however a potential of systemic risk - "the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components" (Kaufman and Scott, 2000). It has shifted from a national level to a European level from 1980 until 2001 that justifies the necessity of a European-wide regulation like the Basel standards (Nijskens and Wagner, 2011). Engle et al. find that the systemic risk of the 196 largest European financial firms, 2000-2012, is much larger than the one borne by US banks: Banks and insurance companies bear approximately 80% and 20% of the systemic risk in Europe. The authors propose that this might even imply that some European institutions are be "too big to be saved", meaning that the costs of taxpayers to rescue the riskiest domestic banks are too high (Engle et al., 2015).

3.3 Literature extension

Building on the outlined literature, this paper wants to add valuable insights into the following areas: Firstly, Pérignon et al. (2008) apply their Matlab-based data extraction method solely to a sample of Canadian banks. The analysis of internal models of European banks will add valuable insights into the model quality and the implied effectiveness of regulations in a different geographic and regulatory environment. Secondly, the study of Pérignon et al. (2008) only contains the time period from 1999 until 2005. Our analysis will focus on the period from 2004 to 2013, which includes the financial crisis, and thereby allow valuable conclusions about possible performance differences of internal models in crisis vs. non-crisis periods and a potential learning effect after the financial crisis. Thirdly, extending the analysis to the comparison of implied regulatory market risk charges for our sample period under the different regulatory frameworks enables conclusions about the impact of the revised Basel II.5 regulation on financial stability. Our study will furthermore test whether the existence of systemic risk in Europe can be confirmed for our sample banks and will thus allow a more thorough understanding of a potential threat to the financial stability in Europe which cannot necessarily be tackled with the regulatory capital charges and that might even be enhanced through them.

4. Theoretical Background

After describing the scope of this thesis and its attribution to the previous literature, the necessary theoretical background for an encompassing comprehension of the analysis will be expounded in this section, divided into an introduction to the concept of VaR and a depiction of the regulatory development from Basel II to Basel II.5.

4.1 Introduction to VaR

As already mentioned, the VaR is an established and widely used measure of potential losses in the area of market risk – one category of financial risk, among liquidity risk, credit risk, and operational risk. Market risk describes the risk of losses in the bank's trading book due to changes in equity prices, interest rates, credit spreads, foreign-exchange rates, commodity prices, and other indicators whose values are set in the public market (Mehta et al., 2012). Intuitively, the VaR measure summarizes the worst loss over a target horizon that will not be exceeded with a given level of confidence. More formally, it describes the quantile of the projected distribution of gains and losses over the target horizon. If c is the selected confidence level, the VaR corresponds to the $1-c$ lower tail level (Jorion, 2001).

Over the last decade, major trading institutions have developed large-scale risk measurement models whereof most gauge and aggregate the market risk in current positions at a highly detailed level, referring to the VaR as a standard risk metric. As described above, the past growth in the trading accounts of large commercial banks, and their rising complexity, led to a rapid rise in the importance of market risk (Berkowitz & O'Brien, 2002), and therefore, the question about its effective management became a focus of attention. A fierce debate emerged whether the common use of the VaR as a sole measure of market risk is an appropriate approach.

In order to better comprehend this debate, some background information about the different VaR estimation methods from a theoretical perspective and their respective limitations are essential. There exist two principal models to design the risk measure by generating simulations: The Monte Carlo Simulation and the Historical Simulation. The Monte Carlo method is generally considered as a better theoretical approach, for example, because i) it enables a more comprehensive picture of potential risks embedded in the tail of the distribution, ii) it allows to modify individual risk factors and correlation assumptions making it more flexible, and iii) it possesses a greater amount of consistency and synergies with other trading-book modeling approaches (e.g. the expected-potential-exposure approach for counterparty risk modeling). This method is however criticized for its complexity, as about 10,000 simulations per risk factor are required, resulting in much longer reaction times compared to an easier but less accurate Historical Simulation method. Its complexity makes the method additionally more difficult to understand for businesses or management (Mehta et al., 2012).

The fact, i) that the non-parametric Historical Simulation approach requires far fewer simulations, ii) that it consists of more transparent calculations, and iii) that it demands fewer assumptions regarding market-factor distribution shapes, enables banks to accommodate large-dimensional portfolios without too much exposure to a model or estimation risk (Pérignon & Smith, 2010). The method furthermore leads to smoother risk market charges through time without huge daily changes in a regulatory framework based on VaR (Jorion, 2002).

Due to the size and complexity of trading positions at commercial banks, forcing them to deal with thousands of risk factors, it is therefore not surprising that many banks favor the Historical Simulation method, choosing not to attempt to estimate their time-varying volatilities and covariances (Andersen et al., 2007). In a survey conducted by McKinsey in 2012, only about 15 percent of 13 large European and North American banks use the Monte Carlo techniques as their main approach, whereas the other banks use either solely Historical Simulation (75%) or a hybrid approach (10%) (Mehta et al., 2012). This is in line with findings of Pérignon and Smith: 73% of the 60 international banks in their sample that disclosed their VaR method (64.9 %) used Historical Simulation in 2005 (Pérignon & Smith, 2010).

Despite its more frequent application by banks, also the Historical Simulation approach exhibits limitations: As its projections are directly derived from the distribution of past occurrences, they may be irrelevant or unhelpful if the future is statistically different from the past (Mehta et al., 2012) and, since it only relies on the one (sometimes two) year unconditional distribution of the risk factors, it is under-responsive to changes in conditional risk (Pritsker, 2006). There exists however no comprehensive research on whether one type of internal model leads to a significantly better VaR estimate in practice, or whether the performance of a bank's internal model only depends on its modeling experience and sophistication independent of the bank’s choice between the Monte Carlo method and Historical Simulation.

It is important to understand the limitations of the VaR when measuring market risk – especially in the light of regulations like the 1996 Market Risk Amendment to the Basel Accord, which refers to the internal VaR models of large banks as a basis for the determination of market risk capital requirements (Berkowitz & O’Brien, 2002). These regulatory specifications add the question of a possible inaccuracy of internal models not only due to inaccuracy of the VaR measure itself, but also due to a conflict of interest: banks’ opportunity costs of holding security capital make their intention to state the true VaR questionable and could lead to a possible VaR understatement. On the other hand, reputation costs of exceptions – trading days when the realized loss exceeds the internally calculated VaR – could possibly lead to an intended VaR overstatement. It is furthermore important to emphasize that even the banks themselves do not solely rely on their VaR-based risk management tools. For instance, Guldimann, Head of J.P. Research states that Risk Metrics – a VaR-based risk management system of J.P. – cannot be seen as a substitute for good management, experience and judgment and its use must therefore be supplemented by stress tests, limits and controls in addition to an independent risk management function.

4.2 From Basel II to Basel II.5

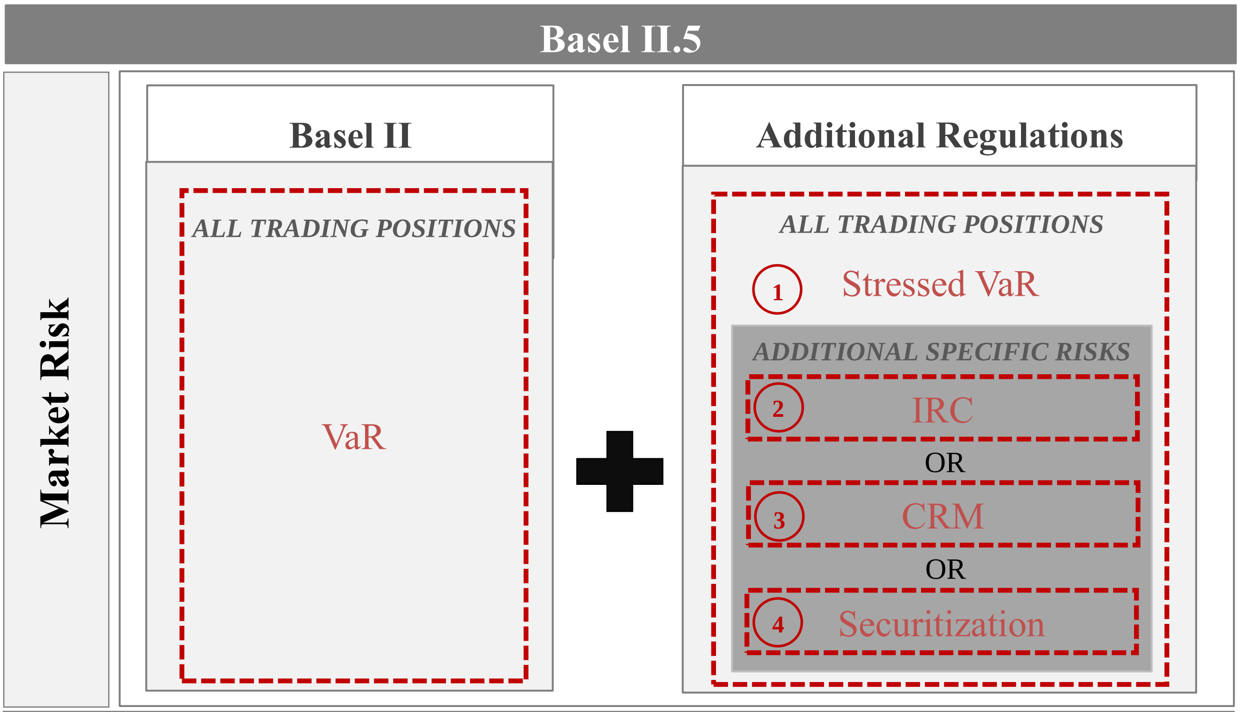
With this in mind, it can be asked whether the recent revisions of the banking regulation in Europe within the area of market risk management, especially the Basel II.5 standards, were able to efficiently address the outlined issues. Before this question will be analyzed, the following section outlines a more detailed description of the regulatory changes in order to enable a more comprehensive understanding of the topic.

The Basel Committee on Banking Supervision (BCBS) is a committee of banking supervisory authorities that was established in 1974. It describes itself as the primary global standard-setter for the prudential regulation of banks and it provides a forum for cooperation on banking supervision matters with the objective to increase the understanding of supervisory issues and to improve the quality of banking supervision. It formulates guidelines and standards, but its member authorities and other nations decide independently on their implementation.

The formulated Basel standards have undergone several revisions and changes concerning the management of market risk over the past. After the initial 1996 Market Risk Amendment to the Basel accord, the Basel II Framework was proposed by the Basel Committee in 2004 and subsequently implemented in Europe. It consists of the three pillars: minimum capital requirements, a supervisory review and market discipline. Within the framework of Basel II, three different risk types determine a bank's minimum capital requirement: its credit risk, operational risk and – the focus of this paper – its market risk. The regulations name the VaR as the preferred approach to estimate market risk and to calculate capital charges, while referring to the banks' internal models for the VaR determination.

As already mentioned, those standards were however fiercely disputed in the aftermath of the Financial Crisis of 2007/2008. The Basel committee reacted to the critique and published Basel II.5 in 2011 with an adjusted approach for the calculation of regulatory capital. The revision's main goal is – besides enhancements referring to the credit risk in the banking book – the increase in capital charges on the market risk of a bank's trading book through four adjustments (see *Figure 1)*.

Figure 1 Measuring Market Risk: From Basel II to Basel II.5



1. Stressed VaR – Describes risks in more volatile markets by referring to historic data when market was in turmoil
2. Incremental Risk Charge (IRC) – Captures default and migration risks for specific positions (e.g. bonds, CDS, traded loan)
3. Comprehensive Risk Measure (CRM) – Captures default and migration risks of correlation trading positions (e.g. CDOs)
4. Securitization – Standardized charge for securitization, re-securitization and n-th to default credit derivate positions

Source: Own Analysis

Firstly, the new standards add a Stressed VaR to the calculation of market risk charges – an additional VaR that intends to capture the more extreme or tail conditions, which the normal VaR does not cover, by using a one-year data set from a period of significant market stress. Secondly, Basel II.5 adds an Incremental Risk Charge (IRC) in order to capture default and credit migration risk of mainly credit products (excluding securitized positions), like corporate bonds, credit default swaps, and tradable loans. The IRC intends to take into account losses from credit downgrades in addition to the losses from defaults, and the applied methodology refers again to the banks' internal risk model. The third extension is a Comprehensive Risk Measure (CRM) dealing with correlation risk of, for example, collateralized debt obligations (CDO) associated with the underlying positions. It determines, among others, the risk of hedges becoming ineffective, the volatility of different factors, recovery rates or the rebalancing of a hedge due to a change in the position. Lastly, standardized charges for securitization and re-securitization positions that are not in a correlation-trading book intend to eliminate accounting arbitrage between the banking and trading book (BCBS303).

Several studies address the regulatory effectiveness of Basel II.5. Quantitative impact assessments by the Basel Committee, for example, estimate an average increase in regulatory capital requirements by a factor of three. Also Mehta et al. (2012) find that Basel II.5 leads to an increase in risk-weighted assets (RWAs) and significantly boost the capital requirements by a factor of two or three. They furthermore outline that an additional improvement will be reached through the more recent regulatory standard Basel III, which was agreed upon by the members of the Basel Committee on Banking Supervision in 2010/2011 and is about to be implemented until 2019. It will bump the stakes even higher, particularly through the implementation of the credit-valuation adjustment (CVA), which measures the market risk in OTC derivatives from counterparty credit spreads (Mehta et al., 2012).

5. Data and Methodology

In order to assess to quality of internal VaR models of European banks, we study the relationship between a daily hypothetical profit or loss (daily P&L) and the respective Value-at-Risk of the preceding trading day, i.e. $P\&L_t$ *and* VaR_{t-1}. *The following part is organized as follows: Section 5.1 presents the data sample and outlines the applied approach to overcome the issue of the sparse amount of available data in the area of risk management and subsequently, section 5.2 introduces the methods used to conduct our analysis.*

5.1 Data overview

5.1.1 Dataset

The underlying data sample of the analysis consists of actual daily VaRs and hypothetical daily P&Ls of the sample banks, retrieved from their annual reports. The banks determine these hypothetical P&Ls according to the buy-and-hold assumption, under which they gauge theoretical changes in their trading portfolios that would occur assuming that the portfolio is static, i.e. the trading portfolio has been left unchanged during the holding period. The value-at-risk is however an actual estimate obtained by the banks' internal VaR models. We present this figure in negative amounts to enable a better visual comparison with the corresponding buy-and-hold income and loss.

Our analysis comprises six European Banks including Deutsche Bank, HypoVereinsbank (a member of UniCredit Group), UBS, Svenska Handelsbanken AB, Banco Bilbao Vizcaya Argentaria S.A. (BBVA S.A.) and Santander. The choice of these banks is motivated by their importance for the European Banking System coupled with the availability of necessary graphs in their annual reports. Five out of the six sample banks (Deutsche Bank, Santander, BBVA S.A., HypoVereinsbank (as a subsidiary of UniCredit Group), UBS) are defined as global systemically important banks (G-SIBs) by the Financial Stability Board using a methodology developed by the Basel Committee on Banking Supervision (BCBS). Additionally, we include Svenska Handelsbanken AB in our analysis because, even though the bank is not big enough for the G-SIB status, it still has a severe domestic systemic importance in Sweden and is defined as a domestic systematically important bank (D-SIB) by the FSB. Furthermore, according to the European Banking Authority (EBA), all the analyzed banks have passed the 2014 EU-wide stress test, which pursues the goal of evaluating the EU banks' resilience to adverse economic scenarios. Deutsche Bank and Santander have however recently failed an US "stress test" designed to examine whether the banks would be able to stand up against another financial crisis (BBC, 11-03-2015), thus making it is especially interesting to analyze the quality of their internal models in our study.

The time frame for the different banks ranges from 4 to 10 years, due to the fact that the banks do not consistently publish the necessary graphs of their backtesting results in their annual reports. In more detail, the time horizon for Deutsche Bank and Santander reaches 10 years (January,1 2004 – December 31, 2013); for BBVA S.A., HypoVereinsbank and Svenska Handelsbanken AB - 9 years (January 1, 2005 – December 31, 2013) and for UBS - 4 years (January 1, 2010 – December 31, 2013).

5.1.2 Data extraction and validation

As mentioned above, the primary dataset for the analysis is extracted from the published graphs applying the innovative Matlab-based data extraction method that Pérignon et al. (2008) developed. After the graphs have been imported into Matlab, the procedure described below allows us to obtain the values of the daily VaRs and hypothetical P&Ls:

1. Display a picture of the graph in Matlab by using the following command: image ('name of the file');
2. Convert the graph scale into a Matlab scale by defining and applying the conversion scale factor, which can be determined as follows:

$$s = \frac{M_1 - M_2}{y_2 - y_1} \qquad (1)$$

   where M_1 and M_2 are Matlab values for point 1 and point 2 on the vertical axis, and y_1 and y_2 are the real values for point 1 and point 2 on the vertical axis.
3. Add vertical lines that cross the VaR/P&L time series at each data point that is supposed to be extracted;
4. Save the Matlab coordinates of each data point by using the following command: ginput(n), where *n* is the number of data points which is intended to be extracted;

5. Convert the Matlab vertical coordinates into graph coordinates by applying the conversion scale factor computed in step 2. For all the data points, the following mathematical expression should be used:

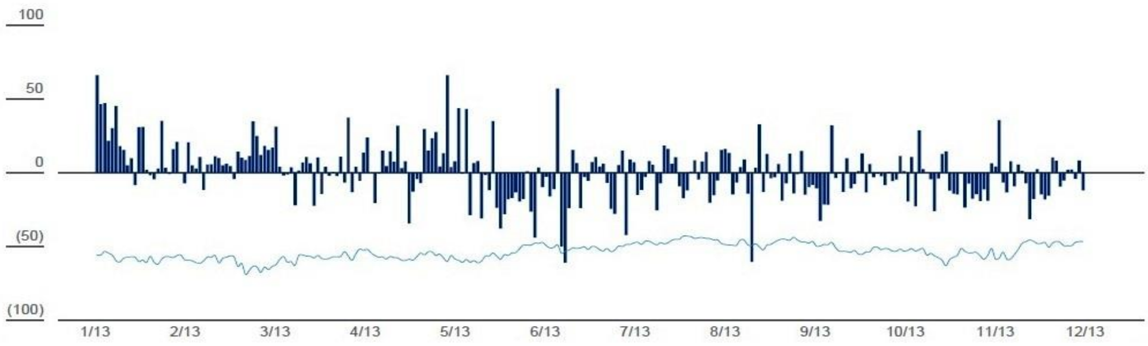
$$\frac{M_0 - M_n}{s} \tag{2}$$

where M_0 denotes the zero value of the vertical axis in Matlab and M_n denotes the respective obtained value of the data point in Matlab.

As an illustrative example, *Figure 2* shows the imported graph of the backtesting results for Deutsche Bank in 2013 and the constructed graph based on the extracted data.

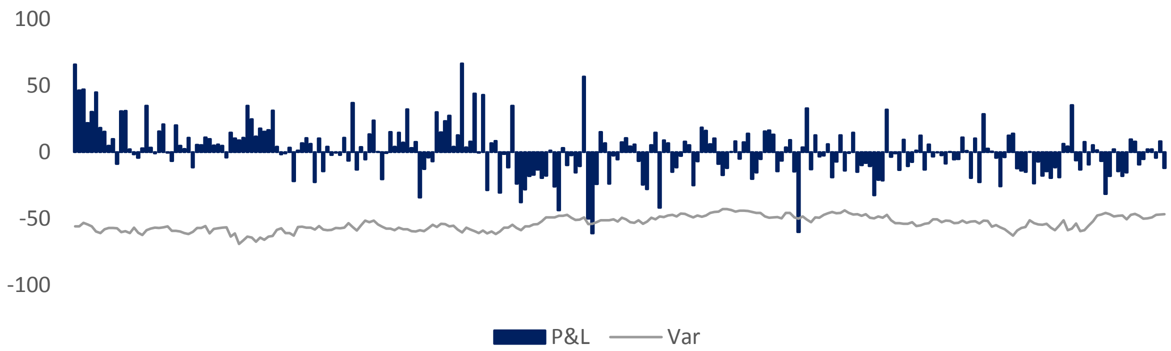
Figure 2 Visual comparison of the original graph and the graph based on the extracted data

Original graph, Deutsche Bank (2013)



Source: Deutsche Bank annual report, 2013

Graph based on the extracted data, Deutsche Bank (2013)



Source: Own analysis

At the next stage of the process, we compare the original graphs from the annual reports and the graphs based on the extracted data (see, for example, *Figure 2*) to reveal possible discrepancies between the extracted and the actual values. We find that our extracted series of data for the six banks are not visually different from the actual data series. We furthermore evaluate the accuracy of the obtained VaRs by calculating the average, minimum and maximum values of the VaRs for each year and by comparing the computed values with the respective figures in the annual reports (see *Appendix A* for the data validation analysis). Based on the visual comparison and the summary statistics, we come to the conclusion that our data sample is reliable.

5.1.3 Sample summary

Our data sample consists of 6 pairs of time series subsamples, including a total of 5 214 data points for Deutsche Banks, 4 532 data points for HypoVereinsbank, 4 504 data points for Svenska Handelsbanken AB, 4 462 data points for BBVA S.A., 5158 data points for Santander and 2 064 data points for UBS – all in all 25 934 data points. Descriptive information covering the following three large sections can be found in *Table 1*: i) Key information on the banks, ii) Information on regulatory capital and iii) Information on the Value-at-Risk. We find that the Tier 1 ratio – the core measure of a bank's financial strength from a regulator's perspective - of the six banks exceeds the 6%-level required by Basel III; it ranges from 10% to 22% depending on the bank. Thus, all the banks are treated as well capitalized. Another interesting insight is that all banks, except for Deutsche Bank, favor the Historical Simulation Approach to compute and disclose their one-day ahead 99%- VaRs on a daily basis.

Table 1 Descriptive information

	Deutsche Bank	**HypoVereins bank**	**Svenska Handelsbanken AB**	**UBS**	**BBVA S.A.**	**Santander**
			Section 1 : Key figures as of Dec 31, 2013			
Market capitalization	€35B	-	SEK 201B	CHF 65B	€52B	€74M
Total assets	€1611B	€290B	SEK 2490B	CHF 1010B	€583B	€1116B
Trading portfolio	€210B	€91B	SEK 171B	CHF 123B	€72B	€116B
Return on RWA, %	-	-	-	11.40%	-	101%
			Section 2: Regulatory capital			
Tier 1 Capital	€50.7B	€18.5B	SEK 100.1B	CHF 42.2B	€39.6B	€61.7B
Tier 1 Capital Ration	14%	22%	10%	19%	12%	13%
Tier 2 Capital	€5.2B	€1.6B	SEK 269M	CHF 8.6B	€8.7B	€9.7B
Total Regulatory Capital	€55.5B	€20.1B	SEK 100.4B	CHF 50.8B	€48.3B	€71.5B
Risk-weighted assets (RWA)	€350.1B	€85.5B	SEK 1016.2B	CHF 225B	€323.6B	€489.7B
thereof :Market risk	€66.9B	€9.2B	SEK 770M	CHF 14B	-	€4B
Total Incremental Risk Charge	€996M	€288M	-	CHF 110M	-	-
			Section 3: Value-at-Risk			
Internal Model	Monte Carlo	Historical	Historical	Historical	Historical	Historical
Confidence level	99% - 1 day	99%-1 day	99% - 1 day	99% -1 day	99% -1 day	99% -1 day
Start Date	Jan 1, 2004	Jan 1, 2005	Jan 1, 2005	Jan 1, 2010	Jan1, 2005	Jan 1, 2004
End date	Dec 31, 2013	Dec 31,2013	Dec31,2013	Dec 31,2013	Dec 31,2013	Dec31,2013
Number of observations	2607	2266	2252	1032	2231	2579
Total VaR, 31 Dec, 2013	€47.9M	€9M	SEK 14M	CHF 17M	€22M	€13.1M
Average VaR over the time horizon	€82.3M	€29.8M	SEK 27.9M	CHF 60.7M	€15.7M	€26.2M
Stressed Value-at-Risk	€105.5M	€27M	SEK 28M	CHF 63M	-	€26.9M

Source: the banks' annual reports and our own analysis

5.2 Methodology

5.2.1 Determination of periods

In order to address the research question of this study, we divide the data sample into three subsamples covering different economic conditions – a pre-crisis, crisis and post-crisis period. Furthermore, for testing Hypothesis 2, the pre-crisis and post-crisis periods are merged into the non-crisis period.

When defining the crisis period, we look at how the global financial crisis unfolded. With a complete vanishing of liquidity (BNP Paribas terminated withdrawals from three hedge funds) and the fall of Northern Rock, we define August 2007 as the starting point of the active phase of the global financial crisis. We furthermore choose the beginning of October 2008 as our end date of the crisis period, since the central banks of many countries started to undertake a number of activities to stop a widespread economic meltdown in this month, including rate cuts, liquidity support, different versions of bailout packages and government guarantees (Zanalda, 2015). Hence, our data sample is split into three following periods:

1. Pre-crisis: start date of the data sample[2] – August 2007
2. Crisis: August 2007- October 2008
3. Post-crisis: October 2008 – end date of the data sample[3].

5.2.2. Backtests

Since the late 1990's, banks with significant trading activities have been required to put aside capital in order to secure against extreme trading portfolio losses by regulatory authorities. The amount of this capital depends directly on both the Value-at-Risk measure and the VaR model's performance in backtests (Campbell, 2007). In our study, in order to verify the adequacy of the banks' internal VaR models, we therefore apply a number of backtesting procedures. They aim to test unconditional coverage properties of a VaR measure, its interdependence properties and both properties simultaneously, as well as the magnitude of

[2,3] The start and end dates differ thereby between the banks and depend on the data availability

exceedance – by how far a loss surpasses the disclosed VaR. These procedures are presented in this section.

a) Unconditional Coverage testing

We firstly employ unconditional coverage tests to investigate whether the obtained fraction of exceptions (violations) of a specific model, $\hat{\pi}$, is significantly different from the acceptable fraction p. We apply the *Basic Frequency-of-tail-loss* test and the *Kupiec* test. The concept of the former lies in defining the failure rate as the percentage of exceptions when portfolio losses exceed the VaR estimates *(3)*. The number of exceptions follows a binominal distribution *(4)* and thus, the test does not require any information on portfolio returns, which classifies it as a non-parametric backtesting procedure. The mathematical expressions are:

$$\hat{\pi} = \frac{N}{T} \tag{3}$$

$$P(N) = \binom{T}{N} p^N (1-p)^{T-N} \tag{4}$$

where N is the number of exceptions and T is the total number of observations. Overall, the adequacy of a VaR measure is determined by either accepting or rejecting the null hypothesis, which states that the model is accurate and hence, the frequency of tail losses is equal to $p = 1 - c$, where c is the confidence level. If the calculated P-value exceeds the threshold level, we fail to reject the null hypothesis and therefore, the underlying VaR model is accepted as being accurate. This procedure could however potentially lead to two types of errors: i) we could either reject a correct model (Type I Error) or ii) we could fail to reject an incorrect model (Type II Error).

The Kupiec Test addresses exactly this limitation of the Basic Frequency-of-tail-loss test - the trade-off between the Type I Error and the Type II Error - by focusing exclusively on the property of unconditional coverage, namely on whether or not the reported VaR is violated more (or less) than α* 100% of the time (Campbell, 2007). The number of exceptions is again assumed to be binomially distributed and the test statistic is identified based on the Frequency-of-tail-loss approach, but in a way that counter-balances Type I and Type II Errors.

Under the Kupiec test, the null hypothesis that $p = \hat{\pi}$ can be checked by using a likelihood ratio test (Kupiec, 1995):

$$LR_{UC} = -2ln[L(p)/L(\hat{\pi})] \tag{5}$$

$$L(\hat{\pi}) = \left(1 - \frac{N}{T}\right)^{(T-N)} * \left(\frac{N}{T}\right)^{N} \tag{6}$$

$$L(p) = (1-p)^{(T-N)} * (p)^{N} \tag{7}$$

The test statistic follows a chi-squared distribution with 1 degree of freedom and, if the value of LR_{UC} exceeds the critical value, the null hypothesis – and therefore the accuracy of the VaR model – is rejected.

However, the Kupiec-test has shortcomings as well. Firstly, the test requires a sufficient amount of information in order to statistically reject an inaccurate model. A sample size of one year, which is in line with regulatory requirements, is not enough to ensure the statistical power of the test. Looking at our data sample, it can therefore be problematic to apply this test to the (relatively short) period of stress. Secondly, the test takes the frequency of losses into account, but not the time of their occurrence. This may lead to not rejecting a model with clustered exceptions, meaning that all the violations occur during the same period of time (Campbell, 2007).

b) Interdependence testing

In order to reveal possibly clustered VaR exceptions, we additionally conduct an interdependence test. If the exceptions are clustered – all the violations occur during the same time period, then in case of a violation today, there exists a more than p*100% probability of another violation tomorrow. The advantage of this interdependence test is the rejection of the accuracy of a VaR model with clustered violations (Christoffersen, 2003). The test is based on the concept of a first-order Markov sequence with a transition probability matrix:

$$\prod = \begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix} \tag{8}$$

The probabilities in the transition matrix stand for the probabilities of a violation tomorrow given a today's violation, e.g. π_{01} denotes the probability of a violation tomorrow given a non-violation today. If there are T observations in a sample, then the mathematical expression for the likelihood function of the first-order Markov process is:

$$L(\Pi) = (1-\pi_{01})^{T_{00}}\pi_{01}{}^{T_{01}}(1-\pi_{11})^{T_{10}}\pi_{01}{}^{T_{11}} \qquad (9)$$

where T_{ij} is the number of observations with a j following an i, e.g. T_{01} is the number of observations when a nonviolation is followed by a violation. Taking the first derivatives with respect to π_{01} and π_{11}, and setting them to zero, the maximum likelihood estimates equal:

$$\widehat{\pi_{01}} = \frac{T_{01}}{T_{00}+T_{01}} \qquad (10)$$

$$\widehat{\pi_{11}} = \frac{T_{11}}{T_{10}+T_{11}} \qquad (11)$$

If violations are interdependent over the time, then $\pi_{01} = \pi_{11} = \pi$ and the transition matrix looks like:

$$\prod = \begin{bmatrix} 1-\hat{\pi} & \hat{\pi} \\ 1-\hat{\pi} & \hat{\pi} \end{bmatrix} \qquad (12)$$

The interdependence hypothesis, $\pi_{01} = \pi_{11}$, can be checked through applying a likelihood ratio test (Christoffersen, 2003):

$$LR_{ind} = -2ln\left[L(\hat{\pi})/L(\hat{\Pi})\right] \sim \mathcal{X}_1^2 \qquad (13)$$

$$L(\hat{\Pi}) = (1-\widehat{\pi_{01}})^{T_{00}}\widehat{\pi_{01}}^{T_{01}}(1-\widehat{\pi_{11}})^{T_{10}}\widehat{\pi_{11}}^{T_{11}} \qquad (14)$$

In case there exists no observation when a violation is followed by another violation, we use the likelihood function determined by Christoffersen, 2003:

$$L(\hat{\Pi}) = (1-\widehat{\pi_{01}})^{T_{00}}\widehat{\pi_{01}}^{T_{01}} \qquad (15)$$

If the value of LR_{ind} exceeds the critical value, the null hypothesis is rejected. This means that violations are clustered (interdependent) and that the VaR model is inaccurate.

c) Conditional Coverage testing

The conditional coverage test simultaneously tackles shortcomings of the tests discussed above: the interdependence issue as well as the correctness of the average number of violations. Applying a conditional coverage test makes it possible to test for interdependence and correct coverage at the same time (Christoffersen, 2003). The null hypothesis $\pi_{01} = \pi_{11} = p$ can be verified by using the following likelihood ratio:

$$LR_{CC} = -2ln\left[\frac{L(p)}{L(\widehat{\Pi})}\right] = LR_{UC} + LR_{ind} \sim \mathcal{X}_2^2 \qquad (16)$$

If the value of LR_{CC} exceeds the critical value, the null hypothesis is rejected and the VaR model is considered inaccurate.

d) Basic size of tail-loss test

Apart from the backtests that study the occurrence of exceptions, we conduct the basic size of tail-loss test, which focuses on the magnitude of an exceedance (Campbell, 2007). This type of backtest is based upon a function of the actual P&L and the corresponding disclosed VaRs, which can be used to construct a general loss function. In this paper, we use the loss function suggested by Lopez (1999), which determines the difference between the VaR and the realized loss under the condition that the loss exceeds the disclosed VaR estimate. The mathematical expression is:

$$L(VaR_t(\alpha), x_{t,t+1} = \begin{cases} 1 + \left(x_{t,t+1} - VaR_t(\alpha)\right)^2 & if\ x_{t,t+1} < -VaR_t(\alpha) \\ 0 & if\ x_{t,t+1} > -VaR_t(\alpha) \end{cases} \qquad (17)$$

where $x_{t,t+1}$ denotes the profit or loss between the end of day *t* and *t+1*. The final step of this backtesting procedure consists in calculating the average loss of the sample *(18)*, which measures the magnitude of the exceedance.

$$\hat{L} = \frac{1}{T}\sum_{t=1}^{T} L(VaR(\alpha), x_{t,t+1}) \qquad (18)$$

The loss function based backtest results are used for a comparative analysis of the VaRs models, i.e. for testing Hypothesis 2 (Comparative analysis of VaR performance: non-crisis vs. crisis) and Hypothesis 3 (Improvement in VaR determination after the financial crisis).

5.2.3 Additional measures of VaR performance

In addition to the outlined backtesting procedures, we use a more intuitive measure – a VaR over-/understatement coefficient. It implies comparing a disclosed VaR (DVaR) and the adjusted VaR defined in a way that leads to the expected number of outliers/exceptions at a given confidence level, i.e. if there are 100 observations, the expected number of outliers is 5 at 1%-confidence level (Pérignon et al., 2008). In other words, we will quantify the over-/understatement of the VaR in terms of magnitude with the underlying mathematical expression:

$$Prob(R_{t+1} < -VaR_t | I_t) = p \qquad (19)$$

where I_t is the information set at time t and p is the threshold level. Hence, Value-at-Risk is inflated, when:

$$DVaR_t > VaR_t = DVaR_t(1-\rho) \qquad (20)$$

where ρ is a risk-overstatement coefficient. In case of VaR understatement, the following equitation holds:

$$DVaR_t < VaR_t = DVaR_t(1+\rho) \qquad (21)$$

We furthermore evaluate how the disclosed VaR numbers relate to subsequent fluctuations in banks' trading revenues by using the following regression proposed by Mincer and Zarnowitz (1969):

$$R_{t+1}^2 = a + b * VaR_{t+1|t}^2 + u_{t+1} \qquad (22)$$

where R_{t+1}^2 is trading P&L on day *t+1* and $VaR_{t+1|t}^2$ is a step-ahead Value-at-Risk estimate done on day *t* for day *t+1*. This regression allows analyzing the forecasting power of a VaR when looking at its R^2, its standard errors and the statistic of the respective Breusch-Godfrey LM test for autocorrelation. It therefore helps to analyze the banks' risk profiles.

5.2.4 Stressed Value-at-Risk

As mentioned above, the Basel Committee on Banking Supervision proposed complementing the original VaR-model based framework with a Stressed Value-at-Risk measure in January 2009, that is based on the 10-day, 99th percentile, one-tailed confidence interval VaR measure of the current portfolio with the model inputs related to a period when relevant market factors were experiencing a continuous 12-month period of significant financial stress. Since banks do, on average, not disclose their SVaRs, we refer to the EBA guidelines on Stressed VaR (2012) to compute this additional market risk measure for our study, with only one difference: instead of identifying periods of downturns, we determine periods when the trading portfolio of the analyzed bank experienced a significant amount of financial stress. We use the 12-month periods characterized by the highest volatilities as this period. The staring date of the stress periods for the different banks is depicted in *Table 2*.

Table 2 Start dates of a stress period by bank

	Yearly Volatility, %	Start date
Deutsche Bank	0.40%	March, 2008
HypoVereinsbank	0.60%	September, 2008
Santander	0.20%	June, 2008
BBVA S.A.	0.30%	July, 2011
Svenska Handelsbanken AB	0.10%	November, 2007

Note: The volatility is calculated assuming no change in the composition of the trading portfolio

Due to the fact that most banks refer to the Historical Simulations Approach when computing their internal VaRs, we also employ this method to calculate the daily 99%- SVaR. In more detail, we simulate 10,000 portfolio changes for each day separately by applying the portfolio returns of the defined period of stress to the corresponding daily value of the trading portfolio. We then compute the 99% - percentile of the portfolio changes. We use the portfolio value reported in the banks' annual report as the end portfolio value of the corresponding year and also as a starting point for the following year (e.g. the portfolio value reported in 2012 as the end value for 2012 and the starting point for 2013) and then, in order to obtain the daily value of the trading portfolio, we adjust the opening balance of the trading portfolio by both the daily P&L and the daily change of the trading portfolio. The daily portfolio change is thereby, for simplicity, assumed to be linear distributed over the year, e.g. the trading portfolio value increases/decreases the same amount every day of a year. The total increase/decrease, which we divide by the number of trading days to obtain daily changes, is the total change of the trading portfolio during the year increased/diminished by the total trading profit/loss over the year. *Appendix B* summarizes the figures discussed in this section.

5.2.5 Market Risk Charges

In order to test our Hypothesis 4 regarding the sufficiency of the Basel amendments in the area of market risk, we determine and compare the initial and revised market risk charges with the sample banks' accumulated losses. According to the framework introduced by the Basel Committee on Banking Supervision (1996), a bank's Market Risk Charge firstly depended solely on its 99% VaR.

$$MCR_{t+1} = \max\left(\frac{m_c}{60}\sum_{i=1}^{60} VaR(99\%)_{t-i+1}; VaR(99\%)_t\right) \qquad (23)$$

The maximum between the previous day's VaR and the average of the last 60 daily VaRs increased by the multiplier $m_c = 3(1+k)$ and $k \in[0;\ 1]$ is defined according to the three-zone approach introduced by BCBS, which incorporates the backtesting results – the number of exceptions – into the calculation of market risk capital requirements. The table below summarizes the impact of the number of exceptions on the scaling factor (k) (Annex 10a, BCBS).

Table 3 Backtesting: the three-zone approach

Zone	Number of exceptions	Increase in scaling factor	Cumulative probability
Green Zone	0	0.00	8.11%
	1	0.00	28.58%
	2	0.00	54.32%
	3	0.00	75.81%
	4	0.00	89.22%
Yellow Zone	5	0.40	95.88%
	6	0.50	98.63%
	7	0.65	99.60%
	8	0.75	99.89%
	9	0.85	99.97%
Red Zone	10 or more	1	99.99%

Note: The boundaries are based on a sample of 250 observations.

Since the initial Basel framework showed a number of limitations during the financial crisis, the revised Basel (2011), among other changes, requires the banks to now base their market capital requirements associated with their trading portfolio on both a 99% VaR and a 99% SVaR.

$$
\begin{aligned}
MCR_{t+1} &= \max\left(\frac{m_c}{60}\sum_{i=1}^{60} VaR(99\%)_{t-i+1}; VaR(99\%)_t\right) \\
&+ \max\left(\frac{m_c}{60}\sum_{i=1}^{60} SVaR(99\%)_{t-i+1}; SVaR(99\%)_t\right)
\end{aligned}
\tag{24}
$$

where the multiplier m_c is defined the same way as in *(23).* As part of this analysis, we additionally compute the accumulated losses of the sample banks in the following way: every day, a new loss is added to the sum of the losses on the previous days until a profit occurs. In this case, the accumulated loss is set back to zero. More specific, if there is a loss on day *t=0*, then the accumulated loss is equal to that loss; if there is another loss on day *t=1*, then the accumulated loss is equal to the sum of the losses on day *t=0* and day *t=1*; in case of a profit on *t=1*, the accumulated loss is set to 0 and the routine starts from the beginning on the following day.

Finally, in order to make judgments on the impact of Basel II.5 on the banks' ability to absorb losses, we compare both, the initial and revised Market Risk Charges, with the calculated accumulated losses and consequently, analyze the difference in the number of events when the accumulated losses exceed each type of MRCs.

6. Empirical Results and Interpretations

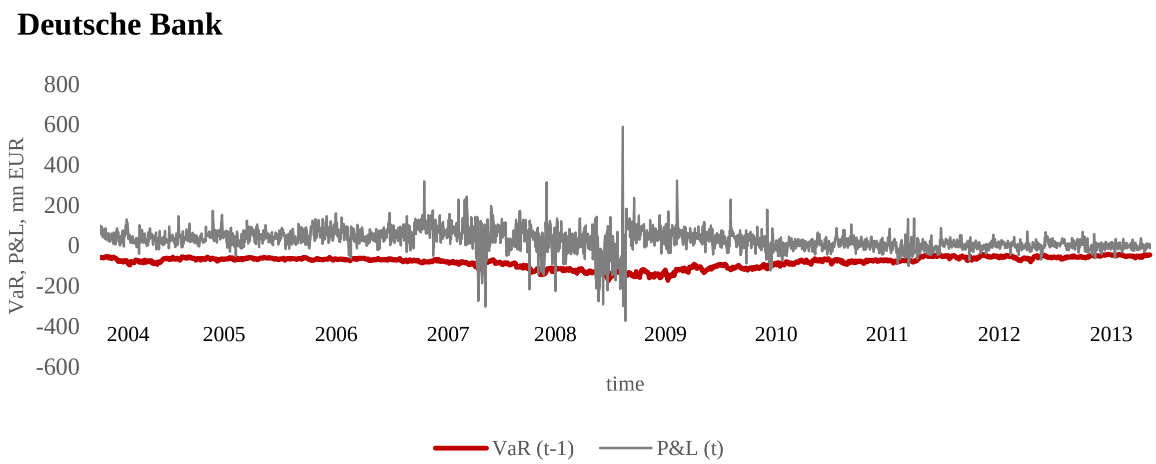
When examining the performance of VaR models in our study, we start with looking at the initial data sample and then move to a comparative analysis of the banks' internal VaR models in different economic conditions. Finally, we discuss the sufficiency of Basel capital requirements and test for a possible existence of the systemic risk within the European Banking system. All the backtests are conducted at a 5%- confidence level.

6.1 Hypothesis 1 – Overall performance of VaR Models

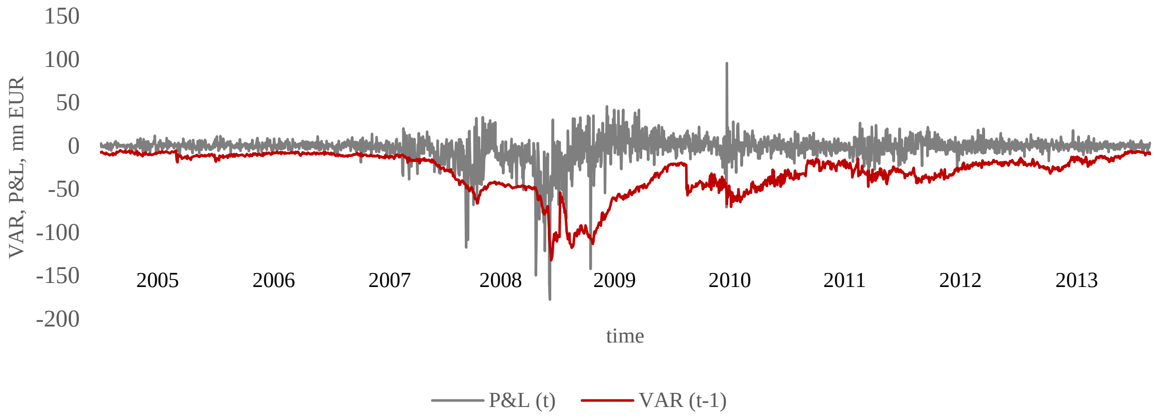
In Hypothesis 1, we aim to shed light on the overall quality of the sample banks' internal VaR models as well as test whether their stated VaR is in line with findings from previous studies, i.e. whether it is an over-conservative measure of the market risk.

We start our analysis with looking at the published graphs of daily hypothetical P&Ls and daily 99%-VaRs. These graphs are plotted in *Figure 3* and they reveal one stylized feature attributable to all six banks – the daily P&Ls can be classified as very volatile.

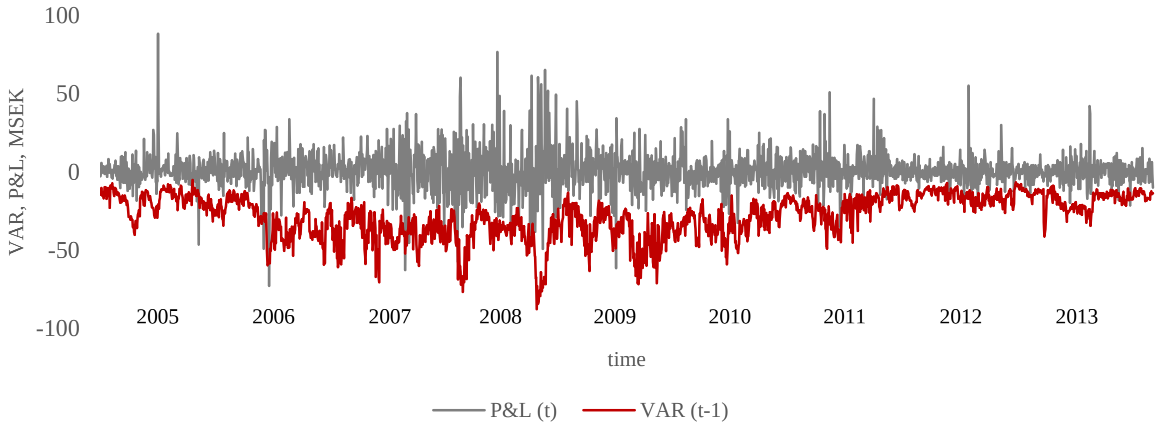
Figure 3 Hypothetical P&Ls versus previous day VaR



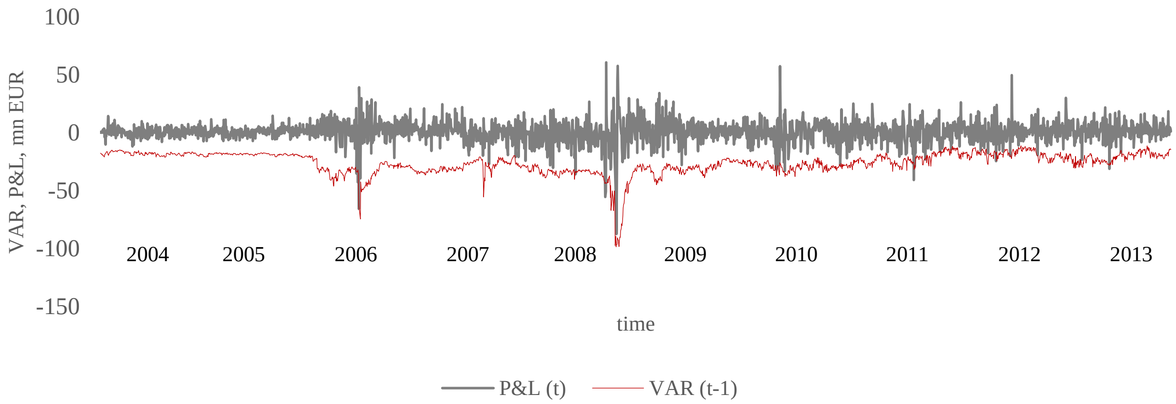
HypoVereinsbank



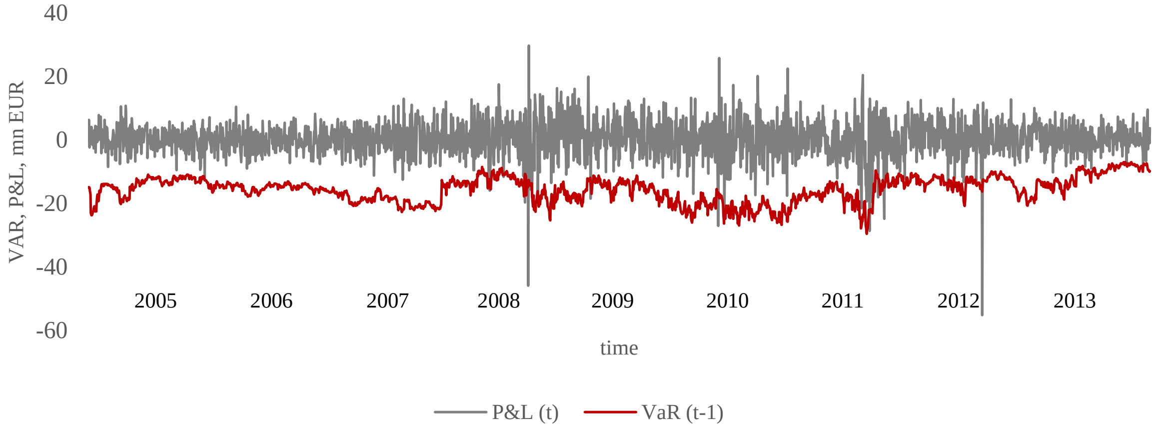
Svenska Handelsbanken AB



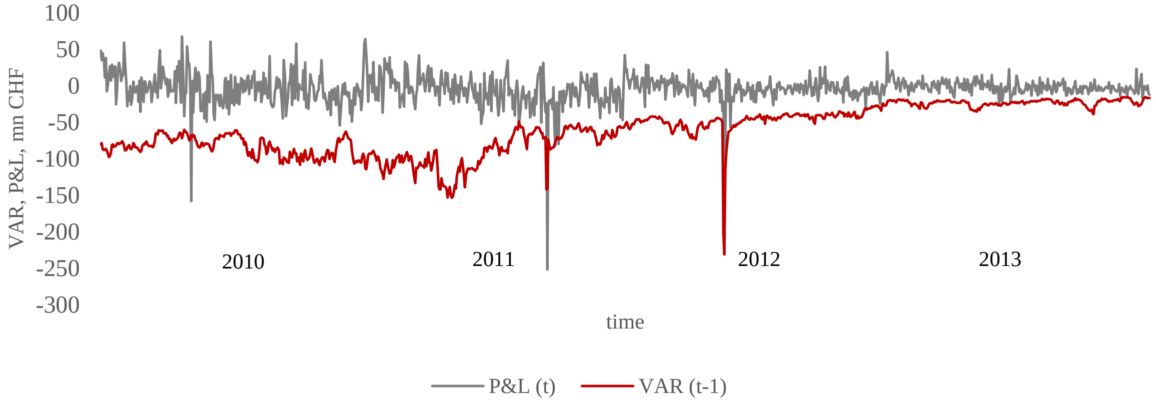
Santander



BBVA S.A.



UBS



Note: the red line illustrates a VaR and the grey line illustrates a hypothetical gain or loss

The daily disclosed VaRs are rather stable for Deutsche Bank, whereas notable fluctuations over time can be found for the other banks. It has to be mentioned, however, that the banks' daily VaR data series are substantially different from each other, as their average VaR differs significantly and their VaR estimates are denominated in different currencies. We therefore look additionally at the banks' coefficients of variation – a statistical ratio between a standard deviation and a mean of a sample. We observe that HypoVereinsbank has the highest coefficient of variation (0.78), while BBVA S.A. has the lowest one (0.26). *Table 4* presents the coefficients of variation for all the banks.

Table 4 Coefficients of variation

Bank	Coefficient of Variation
HypoVereinsbank	0.78
Deutsche Bank	0.33
Svenska Handelsbanken AB	0.37
UBS	0.53
BBVA S.A.	0.26
Santander	0.37

Note: the coefficient of variation is the relationship between a standard deviation and a mean of a data series

As Deutsche Bank employs the Monte Carlo approach to define its VaR while the other banks apply the Historical Simulation approach, Deutsche Bank should possess the highest coefficient of variation according to Jorion (2002) who finds that Historical Simulation leads to a less volatile VaR output. This finding is not confirmed in our sample (Deutsche Bank has the second lowest coefficient) and we therefore conclude that the stability of an internal model – the property to have small variations in daily VaRs and a low likelihood of large VaR jumps for changes in the trading portfolio – might not solely depend on the applied VaR computation approach, but rather be a bank-specific feature that is influenced by, for example, internal learning effects.

Looking at the number of exceptions/outliers – events when a hypothetical buy-and-hold trading loss exceeds the previous day's VaR estimate **-** we do not find uniform results for all six banks over our sample period (see *Appendix C*). In order to compare the number of the banks' outliers, we have to transform the total value of exceptions into a relative figure because our data sample consists of a different number of data points per bank. We use the empirical *p* for our comparison, defined as the number of exceptions divided by the total number of observations. In our sample, the two German banks (Deutsche Bank and HypoVereinsbank) exceed the allowed number of exceptions implied by a 1% - VaR because their empirical *p* is higher than 1%. The conclusion of this excess of exceptions is that the two banks understate their internal VaRs on average. The exact amount of understatement in terms of magnitude is 14% for Deutsche Bank and 18% for HypoVereinsbank. In contrast to that, we find a tendency for VaR overstatement for the other sample banks ranging from 11% to 15%: Santander, BBVA S.A., Svenska Handelsbanken AB and UBS exhibit a lower number of exceptions than the expected value for a 1% - VaR.

When reviewing the years separately, we observe that for all sample banks and during most years, the number of exceptions lies in the green zone – the zone with up to 4 occurred outliers per year – implying a zero-multiplier for the MRCs according to the Basel Committee. During the period of the financial crisis (2007-2008), Deutsche Bank and HypoVereinsbank experienced their worst years in terms of days when a loss exceeded the corresponding VaR: during those two years, the number of exceptions lies within the red zone, implying the highest possible multiplier when computing the respective Market Risk Charges. An interesting point is that we do not observe the same evidence for the other sample banks: during the year of the financial crisis, the number of outliers of Svenska Handelsbanken AB and Santander lies in the green zone, while the number of exceptions for BBVA lies in the green zone in 2007 and in the yellow zone in 2008. The results for the full data sample are summarized in *Table 5*.

Table 5 Outliers: the full data sample

	Deutsche Bank	HypoVereins-bank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
2004	0	-	0	-	-	-
2005	0	0	0	0	2	-
2006	0	1	3	0	2	-
2007	10	13	0	0	2	-
2008	22	16	3	7	2	-
2009	0	1	0	1	2	-
2010	2	1	0	2	0	1
2011	3	0	4	3	3	4
2012	2	0	2	1	0	1
2013	2	0	2	0	2	1
Total	41	32	14	14	15	7
Number of observations	2607	2266	2579	2231	2252	1032
Empirical *p*	1.6%	1.4%	0.6%	0.6%	0.7%	0.7%
Over-/Understatement Coefficient	-14%	-18%	15%	15%	11%	12%

Note: the negative value for over-understatement coefficient stands for the understatement of VaR and the positive value – for the overstatement of VaR, correspondingly.

When evaluating the adequacy of the banks' internal VaR models, the different conducted backtests lead to rather controversial results. Two banks – HypoVereinsbank and Deutsche Bank – fail the Frequency-of-tail-loss one-sided test, while the others pass it. Four banks (HypoVereinsbank, BBVA S.A., Svenska Handelsbanken AB and UBS) pass the unconditional coverage backtest at 5%-confidence level, whereas the null hypothesis of a correct model is rejected for Santander and Deutsche Bank. When checking for the interdependence of violations, we find that the exceptions of HypoVereinsbank and Deutsche Bank are significantly clustered, while the violations of the other banks do not tend to occur at the same time. Looking at the more comprehensive conditional coverage test, which simultaneously controls for the correctness of the average number of exceptions and the interdependence of the violations, three out of the six banks pass (BBVA S.A., Svenska Handelsbanken AB and UBS). Based on our backtest results, we therefore doubt the accuracy of the internal VaR models of HypoVereinsbank, Santander and Deutsche Bank. More detailed results can be found in *Appendix D1*.

Finally, we obtain a positive and significant coefficient for each sample bank when applying the Mincer and Zarnowitz regression implying that the VaR figures are correlated with the future volatility of the trading revenues. The R^2 are however very low and range from 0.01 (BBVA S.A.) to 0.17 (Santander), which is typical of this regression though, because a squared trading revenue constitutes solely a noisy proxy for the true volatility (Andersen and Bollerslev, 1998*)*. We also detect autocorrelation in the trading revenues for all the banks (except for UBS) with the Breusch-Godfrey LM test, what may affect the relationship between the VaR estimates and the squared returns. Our variance forecasting regression coefficient, the R^2 and the Breusch-Godfrey LM test results can be found in *Appendix G*.

Overall, we do not find strong evidence that banks tend to be conservative in disclosing their VaRs based on our primary data sample. One possible reason might be the trade-off between VaR returns and the multiplier used in the Market Risk Charge computation.

6.2 Hypothesis 2 – Comparative analysis of VaR performance: non-crisis vs. crisis

The analysis in this part intends to reveal possible discrepancies between the performance of an individual banks' internal VaR model in normal times and during the period of stress. We also aim to prove that our sample banks understate their VaRs during the period of stress, meaning that they disclose a too low value. The sample for this hypothesis comprises only five banks: Deutsche Bank, HypoVereinsbank, Svenska Handelsbanken AB, Santander and BBVA S.A (due to the lack of required data for UBS).

6.2.1 Outliers

Comparing the number of outliers during the crisis period with the number during the non-crisis period, we find that the amount of violations exceeds the permitted number for all analyzed banks except for Santander during the period of stress, while the amount of experienced violations lies within limits under normal conditions.

Table 6 Outliers: Non-crisis vs Crisis

		Crisis	Non-Crisis
	Number of Exceptions	19	22
	Number of Observations	305	2302
Deutsche Bank	Empirical p	6.2%	1.0%
	Number of Exceptions	19	13
	Number of Observations	296	1970
HypoVereinsbank	Empirical p	6.4%	0.7%
	Number of Exceptions	3	11
	Number of Observations	301	2278
Santander	Empirical p	1.0%	0.5%
	Number of Exceptions	4	10
	Number of Observations	291	1940
BBVA S.A.	Empirical p	1.4%	0.5%
	Number of Exceptions	4	11
	Number of Observations	288	1964
Svenska Handelsbanken AB	Empirical p	1.4%	0.6%

Based on the outlier criteria, the banks' VaR models perform therefore better in the normal regime. The higher frequency of outliers during the financial crisis may be evidence that the banks' internal models were not responsive enough to the changes in the loss distribution.

6.2.2 Accuracy

Based on the Frequency-of-tail-loss one-sided test, the banks' internal VaR models perform better during the non-crisis period: we fail to reject the null hypothesis that the model is correctly specified for all the banks in the normal regime. However, it is not correctly specified during the period of stress for every bank: the null hypothesis of this test is rejected for HypoVereinsbank and Deutsche Bank. When applying the Kupiec test, we do not find uniform results for all five banks. However, an interesting finding is that the banks that fail the test under normal conditions pass it successfully during the period of stress and vice versa. In more detail, the two German banks (HypoVereinsbank and Deutsche Bank) fail the Kupiec test during the crisis and pass it during the non-crisis period, while the opposite is true for Svenska Handelsbanken AB, Santander and BBVA S.A.

Conducting the interdependence test, we observe that violations are clustered during the period of stress for HypoVereinsbank, Santander and Deutsche Bank, while the other banks do not experience ‘hits’ taking place around the same time. Under normal conditions, the test results improve only for Santander, while they remain the same for the other banks.

Finally, we observe that HypoVereinsbank and Deutsche Banks fail the conditional coverage test in both economic conditions, i.e. during both the non-crisis and crisis period, whereas the models of BBVA S.A. and Svenska Handelsbanken AB are always accurate and the model of Santander works even better during the period of stress. A short summary of the backtest results is presented in *Table 7* and the T-statistics and P-values of all the conducted tests can be found in *Appendix D2***.**

To sum up, the results of the conducted backtests do therefore neither uniformly confirm nor reject our hypothesis that the banks’ internal VaR models generally work better under normal conditions.

Table 7 Backtest results: Non-crisis vs. Crisis

	Frequency-of-tail-loss test		**Kupiec test**		**Interdepence test**		**Conditional Coverage test**	
	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-Crisis	Crisis	Non-crisis
HypoVereinsbank	-	√	-	√	-	-	-	-
Santander	√	√	√	-	-	√	√	-
BBVA S.A.	√	√	√	-	√	√	√	√
Svenska Handelsbanken AB	√	√	√	-	√	√	√	√
Deutsche	-	√	-	√	-	-	-	-

Note: √ *- denotes the case when a bank passes the test and ’ – ’ denotes the case when a bank fails the test*

When looking at the loss function, we observe that a bank's VaR model behaves in general much better under normal conditions. However, also these results are not uniform as the VaR model of Svenska Handelsbanken AB provides a better risk assessment during the period of stress.

Looking at the over-/understatement coefficients, we find that all sample banks understate their VaRs during the crisis period by an amount ranging from 16% to 59% (except for Santander which exhibits the expected number of exceptions during the crisis), while they tend to be conservative in the normal conditions, inflating their VaRs by 6% to 19%.

Table 8 Additonal accuracy measures: Non-crisis vs. Crisis

	Loss Function		**Over-/understatement coefficient**	
	Crisis	Non-crisis	Crisis	Non-crisis
HypoVereinsbank	82.14	5.86	-59%	6%
Santander	0.72	0.16	0%	19%
BBVA S.A.	4.08	0.94	-18%	15%
Svenska Handelsbanken AB	0.95	1.16	-16%	18%
Deutsche bank	534.50	54.81	-51%	8%

Note: the negative value for over-understatement coefficient stands for the understatement of VaR and the positive value – for the overstatement of VaR, correspondingly.

6.3 Hypothesis 3 – Improvement in VaR determination after the financial crisis

The analysis in this part aims to check whether a learning effect on the quality of the banks' VaR models can be found in the aftermath of the global financial crisis of 2007-2008, and it again comprises only five banks – Deutsche Bank, HypoVereinsbank, Svenska handelsbanken AB, Santander and BBVA S.A.

6.3.1 Outliers

When reviewing the empirical *p* during the pre-crisis and post-crisis period, we observe values within the limits for all banks except for Deutsche Bank after the global financial crisis. Therefore, this assessment criterion alone does not give any insight whether the crisis has affected the banks' risk management in terms of a better VaR model performance. *Table 9* summarizes the key figures for this criterion.

Table 9 Outliers: Pre-crisis vs. Post-crisis

		Pre-Crisis	Post-Crisis
Deutsche Bank	Number of Exceptions	0	22
	Number of Observations	935	1367
	Empirical p	0.0%	1.6%
HypoVereinsbank	Number of Exceptions	6	7
	Number of Observations	658	1312
	Empirical p	0.9%	0.5%
Santander	Number of Exceptions	3	8
	Number of Observations	925	1353
	Empirical p	0.3%	0.6%
BBVA S.A.	Number of Exceptions	0	10
	Number of Observations	639	1301
	Empirical p	0.0%	0.8%
Svenska Handelsbanken AB	Number of Exceptions	4	7
	Number of Observations	642	1322
	Empirical p	0.6%	0.5%

6.3.2 Accuracy

The backtests reveal results only for HypoVereinsbank, Santander and Svenska Handelsbanken AB since the *t*-statistics of the pre-crisis period cannot be defined for BBVA S.A. and Deutsche Bank. All of these three banks pass the Frequency-of-tail-loss test in both periods. HypoVereinsbank and Svenska Handelsbanken AB furthermore pass the unconditional coverage test in both periods, whereas Santander passes it only during the post-crisis period. When testing for an interdependence of violations, we find that only HypoVereinsbank experiences this problem in both periods, whereas Santander and Svenska Handelsbanken AB successfully pass the test in both economic conditions. The conditional coverage test is only failed by HypoVereinsbank in the post-crisis period due to its clustered violations. A short summary of the backtest results is presented in *Table 10* and the T-statistics and P-values of all conducted tests can be found in *Appendix D3.*

Table 10 Backtest results: Pre-crisis vs Post-crisis

	Frequency-of-tail-loss test		**Kupiec test**		**Interdepence test**		**Conditional Coverage test**	
	Pre-Crisis	Post-crisis	Pre-Crisis	Post-crisis	Pre-Crisis	Post-Crisis	Pre-Crisis	Post-crisis
HypoVereinsbank	√	√	√	√	-	-	√	-
Santander	√	√	-	√	√	√	√	√
Svenska Handelsbanken AB	√	√	√	√	√	√	√	√

Note: √ - denotes the case when a bank passes the test and ' – ' denotes the case when a bank fails the test

The loss function figures increase in the post-crisis period compared to the pre-crisis periods for all banks except for Svenska Handelsbanken AB. Hence, we do not find an empirical support for improvements in the banks' internal models in the aftermath of the crisis.

Looking at the over-/understatement coefficients, we find that all banks (except HypoVereinsbank) were more conservative when estimating their VaRs before the crisis: in the pre-crisis period, the overstatement coefficient ranges from 45% to 138%, while in the post-crisis period, Deutsche Bank understates its VaR by 13% and the other four banks inflate their VaRs only by 6%-13%. These results might be a consequence of the Basel amendments regarding Market Risk Charges, as according to the revised Basel framework, capital charges for Market Risk are not only calculated based on a VaR, like in the initial Basel Accord, but also on a SVaR leading to significant increase in MRCs. This might force banks to assess their market risk less conservatively in order to minimize their capital requirements. *Table 11* presents the loss-function and the over-/understatement coefficients.

Table 11 Additional accuracy measures: Pre-crisis vs Post-Crisis

	Loss Function		**Over-/understatement coefficient**	
	Pre-Crisis	Post-crisis	Pre-Crisis	Post-crisis
HypoVereinsbank	1.64	7.97	0%	13%
Santander	0.14	0.18	77%	10%
BBVA S.A.	0.00	1.41	70%	6%
Svenska Handelsbanken AB	2.84	0.35	45%	16%
Deutsche Bank	0.00	92.31	138%	-13%

Note: the negative value for over-understatement coefficient stands for the understatement of VaR and the positive value – for the overstatement of VaR, correspondingly.

6.4 Hypothesis 4 – Sufficiency of Basel II.5 MRCs and systemic risk in Europe

In the aftermath of the global financial crisis, a number of new regulations have emerged. This section aims to reveal the impact of changes in the Basel standards on managing market risk (Basel II.5) by testing the sufficiency of minimum capital requirements. It furthermore intends to enable a better understanding of the safety of the European banking system by examining a possible existence of systemic risk.

6.4.1 Market risk charges

Since 2011, banks are required to base their market risk charges not only on their VaR but also on their SVaR. As a result, we observe that the banks' MRCs increase by a factor of 2 to 3, which is in line with the findings of Mehta et al (2012). *Table 12* shows the banks' average MRCs under both the initial and revised Basel frameworks as well as a multiple change of the corresponding figures.

Table 12 Market rik charges

	Average MRC (Initial Basel)	**Average MRC (Revised Basel)**	**Change (x)**
Deutsche Bank	€334.08 mn	€1027.92 mn	3.08
HypoVereinsbank	€275.13 mn	€550.24 mn	2.00
Santander	€79.99 mn	€ 1027.92 mn	3.34
BBVA S.A.	€275.13 mn	€550.24 mn	2.00
Svenska Handelsbanken AB	SEK 149.41 mn	SEK 299.74 mn	2.01

Applying the technique defined in the Methodology part, which allows us to make judgments on the sufficiency of Market Risk Charges, we notice that the accumulated losses exceed the MRCs according to the revised Basel framework substantially less often than the MRCs according to the initial Basel framework. The results are depicted in *Table 13* and a graphical analysis can be found *in Appendix E.*

Table 13 Sufficiency of MRCs

	Intial Basel Framework	Revised Basel Framework
Deutsche Bank	46	2
HypoVereinsbank	20	10
Santander	12	0
BBVA S.A.	6	1
Svenska Handelsbanken AB	0	0

An interesting finding is the fact that, under the revised Basel framework, the accumulated losses of the sample banks exceed their corresponding Market Risk Charges for each bank only during the defined periods of stress. In particular, these events occur only in October 2008 for Deutsche Bank and HypoVereinsbank, and in August 2011 for BBVA S.A. A possible conclusion may therefore be that the introduced Basel amendments are leading to sufficient minimum capital requirements, implying that if BCBS had introduced the new framework before the crisis, the severity of the global financial crisis could have potentially been mitigated.

6.4.2 Systemic risk

In the last subsection, we test for systemic risk within the European banking sector by analyzing the correlations between P&Ls and/or VaRs across the banks. We obtain extremely low and mostly positive correlation coefficients across the banks' daily P&Ls except for two pairs of banks: For Deutsche Bank and Svenska Handelsbanken AB (correlation coefficient: -0.01) and BBVA S.A. and UBS (correlation coefficient: -0.03). Furthermore, during the crisis period, the daily correlations were even lower, with the highest correlation between Svenska Handelsbanken AB and Santander (correlation coefficient: 0.16). On average, the daily correlations do however not vary substantially when analyzing crisis and non-crisis periods separately (see *AppendixF1*). Therefore, our findings can be described as follows: even when large scale market disruptions occur, the stress events do not necessarily happen simultaneously for all banks, potentially due to their differences in portfolio composition. However, we doubt the absence of systemic risk in the European banking industry despite these findings, due to some limitations of our analysis. Firstly, the sample banks do not disclose the exact timing for their losses and gains and secondly, the used P&L values are hypothetical, not actual. In order to tackle the first limitation of our data sample, we aggregate the daily P&Ls to weekly data and re-calculate the correlation matrix. We observe a substantial increase in cross-correlations that confirms our sepsis: according to the weekly correlation matrix, especially Santander is highly interconnected with the other banks and thus, the bank is very likely to be a source of systemic risk in the European banking industry. It is also notable that the correlation coefficients of Deutsche Bank with the other banks are significantly different from zero (except with BBVA S.A.), confirming the systemic importance of Deutsche Bank for Europe.

We furthermore want to emphasize that we do not consistently observe the highest correlation between banks from the same country and during the period of stress. This leads to the conclusion that systemic risk equally exists in different economic conditions and it is not locally concentrated, but rather a problem of the European Banking System as a whole. *Table14* depicts the cross-correlations between the matched weekly P&Ls across the six banks.

Table 14 Weekly P&L Correlation coefficients

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
Deutsche Bank	1.00	0.31*	0.22*	0.05	0.11*	0.52*
	[-]	*[0.00]*	*[0.00]*	*[0.30]*	*[0.02]*	*[0.00]*
HypoVereinsbank	0.31*	1.00	0.29*	0.03	0.01	0.10
	[0.00]	*[-]*	*[0.00]*	*[0.59]*	*[0.83]*	*[0.15]*
Santander	0.22*	0.29*	1.00	0.19*	0.18*	0.28*
	[0.00]	*[0.00]*	*[-]*	*[0.00]*	*[0.00]*	*[0.00]*
BBVA S.A.	0.05	0.03	0.19*	1.00	0.05	0.03
	[0.30]	*[0.59]*	*[0.00]*	*[-]*	*[0.50]*	*[0.70]*
Svenska Handelsbanken AB	0.11*	0.01	0.18*	0.05	1.00	-0.05
	[0.02]	*[0.83]*	*[0.00]*	*[0.50]*	*[-]*	*[0.47]*
UBS	0.52*	0.10	0.28*	0.03	-0.05	1.00
	[0.00]	*[0.15]*	*[0.00]*	*[0.70]*	*[0.47]*	*[-]*

Note: Correlation coefficients for banks' P&Ls are calculated with a matched sample for each pair of banks separately; p-values are displayed in parentheses.

In *Table 15*, the correlations of the changes in daily VaRs across the banks are displayed. These correlation coefficients are not significantly different from zero and we therefore do not find a clear pattern of VaR co-movements, what is consistent with the VaR graphs displayed in *Figure 2*. Even when we calculate the changes in average weekly VaRs, the correlation coefficients do not substantially change, implying that the limitation regarding the impossibility to match the values of the banks' VaRs perfectly is not relevant in this case. One possible explanation of these findings is a bank-specific VaR computation, meaning that the applied methodology varies significantly from bank to bank – despite the fact that five out of six banks employ the Historical Simulation Approach: the banks could, for example, apply different techniques, like equal weighting, time weighting or volatility scaling.

Table 15 Correlations of the changes in daily VaRs

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
Deutsche Bank	1.00	0.02	0.01	-0.04*	0.02	-0.05
	[-]	*[0.39]*	*[0.58]*	*[0.04]*	*[0.26]*	*[0.08]*
HypoVereinsbank	0.02	1.00	-0.02	0.03	0.07*	0.06
	[0.39]	*[-]*	*[0.33]*	*[0.15]*	*[0.00]*	*[0.06]*
Santander	0.01	-0.02	1.00	0.01	-0.05*	0.03
	[0.58]	*[0.33]*	*[-]*	*[0.68]*	*[0.02]*	*[0.37]*
BBVA S.A.	-0.04*	0.03	0.01	1.00	0.02	-0.05
	[0.04]	*[0.15]*	*[0.68]*	*[-]*	*[0.25]*	*[0.12]*
Svenska Handelsbanken AB	0.02	0.07*	-0.05*	0.02	1.00	0.07*
	[0.26]	*[0.00]*	*[0.02]*	*[0.25]*	*[-]*	*[0.02]*
UBS	-0.05	0.06	0.03	-0.05	0.07*	1.00
	[0.08]	*[0.06]*	*[0.37]*	*[0.12]*	*[0.02]*	*[-]*

Note: Correlation coefficients for changes in banks' VaRs are calculated with a matched sample for each pair of banks separately; p-values are displayed in parentheses.

An additional analysis of correlations can be found in *Appendix F*.

7. Conclusion

In the last section, firstly, the obtained results of our study and their interpretations are summarized. Subsequently, some possible limitations of our approach are displayed and possibilities for future research are outlined.

7.1 Summary of Results

Our empirical analysis intends to shed light upon the performance of the internal VaR Models of our six European sample banks between 2004/2005-2013. When testing our four hypotheses, we obtain the following findings regarding i) the model performance over the whole period, ii) the difference in performance during non-crisis and crisis periods, iii) a possible improvement effect after the financial crisis, and regarding iv) the impact of Basel II.5 on MRCS as well as the existence of systemic risk between the banks.

Looking at the extracted data and addressing Hypothesis 1, we firstly observe a contradiction to Jorion findings (2002), which state that the Historical Simulation method should generally lead to smoother risk market charges through time (Jorion, 2002). Our results demonstrate the higher importance of individual specifics of a banks' internal model than the choice of the applied method in general. Furthermore, we find mixed results regarding the over-conservativeness of the banks' models over the whole period from 2004/2005 until 2013 (2010-2013 for UBS): Two banks, Deutsche Bank and HypoVereinsbank understate their internal VaRs by 14% and 18% correspondingly, whereas Santander, BBVA S.A., Svenska Handelsbanken AB and UBS tend to overstate their VaRs by 11% - 15%. Despite controversial backtest results, for three of the sample banks – BBVA S.A., Svenska Handelsbanken AB and UBS – the accuracy of the internal VaR model cannot be rejected, whereas the accuracy of the models of HypoVereinsbank, Santander and Deutsche Bank is unproven according to the comprehensive conditional coverage test. Even though four sample banks tend to inflate their internal VaRs, the two German banks understate their respective VaRs. We therefore have to reject the first hypothesis that European banks generally tend to overstate their VaR by using a too conservative model.

When analyzing the second Hypothesis, we find that the banks' VaR models lead to fewer outliers in a non-crisis environment, which may be evidence that the models are more conservative during these periods. We however find contradicting results when analyzing the model accuracy for non-crisis vs. crisis periods and in general, the conducted backtests do not confirm the hypothesis that the banks' internal models work better under normal conditions. When looking at the loss functions, we observe that a bank's VaR model behaves generally much better under normal conditions. However, also these results are not uniform as the VaR model of Svenska Handelsbanken AB provides a better risk assessment during the period of stress. We find that five banks understate their VaRs during the crisis period by 18% - 59% (except for Santander which experiences the expected number of exceptions during the crisis), while they tend to be conservative in normal conditions, inflating their VaRs by 6% - 19%. Therefore, on average, we can accept Hypothesis 2.

When looking at Hypothesis 3, the results of our Kupiec test as well as of our Independence test reveal a slight improvement in the performance of the disclosed VaRs in the post-crisis period compared to the pre-crisis, which is however not significant. Looking at the conditional coverage test, the overall performance within the pre-crisis period is better than in the post-crisis period. We however want to pinpoint the fact that the post-crisis period is not a truly normal regime because of the European sovereign debt crisis, which could have had an impact on the performance of the VaR model during this period.

Lastly, looking at the forth hypothesis, we find that, even though banks tended to be very conservative during the pre-crisis period, it was not sufficient to insure against the large losses occurred during the global financial crisis. However, according to the revised Basel framework, the accumulated losses exceed MRCs less often than under the initial Basel framework. The accumulated losses under the revised Basel framework furthermore exceed the corresponding Market Risk Charges only during the defined underlying periods of stress. Therefore, the introduced amendments in Basel are likely to be sufficient in terms of minimum capital requirements and if Basel II.5 had already been introduced before the crisis, the severity of the global financial crisis would have potentially been reduced. Looking at the correlations of the daily P&Ls as a source of systemic risk, we find that even under large market disruptions, stress events do not necessarily occur simultaneously for the sample banks. But when aggregating daily P&Ls to weekly data, we observe a substantial increase in cross-correlations that confirm systemic risk in the European banking industry. As the highest correlations cannot be found between the banks from the same country, this systemic risk seems to furthermore concern the European Banking System as a whole, not only its single member countries individually. As outlined above, even though the new regulatory framework significantly increases the Market Risk Charges, and therefore the safety of single banks, the existence of systemic risk in Europe might still jeopardize the safety of the European Banking System in the future, especially considering potential procyclical regulatory effects.

7.2 Possible Limitations

When looking at our results and interpretations, it is important to be aware of some limitations of our analysis. The first limitation results from our dependence on the estimated values of VaRs and P&Ls, obtained through applying the data extraction technique introduced by Pérignon et al. (2008). Even though, in comparison to the approach of Berkowitz and O'Brien (2002), this method has the advantage of a preservation of the banks' identity, a potential limitation is the fact that there might arise discrepancies between estimated and actual values during the extraction process. Our applied validation approach however addresses this issue and is conducted in order to assure contingency. Yet, another limitation cannot be overcome: Our empirical analysis is based on the extracted VaRs and P&Ls, which might be only estimates of the actual figures because the graphs that are published in banks' annual reports might be smoothed transformations of the real input data without possible visual detection. The banks furthermore do not disclose the exact timing of their data points and our analysis is referring to the disclosed hypothetical values, not to the actual ones, which is additionally restricting the accuracy of our analysis. Besides that, aggregating the pre-crisis period and the post-crisis period into a normal regime is a simplified approach, which does not adjust for other periods of stress, e.g. the European sovereign debt crisis. Those limitations could influence our results. Regarding our interpretations, a generalization of our outcome might be jeopardized by the relatively small size of our sample (six banks), which is however still big enough to obtain an interesting insight into the internal VaR models of several important banks within the European banking system.

7.3 Possibilities for Future Research

Our study extends the scope of the analysis of Pérignon et al. (2008) by focusing on banks that operate in a different geographic location and therefore in a different regulatory environment. Future research could however address several other attributes: For example, obtaining an insight into the VaR models of smaller banks would be a valuable research extension. As Pérignon et al. (2008) outline, it would furthermore be useful to compare the levels of VaR overstatement across different aggregation levels, like for example on a trader, trading desk, business line and bank level. While we analyze a possible difference in the VaR performance during the financial crisis vs. normal times, as well as a potential improvement effect after the crisis, analyzing further different economic conditions would be informative, like for example the period of the European sovereign debt crisis. Lastly, also investigating the effects of additional regulatory advances, like the emerging implementation of Basel III, would enable valuable insights.

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Appendix

Appendix A Validation of VaR

Deutsche Bank

	Average (extracted)	Average (actual)	Min (extracted)	Min (actual)	Max (extracted)	Max (actual)
2013	53.6	53.6	42.7	43.0	69.0	69.0
2012	57.8	57.1	44.3	43.3	81.6	80.1
2011	72.1	71.8	44.7	44.9	94.0	94.3
2010	92.4	95.6	65.1	67.5	121.7	126.4
2009	126.1	126.8	92.0	91.9	173.6	180.1
2008	126.9	122.0	97.8	97.5	175.1	172.9
2007	85.6	85.6	68.0	66.5	118.5	118.8
2006	69.6	69.5	59.1	58.3	81.4	82.0
2005	65.3	65.8	57.9	57.8	78.2	79.2
2004	70.5	71.6	53.9	54.5	96.9	97.9

Note: All numbers are in MEUR

UBS

	Average (extracted)	Average (actual)	Min (extracted)	Min (actual)	Max (extracted)	Max (actual)
2013	23	23	15	15	39	42
2012	48	47	24	23	231	239
2011	89	-	49	-	153	-
2010	83	-	60	-	109	-

Note: All the numbers are in MCHF. The actual VaR values are not reported for 2011 and 2010.

Svenska Handelsbanken AB

	Average (extracted)	Average (actual)	Min(extracted)	Min (actual)	Max(extracted)	Max (actual)
2013	18	18	9	9	41	42
2012	15	15	7	7	26	26
2011	22	22	9	8	49	48
2010	31	30	13	13	59	59
2009	38	38	13	13	72	72
2008	42	41	20	18	88	86
2007	38	39	17	18	70	72
2006	31	32	12	10	60	61
2005	18	20	5	7	40	42

Note: All numbers are in MSEK

Santander

	Average (extracted)	Average (actual)	Min(extracted)	Min (actual)	Max (extracted)	Max (actual)
2013	21.2	17.4	11.4	9.4	30.6	25.6
2012	18.3	14.9	11.5	9.4	27.4	22.4
2011	22.5	22.4	12.0	12.0	27.4	33.2
2010	29.0	28.7	21.5	21.2	37.9	37.5
2009	30.3	30.2	21.9	21.9	44.9	45.1
2008	40.6	40.0	26.8	26.1	98.4	97.1
2007	28.9	28.9	20.0	19.6	55.4	56.1
2006	34.2	35.7	25.0	26.4	74.5	75.0
2005	19.1	19.3	17.3	17.4	24.6	27.0
2004	18.2	19.2	15.0	15.6	21.3	22.5

Note: All the numbers are in MEUR. For 2011-2013, the extracted values of data are different from the values reported in the annual reports. However, they correspond the numbers that can be found on the graphs. Therefore, we do not see it as a problem.

HypoVereinsbank

	Average (extracted)	Average (Real)	Min(extracted)	Min (actual)	Max(extracted)	Max (actual)
2013	16.7	-	6.2	-	31.9	-
2012	26.3	-	13.9	-	43.1	-
2011	27.5	-	15.1	-	47.4	-
2010	45.1	-	27.5	-	70.6	-
2009	59.4	-	19.6	-	116.5	-
2008	59.2	-	34.1	-	132.2	-
2007	15.3	-	8.2	-	30.9	-
2006	9.6	-	6.7	-	13.8	-
2005	9.9	-	5.1	-	19.2	-

Note: All the numbers are in MEUR.The average, minimum and maximum values of VaR are not reported in the annual reports. However, visual validation has been conducted.

BBVA S.A.

	Average (extracted)	Average (Real)	Min(extracted)	Min (actual)	Max(extracted)	Max (actual)
2013	11	-	7	-	20	-
2012	14	-	10	-	21	-
2011	16	-	10	-	30	-
2010	22	-	15	-	27	-
2009	16	-	11	-	22	-
2008	14	-	8	-	25	-
2007	19	-	15	-	23	-
2006	15	-	13	-	18	-
2005	14	-	11	-	24	-

Note: All the numbers are in MEUR. The data validation analysis cannot be conducted for BBVA S.A. because the reported values are for the group, not the parent company.

Appendix B SVaR Computation

Deutsche Bank

	Trading assets, as of the end of the year	Total yearly change	Total yearly P&L	Number of days	Daily change
2003	345 371				
2004	373 147	27 776	9 451	261	70
2005	448 393	75 246	11 392	261	245
2006	516 839	68 446	14 984	261	205
2007			15 172	261	
2008	247 462	-269 377	-499	261	-544
2009	234 910	-12 552	13 892	261	-101
2010	271 291	36 381	1 941	261	132
2011	240 924	-30 367	-217	260	-116
2012	254 459	13 535	457	260	50
2013	210 070	-44 389	169	260	-171

Note: All the numbers are in MEUR. The daily change is the total change during the year increased/diminished by the total trading P&L over the year.

UBS

	Trading assets, as of the end of the year	Total yearly change	Total yearly P&L	Number of days	Daily change
2009	232 258				
2010	228 815	-3 443	-953	258	-10
2011	181 525	-47 290	-1 990	257	-176
2012	160 564	-20 961	-867	258	-78
2013	122 848	-37 716	-336	259	-144

Note: All the numbers are in MCHF. The daily change is the total change during the year increased/diminished by the total trading P&L over the year.

HypoVereinsbank

	Trading assets, as of the end of the year	Total yearly change	Total yearly P&L	Number of days	Daily change
2004	91 711				
2005	103 519	11 808	37	259	45
2006	107 628	4 109	82	256	16
2007	180 855	73 227	-761	246	301
2008	199 019	18 164	-5 647	257	93
2009	133 389	-65 630	763	247	-269
2010	133 389	0	1213	258	0
2011	149 056	15 667	-358	238	67
2012	131 017	-18 039	210	248	-74
2013	91 301	-39 716	25	257	-155

Note: All the numbers are in MEUR. The daily change is the total change during the year increased/diminished by the total trading P&L over the year.

Santander

	Trading assets, as of the end of the year	Total yearly change	Total yearly P&L	Number of days	Daily change
2003					
2004	111 756		165		
2005	154 208	42 452	259	262	161
2006	170 423	16 215	762	257	60
2007	158 807	-11 616	-5	251	-46
2008	151 817	-6 990	-639	262	-24
2009	135 054	-16 763	555	255	-68
2010	156 762	21 708	-181	259	85
2011	172 637	15 875	-30	260	61
2012	177 917	5 280	338	254	19
2013	115 287	-62 630	480	259	-244

Note: All the numbers are in MEUR. The daily change is the total change during the year increased/diminished by the total trading P&L over the year.

BBVA S.A.

	Trading assets, as of the end of the year	Total yearly change	Total yearly P&L	Number of days	Daily change
2003	27 660				
2004	47 036	19 376			
2005	44 012	-3 024	104	247	-13
2006	51 835	7 823	-43	249	32
2007	62 336	10 501	24	246	43
2008	73 299	10 963	155	251	43
2009	69 733	-3 566	305	252	-15
2010	63 283	-6 450	-32	247	-26
2011	70 602	7 319	-89	250	30
2012	79 954	9 352	160	246	37
2013	72 000	-7 954	134	243	-33

Note: All the numbers are in MEUR. The daily change is the total change during the year increased/diminished by the total trading P&L over the year.

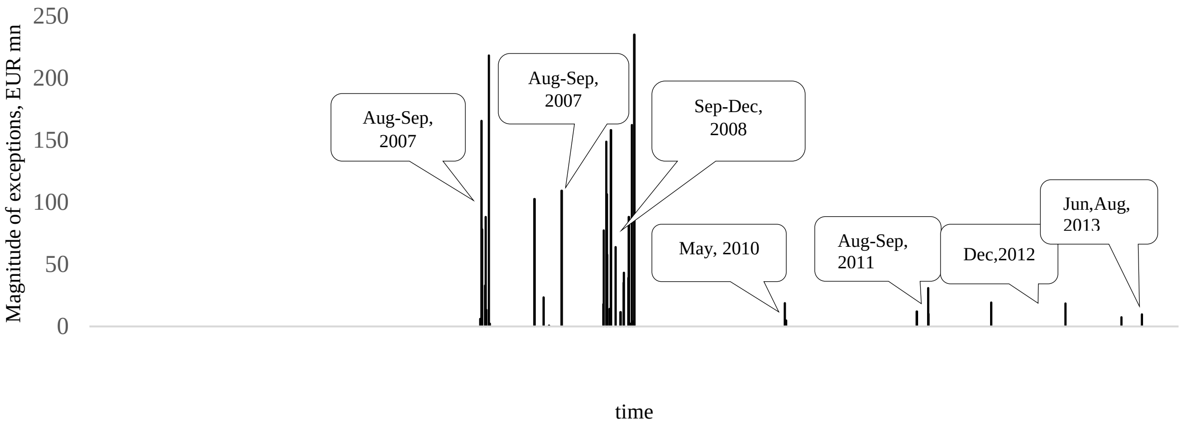
Svenska Handelsbanken AB

	Trading assets, as of the end of the year	Total yearly change	Total yearly P&L	Number of days	Daily change
2004	258 473				
2005	258 822	349	349	252	0
2006	391 991	133 169	324	252	527
2007	208 808	-183 183	389	237	-775
2008	232 009	23 201	132	252	92
2009	152 671	-79 338	354	253	-315
2010	157 850	5 179	-126	253	21
2011	166 900	9 050	533	252	34
2012	163 701	-3 199	-65	250	-13
2013	171 073	7 372	92	251	29

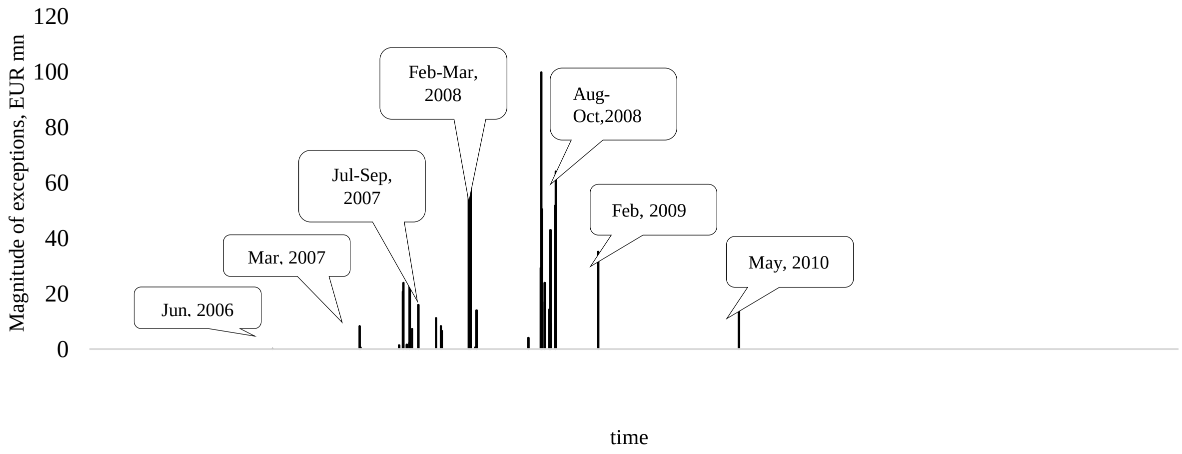
Note: All the numbers are in MSEK. The daily change is the total change during the year increased/diminished by the total trading P&L over the year.

Appendix C Exceptions

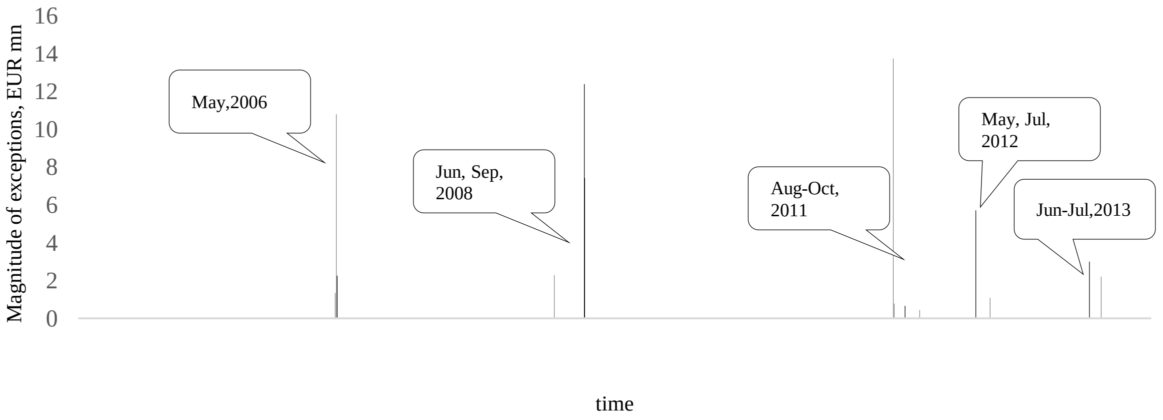
Deutsche Bank



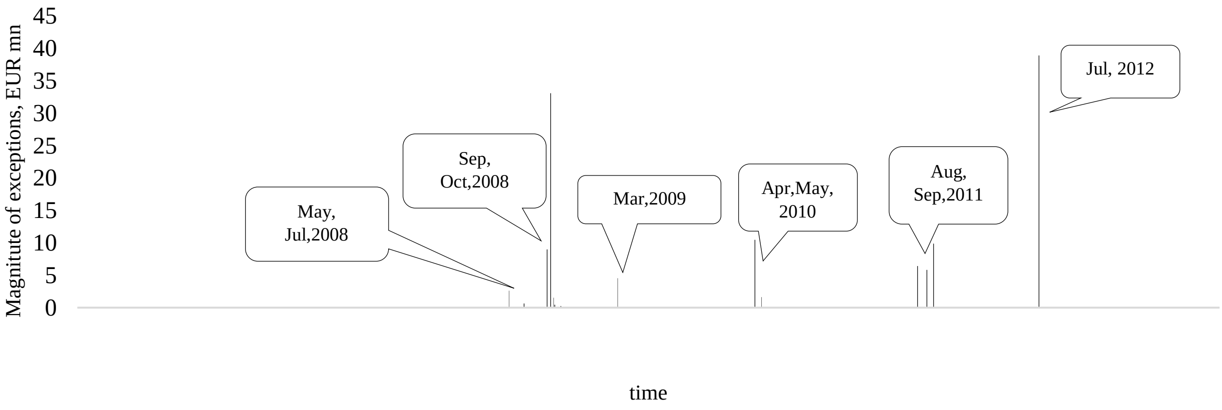
HypoVereinsbank



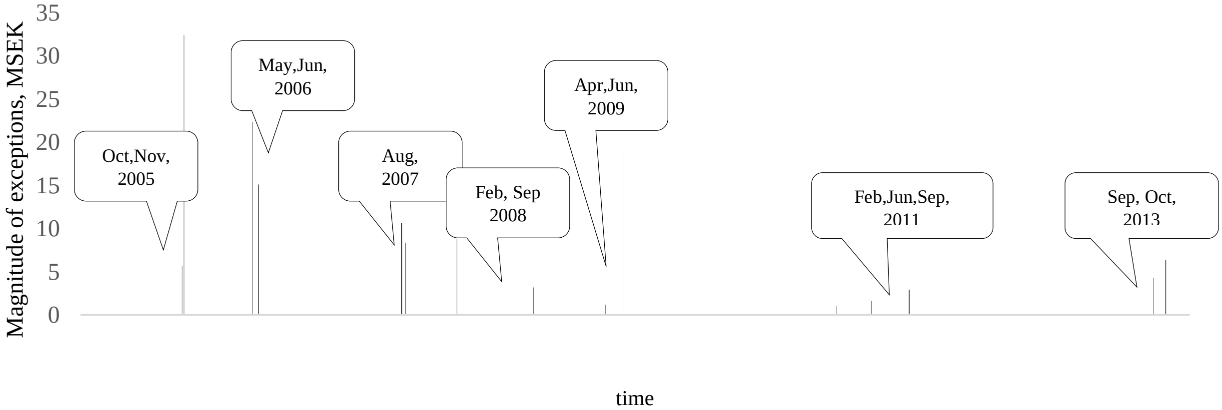
Santander



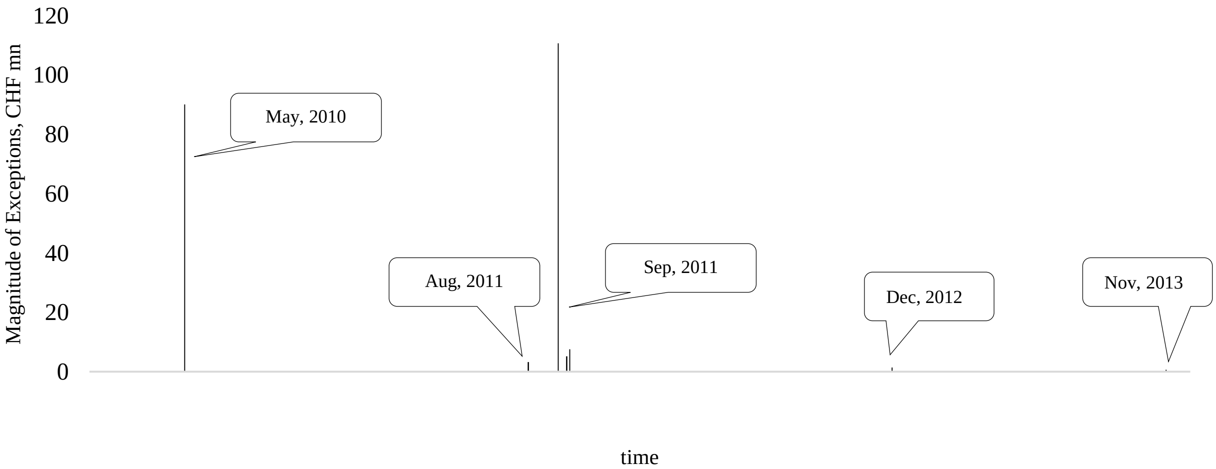
BBVA S.A.



Svenska Handelsbanken AB



UBS



Appendix D Backtest Results

Appendix D1

		Data Sample			
		Basic Frequency (1-sided)	Kupiec	Interdependdce test	Conditional Coverage
HypoVereinsbank	T-statistics	3.63%	3.45	34.87	38.32
	P-Value		6.33%	0.00%	0.00%
Santander	T-statistics	99.59%	6.53	3.44	9.97
	P-Value		1.06%	6.36%	0.68%
BBVA S.A.	T-statistics	97.64%	3.60	0.19	3.79
	P-Value		5.76%	66.33%	15.01%
Svenska Handelsbanken AB	T-statistics	96.24%	2.87	0.21	3.09
	P-Value		9.00%	64.32%	21.34%
UBS	T-statistics	89.00%	1.22	0.11	1.33
	P-Value		27.01%	74.09%	51.54%
Deutsche bank	T-statistics	0.39%	7.36	54.62	61.98
	P-Value		0.67%	0.00%	0.00%

Appendix D2

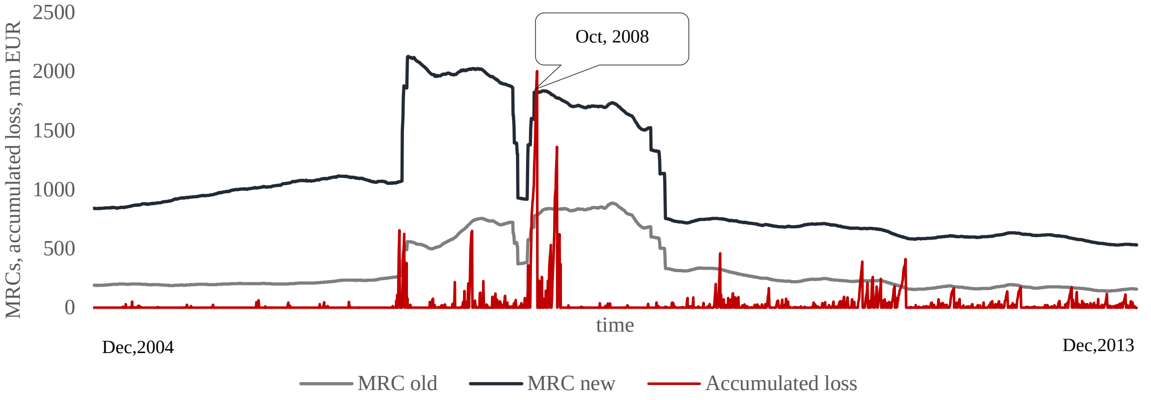
		Crisis				Non-crisis			
		Basic Frequency (1-sided)	Kupiec	Interdependce test	Conditional Coverage	Basic Frequency (1-sided)	Kupiec	Interdependce test	Conditional Coverage
HypoVereinsbank	T-statistics	0.00%	39.47	8.44	47.91	95.61%	2.62	16.94	19.56
	P-Value		0.00%	0.37%	0.00%		10.58%	0.00%	0.01%
Santander	T-statistics	58.02%	0.00	5.81	5.81	99.78%	6.53	0.12	7.72
	P-Value		99.54%	1.59%	5.47%		0.58%	73.29%	2.10%
BBVA S.A.	T-statistics	33.25%	0.37	0.14	0.51	99.31%	5.59	0.11	5.71
	P-Value		54.34%	70.87%	77.54%		1.80%	73.56%	5.77%
Svenska Handelsbanken AB	T-statistics	32.58%	0.39	0.14	0.53	98.72%	4.57	0.14	4.70
	P-Value		53.10%	70.72%	76.59%		3.26%	71.31%	9.53%
UBS	T-statistics	No Data				89.00%	1.22	0.11	1.33
	P-Value						27.01%	74.09%	51.54%
Deutsche bank	T-statistics	0.00%	38.47	30.83	69.30	61.30%	0.05	17.41	17.46
	P-Value		0.00%	0.00%	0.00%		82.96%	0.00%	0.02%

Appendix D3

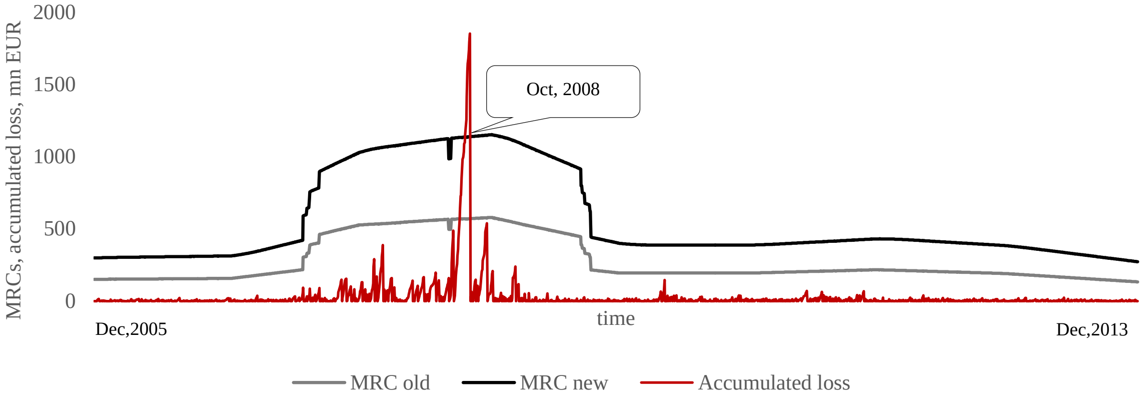
		Pre-crisis period				Post-crisis period			
		Basic Frequency (1-sided)	Kupiec	Interdependce test	Conditional Coverage	Basic Frequency (1-sided)	Kupiec	Interdependce test	Conditional Coverage
HypoVereinsbank	T-statistics	64.36%	0.05	4.26	4.31	97.64%	3.47	13.24	16.71
	P-Value		81.76%	3.91%	11.60%		6.24%	0.03%	0.02%
Santander	T-statistics	99.51%	5.79	0.03	5.81	95.99%	2.68	0.11	2.78
	P-Value		1.61%	87.18%	5.47%		10.19%	74.35%	24.88%
BBVA S.A.	T-statistics	No Exceptions				83.62%	0.76	9.98	10.74
	P-Value						38.20%	0.16%	0.46%
Svenska Handelsbanken AB	T-statistics	88.38%	1.06	0.06	1.13	97.77%	3.57	0.09	3.65
	P-Value		30.23%	80.22%	56.92%		5.89%	77.04%	16.10%
UBS	T-statistics	No Data				89.00%	1.22	0.11	1.33
	P-Value						27.01%	74.09%	51.54%
Deutsche bank	T-statistics	No Exceptions				2.25%	4.33	13.45	17.77
	P-Value						3.75%	0.02%	0.01%

Appendix E Market Risk Charges

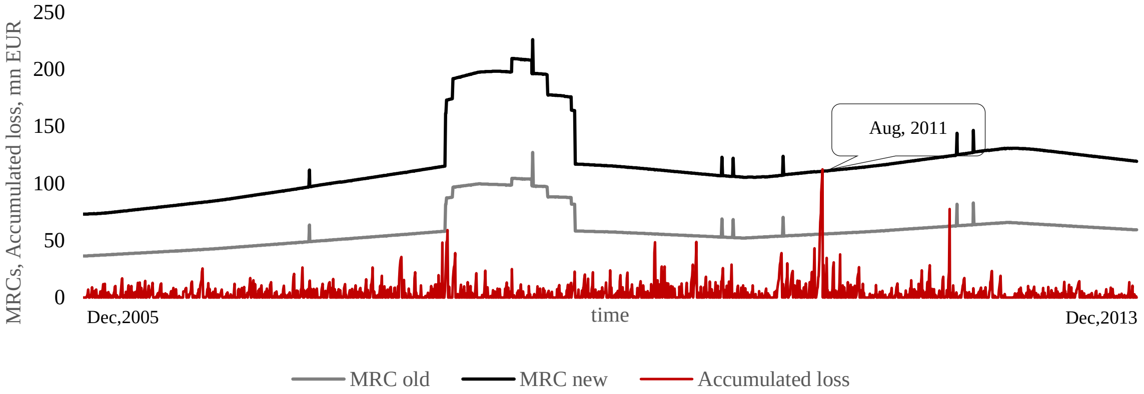
Deutsche Bank



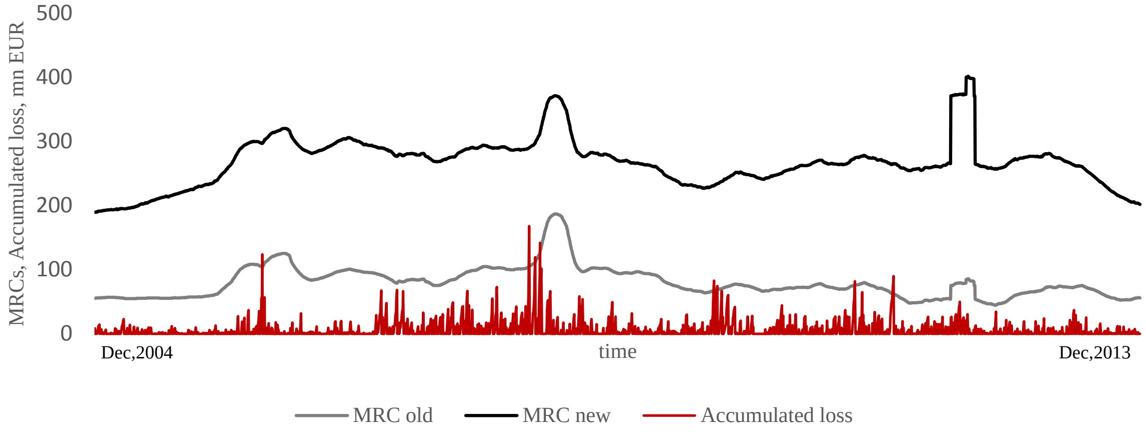
HypoVereinsbank



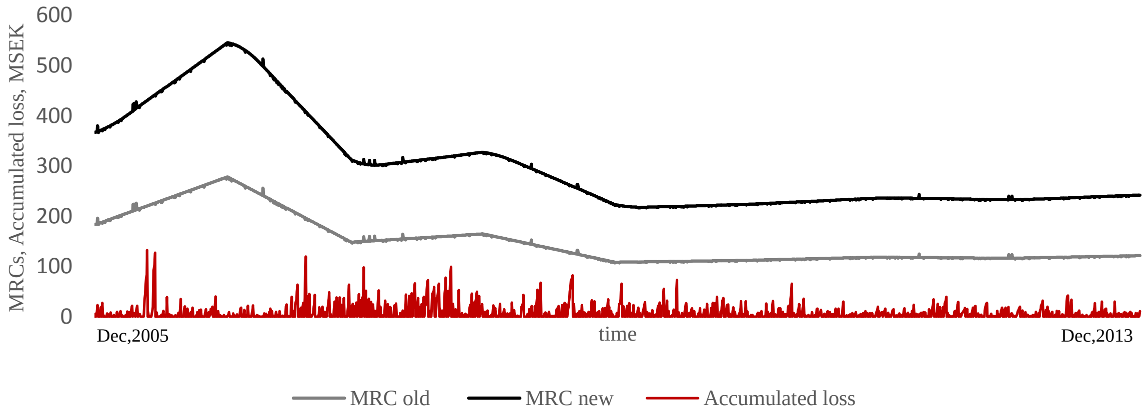
BBVA S.A.



Santander



Svenska Handelsbanken AB



Appendix F Systemic Risk

Appendix F1

Daily P&L Correlation Coefficients, the full sample

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
Deutsche Bank	1.00	0.17*	0.11*	0.03	-0.01	0.21*
	[-]	*[0.00]*	*[0.00]*	*[0.15]*	*[0.77]*	*[0.00]*
HypoVereinsbank	0.17*	1.00	0.06*	0.01	0.03	0.02
	[0.00]	*[-]*	*[0.00]*	*[0.54]*	*[0.17]*	*[0.53]*
Santander	0.11*	0.06*	1.00	0.06*	0.06*	0.13*
	[0.00]	*[0.00]*	*[-]*	*[0.01]*	*[0.01]*	*[0.00]*
BBVA S.A.	0.03	0.01	0.06*	1.00	0.04	-0.03
	[0.15]	*[0.54]*	*[0.01]*	*[-]*	*[0.06]*	*[0.36]*
Svenska Handelsbanken AB	-0.01	0.03	0.06*	0.04	1.00	-0.05
	[0.77]	*[0.17]*	*[0.01]*	*[0.06]*	*[-]*	*[0.15]*
UBS	0.21*	0.02	0.13*	-0.03	-0.05	1.00
	[0.00]	*[0.53]*	*[0.00]*	*[0.36]*	*[0.15]*	*[-]*

Note: Correlation coefficients for banks' P&Ls are calculated with a matched sample for each pair of banks separately; p-values are displayed in parenthesis.

Daily P&L correlations, the non-crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
Deutsche Bank	1.00	0.22	0.10	0.02	-0.02	0.21
HypoVereinsbank	0.22	1.00	0.05	0.01	0.02	0.02
Santander	0.10	0.05	1.00	0.08	0.04	0.13
BBVA S.A.	0.02	0.01	0.08	1.00	0.05	-0.03
Svenska Handelsbanken AB	-0.02	0.02	0.04	0.05	1.00	-0.05
UBS	0.21	0.02	0.13	-0.03	-0.05	1.00

Note: Correlation coefficients for banks' P&Ls are calculated with a matched sample for each pair of banks separately

Daily P&L correlations, the crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB
Deutsche Bank	1.00	0.04	0.06	-0.01	0.07
HypoVereinsbank	0.04	1.00	0.03	0.02	-0.01
Santander	0.06	0.03	1.00	0.01	0.16
BBVA S.A.	-0.01	0.02	0.01	1.00	0.06
Svenska Handelsbanken AB	0.07	-0.01	0.16	0.06	1.00

Note: Correlation coefficients for banks' P&Ls are calculated with a matched sample for each pair of banks separately

Weekly P&L correlations, the non-crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
Deutsche Bank	1.00	0.36	0.20	0.09	0.09	0.52
HypoVereinsbank	0.36	1.00	0.23	0.10	0.00	0.10
Santander	0.20	0.23	1.00	0.20	0.13	0.28
BBVA S.A.	0.09	0.10	0.20	1.00	0.07	0.03
Svenska Handelsbanken AB	0.09	0.00	0.13	0.07	1.00	-0.05
UBS	0.52	0.10	0.28	0.03	-0.05	1.00

Note: Correlation coefficients for banks' P&Ls are calculated with a matched sample for each pair of banks separately

Weekly P&L correlations, the crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB
Deutsche Bank	1.00	0.22	0.21	0.15	0.02
HypoVereinsbank	0.22	1.00	0.22	0.16	-0.07
Santander	0.21	0.22	1.00	-0.03	0.20
BBVA S.A.	0.15	0.16	-0.03	1.00	0.04
Svenska Handelsbanken AB	0.02	-0.07	0.20	0.04	1.00

Note: Correlation coefficients for banks' P&Ls are calculated with a matched sample for each pair of banks seperately

Appendix F2

Correlations between changes in daily VaR, the non-crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
Deutsche Bank	1.00	0.08	0.02	-0.06	0.04	-0.05
HypoVereinsbank	0.08	1.00	-0.03	0.01	0.06	0.06
Santander	0.02	-0.03	1.00	0.01	-0.05	0.03
BBVA S.A.	-0.06	0.01	0.01	1.00	0.03	-0.05
Svenska Handelsbanken AB	0.04	0.06	-0.05	0.03	1.00	0.07
UBS	-0.05	0.06	0.03	-0.05	0.07	1.00

Note: Correlation coefficients for changes in banks' VaRs are calculated with a matched sample for each pair of banks seperately

Correlations between changes in daily VaR across banks, the crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB
Deutsche Bank	1.00	0.00	-0.15	-0.02	-0.04
HypoVereinsbank	0.00	1.00	-0.01	-0.08	0.07
Santander	-0.15	-0.01	1.00	0.04	-0.11
BBVA S.A.	-0.02	-0.08	0.04	1.00	-0.03
Svenska Handelsbanken AB	-0.04	0.07	-0.11	-0.03	1.00

Note: Correlation coefficients for changes in banks' VaRs are calculated with a matched sample for each pair of banks seperately

Correlations between changes in weekly VaR, the non-crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB	UBS
Deutsche Bank	1.00	0.19	0.07	-0.08	0.02	0.02
HypoVereinsbank	0.19	1.00	0.10	-0.03	0.11	0.17
Santander	0.07	0.10	1.00	0.01	0.06	-0.09
BBVA S.A.	-0.08	-0.03	0.01	1.00	-0.10	0.16
Svenska Handelsbanken AB	0.02	0.11	0.06	-0.10	1.00	0.14
UBS	0.02	0.17	-0.09	0.16	0.14	1.00

Note: Correlation coefficients for changes in banks' VaRs are calculated with a matched sample for each pair of banks separately

Correlations between changes in weekly VaR, the crisis period

	Deutsche Bank	HypoVereinsbank	Santander	BBVA S.A.	Svenska Handelsbanken AB
Deutsche Bank	1.00	0.26	0.04	-0.12	0.15
HypoVereinsbank	0.26	1.00	0.01	-0.15	-0.02
Santander	0.04	0.01	1.00	0.04	-0.19
BBVA S.A.	-0.12	-0.15	0.04	1.00	-0.01
Svenska Handelsbanken AB	0.15	-0.02	-0.19	-0.01	1.00

Note: Correlation coefficients for changes in banks' VaRs are calculated with a matched sample for each pair of banks separately

Appendix G Mincer and Zarnowitz Regressions

Deutsche Bank

Regression

Source	SS	df	MS
Model	**1.3159e+10**	**1**	**1.3159e+10**
Residual	**2.6632e+11**	**2605**	**102235317**
Total	**2.7948e+11**	**2606**	**107245543**

Number of obs	=	**2607**
F (1, 2605)	=	**128.71**
Prob > F	=	**0.0000**
R-squared	=	**0.0471**
Adj R-squared	=	**0.0467**
Root MSE	=	**10111**

P&L squared	Coef.	Std. Err.	t	P > | t |	95% Conf. Interval	
VaR squared	**.4284324**	**.0377636**	**11.35**	**0.000**	**.3543828**	**.5024821**
Constant	**330.8777**	**344.4401**	**0.96**	**0.337**	**-344.5264**	**1006.282**

Breusch-Godfrey LM test for autocorrelation

Lags(p)	chi2	df	Prob > chi2
1	**141.953**	**1**	**0.0000**

H0: no serial correlation

Svenska Handelsbanken AB

Regression

Source	SS	df	MS
Model	**25027851.7**	**1**	**25027851.7**
Residual	**363569364**	**2250**	**161586.384**
Total	**388597215**	**2251**	**172633.148**

Number of obs	=	**2252**
F (1, 2605)	=	**154.89**
Prob > F	=	**0.0000**
R-squared	=	**0.0644**
Adj R-squared	=	**0.0640**
Root MSE	=	**401.98**

P&L squared	Coef.	Std. Err.	t	P > | t |	95% Conf. Interval	
VaR squared	**.1096426**	**.0088099**	**12.45**	**0.000**	**.0923663**	**.1269189**
Constant	**33.11277**	**11.98519**	**2.76**	**0.006**	**9.609593**	**56.61594**

Breusch-Godfrey LM test for autocorrelation

Lags(p)	chi2	df	Prob > chi2
1	**32.751**	**1**	**0.0000**

H0: no serial correlation

BBVA S.A.

Regression

Source	SS	df	MS
Model	**310346.615**	**1**	**310346.615**
Residual	**21051758.1**	**2229**	**9444.485494**
Total	**21362104.8**	**2230**	**9579.41918**

Number of obs	=	**2231**
F (1, 2605)	=	**32.86**
Prob > F	=	**0.0000**
R-squared	=	**0.0145**
Adj R-squared	=	**0.0141**
Root MSE	=	**97.183**

P&L squared	Coef.	Std. Err.	t	P > | t |	95% Conf. Interval	
VaR squared	**.0883214**	**.0154075**	**5.73**	**0.000**	**.0581069**	**.1185359**
Constant	**9.316054**	**4.525249**	**2.06**	**0.040**	**0.4419108**	**18.1902**

Breusch-Godfrey LM test for autocorrelation

Lags(p)	chi2	df	Prob > chi2
1	**47.132**	**1**	**0.0000**

H0: no serial correlation

HypoVereinsbank

Regression

Source	SS	df	MS
Model	**370482236**	**1**	**370482236**
Residual	**3.6413e+09**	**2264**	**1608350.94**
Total	**4.0118e+09**	**2265**	**1771209.17**

Number of obs	=	**2266**
F (1, 2605)	=	**230.35**
Prob > F	=	**0.0000**
R-squared	=	**0.0923**
Adj R-squared	=	**0.0919**
Root MSE	=	**1268.2**

P&L squared	Coef.	Std. Err.	t	P > | t |	95% Conf. Interval	
VaR squared	**.1697315**	**.0111833**	**15.18**	**0.000**	**.147801**	**.191662**
Constant	**-2.354653**	**31.06024**	**-0.08**	**0.940**	**-63.26417**	**58.55487**

Breusch-Godfrey LM test for autocorrelation

Lags(p)	chi2	df	Prob > chi2
1	**389.994**	**1**	**0.0000**

H0: no serial correlation

Santander

Regression

Source	SS	df	MS
Model	**33559320.3**	**1**	**33559320.3**
Residual	**165093632**	**2577**	**64064.2733**
Total	**198652953**	**2578**	**77057.0026**

Number of obs	=	**2579**
F (1, 2605)	=	**523.84**
Prob > F	=	**0.0000**
R-squared	=	**0.1689**
Adj R-squared	=	**0.1686**
Root MSE	=	**253.11**

P&L squared	Coef.	Std. Err.	t	P > | t |	95% Conf. Interval	
VaR squared	**.1421973**	**.0062129**	**22.89**	**0.000**	**.1300146**	**.1543801**
Constant	**-25.6363**	**6.951959**	**-3.69**	**0.000**	**-39.2683**	**-12.00431**

Breusch-Godfrey LM test for autocorrelation

Lags(p)	chi2	df	Prob > chi2
1	**30.743**	**1**	**0.0000**

H0: no serial correlation

UBS

Regression

Source	SS	df	MS
Model	**214352773**	**1**	**214352773**
Residual	**4.9589e+09**	**1030**	**4814512.26**
Total	**5.1733e+09**	**1031**	**5017750.15**

Number of obs	=	**1032**
F (1, 2605)	=	**44.52**
Prob > F	=	**0.0000**
R-squared	=	**0.0414**
Adj R-squared	=	**0.0405**
Root MSE	=	**2194.2**

P&L squared	Coef.	Std. Err.	t	P > | t |	95% Conf. Interval	
VaR squared	**.0963421**	**.014387**	**6.67**	**0.000**	**.0680095**	**.1246746**
Constant	**-51.60455**	**96.36636**	**-0.54**	**0.592**	**-240.7013**	**137.4923**

Breusch-Godfrey LM test for autocorrelation

Lags(p)	chi2	df	Prob > chi2
1	**0.345**	**1**	**0.5567**

H0: no serial correlation