Too-Big-to-Fail: A Study on the Swedish Banking System during the Financial Crisis

Henrik Nilsson* Sten Tärnbro†

June 1, 2013

Abstract

Too-big-to-fail is a highly debated subject that has gained widespread attention during the latest financial crisis of 2007-2009. Many negative externalities are associated with too-big-to-fail such as excessive risk-taking and overleveraging. In our paper, we present an overview of what too-big-to-fail is and its consequences. In addition, we analyse the effect of too-big-to-fail on the Swedish banking system during the crisis. This analysis is performed by implementing a structural model to value CDS contracts and compare the model spreads to actual market spreads. We find signs of overestimation of CDS spreads for the Swedish banks and the magnitude of the deviations are affected by government intervention during this period. The findings indicate a deviation in default estimations between shareholders and creditors in times of government intervention, which is a sign of too-big-to-fail.

JEL Classification Numbers: G01, G12, G14, G21

Keywords: Too-big-to-fail, Credit default swaps, CreditGrades, Financial crisis

Tutor: Professor Peter Englund

Stockholm School of Economics
Department of Finance
Course 4350: Thesis in Finance

Thanks to our tutor, Professor Peter Englund, for his helpful insights and guidance through the writing process. We would also like to thank Axel Andersson and Jens Friedrich for their helpful comments.

*21667@student.hhs.se
†21699@student.hhs.se

Contents

List of Figures

List of Tables

1 Introduction

Not surprisingly, the debate regarding the problem of too-big-to-fail has exploded since the financial crisis in 2007-2009. As of June 2009, the US had committed to guarantees, capital injections, and asset purchases worth of EUR 2.5 trillion which corresponds to 25 percent of total assets in the national banking sector, while globally, this number is reported to be at least twice as high (Tsesmelidakis and Schweikhard, 2011). Leading policymakers have expressed great concern of the existence of too-big-to-fail. Mervyn King, governor of Bank of England, said in June 2009 that "if some banks are thought to be too-big-to-fail then they are too big" and Federal Reserve chairman, Ben Bernanke concluded in a hearing, before the US Financial Crisis Inquiry Commission that "if the crisis has a single lesson, it is that the too-big-to-fail problem must be solved". Nauturally, significant attention has been focused on creating regulations that will avoid leaving policymakers with a choice of either baling out major institutions or face a financial havoc (Goldstein and Véron, 2011).

> *The EEA Council affirms its commitment that in all circumstances the necessary measures will be taken to preserve the stability of the financial system, to support the major financial institutions, and to protect savers deposits.*
> EEA Council in November, 2008 (EEA Council, 2008)

Preventing a financial institution from failure in a crisis situation can be justified due to the risks that a failure will pose a significant risk to the stability of the financial system. A firm considered too-big-to-fail exhibits a particular systematic threat to the financial system, and ultimately the whole economy, on both a global and domestic level. Judging by the size of the banks as an indicator of the risks associated by a collapse, the risks to the financial system have only grown. The largest banks have steadily increased their share of the market in the last decade, with a particularly fast pace during the crisis (Goldstein and Véron, 2011). This trend is in line with the development in Sweden. From 1990 to 2009, the combined assets relative to gross domestic product (GDP) of the top five Swedish banks has increased from 120 percent to 409 percent (Goldstein and Véron, 2011). The increased concentration of banking assets in the largest banks makes the Swedish banking system interesting from a too-big-to-fail perspective. The Swedish banking system is also a good representative of the oligopolistic banking systems who weathered the crisis relatively well and are becoming more common in the wake of the financial crisis. It is also a banking system that is highly vulnerable to distress in other banking systems, making it a particularly interesting subject to study during the financial crisis of 2007-2009 (Goldstein and Véron, 2011). We turn to the credit default swap (CDS) market to analyse the problem of too-big-to-fail in the Swedish banking system during the crisis period. The analysis will be performed by using a structural model to compare predicted to observed CDS spreads. Observed deviations in this setting can then be a sign of differing perceptions of default probability between shareholders and creditors which is an indication of the existence of too-big-to-fail banking institutions.

In Section 2, we start with a literature review covering previous studies on the too-big-to-fail subject and the CreditGrades model. We continue in Section 3 with an overview of why too-big-to-fail should be considered a problem and its implications. We next describe the characteristics of the Swedish banking system and provide an introduction to the financial crisis of 2007-2009, which is included in Section 4. In Section 5, a description of CDS contracts and introduction to structural models are provided while Section 6 discusses the data used in the study and the implementation of the CreditGrades model. The results are presented in Section 7 and further discussed in the conclusion in Section 8.

2 Literature Review

2.1 Too-Big-to-Fail

After the bailout of Continental Illinois National Bank and Trust Company of Chicago (Continental Illinois) in 1984, the too-big-to-fail term gained widespread attention and an extensive field of research emerged (Kaufman, 2002).

The issue of too-big-to-fail appeared again in the late 1990s and the early 2000s with the seminal work of Stern and Feldman (2004). Stern and Feldman (2004)'s work provides an extensive overview of the too-big-to-fail subject and the regulatory difficulties it creates. Another important paper is Dowd (1999)'s work on the bailout of the hedge fund Long-Term Capital Management (LTCM) and its effect on bailout expectations. It is also one of the first papers that touch on the issue of interconnectedness. Barth and Schnabel (2012) also addresses the debate between size and interconnectedness, and they find that interconnectedness, measured by Adrian and Brunnermeier (2011)'s CoVaR measure is the significant variable when determining what banks that can be considered too-big-to-fail.

There is extensive research focusing on finding empirical evidence supporting the existence of too-big-to-fail banks. A notable paper by Völz and Wedow (2011) examines distortions in the CDS market, where they find a relationship between the size and the level of CDS spreads. They find that an increase in size of one percentage point reduces the CDS spread with two basis points. Another influential paper is the study by Tsesmelidakis and Schweikhard (2011) who studies too-big-to-fail by comparing market spreads to spreads calculated using a structural model. This study focuses on the US market and the effect of too-big-to-fail on banks during the recent financial crisis. Tsesmelidakis and Schweikhard (2011) find discrepancies in the perceived default risk between equity and debt holders, pointing to evidence of too-big-to-fail. A recent extension in the research on the too-big-to-fail problem is the topic of too-big-to-save. Papers in this area of research have found signs of too-big-to-save in the CDS market, notable examples being Völz and Wedow (2011), Barth and Schnabel (2012) and Demirgüc-Kunt and Huizinga (2010) who all find that CDS spreads starts to increase when banks reach a certain size compared to their host countries GDP.

Furthermore, research has been done on the negative effects associated with the too-big-to-fail problem. Boyd and Gertler (1994) finds that large banks had disproportionately large loan losses during the 1980s US banking crisis. Similarly, Haldane (2010) finds that larger banks has a higher percentage of write downs per assets.

A recent paper that has received a lot of attention is the work by Ueda and di Mauro (2012) where the authors tries to measure the funding cost subsidy for too-big-to-fail banks. An increase in the subsidy from 60 basis points at the end of 2007 to 80 basis points at the end of 2009 is observed. This subsidy has given rise to the recent debate in the financial press regarding the societal cost of too-big-to-fail (Bloomberg, 2013).

2.2 Structural Models

The foundation for the structural models was set by Merton (1974) and Black and Scholes (1973) who observed that equity can be viewed as a call option on the firm's assets. This implies that option techniques can be applied to asses the credit risk of a company. New models have been introduced that extends the strucutral approach, such as the model developed by Black and Cox (1976) that examined the effect of bond indentures, and later the CreditGrades model by Finger et al. (2002). Generally, the empirical support of the structural models are rather weak (Rodrigues and Agarwal, 2011). However, support of the CreditGrades as a satisfactory model for modelling CDS spreads is given by, for example, Byström (2006), Rodrigues and Agarwal (2011) and Yeh (2010). Yeh (2010) states that the CreditGrades model appears to be a significant improvement on most other structural models. Specifically, the introduction of a stochastic default barrier improves the predictive power of the model.

Focus has also been on using structural models to implement trading strategies to take advantage of mispricing of credit risk, so called capital structure arbitrage[1]. The most influential paper in this research area is the paper by Yu (2005). Yu (2005) successfully implements a trading strategy for capital structure arbitrage using the CreditGrades model to estimate CDS spreads.

[1]A capital structure arbitrage exploits a mispricing between a company's debt and equity using a structural model to produce a theoretical CDS spread. A convergence type trading strategy is then implemented to take advantage of the "mispricing" (Yu, 2005).

3 Overview of Too-Big-to-Fail

Too-big-to-fail refers to the practice by regulators of protecting creditors, and in some instances shareholders, of large banks in the event of financial distress. The decision to close a bank is subsequently transferred from creditors to regulators (Hetzel, 1991). The reason of intervention by the government is the fear of the serious consequences that a failure would have on the banking system and on the economy as a whole.

3.1 Interconnectedness

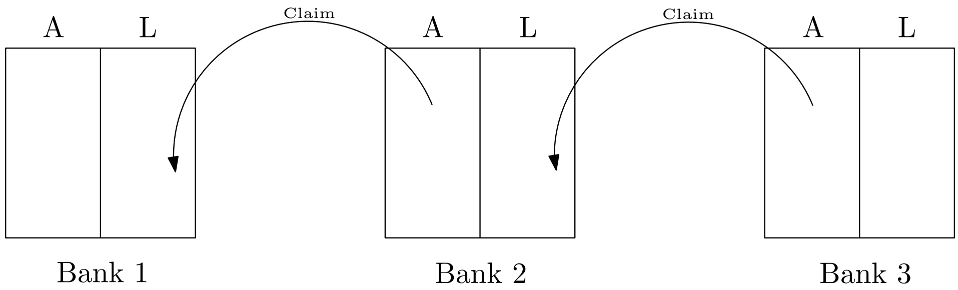
In recent years as the financial markets have become more globalized and more interconnected, the too-big-to-fail issue has evolved from focusing exclusively on bank size to focus more on interconnectedness, i.e. how interconnected the banks are in the financial markets (Brunnermeier et al., 2009). An example of this shift of focus is the Swedish Riksbank's updated definition of systemically important institutions as "institutions that in case of financial distress causes disturbances in the financial system with potentially large socio-economic consequences" (Sveriges Riksbank, 2013). Why interconnectedness is important is easily illustrated by a domino model, illustrated in Figure 1, where banks are interconnected to each other, for example through interbank lending or repurchase agreements. Through contagion stemming from one struggling bank, losses spreads through the chain of banks, ultimately posing a risk to the whole banking system (Brunnermeier et al., 2009). Another part of the contagion issue is the information-contagion stemming from a bank failure. If a bank fails, banks with similar characteristics might be subject to financial distress, such as a bank run, because of the perceived shared characteristics. An example of the power information contagion from the recent crisis is the Lehman Brothers Holdings Inc. (Lehman Brothers) failure that eventually led to the demise of US securities firms (Brunnermeier et al., 2009).[2]

The main concern by using interconnectedness to measure too-big-to-fail is the difficulty to measure the degree of interconnectedness; the European Central Bank (ECB) used a composite index of 19 indicators to define large and complex banking groups operating in the European market, claiming that size alone was not enough to properly define too-big-to-fail.

[2]Goldman Sachs Group, Inc. and Morgan Stanley became regular banks while Merrill Lynch & Co., Inc. was acquired by Bank of America Corp (Goldstein and Véron, 2011).

In the end ECB found that total assets capture almost the entire composite index, reporting an r-square as high as 0.93 percent (Goldstein and Véron, 2011).

Figure 1: Domino Model



This model illustrates financial contagion in the case of default of bank 1. Because bank 2 has claims on the failed bank, there is a possibility that also bank 2 will default. This would in turn create a risk of default by bank 3 that has claims on bank 2.

3.2 Historical Overview

The rise of the term too-big-to-fail can be dated back to May 1984 when Continental Illinois ran into problems. Continental Illinois was the seventh-largest bank in the US at the time and was rescued with liquidity support from the Federal Reserve along with guarantees from the Federal Deposit Insurance Corporation (FDIC) (Goldstein and Véron, 2011). In the end, the FDIC protected all of the depositors of Continental Illinois even though only 10 percent of its deposits were formally insured (Hetzel, 1991). The rescue gave rise to a hectic debate regarding whether large banks had to be treated differently than small intuitions, and it did not take long before the concept of too-big-to-fail was born (FDIC, 1997). In the hearings after the bailout, the US Comptroller of Currency admitted that the largest 11 banks in US would not be allowed to fail by the regulators (Goldstein and Véron, 2011). Furthermore, the event resulted in a new resolution regime where the FDIC was given the mandate to administer it. However, this regime would not be tested on a large scale, i.e. on a too-big-to-fail institution, until the crisis in 2008 (Goldstein and Véron, 2011).

The interconnectedness dimension of the too-big-to fail problem was illustrated with the crisis of the hedge fund LTCM in 1998. LTCM experienced heavy losses and liquidity constraints as a result of the Asian and Russian financial crisis in 1997-1998, and in September 1998 the Federal Reserve organized a rescue of LTCM (Goldstein and Véron, 2011). With respect to size, LTCM could not be considered huge, but the main fear and the reasons of the bailout was its interconnectedness with the rest of the banking industry, i.e. an example of too-interconnected-to-fail (Goldstein and Véron, 2011). Since the failure of Continental Illinois, the official stance from Federal Reserve officials had been that large institutions could not count on support if they would run into problems (Dowd, 1999). However, as the case of LTCM illustrates, even relatively small financial institutions could be considered too important to be let fail.

3.2.1 The European Perspective

The biggest difference between Europe and the US is the view on banking failures. In Europe it is rare for governments to let banks fail irrespective of size. Instead banks are bailed-out before failure. An explanation put forward is that this can be explained by the cultural differences between Europe and the US in regards to bankruptcy, and the European experience of bank failures and their consequences, mostly related to the 1930s (Goldstein and Véron, 2011).

There is a long European history of government intervention in the banking sector, an early example being the creation of Deutsche Bank AG in 1870 to combat the Anglo-French domination in the international banking market. Other examples of government intervention are the nationalizations of the banking sectors in Italy and France in 1933 and 1946 respectively and the bailout of the Swedish banking system in 1992 (Goldstein and Véron, 2011; Englund, 1999). Furthermore, outright government ownership of banks is more common in Europe compared to the US. Before the wave of banking privatizations during the 1970-1980s, government ownership was prevalent (Goldstein and Véron, 2011). Today, government ownership has become more prevalent due to the increased number of bank bailouts. Examples of recent interventions are the UK government's bailout of Royal Bank of Scotland Plc (RBS), and the Spanish government's bailout of Bankia S.A. (BBC, 2012a,b). In Sweden, the government is still the second largest shareholder, holding 13.5 percent, in Nordea Bank AB, which is a legacy of the bailout in 1992 (Nordea, 2013). This example clearly illustrates that government bailouts can turn into long-term ownership of the bailed out banks.

3.3 Implications

The existence of too-big-to-fail creates distortions in the banking sector and in the financial markets. The main implication of too-big-to-fail is that the risk in the banking sector becomes too high compared to what is optimal for society. The main reasons for the increased riskiness are moral hazard and the incentive for banks to overleverage to reach a too-big-to-fail status (Stern and Feldman, 2004). To study the problem of too-big-to-fail, we examine the effect on both shareholders and creditors, and the subsequent implications.

The banks shareholders have a partial government insurance depending upon how the bailout is structured. If the bailout of the bank depletes the equity capital the shareholders have no insurance. An example is the bailout of Nordbanken by the Swedish government where the government decided to save the bank while not bailing out the shareholders (Englund, 1999). An additional kind of bailout is equity infusion. A recent example is the British government taking an 82 percent stake in RBS (BBC, 2012a). In this type of bailout, the shareholders face a share dilution but they keep some upside, as default is avoided and they keep their shares. Another example is the Troubled Asset Relief Program (TARP) launched in October 2008 by the US government. In this program the government purchased preferred stock from a number of US banks which in effect was an equity investment aimed to avoid hurting existing shareholders (Solomon et al., 2013).

By contrast, the creditors of too-big-to-fail banks receive a more direct form of implied government insurance. Based on recent bailouts, the creditors have been fully insured, and consequently this insurance significantly reduces the need to monitor the bank and its management. An example is the bailout of the Irish banking system where the EU insisted on protecting the senior bondholders as to avoid a run on other troubled banks (Goldstein and Véron, 2011). Apart from lower monitoring costs, too-big-to-fail banks have a funding cost advantage as creditors demand lower yields compared to non-too-big-to-fail banks due to the implied government insurance. The artificially low funding cost leads to overinvestment and increased risk taking. It also creates incentives for non-too-big-to-fail banks to leverage up and become too-big-to-fail to exploit the funding cost advantage. This leads to banks overleveraging, which in turn increases the riskiness for individual banks and for the financial system as a whole (Stern and Feldman, 2004). Empirical evidence supporting overleveraging can be found in Hoenig (2013)'s speech where he presents evidence that the leverage ratio for the biggest bank groups is 400-475 basis points higher compared to smaller non systemic banks.

An externality of overleveraging is the recent issue called too-big-to-manage. As financial scandals have rocked some of the worlds largest banks,[3] a common opinion has been growing that the largest banks have become too big to manage. This notion is based on the belief that when banks increase their size trying to reach too-big-to-fail status, diseconomies of scale appear and it becomes hard to implement management practices, such as efficient risk management practices (Goldstein and Véron, 2011). Evidence of diseconomies of scale in the banking sector can be found in for example Haldane (2010), who finds a weak positive relationship between the size of a bank and the percentage of write-downs per asset. Haldane (2010) also finds that banks that are more diversified have a higher percentage of write-downs per asset, indicating that larger and more diversified banks are less efficient. In contrast, some studies find evidence of economies of scale but only up to a certain threshold. Berger and Mester (1997) find that economies of scale cease to exist below the $10 billion threshold while Amel et al. (2004) finds that operational costs as a percentage of gross income decreases with size up to a $50 billion threshold. For banks over the $50 billion threshold the percentage of costs starts to increase.

Besides the increased riskiness there are other externalities stemming from the existence of too-big-to-fail. First, market data indicate that some banks have grown so big that they are in practice too-big-to-save (Goldstein and Véron, 2011). A major reason for the too-big-to-save problem is illustrated by following quote by Bank of England governor Mervyn King: "global banks are global in life, but national in death" (Schifferes, 2009). Too-big-to-save paradoxically increases the market discipline for the banks, but it is a significant issue for regulators since they now have a bank that is considered too-big-to-fail that they cannot afford to bailout in case of a banking crisis (Völz and Wedow, 2011). An example of banks being too-big-to-save was the Icelandic banks during the crisis in Iceland in 2008 when all of the three major banks[4] defaulted (Iceland Chamber of Commerce, 2009).

[3] Recent examples related to too-big-to-manage are: HSBC Holding Plc's and Standard Chartered Plc's money laundering scandals, JPMorgan Chase & Co. and the "London Whale" trading loss, and the London Interbank Offered Rate (LIBOR) fixing scandal (Johnson, 2012).

[4] The three major banks were Glitnir Banki hf., Kaupthing Bank hf. and Landsbanki hf.

3.4 Regulatory Response

To provide a comprehensive overview of the too-big-to-fail problem, we find it necessary to provide a brief introduction to proposals that has been made to address the problem. We do not intend to provide a complete overview or further discuss regulatory issues associated with too-big-to-fail since such a complex issue would deserve its own paper.

A first step by regulators has been to try to internalize the externalities associated with too-big-to-fail. Here, available options are: capital and liquidity surcharges, size-related taxes and competition policy (Goldstein and Véron, 2011). Tougher capital and liquidity standards have been proposed through the new Basel III requirement that aims to make the banks safer and thereby alleviate the problem. An approach to discourage size through tax-related incentives has not been widely adopted by governments so far even though it was proposed in the initial outline of the Dodd-Frank Act in US (Goldstein and Véron, 2011). Using competition policy as a solution to the size problem has mainly been used by the European Commission to limit the size of rescued firms in cases when bailouts in member states have occurred. In the US, the Dodd-Frank Act enables legislators to force a systemically important institution to divest activities that are considered to contribute to excessive systemic risk. However, it is unclear how this will work in practice (Goldstein and Véron, 2011).

More direct approaches to force banks to shrink, or not reach a too-big-to-fail size, are size caps. The Dodd-Frank Act in the US includes prohibition of mergers if the total liabilities of the resulting banks exceed 10 percent of the aggregate consolidated liabilities of all banks (Goldstein and Véron, 2011). The problem of introducing more direct size caps of banks on a global scale is the difficulty in finding a relevant measure of size and the fundamentally different nature of the banking industry in the US versus the EU. For further discussion on the practical issues with size limitations, Goodhart (2010) provides an extensive overview.

Instead of trying to deal with the problem of too-big-to-fail pre-emptily, solutions aimed at letting banks fail under controlled forms have been proposed. Such a solution is the requirement to force banks to prepare a "living will", which would provide regulators with a guide during the wind-down of the bank's activities. Another solution is special resolution regimes for failed banks, which is included in the new Dodd-Frank Act. Similar approaches have also been introduced, or are being introduced, in several EU-member states (Goldstein and Véron, 2011). Another approach to reduce the complexity of banking groups is to introduce legislations aimed at legally separate certain activities within the bank, so called “ring-fencing”. An example is the report by Liikanen (2013) for the European Commission, which proposes to legally separate “more risky” trading activities from retail banking activities to keep, what can be considered, the socially most important part of the bank separated from the trading activities, hence reducing the explicit and implicit stake of taxpayers in the trading activities.

To conclude, there are three main types of solutions to deal with the too-big-to-fail problem: decrease the size or discourage further growth of banks, introduce organized bankruptcy routines or make too-big-to-fail banks safer through new regulation. Naturally, there are both pros and cons associated with the proposals aimed at resolving those types of solutions and the debate regarding the potential solutions is far from settled.

4 Introduction to Empirical Test of Too-Big-to-Fail

The Swedish banking system is highly concentrated to a few large institutions. The so called big four banks, Nordea Bank AB (Nordea), Skandinaviska Enskilda Banken AB (SEB), Svenska Handelsbanken AB (SHB) and Swedbank AB (Swedbank), control 75 percent of the banking assets in Sweden (Sveriges Riksbank, 2012) and 66 percent of the deposits (The Swedish Bankers' Association, 2013). Goldstein and Véron (2011) states that concentration in the banking system can be used as an indication of too-big-to-fail presence where a higher concentration makes too-big-to-fail more likely. The high level of government interventions during the crisis period of 2007-2009 and the highly concentrated banking industry in Sweden makes this period in general, and the Swedish market in particular, very interesting for further studying of the too-big-to-fail problem in practice.

We use a structural model, outlined in subsequent sections, to predict CDS spreads and compare those to observed spreads. Deviations in this setting can then be a sign of differences in the perceived default risk between equity and debt. If those deviations occur during government interventions we argue that this is in favour of too-big-to-fail argumnet since government interventions when bailing out too-big-to-fail banks are particular focused on saving the creditors of the bank. Next, we provide a short introduction and a brief overview of the events that shaped the crisis.

4.1 The Financial Crisis of 2007-2009

A period of relatively high growth and low inflationary pressures, commonly referred to as the "great moderation", ended abruptly with a period of crisis between 2007-2009 (Davis, 2012). After a liquidity crisis in the money market in 2007, a full-blown financial crisis erupted in 2008 that led to a wave of bank nationalizations and recapitalizations across North America and Europe (Barrell and Davis, 2008). Worldwide, central banks and governments responded with extraordinary measures in trying to stem the financial crisis, a crisis that clearly demonstrated the interconnected nature of the financial industry (Petrovic and Tutsch, 2009).

Despite the central banks offering massive volume of liquidity support in 2007 in trying to restore short-term funding markets, problems escalated in 2008 with the failure of Bear Sterns Companies, Inc. (Bear Sterns), taken over by JPMorgan Chase & Co. with the help of government guarantees, and Fanny Mae and Freddy Mac, both nationalized (Barrell and Davis, 2008). After the failure of Lehman Brothers in September 2008, fiscal authorities started to intervene on a new scale with adoption of measures such as recapitalisation schemes and government guarantees, with a goal of avoiding a collapse of systemically important financial institutions (ECB, 2010).[5] Early examples of interventions are the nationalization of the American Insurance Group Inc. (AIG) in the US and of Bradford and Bingley Plc. in the UK (Barrell and Davis, 2008). As the crisis escalated, further nationalizations occurred such as RBS and Lloyds Banking Group Plc. in the UK, and the announcement in October 2008 by Treasury Secretary, Henry Paulsson, that $250 billion was made available to US banks in return for equity stakes as part of a revision of the TARP (Barrell and Davis, 2008). The level of interventions has varied considerably among countries, where estimates have shown that the UK stands out with commitments as a percentage of GDP of over 40 percent[6] (Faeh et al., 2009).

4.1.1 The Situation in Sweden

As the financial crisis worsened during September 2008, Swedish authorities acted in an attempt to stop financial contagion spreading to the Swedish banking system. In September, the Swedish National Debt Office (SNDO) issued additional short-term debt, which was used in reverse repos using mortgage paper. Later, the Riksbank eased its collateral policy for mortgage bonds from 25 percent to 75 percent. At the same time, long-term lending facilities in both Swedish krona and US dollar was set up and the deposit insurance was increased from 250,000 SEK to 500,000 SEK (Sveriges Riksbank, 2008). In October, the Swedish Government announced the Support To Credit Institutions Act consisting of a guarantee program where eligible institutions could get up to 1,500 billion SEK guaranteed by the government. Additional measures were a capital support program including recapitalization with Tier 1 capital and state loans for banks in liquidity difficulties, the establishment of a stabilization fund for future crisis and the appointment of SNDO as the support authority for the support program (Petrovic and Tutsch, 2009). Both Swedbank and SEB joined the guarantee

[5]For example the Emergency Economic Stabilisation act in the US that included a commitment of up to $700 billion to purchase bad assets (TARP) (Faeh et al., 2009).

[6]This should not be any surprise because of the size of the banking system relative the real economy and the number of large institutions that were hit.

program, although in the end, SEB decided not to use the program (Swedish National Debt Office, 2012).

As the government intervened the situation eventually stabilized. The Stockholm Interbank Offered Rate (STIBOR) fell 4.67 percentage points from October 13 2008 until April 22 2009. The rate for secured bonds fell 2.8 percentage points for the same period (Finansinspektionen, 2009a). During late 2009, the need for dollar financing stopped as the Swedish banks could finance themselves in the dollar market, and in April 2010 the Riksbank announced the closure of all long term lending facilities (Sveriges Riksbank, 2009, 2010).

4.1.2 The Baltics

What can be considered to be the biggest risk facing the Swedish banking system was the exposure to the Baltic markets; of the four big banks all of them except for SHB had exposure to the Baltic's. The Baltic countries faced severe economic difficulties in 2008 after several years of booming economic growth. The situation in Latvia was especially severe and Latvia later received a bailout from the European Union and the International Monetary Fund (Finansinspektionen, 2009c). Given the economic difficulties in the Baltics, the Swedishs banks faced significant potential credit losses (Finansinspektionen, 2008).

Of the banks with Baltic exposure, Swedbank had the biggest exposure, with 13.6 percent of total lending, while SEB had the second highest exposure with 12.9 percent and Nordea had the lowest with 2.3 percent, see Table 1. The notion that Swedbank and SEB had the most high-risk assets in their credit portfolios where supported by the stress tests performed by Finansinspektionen during 2008 and 2009 (Yazdi, 2008; Finansinspektionen, 2009b).

Table 1: Baltic Exposure

	Nordea	SEB	SHB	Swedbank
Total Exposure	2817	1351	1554	1394
Baltic Exposure	65	175	-	190
Percent of Total Exposure	2.3	12.9	-	13.6

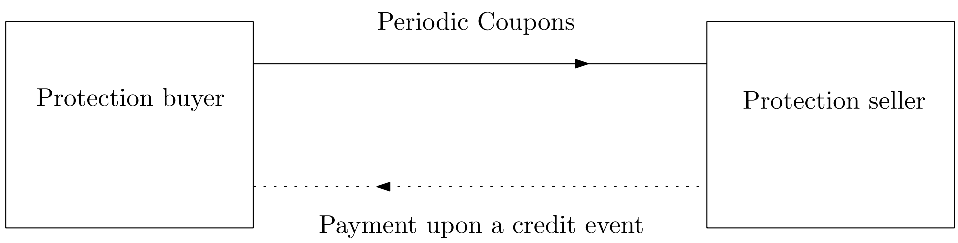
NOTE: The numbers are collected from Finansinspektionen (2008)

5 Credit Default Swaps

5.1 Description

The market for CDS contracts has exploded in the recent couple of years. In 2000, the notional principal of outstanding contracts was less than $1 trillion (Hull, 2009), while the same number in 2011 had grown to over $26 trillion (IOSCO, 2012). Focusing on CDS spreads rather than bond spreads to measure credit risk is warranted due to the distinctive advantages that are inherent in CDS spreads. Specifically, CDS spreads provide a pure measure of the default risk due to advantages such as absence of short sale restrictions, liquidity, call provisions and interest rate risk (Tsesmelidakis and Schweikhard, 2011; Rodrigues and Agarwal, 2011). In addition, CDS contracts are traded on very standardized terms compared to the bond market where multiple differentiations exist. Furthermore, several papers have shown that the CDS market reflects new information more rapidly than the bond market (Völz and Wedow, 2011).

Figure 2: CDS Payment Structure



The CDS contract is the most popular type of credit derivative, and it is a bilateral credit derivative contract where two counterparties exchange credit risk (Hull, 2009). The buyer of the CDS receives credit protection by paying periodic coupons to the seller, known as the fee leg. The seller in turn receives the coupons but is obligated to pay a contingent payment, known as the contingent leg, in case of a pre-defined credit event, e.g. bankruptcy. From an economic point of view the buyer of the CDS is short credit risk while the seller is long credit risk.

There are five parameters that define the CDS contract (Goldman Sachs FICC Credit Strategies, 2009):

- Reference Entity. The issuer of the credit being protected defined by a reference obligation. The most common reference entities are companies and sovereigns. There are also

CDS's available for indexes and baskets of reference entities as well as for structured products such as CDO's. The reference obligation defines the seniority of the claim, for example different tranches or different seniority in mezzanine structures (JPMorgan Corporate Quantitative Research, 2006).

- Notional amount. The amount of credit risk being transferred by the CDS (JPMorgan Corporate Quantitative Research, 2006).
- Price/Spread. The periodic payments the seller receives for selling credit. The payments are usually paid quarterly but the spread is expressed as annualized percent (JPMorgan Corporate Quantitative Research, 2006).
- Maturity. The maturity of the contract where the most common maturities are five, seven and ten years (JPMorgan Corporate Quantitative Research, 2006).
- Credit Events. Determines the credit events that will trigger settlement of the CDS contract and are predefined according to market standards. Common types are complete restructuring (CR) and modified-modified (MM) (Markit, 2008).

5.2 Valuation

A CDS contract is defined by the no arbitrage condition that the present value of the periodic payments must be equal to the present value of the protection. Given this no arbitrage condition, the initial value of a CDS contract must be equal to zero. When performing the net present value (NPV) calculation, we must calculate the cash flows stemming from both the fee and the contingent leg. Both legs are weighted according to the probabilities of survival and default respectively, and are discounted using the risk-free rate. Total cash flows can be summarized by

$$NPV = \sum_{N}^{i=1}(1-R)\times(p_{i-1}-p_i)\times d_i - \sum_{N}^{i=1} s\times p_{i-1}\times d_i,$$

where s is the spread paid and the NPV equals zero (Goldman Sachs FICC Credit Strategies, 2009).

5.3 CDS Models

There are two major approaches for modelling theoretical CDS spreads, the reduced-form approach and the structural approach. The reduced-form approach treats default as an unpredictable Poisson event and do not offer a clear relation between the firms capital structure and corresponding default risk (Zhou, 2001). Furthermore, the reduced-form models do not offer a clear picture regarding the economic mechanisms of default, and the parameters are reported to be unstable when the models are calibrated to observed CDS spreads (Zhou, 2001).

Structural models provide a way to predict the CDS spreads by linking the firms liability structure to the market value of equity. The structural models are based on the seminal work by Black and Scholes (1973) and Merton (1974) on option pricing. In essence, they show that equity owners can be viewed as having a call option on the firm's assets, while subsequently the value of the debt can be viewed as the asset value minus the equity call option value. These models have been widely adopted even though the underlying assumptions often not reflect economic reality. Such assumptions include a constant risk-free rate, default can only occur at maturity, continuously traded assets and no transaction costs or taxes (Rodrigues and Agarwal, 2011). Black and Cox (1976) further developed this approach by introducing an exogenous default barrier and an event of default if the asset value of the company crosses this predetermined threshold (Tsesmelidakis and Schweikhard, 2011). This model is the structural model that the CreditGrades framework is based on (Finger et al., 2002).

The CreditGrades model was developed by RiskMetrics together with Deutsche Bank AG, Goldman Sachs Group Inc. and JPMorgan Chase & Co. Since its launch in 2002, the model has become widely adopted among practitioners, and an industry benchmark for identifying relative value trading opportunities (Cao et al., 2010). The CreditGrades model calculates theoretical spreads based on stock and balance sheet data which makes the model straightforward to implement (Byström, 2006). A problem with the original structural model developed by Merton (1974) is that it produces too low short-term credit spreads. To solve this problem, the CreditGrades model introduce uncertainty in the default barrier which allows the firm to be closer to the barrier than otherwise should be expected (Finger et al., 2002). Another method used in the literature to capture the uncertainty is to incorporate jumps into the asset process, see for example Zhou (2001).

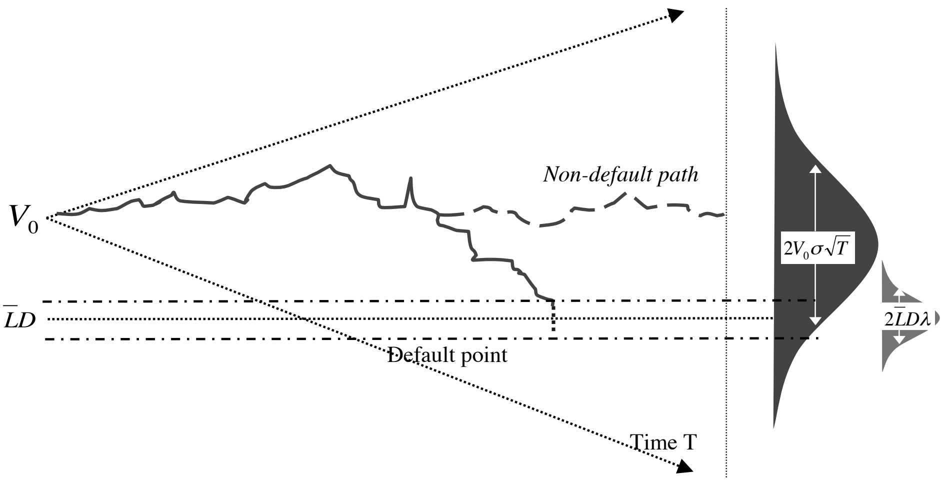
5.3.1 CreditGrades

The CreditGrades Technical Document by Finger et al. (2002) gives a detailed walk-through of the model and its parameters. In the CreditGrades model, a stochastic process V is assumed, and default is defined as the first time that V crosses the default barrier. Intuitively, V is the asset value process on a per share basis for the firm. We start to define the asset value process

$$\frac{dV_t}{V_t} = \sigma dW_t + \mu_D dt, \tag{5.1}$$

where W is a standard Brownian motion and σ is the asset volatility. The asset value is assumed to have a zero drift in this framework which is justified by assuming that the firm on average issues debt to maintain a steady level of leverage.

Figure 3: The Asset Value Process



NOTE: This figure is reprinted from Finger et al. (2002).

The default barrier in the model is defined as the amount of a firms assets that remain in case of default, LD, where L is the recovery rate and D is the firms debt per share. Randomness in the recovery value is introduced to produce more realistic short-term credit spreads (Finger et al., 2002). The random recovery value is modelled using a lognormal distribution with mean $\bar{L}$ and standard deviation λ

$$\bar{L} = \mathbf{E}L, \tag{5.2}$$

$$\lambda^2 = Var\,log(L), \tag{5.3}$$

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2}, \tag{5.4}$$

where Z is a standard normal random variable. By letting Z be a standard normal random variable, uncertainty regarding the debt-per-share level is captured and a possibility of hitting the default barrier instantaneously is introduced.

If we denote V_0 as the initial asset value, default in the CreditGrades framework does not occur as long as

$$V_0 e^{\sigma W_t - \sigma^2 t/2} > \bar{L}De^{\lambda Z - \lambda^2/2}. \tag{5.5}$$

The probability of survival of the company up to time t is the probability that the asset value does not reach the barrier before time t. This survival probability is calculated by introducing a new process X

$$X_t = \sigma W_t - \lambda Z - \frac{\lambda^2 t}{2} - \frac{\lambda^2}{2}. \tag{5.6}$$

X_t follows a normal distribution for $t > 0$ with

$$\mathbf{E}X_t = -\frac{\sigma^2}{2}(t + \lambda^2/\sigma^2), \tag{5.7}$$

$$Var X_t = \sigma^2(t + \lambda^2/\sigma^2). \tag{5.8}$$

We can now find an approximate closed form solution to the survival probability $P(t)$ that the firm does not hit the default barrier using a process that does not contain Z

$$P(t) = \phi\left(-\frac{A_t}{2} + \frac{log(d)}{A_t}\right) - d \times \phi\left(-\frac{A_t}{2} - \frac{log(d)}{A_t}\right), \tag{5.9}$$

with

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L}D}, \tag{5.10}$$

$$A_2^t = \sigma^2 t + \lambda^2, \tag{5.11}$$

where ϕ is the cumulative normal distribution.

An alternative to using the approximated formula for the survival probability is to integrate out the random variable Z and thereby obtain a closed form solution. It is claimed in the CreditGrades technical document (Finger et al., 2002) that the difference between the two solutions are marginal. However, when considering firms with a very high level of debt-per-share, the two alternatives can differ considerably as shown by Kiesel and Veraart (2008). The exact survival probability can be calculated up to time t as

$$\prod(t) = \phi_2\left(-\frac{\lambda}{2}+\frac{log(d)}{\lambda},-\frac{A_t}{2}+\frac{log(d)}{A_t};\frac{\lambda}{A_t}\right)$$
$$-d\times\phi_2\left(\frac{\lambda}{2}+\frac{log(d)}{\lambda},-\frac{A_t}{2}-\frac{log(d)}{A_t};-\frac{\lambda}{A_t}\right), \tag{5.12}$$

where A and d are defined as in (5.11) and (5.10), and ϕ is the cumulative bivariate normal distribution. As Kiesel and Veraart (2008) points out, this exact survival probability is not the formula that Finger et al. (2002) claims in the technical document. Based on the very high debt levels in financial firms, we choose to incorporate the exact survival probability solution in the CreditGrades framework to produce an estimation of the survival probability that is as accurate as possible.

To price the CDS contract, the risk-free rate, r, and the asset specific recovery rate, R, of the underlying credit is introduced. The continuously compounded spread, c^*, can be calculated according to the no-arbitrage condition that the present value of the periodic payments must equal the present value of the protection

$$c^* = r(1-R)\frac{1-P(0)+e^{r\xi}(G(t+\xi)-G(\xi))}{P(0)-P(t)e^{-rt}-e^{r\xi}(G(t+\xi)-G(\xi))}, \tag{5.13}$$

where $\xi = \lambda^2/\sigma^2$ and the function G is given by

$$G(u) = d^{z+1/2}\phi\left(-\frac{log(d)}{\sigma\sqrt{u}}-z\sigma\sqrt{u}\right)+d^{-z+1/2}\phi\left(-\frac{log(d)}{\sigma\sqrt{u}}+z\sigma\sqrt{u}\right), \tag{5.14}$$

with $z = \sqrt{1/4\,+\,2r/\sigma^2}$.

To implement the model and solve for the survival probabilities we need to calibrate the model to market observables. For the initial asset value we have

$$V_0 = S_0 + \bar{L}D, \tag{5.15}$$

where S_0 is the stock price at $t = 0$.

Finally, the asset volatility is estimated from the market, where σ_s^* can be estimated using either implied volatility or historical estimates. In the estimation of the final asset volatility, we will deviate from the CreditGrades model and use an alternative specification according to the model proposed by Bharath and Shumway (2008), where the asset volatility is weighted according to the capital structure. We prefer this specification due to its simplicity, while still being economically feasible, and its straightforward implementation. The total volatility of the firm is approximated according to

$$\sigma = \frac{E}{E+D} \times \sigma_s^* + \frac{D}{E+D} \times \sigma_d. \tag{5.16}$$

6 Data and Implementation

6.1 Sample

Our sample is restricted to the four largest Swedish commercial banks, the so-called big four; Nordea, SEB, SHB and Swedbank (The Swedish Bankers' Association, 2013). Daily CDS data are collected using historical five-year USD-denominated senior unsecured CDS quotes from 2007 to 2010. All of the CDS data are collected from Nordea Analytics (Nordea Bank AB, 2013). The restructuring clause for the CDS contracts included in the data is Modified-Modified which is the restructuring clause most commonly used in Europe (Markit, 2008). For descriptive statistics on the CDS data, see Table 2. For a time series graph over the CDS data, see Figure 4.

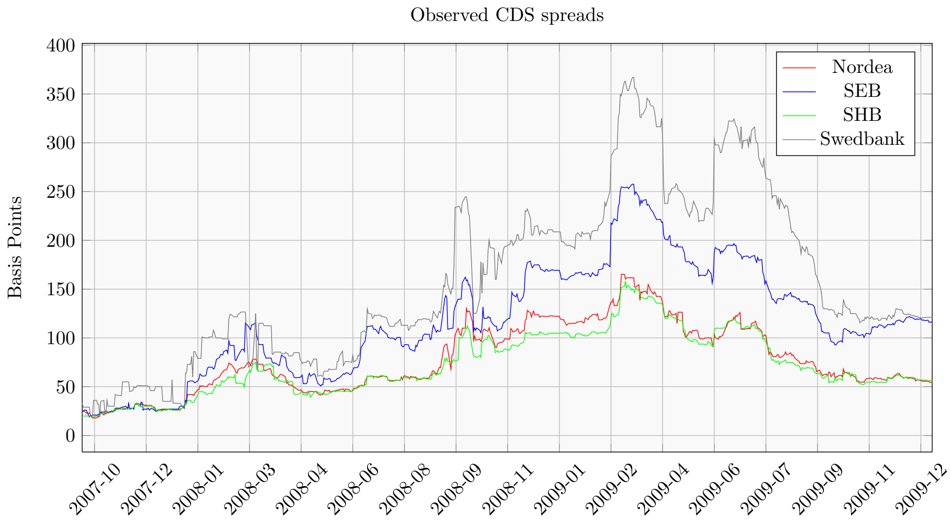
In addition to the CDS data, we collect quarterly balance sheet data and market data for all companies using Thomson Reuters Datastream (Thomson Reuters Datastream, 2013). In line with Rodrigues and Agarwal (2011), all balance sheet data are collected from the latest publically available quarterly report. This methodology implies that all data are lagged and we thereby avoid a forward-looking bias. Finally, we collect data over the five-year US treasury rate and the five-year LIBOR SWAP rate from the Federal Reserves online database (Federal Reserve System, 2013).

Table 2: Descriptive Statistics

Firm	Observations	Mean	Std Dev	Max	Min
Nordea	590	77.7	35.4	165.2	18.0
SEB	590	117.2	57.7	257.6	19.0
SHB	590	72.6	32.3	157.5	19.0
Swedbank	590	156.7	86.6	367.0	19.0

As can be seen in Figure 4, observed CDS spreads basically move in tandem during the sample period. Looking at levels, Swedbank stands out as trading relatively high during the period while spreads for Nordea and SHB are trading substantially lower. In an international perspective and specifically looking at the banking sector in the US, all of the Swedish banks traded on relatively low levels during the period (Tsesmelidakis and Schweikhard, 2011).

Figure 4: Observed CDS Spreads



6.2 Model Implementation

For the CreditGrades model, we need the following inputs:

- *Maturity* (T): Five-year maturity CDS contracts are used. Five-year CDS contracts have emerged as the most common type of contract and are considered to be the most liquid (Cao et al., 2010; Rodrigues and Agarwal, 2011).

- *Risk free rate* (r): The risk free interest rate is assumed to be the five-year US Treasury rate.

- *Reference stock price* (S^*): Stock prices are collected end-of-day on a daily basis and are adjusted for dividends and splits.

- *Debt-per-share* (D): Debt-per-share is calculated as total liabilities divided by the number of common shares outstanding.

- *Global debt recovery* ($\bar{L}$): $\bar{L}$ is firm-specific and is calculated by calibrating the parameter for each firm. The calibration is performed by minimizing the sum of squared errors between the model and the market spreads.

- *Debt class specific recovery* (R): R is set to 0.5 as proposed in Finger et al. (2002).

- *Standard deviation of the default barrier* (λ): λ is treated as firm-specific and calibrated together with $\bar{L}$.

- *Asset volatility* (σ): Asset volatility is calculated as outlined by Equation 5.16 in Section 5.3.1. Equity volatility σ_S^* is estimated by using a historical volaity measure with an estimation horizon of 1000 days and annualized assuming 250 trading days. For robustness, we also test the model using a 250-day historical estimation horizon as well as an implied volatility measure.

The choice of R and the estimation horizon of σ_S^* are motivated in the CreditGrades Technical Document (Finger et al., 2002). Finger et al. (2002) finds that the 1000-day estimation horizon produce good estimates of the implied volatility of five-year CDS quotes and that the true asset volatility is stable over time. Our calculation of debt-per-share differs from the more complex definition[7] used in Finger et al. (2002) where the focus is on industrial companies, but is in line with other papers such as Yu (2005) and especially Tsesmelidakis and Schweikhard (2011) that specifically study the financial sector.

The choice of $\bar{L}$ differs from the CreditGrades Technical Document where it is exogenously specified and set to 0.5. It follows from the definition of the default barrier $\bar{L}D$ in the CreditGrades model that firm leverage is crucial in determining the credit spread in the model. Instead of defining $\bar{L}$ as the global recovery rate, it can be treated as an adjustment factor to book value because of the uncertainty of measuring the market value of debt (Tsesmelidakis and Schweikhard, 2011). This uncertainty and the corresponding difficulty in precisely assessing firm leverage calls for adjusting the leverage using CDS market observations. We implement this by letting $\bar{L}$ be firm-specific and calibrated by fitting the model to market data over a 1-month time horizon, an approach suggested by Yu (2005). In addition, we let λ be firm-specific and calibrated simultaneously with $\bar{L}$, an approach implemented by for example Byström (2006) and Yeh (2010). The calibration is performed using the observations of the first month of the sample period. Specifically, we minimize the sum of squared errors between model ($\overline{CDS}$) and market spreads (CDS)

$$\min_{\bar{L}_i,\lambda_i} \sum_{n=1}^{N} \left(\overline{CDS}_{i,n}(\bar{L}_i,\lambda_i) - CDS_{i,n}\right)^2.$$

[7] The more complex definition of debt-per-share takes into account the difference between long-term and short-term, and financial and non-financial obligations (Finger et al., 2002).

6.2.1 Non-Financials Comparison

To compare the banks to other non-financial companies we create an equal weighted index of large Swedish firms with reasonable liquid trading in their CDS contracts. The equal weighted methodology used in creating the index has been used in several other papers examining the predictability of CDS spreads such as Byström (2006), and is also the norm in the credit indices market (Markit, 2008). Companies included in the index are: AB Volvo, AB SKF, Scania AB, Telefonaktiebolaget L.M. Ericsson, Telia Sonera AB, Svenska Cellulosa Aktiebolaget, Atlas Copco AB, AB Electrolux and Assa Abloy AB. The length of the sample period, as well as the data sources, are the same as for the individual banks outlined above. An equal weighted index containing the four Swedish banks, hereafter referred to as the financial index, is also constructed to highlight the difference between financial and non-financial companies. For descriptive statistics on the CDS indices, see Table 3. For a time series graph over the CDS indices data, see Figure 5.

Table 3: Descriptive Statistics for Indices

Firm	Observations	Mean	Std Dev	Max	Min
Non-Financial Index	590	132.5	69.1	320.1	27.0
Financial Index	590	106.0	52.1	234.1	19.5

Figure 5: Observed CDS Spreads for Indices

7 Results

7.1 Calibration Results

After calibration of the model parameters, $\bar{L}$ and λ, we obtain values as displayed in Table 4. $\bar{L}$ fluctuates around 0.1 which is substantially lower than the value found in Finger et al. (2002). This relatively low value is expected due to the special liability structure of banks (Tsesmelidakis and Schweikhard, 2011), and it is also the value proposed by Veraart (2004). As pointed out in Finger et al. (2002), λ is expected to be lower in the financial sector than the proposed value of 0.3 due to sector specific government regulation, which decreases asset volatility. This proposition is consistent with our results, where we obtain values of λ close to but consistently below 0.3.

Table 4: Calibration Results

Firm	$\bar{L}$	λ
Nordea	0.12	0.28
SEB	0.10	0.26
SHB	0.12	0.23
Swedbank	0.10	0.29

The calibration results for the financial index are in-line with the results for the individual banks and are expected. For the non-financial index the results for both $\bar{L}$ and λ are substantially higher than for the banks. Values of $\bar{L}$ close to 1 is consistent with the findings in both Tsesmelidakis and Schweikhard (2011) and Yu (2005). Further, a relatively high value of λ for the non-financial index is consistent with the finding in Byström (2006).

Table 5: Calibration Results for Indices

Firm	$\bar{L}$	λ
Non-Financial Index	0.71	0.72
Financial Index	0.13	0.22

In this section, it is worth commenting on the proxy for asset volatility as outlined in Equation 5.16. As mentioned, the results from the calibration of the model parameters are all in-line with previous studies and reasonably close to the proposed values in Finger et al. (2002). This is encouraging in that our simplified model for asset volatility seems to be a good approximation, which is also evident by looking at the predicted spreads in Figure 6. A further discussion of the impact of asset volatility can be found in Section 7.4 where we discuss the robustness of the results.

7.2 Results for the Swedish Banks

Generally, the results are conclusive in that the CreditGrades model consistently overestimates the CDS spreads during the most acute phase of the financial crisis for three of the banks: Nordea, SEB and Swedbank. This can be seen from the results presented in Figures 6a, 6b, 6c and 6d. To further analyse the size of overestimations and obtain a relative measure, we take the residuals between the model spreads and market spreads and divide by the market spreads. Those relative deviations, hereafter called residuals, for the banks are presented in Appendix A and formally defined as

$$RelativeDeviation_i = \frac{\overline{CDS}_i - CDS_i}{CDS_i}.$$

From the bailout of Bear Stearns, illustrated by the first line in the graphs, the observed market spreads begins to decrease while the predicted spreads start to increase. This finding is consistent for all banks. Even though the CDS spreads decreases while the model spread increases after bailout, there was no immediate market response and therefore no clear evidence of too-big-to-fail.

Rather surprisingly, the immediate effect on the residuals by the Lehman Brothers failure, illustrated by the second line, is not substantial. Instead, the residuals are most pronounced after the third and fourth lines illustrated in the graphs, which represents government intervention through the TARP revision in the US and the presentation of the Support to Credit Institutions Act in Sweden. Considering that the TARP revision and the Swedish support act are bailout schemes, the increase in residuals and subsequent overestimation of CDS spreads is highly interesting. When the US announced the revised TARP the risk of further bank collapses in the US probably decreases, and given the interconnected financial markets, a reduction of risk in the US banking sector also reduces contagion risk in Sweden. After the government interventions, the market spreads of the CDS contracts continue to increase, but at a slower pace than the model predicts which creates large model deviations i.e. residuals.

This indicates that the default probability actually continues to increase, although less than the model predicts.

This finding leads us to the too-big-to-fail argument. If the market, when observing government interventions, changes its expectations regarding a Swedish bailout for too-big-to-fail banks, i.e. the expectations that the banks will be bailed out increases, the result should be a marked difference in default expectations between shareholders and creditors since creditors are usually favoured in a bailout situation (Tsesmelidakis and Schweikhard, 2011). This change in expectations is indicated by the overestimation of CDS spreads and the subsequent large positive residuals, as the market spreads increases less than the model predicts. Nordea and SEB, the two largest banks in Sweden, show the largest overestimations, which is expected under the too-big-to-fail hypothesis, as the largest banks are more likely to be too-big-to-fail. Table 1 and Figure 4 show that Swedbank had the highest Baltic exposure and the highest CDS spreads, it was also the only bank that actively participated in the guarantee program facilitated by SNDO. All of this indicates that Swedbank was the bank that the market deemed most likely to default. A potential explanation for the smaller residuals observed in the case of Swedbank can be due to uncertainties regarding the probability of an eventual bailout. There are a number of potential explanations for this increased uncertainty. First, Swedbank is the smallest of the four Swedish banks included in our study (Sveriges Riksbank, 2012), which suggests a lower probability of a bailout simply due to the smaller size. Second, the relatively high Baltic exposure might have created difficulties in a bailout situation due to the problems of coordinating a mutual bailout-plan, not least because the Baltic countries experienced severe economic difficulties during this period.

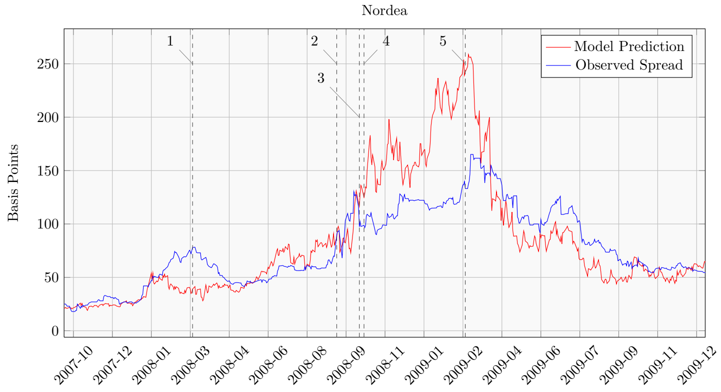
Compared to the other banks, SHB shows much less positive mispricing during the peak of the financial crisis. The issue with measuring too-big-to-fail using our methodology is that we only expect to observe any signs of differences in default expectations if the risk of default is real. As explained in Section 4 and illustrated by Figure 4, SHB was at the time the bank with the lowest CDS spreads and it had no exposure to the Baltic market. SHB also has a track record from previous crises as being a stable bank (Englund, 1999). Therefore, we believe that the market priced a very low default probability for SHB and subsequently there is no sign of too-big-to-fail even if it exists latently. Figure 4 also shows that the observed market spreads for Nordea and SHB are very close, indicating that the market had the same default probability for the two banks. However, the residuals in Appendix A shows much larger positive deviations for Nordea compared to SHB. This indicates that the market had the same default probability for both Nordea and SHB, but while the low default probability for SHB is based on its security, Nordea's might be based on too-big-to-fail tendencies.

7.3 Results for Indices

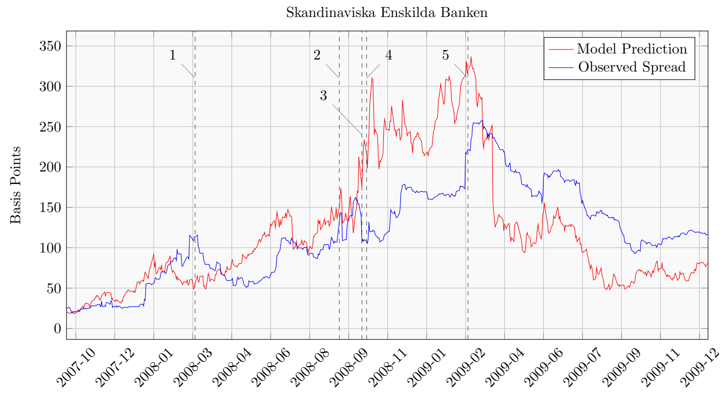
The difference between banks and non-financial companies are highlighted by constructing two indices and illustrated in Figure 7. Under the acute phase of the crisis, the difference is largest which probably represents the sector specific targeted rescue measures for the banking sector. The consistent underestimation of CDS spreads, observed for the non-financial index, is not unexpected but actually shown to be the standard result when using structural models such as CreditGrades (Rodrigues and Agarwal, 2011). The underestimation is normally explained by a liquidity premium in the CDS market (Tsesmelidakis and Schweikhard, 2011), but Rodrigues and Agarwal (2011) also finds additional credit risk not captured by structural models. Furthermore, because of the exceptional crisis situation during 2007-2009 we expect to observe market CDS spreads that are elevated due to increased counterparty credit risk and liquidity premium. Those factors would not be captured by the model which would further increase the underestimation of CDS spreads.

Rather, the interesting part is the overestimation of CDS spreads and the differences in deviations when examining the financial index compared to the non-financial index, which suggests that the measures taken under the financial crisis had a substantial effect on the probability of default on the banks and created a divergence in default probability estimations between shareholders and creditors. This finding is illustrated in Figure 7c and is in clear support of the too-big-to-fail argument.

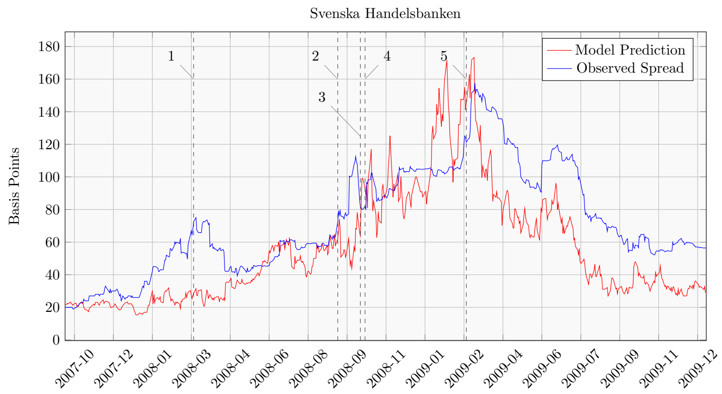
Figure 6: Model Spreads



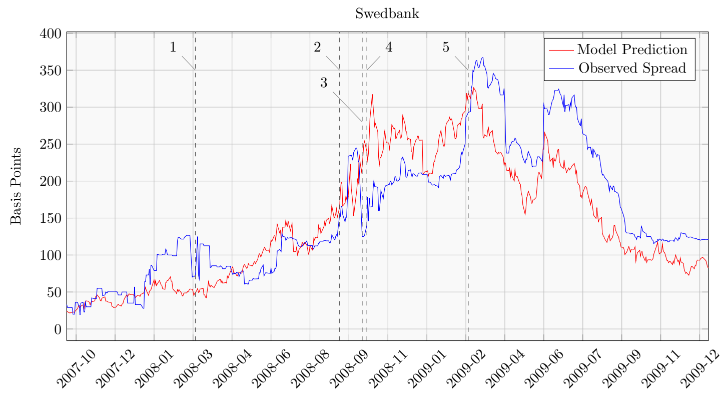
(a) Nordea



(b) SEB



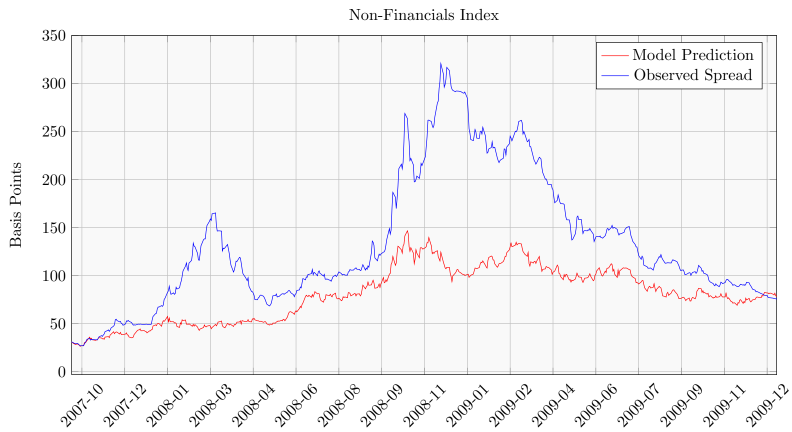
(c) SHB



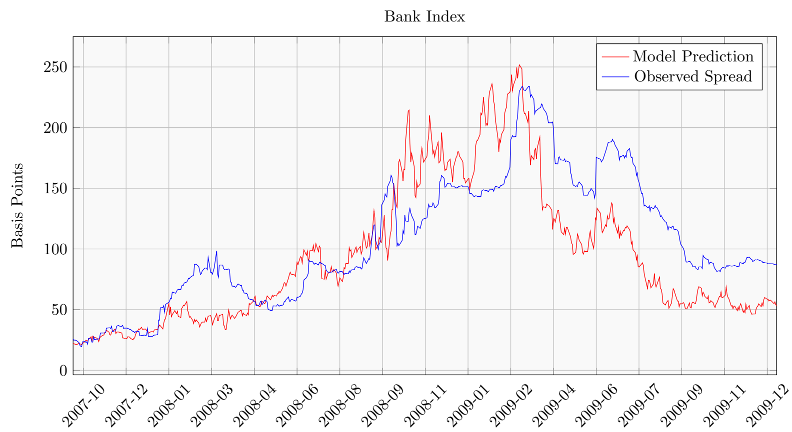
(d) Swedbank

NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis

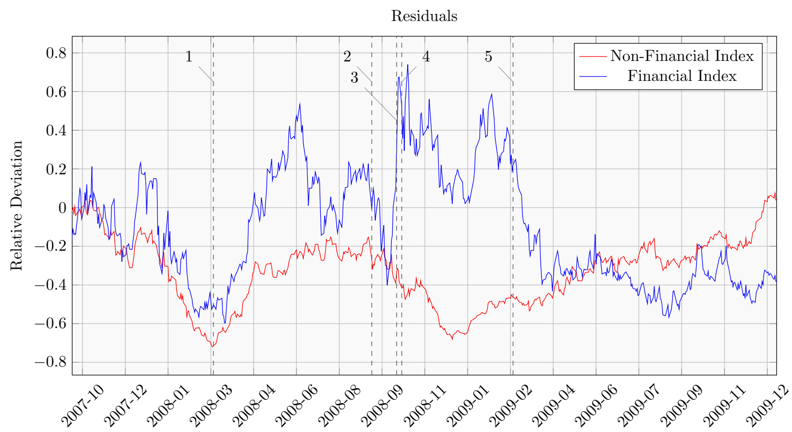
Figure 7: Index Model Spreads



(a) Non-Financial Index



(b) Financial Index



(c) Residuals Plot

NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis

7.4 Robustness of Results

Naturally, the model spreads depends on how the CreditGrades model is implemented. First, the procedure for estimating volatility has been subject to debate and some papers have advocated using option-implied volatility instead of historical data (Stamicar and Finger, 2006). To address this, we test the model using two different measures of equity volatility. First, we change the historical 1000-day equity volatility to a 250-day historical equity volatility. A shorter estimation horizon would incorporate sudden changes in equity volaility faster which could be benificial during the crisis period. Second, we also test the model with a more forward-looking estimation using implied volatility backed out from continuous put-options. [8]

It can be argued that using option-implied volatilities provides a more forward-looking measure compared to historical estimates. Furthermore, option-implied volatilities can be used to infer leverage when leverage is hard to assess (Stamicar and Finger, 2006). The results from using a 250-day estimation of volatility as well as option-implied volatility are reported in Appendix B. As shown in Appendix B, the results from changing equity volatility to a 250-day historical measure are somewhat lower modelled spreads, although the difference is negligible. When using implied volatility, the result is once again very similar to our original method. For SHB and Swedbank, the model spreads are somewhat lower, while the model spread is higher for SEB. In the case of Nordea, the result is identical.

In our original model we use the Treasury rate as the benchmark risk-free rate. However, reasons such as forward liquidity and tax reasons could imply a too low measure of the true risk-free rate (Tsesmelidakis and Schweikhard, 2011). To deal with this we test the model using the five-year LIBOR SWAP rate and report the results in Appendix B. The effect of changing the risk-free rate leads to a small increase in model prediction, although we consider the effect negligible. Furthermore, using a LIBOR rate can be questionable because of the counter-party risk inherent in the measure. There are also uncertainty regarding the "true" value of the LIBOR rate in light of LIBOR-fixing scandals during this period (BBC, 2013).

Regarding our measure of asset volatility, we extend this by including debt volatility. In

[8] Specifically, the option-implied volatility data is obtained from Thomson Reuters Datastream and interpolated using two at-the-money options: one above and one below the underlying price (Thomson Reuters Datastream, 2013).

line with Bharath and Shumway (2008), we estimate debt volatility according to

$$\sigma_d = 0.05 + 0.25 \times \sigma_s^*,$$

where five percentage points represents term structure volatility, and 25 percent times equity volatility is included to allow for volatility associated with default risk (Bharath and Shumway, 2008). Implementing this change to asset volatility does not change the results dramatically, as indicated by B12. The modelled spreads are generally somewhat lower but the overall development of CDS spreads in times of government interventions is the same as in our original results, hence the conclusion remains the same. What is more worrying by implementing this change is the difficulty in estimating debt volatility and the necessity in making arbitrary decisions regarding the inputs. Further, when calibrating the model the calibrated model parameters, $\bar{L}$ and λ, takes unreasonably values. $\bar{L}$ is generally very low, with values around 0.03 for all of the banks. On the other hand, the values of λ are unreasonable high. As previously stated, we expect the values of λ for the banks to be lower than the proposed value of 0.3 given in Finger et al. (2002). In light of this, we decide to limit the values of λ to a maximum of 0.7 which still can be considered too high. Lowering the values of λ further increases the model spreads substantially.

For the purpose of completeness, we also include the results when we specify asset volatility according to the original CreditGrades model in Figure B13. Although, we observe results in favour of our too-big-to-fail hypothesis we dont expect results of this magnitude. In addition, the calibrated model parameters takes unexpected values with $\bar{L}$ and λ at around 0.2 and 0.01 respectively, and the general model fit is not satisfactory.

8 Conclusion

In this paper, we examine the existence of too-big-to-fail in the Swedish banking system during the peak of the financial crisis 2007-2009, as we expect the too-big-to-fail problem to have been accentuated during this period due to the high degree of government intervention. The examination is performed by comparing market CDS spreads to modelled spreads, using the CreditGrades model, both for the largest Swedish banks and for two constructed indices. The indices used in the paper are an index consisting of the Swedish banks and an index consisting of large non-financial Swedish companies. We find evidence of overestimation of CDS spreads when comparing model spreads to the market spreads for the Swedish banks. This overestimation leads to increased positive residuals in times of government intervention. By contrast, the non-financial index shows no evidence of too-big-to-fail and there is no visible effect from the government interventions.

By comparing the banks, we find that SHB displays the lowest too-big-to-fail tendencies. One possible explanation is that too-big-to-fail is not observable due to SHB's low probability of default. Furthermore, our results indicate that Swedbank had the second lowest too-big-to-fail tendencies among the four banks included. Most likely, this is due to lower expectations of a bailout because of certain firm characteristics, for example a high Baltic exposure. Nordea and SEB have the largest positive residuals of the banks included and thereby exhibit the strongest too-big-to-fail tendencies. As expected, there is a clear correlation between bank size and the degree of too-big-to-fail, where a larger size corresponds to a higher degree of too-big-to-fail.

We conclude that it is likely that the government interventions and bailouts during the financial crisis changed the perceived probability of default for creditors and shareholders. This change in perceived default probability is most likely due to the favourable treatment of creditors in a bailout situation. This is illustrated by the model deviations in connection with government intervention, and is in line with the study on the US market performed by Tsesmelidakis and Schweikhard (2011). Due to the number of externalities associated with too-big-to-fail, such as moral hazard and overleveraging, which increases the riskiness in the financial banking system, this subject is of critical importance for regulators going forward.

8.1 Limitations and Further Research

The most obvious limitation in this study is the reliability of the structural model. The results and the subsequent conclusions are reliant on the model, and although the CreditGrades model is a well-established model to predict CDS spreads, this can be considered a weakness. Obviously, we are also dependent on the reliability of the data available as poor data would clearly affect the model results. However, since we are dealing with publically traded companies and use well-known data providers, we consider this to be a limited problem. Furthermore, the limited number of banks included in our study reduces the possibility to draw general conclusions outside of the Swedish banking system. To provide more general conclusions, further research on banks outside of Sweden is needed. Finally, too-big-to-fail might be easier to identify if smaller banks could be included and be contrasted to larger banks. The issue with potentially expanding the study is the limited availability of data, for example CDS contracts are only available for the four largest Swedish banks.

A possibility for further research could be to test too-big-to-fail by including several structural models and compare the results of those, which would decrease the dependence on a single model. Another method could be to test too-big-to-fail using funding cost measures, and compare large banks to small banks using this measure. An issue with this method is that certain firm characteristics would most likely have a large impact on the funding cost measure.

As we mentioned in Section 3.2.1, the perception of too-big-to-fail bailouts differs between Europe and the US, and the too-big-to-fail problem is probably more manifested in Europe where government involvement is more likely. To further study this difference, for example if the magnitude of too-big-to-fail is larger in Europe compared to the US, would contribute to the understanding of the too-big-to-fail problem and how it differs across regions. Another interesting topic for future research is to further study how too-big-to-fail is accentuated during times of crisis, particularly by examining the effect of too-big-to-fail on different bailout characteristics. This could provide valuable information on how to construct rescue packages that are more optimal than others from a moral hazard point of view. Interesting in a broader perspective would also be to put forward potential regulations dealing with the problem of too-big-to-fail and thereby contribute to the important debate about financial regulation.

References

Adrian, T., Brunnermeier, M.K., 2011. CoVaR. Federal Reserve Bank of New York Staff Reports .

Amel, D., Barnes, C., Panetta, F., Salleo, C., 2004. Consolidation and Efficiency in the Financial sector: A Review of the International Evidence. Journal of Banking & Finance 28, 2493–2519.

Barrell, R., Davis, E.P., 2008. The Evolution of the Financial Crisis of 2007-8. National Institute Economic Review 206, 5–14.

Barth, A., Schnabel, I., 2012. Too Big to Fail or to Save?–Evidence From the CDS Market. Draft for 56th Panel Meeting of Economic Policy, October 2012.

BBC, 2012a. MP:s Sale of RBS or Lloyds 'Not For Years'. Available at: `http://www.bbc.co.uk/news/business-20349579`. Accessed on: 2013-04-15.

BBC, 2012b. Spanish Lender Bankia is Partly Nationalised. Available at: `http://www.bbc.co.uk/news/business-18014077`. Accessed on: 2013-04-15.

BBC, 2013. Timeline: Libor-Fixing Scandal. Available at: `http://www.bbc.co.uk/news/business-18671255`. Accessed on: 2013-04-23.

Berger, A.N., Mester, L.J., 1997. Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? Journal of Banking & Finance 21, 895–947.

Bharath, S.T., Shumway, T., 2008. Forecasting Default With the Merton Distance to Default Model. Review of Financial Studies 21, 1339–1369.

Black, F., Cox, J.C., 1976. Valuing Corporate Securities: Some Effects of Bond Indenture Provisions. The Journal of Finance 31, 351–367.

Black, F., Scholes, M., 1973. The Pricing of Options and Corporate Liabilities. The journal of Political Economy , 637–654.

Bloomberg, 2013. What We've Written About Bank Subsidies. Available at: http://www.bloomberg.com/news/2013-03-13/what-we-ve-written-about-bank-subsidies.html. Accessed on: 2013-04-16.

Boyd, J.H., Gertler, M., 1994. The Role of Large Banks in the Recent US Banking Crisis. Federal Reserve Bank of Minneapolis Quarterly Review 18, 2–21.

Brunnermeier, M., Crockett, A., Goodhart, C., Persaud, A., Shin, H., 2009. The Fundamental Principles of Financial Regulation. 11th Geneva Report on the World Economy, in: Preliminary Conference Draft. London: Centre for Economic Policy Research (CEPR).

Byström, H., 2006. CreditGrades and the iTraxx CDS Index Market. Financial Analysts Journal , 65–76.

Cao, C., Yu, F., Zhong, Z., 2010. The Information Content of Option-Implied Volatility for Credit Default Swap Valuation. Journal of Financial Markets 13, 321–343.

Davis, E.P., 2012. The Evolution of Financial Structure in the G-7 Over 1997-2010. National Institute Economic Review 221, R11–R22.

Demirgüc-Kunt, A., Huizinga, H., 2010. Are Banks Too Big to Fail or Too Big to Save? International Evidence From Equity Prices and CDS Spreads. CentER Discussion Paper .

Dowd, K., 1999. Too Big to Fail? Long-Term Capital Management and the Federal Reserve Cato Institute Briefing Papers 52.

ECB, 2010. The ECB's Response to the Financial Crisis. Monthly Bulletin. European Central Bank.

EEA Council, 2008. Conclusions of the 30th meeting of the EEA Council Brussels, 13 November 2008. Press Report. European Economic Area.

Englund, P., 1999. The Swedish Banking Crisis: Roots and Consequences. Oxford Review of Economic Policy 15, 80–97.

Faeh, T., Grande, G., Ho, C., King, M., Levy, A., Panetta, F., Signoretti, F., Taboga, M., Zaghini, A., 2009. An Assessment of Financial Sector Rescue Programmes. Bank of Italy Occasional Paper .

FDIC, 1997. History of the Eighties - Lessons for the Future. Volume An Examination of the Banking Crises of the 1980s and Early 1990s. Federal Deposit Insurance Corporation.

Federal Reserve System, 2013. FRB: Economic Research and Data. Available at: `http://www.federalreserve.gov/econresdata/default.htm`. Accessed on: February 2013.

Finansinspektionen, 2008. Finanssektorns stabilitet. Rapport 18. Finansinspektionen.

Finansinspektionen, 2009a. Effekterna av de statliga stabilitetsåtgärderna - Fjärde rapporten 2009. Rapport. Finansinspektionen.

Finansinspektionen, 2009b. Finansinspektionens stresstester av storbankerna. Promemoria. Finansinspektionen.

Finansinspektionen, 2009c. Risker i det finansiella systemet. Rapport. Finansinspektionen.

Finger, C., Finkelstein, V., Lardy, J.P., Pan, G., Ta, T., Tierney, J., 2002. Creditgrades Technical Document. Technical Report. RiskMetrics Group.

Goldman Sachs FICC Credit Strategies, 2009. CDS 101. Technical Report. Goldman Sachs Group, Inc.

Goldstein, M., Véron, N., 2011. Too Big to Fail: The Transatlantic Debate. Peterson Institute for International Economics Working Paper .

Goodhart, C.A.E., 2010. The Emerging New Architecture of Financial Regulation. The Emerging New Architecture of Financial Regulation.

Haldane, A.G., 2010. The $100 Billion Question. Speech to Institute of Regulation and Risk, Hong Kong, March 2010.

Hetzel, R., 1991. Too Big to Fail: Origins, Consequences, and Outlook. FRB Richmond Economic Review 77, 3–15.

Hoenig, T.M., 2013. Basel III Capital: A Well-Intended Illusion. Speech to Association of Deposit Insurers 2013 Research Conference in Basel, Switzerland, April 2013.

Hull, J., 2009. Options, Futures, and Other Derivatives. 7 ed., Pearson Education, Inc., Upper Saddle River, New Jersey.

Iceland Chamber of Commerce, 2009. Iceland's Financial Crisis. Presentation. Iceland Chamber of Commerce.

IOSCO, 2012. The Credit Default Swap Market. Report. The International Organization of Securities Commissions.

Johnson, S., 2012. The Real Conservative Opportunity This November. Bloomberg View. Available at: `http://www.bloomberg.com/news/2012-08-19/the-real-conservative-opportunity-this-november.html`. Accessed on: 2013-04-24.

JPMorgan Corporate Quantitative Research, 2006. Credit Derivatives Handbook. Technical Report. JPMorgan Chase & Co.

Kaufman, G.G., 2002. Too Big to Fail in Banking: What Remains? The Quarterly Review of Economics and Finance 42, 423–436.

Kiesel, R., Veraart, L.A., 2008. A Note on the Survival Probability in CreditGrades. Journal of Credit Risk 4, 65–74.

Liikanen, E. (Ed.), 2013. High-Level Expert Group on Reforming the Structure of the EU Banking Sector, European Union.

Markit, 2008. Markit Credit Indices Primer. Technical Report. Markit Group Limited.

Merton, R.C., 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. Journal of Finance 29, 449–70.

Nordea, 2013. Annual Report 2012. Annual Report. Nordea Bank AB.

Nordea Bank AB, 2013. Nordea Analytics. Available at: `SubscriptionService`. Accessed on: February 2013.

Petrovic, A., Tutsch, R., 2009. National Rescue Measures in Response to the Current Financial Crisis. Legal Paper Working Series .

Rodrigues, M., Agarwal, V., 2011. The Performance of Structural Models in Pricing Credit Spreads, in: Midwest Finance Association 2012 Annual Meetings Paper.

Schifferes, S., 2009. Can Banking Regulation Go Global?. BBC. Available at: `http://news.bbc.co.uk/2/hi/business/7950758.stm`. Accessed on: 2013-04-22.

Solomon, D., Paletta, D., Hilsenrath, J., Lucchetti, A., 2013. U.S. to Buy Stakes in Nation's Largest Banks. Wall Street Journal. Available at: `http://online.wsj.com/article/SB122390023840728367.html`. Accessed on: 2013-04-22.

Stamicar, R., Finger, C.C., 2006. Incorporating Equity Derivatives into the CreditGrades Model. Journal of Credit Risk 2.

Stern, G.H., Feldman, R.J., 2004. Too Big to Fail: The Hazards of Bank Bailouts. Brookings Institution Press, Washington, D.C.

Sveriges Riksbank, 2008. Penningpolitisk rapport. Rapport 3. Sveriges Riksbank.

Sveriges Riksbank, 2009. Penningpolitisk rapport. Rapport. Sveriges Riksbank.

Sveriges Riksbank, 2010. Riksbanken upphör med lån till tre och sex månaders löptid, men erbjuder istället lån till 28 dagars löptid. Pressmeddelande 20. Sveriges Riksbank.

Sveriges Riksbank, 2012. Den svenska finansmarknaden. Rapport. Sveriges Riksbank.

Sveriges Riksbank, 2013. Riksbanken och finansiell stabilitet. Rapport. Sveriges Riksbank.

Swedish National Debt Office, 2012. Riksgäldens åtgärder för att stärka stabiliteten i det finansiella systemet (2012:1). PM. Swedish National Debt Office.

The Swedish Bankers' Association, 2013. Banks in Sweden. Publication. The Swedish Bankers' Association.

Thomson Reuters Datastream, 2013. Datastream. Available at: `SubscriptionService`. Accessed on: February 2013.

Tsesmelidakis, Z., Schweikhard, F., 2011. The Impact of Government Interventions on CDS and Equity Prices, in: Paris December 2011 Finance Meeting EUROFIDAI-AFFI.

Ueda, K., di Mauro, B.W., 2012. Quantifying Structural Subsidy Values for Systemically Important Financial Institutions. IMF Working Paper .

Veraart, L.A., 2004. Asset-Based Estimates for Default Probabilities for Commercial Banks. Diplomarbeit Universität Ulm.

Völz, M., Wedow, M., 2011. Market Discipline and Too-Big-to-Fail in the CDS Market: Does Banks' Size Reduce Market Discipline? Journal of Empirical Finance 18, 195–210.

Yazdi, M., 2008. Finansinspektionens stresstester av storbankerna. Promemoria. Finansinspektionen.

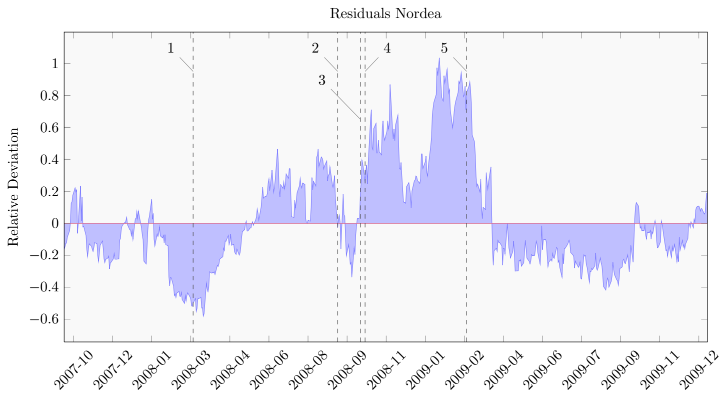
Yeh, A.J.Y., 2010. An Empirical Implementation of CreditGrades. The Journal of Credit Risk 6, 89–98.

Yu, F., 2005. How Profitable is Capital Structure Arbitrage? Financial Analysts Journal 62, 47–62.

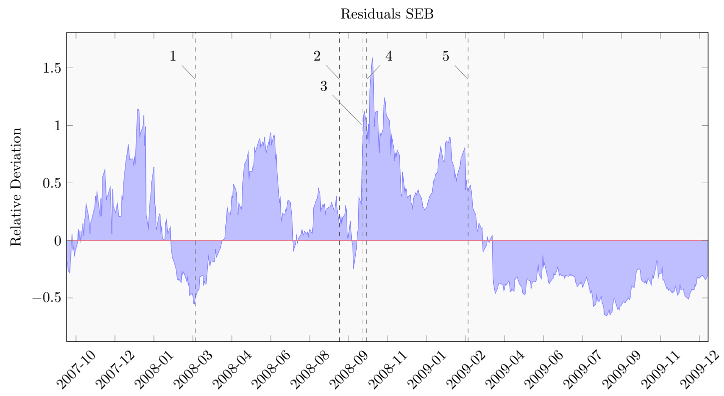
Zhou, C., 2001. The Term Structure of Credit Spreads With Jump Risk. Journal of Banking & Finance 25, 2015–2040.

Appendix A Residuals

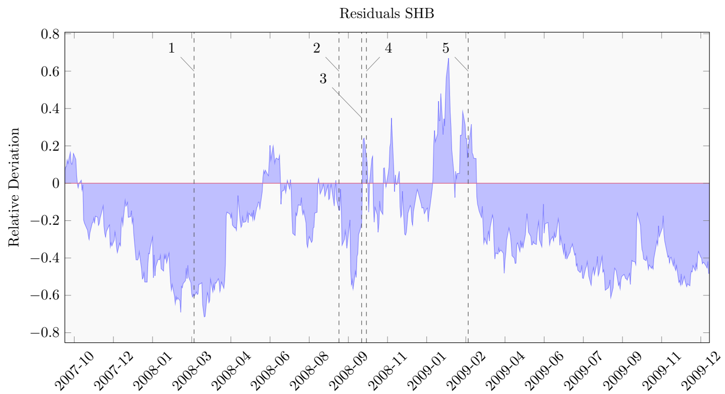
Figure A8: Deviations from the Model



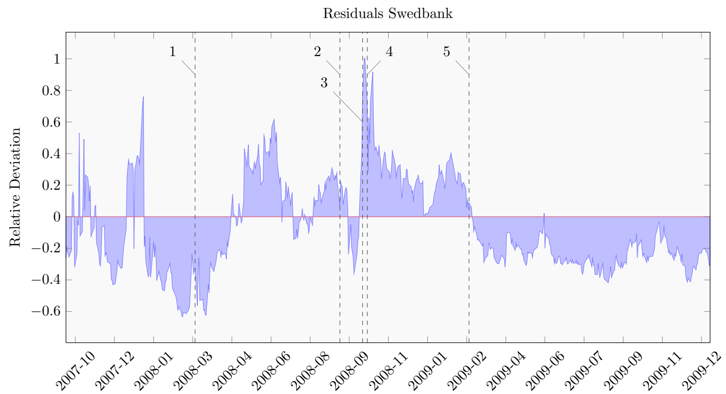
(a) Nordea



(b) SEB



(c) SHB

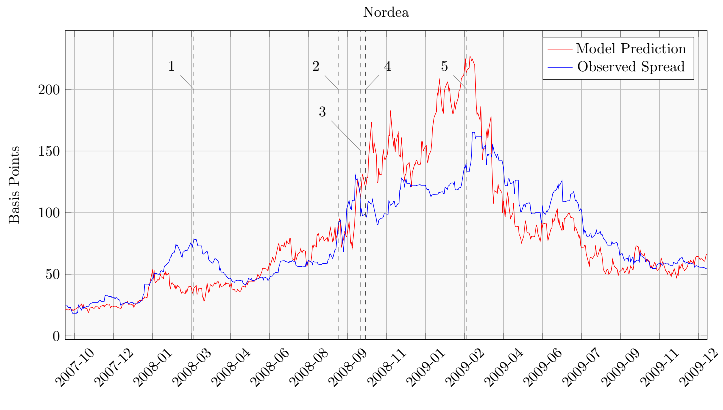


(d) Swedbank

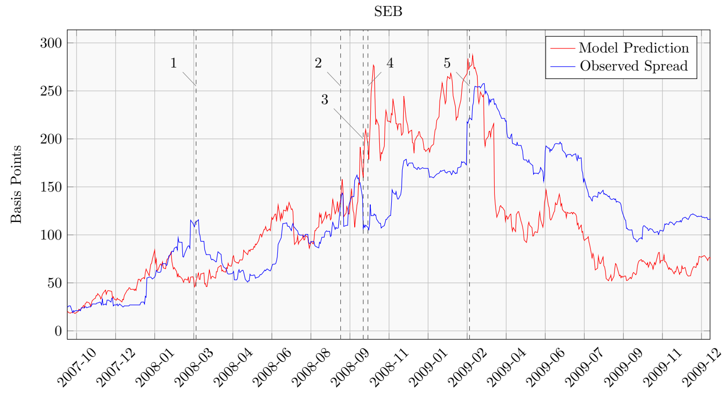
NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis

Appendix B Robustness

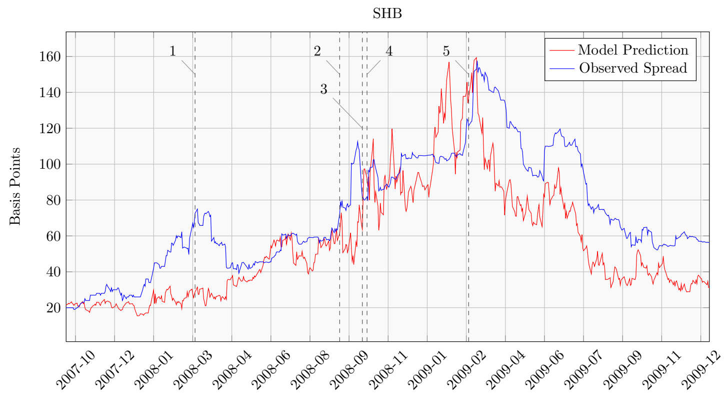
Figure B9: 250-Day Volatility Estimation Horizon



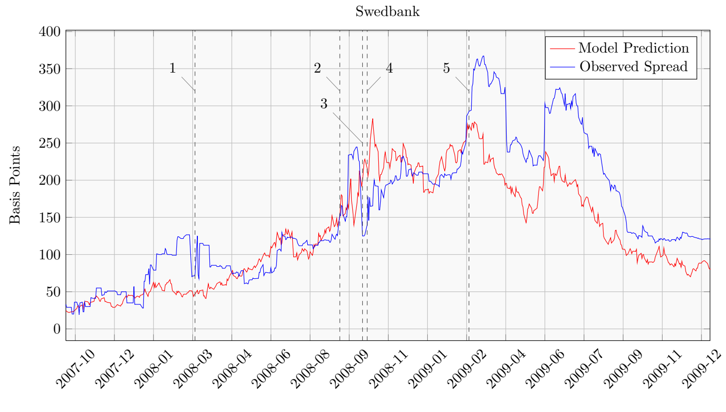
(a) Nordea



(b) SEB



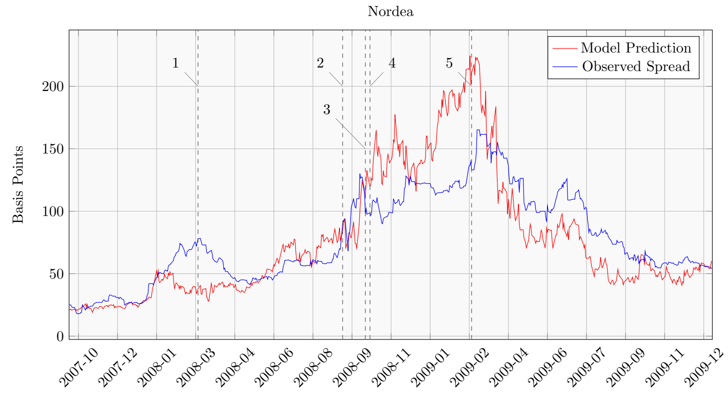
(c) SHB



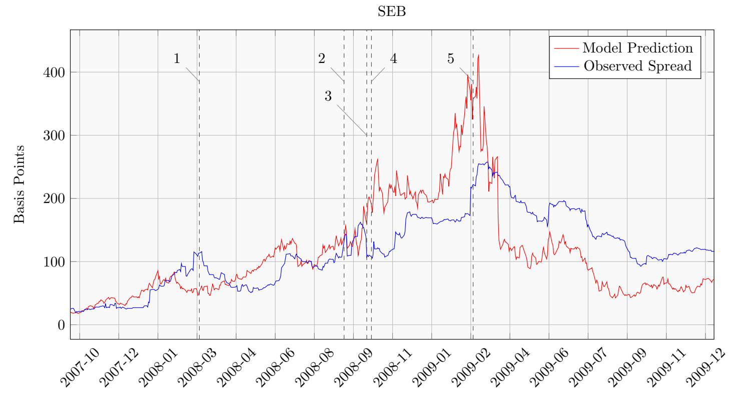
(d) Swedbank

NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis

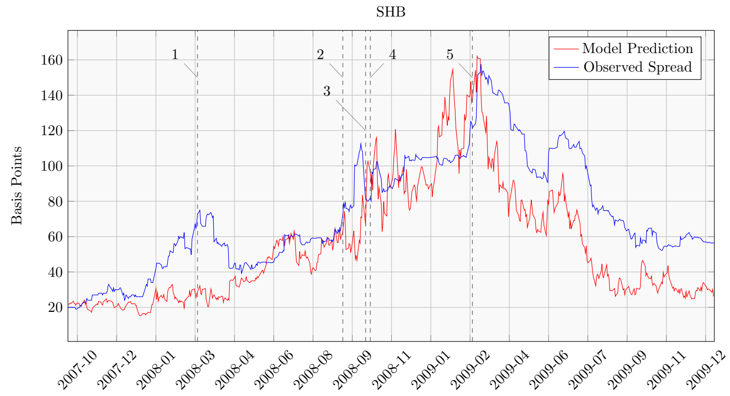
Figure B10: Implied Volatility



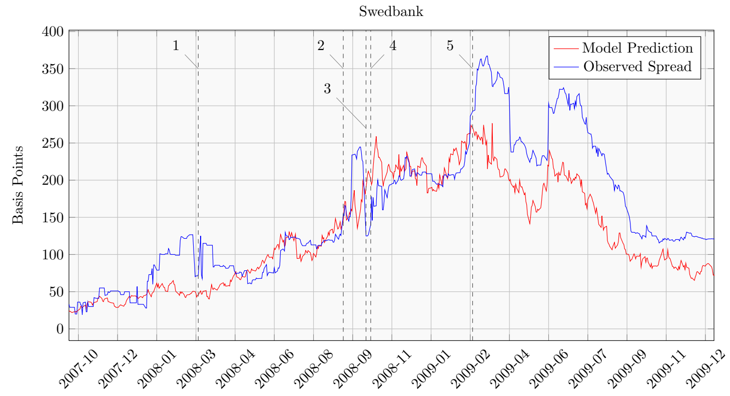
(a) Nordea



(b) SEB



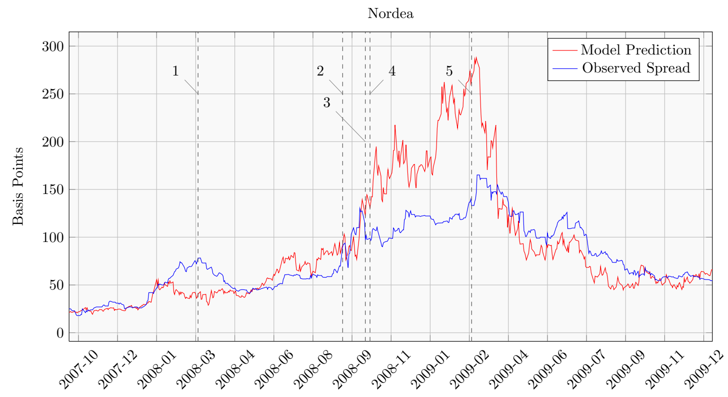
(c) SHB



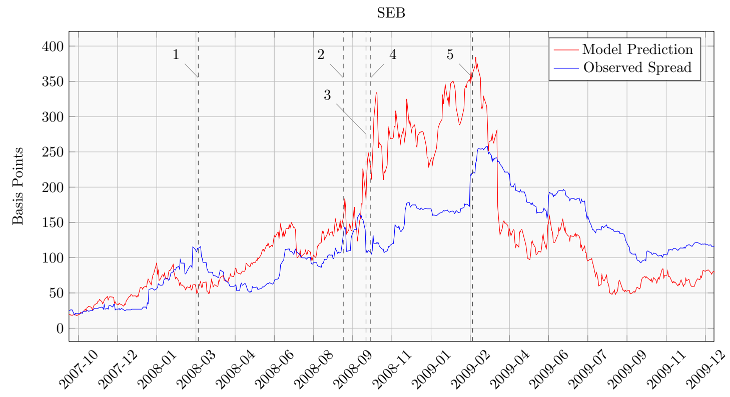
(d) Swedbank

NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis

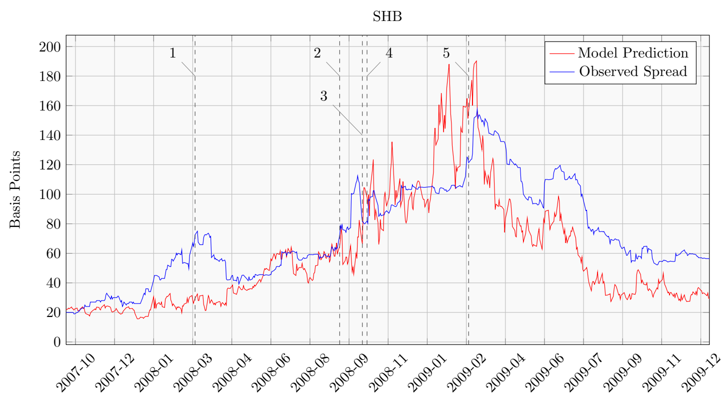
Figure B11: Five-year SWAP Rate as Risk-Free Rate



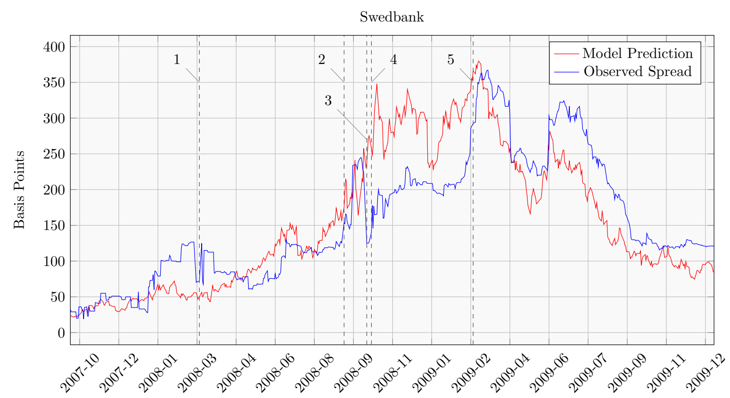
(a) Nordea



(b) SEB



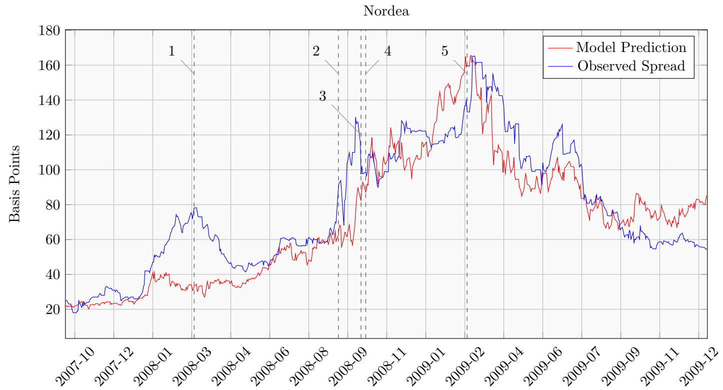
(c) SHB



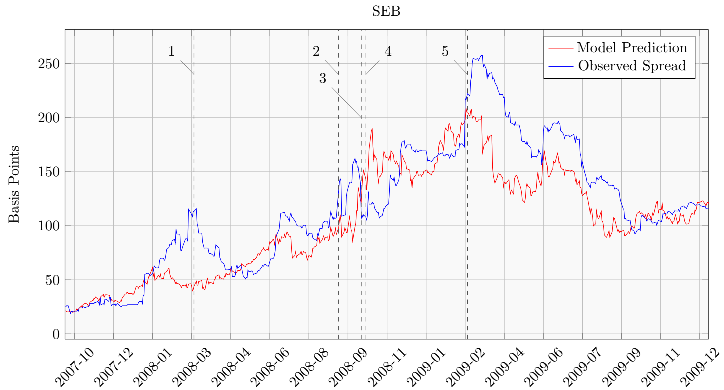
(d) Swedbank

NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis

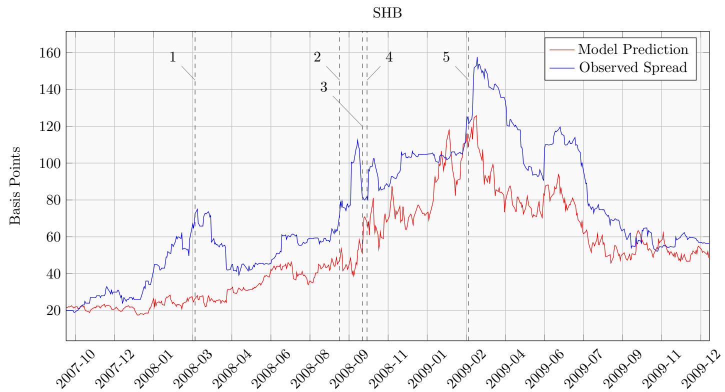
Figure B12: Asset Volatility Including Debt Volatility



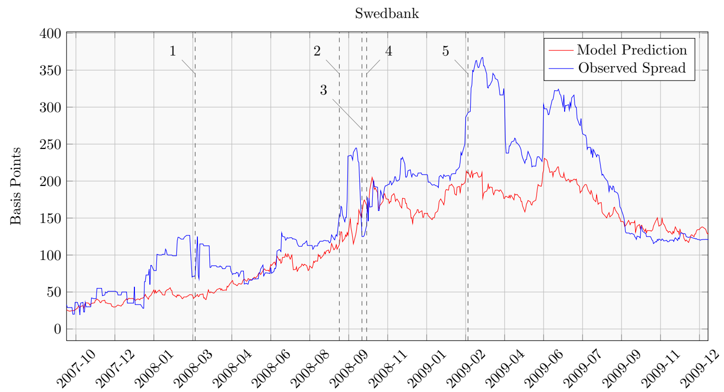
(a) Nordea



(b) SEB



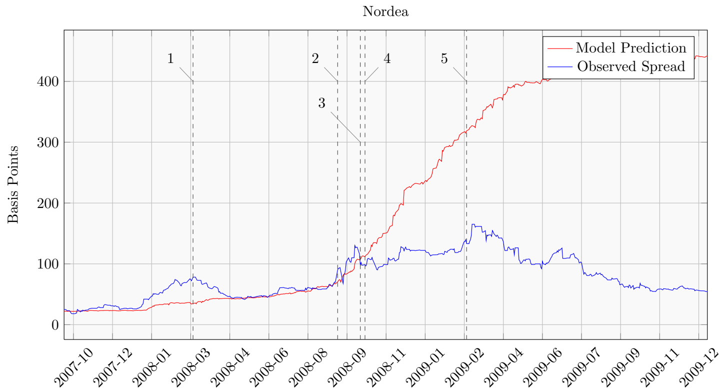
(c) SHB



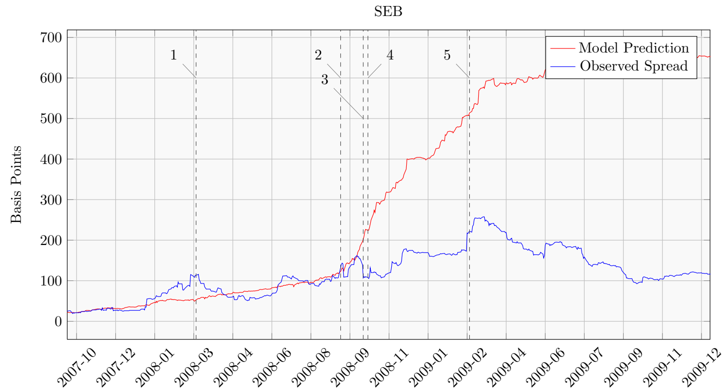
(d) Swedbank

NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis

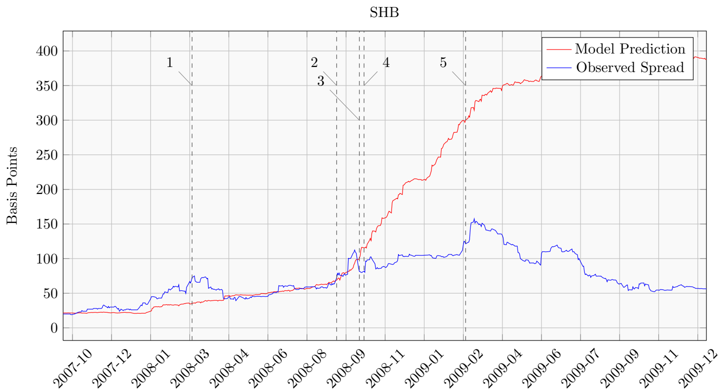
Figure B13: Original CreditGrades Volatility



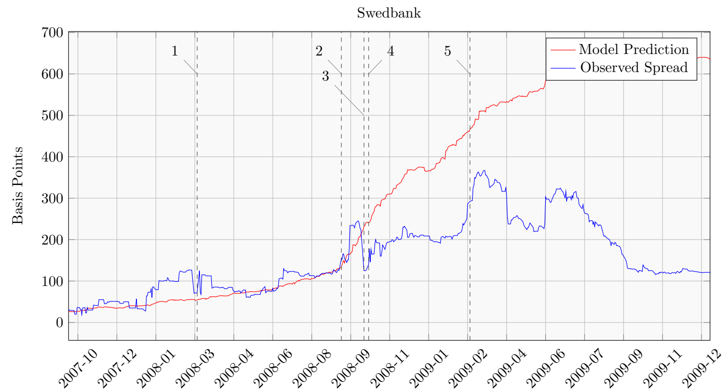
(a) Nordea



(b) SEB



(c) SHB



(d) Swedbank

NOTE: In the graphs, the following events are illustrated:
1: Sale of Bear Stearns, 2: Lehman Brothers Bankruptcy, 3: Revised TARP Announcement, 4: Swedish Government Support, 5: Baltic Crisis