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Essays on Measuring Systemic Risk

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ESSAYS ON MEASURING SYSTEMIC RISK

A dissertation submitted in partial satisfaction of the requirements for the degree of

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in

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by

Manizha Sharifova

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Abstract

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by

Manizha Sharifova

This study explores various approaches to measure systemic risk and global financial linkages. It consists of three chapters. Chapter 2 examines the degree of risk interconnectedness between U.S. and European banks using the conditional value-at-risk (CoVaR) approach. The results show that the pairwise CoVaR measure brings value added over value-at risk measure in quantifying the degree of risk dependence between global banks. Chapter 3 compares two distinct methods of estimating systemic risk measures that focus on tail dependence in financial institutions' equity returns: $\Delta CoVaR$, *MES* and *SRISK*. The results highlight the relevance of the simpler estimation methods in identifying and ranking systemically important financial firms. Chapter 4 empirically investigates the determinants of nonperforming loans in the transition economies of Europe. It also study compares the drivers of credit risk for foreign and domestic banks. The empirical results show that macroeconomic environment is a principle factor that impacts banks' loan quality. More importantly, foreign ownership is associated with higher credit risk.

To my family.

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Chapter 1

Introduction

The global crisis of 2007-2009 has made policymakers and regulators reconsider the institutional framework for overseeing the stability of financial systems. The crisis has clearly demonstrated that even though individual risks may be forecast and limited, financial shocks to a single firm can quickly spread across a large number of institutions and markets, threatening the whole system. The policy agenda has since shifted toward the macroprudential approach to bank regulation, which focuses on the soundness of the financial system as a whole. The major challenge for academic researchers and policy makers has been to define and measure systemic risk. My research contributes to most recent efforts of quantifying systemic risk and assessing interlinkages across the global financial networks.

Chapter 2 investigates the degree of risk interconnectedness between internationally active U.S. and European banks. The major question the study aims to address is the following: What are the risk spillovers between U.S and European banks? This question is important given that risk interconnectedness is closely linked to the notions of contagion and financial crises spillovers. In this context the measure of risk dependence derived in the study allows capturing direct and indirect spillovers effects from one institution to another. As regulators and policy makers seek for meaningful measures to deal with the "too-interconnected to fail" paradigm this work makes a step forward in better understanding the international financial networks.

I use the conditional value-at-risk (CoVaR) approach due to Adrian and Brunnermeier (2011) to estimate a pair-wise risk measure defined as an increase in a bank's value-at-risk induced by its cross-Atlantic peer bank in a distress condition. Using this measure I calculate the indicators of individual bank's cross border risk exposure and risk contribution to identify most internationally risky banks. I further investigate the determinants of banks' interlinkages via fixed effects panel data regressions. The results show that the pairwise CoVaR: (1) brings value added over VaR in assessing risk interdependence between U.S. and European banks, and (2) is suited to identify internationally important banks. More interestingly, the results also shed light on the controversy surrounding the bailout of Bear Stearns and the bankruptcy of Lehman Brothers. Contagion effects, as implied from stock prices, do not appear to justify the policy decision to bailout Bear Stearns instead of Lehman Brothers. The apparent contradiction between what markets imply and the policy decision suggests that markets exhibit, at best, semi-strong efficiency and do not incorporate private information. These results highlight the importance of improving access to granular data to better quantify the interlinkages that may generate cross-border spillovers between financial institutions. I find weaker evidence that size is a significant driver of an institution's cross-border importance. Larger banks do not appear to be more connected to each other.

Chapter 3 "Identifying Systemically Important Financial Institutions: Toward a Simpler Approach" is a joint work with Sylvain Benoit and Jeremy Dudek. The study compares the estimation methods of the recently proposed systemic risk measures that focus on tail dependence in financial institutions' equity returns. We focus on three measures that have been widely discussed in the literature and used by regulators to monitor systemically important financial institutions: Conditional Value-at-Risk (CoVaR) of Adrian and Brunnermeier (2011), Marginal Expected Shortfall (MES) of Acharya et al. (2010), and the Systemic Risk Measure (SRISK) of Acharya, Engle and Richardson (2012) and Brownlees and Engle (2012). CoVaR corresponds to the value-at-risk of the financial system conditional on a distress state of a given institution. The contribution of this institution to systemic risk is measured by ΔCoVaR as the difference between its CoVaR when the institution is, or is not, financial distress. MES measures an institution's expected equity loss when market falls below a certain threshold over a given horizon, namely a 2% market drop over one day. Finally, SRISK corresponds to the expected capital shortfall of an institution conditional on a crisis. The estimation of these measures usually requires the refined techniques that account for nonlinear tail dependence in stock prices, such as percentile regressions or non-parametric tail estimation.

Our study tries to shed light on the following question: Is a simpler estimation method of a systemic risk measure comparable with the heavy tail techniques in terms of identifying systemically important financial institutions (SIFIs)? The analysis consists of two steps. First, we estimate all three systemic risk measures by modeling tail dependence via quantile regression and nonparametric tail estimator. Next, we model dependence in a linear fashion by assuming that dependence in stock return is fully captured by correlations. We use two metrics - Kendal rank order correlation and percentage of concordant pairs - to compare the rankings of financial firms according to the estimated risk measures. Our analysis shows that systemic risk rankings of firms based on the simplified estimation methods are comparable with the rankings produced by more refined estimation techniques. Simple methods appear to be sufficient to identify and rank SIFIs.

The last chapter analyzes the sources of systemic risk in the transition economies of Europe. Credit risk is a key risk for financial stability of Central, Eastern and Southeastern Europe and the Commonwealth of Independent States, where banks rely on the traditional business model of accepting deposits and granting loans. Since the onset of the global crisis the rate of nonperforming loans (NPLs) in the region has increased sharply from an average of 3% in 2007 to 12% in 2013. The rapidly increasing ratio may be a signal of deterioration in the banking sectors and pose a threat to the stability of the region's financial system.

Using dynamic panel data methods I investigate two distinct types of the determinants of nonperforming loans in transition Europe in the period between 2000 and 2012. The analysis covers a large set of banks in i) Central Europe and Baltic States: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic, and Slovenia; ii) South-Eastern Europe: Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Macedonia, Romania, and Serbia; and iii) the Commonwealth of Independent States: Belarus, Kazakhstan, Moldova, Russia, and Ukraine. Second, the study compares the drivers of NPLs for foreign and domestic banks using the dataset from Claessens and van Horen (2013), which tracks the ownership of individual banks over time.

The results show that macroeconomic environment is a key factor that drives banks' credit risk. In particular, rising unemployment rate, nominal exchange rate depreciation and higher inflation contribute to higher NPLs while higher GDP growth lowers the NPL ratio. I also find that banks' own fundamentals influence their asset quality. The NPL ratios are likely to increase for less solvent and less profitable banks.

More importantly, my findings show that foreign ownership, after controlling other factors, is associated with higher level of NPLs. The estimation results indicate that foreign ownership increases banks' annual NPLs by about 0.5 percentage points.

Chapter 2

Measuring Cross-Border Linkages between U.S. and European Banking Institutions

2.1 Introduction

The recent crisis has illustrated that the increased integration of international financial markets had been associated with stronger risk dependences. The growth of cross-border linkages has expanded the scope for financial shocks to a single market in one country to be quickly transmitted to other markets and institutions across borders and mutate into systemic problems with global implications. The crisis originated in the U.S. subprime mortgage market, the sector seemingly of little significance for financial stability, but spread across a large number of markets and led to the collapse and near-collapse of many financial institutions in the U.S., Europe and elsewhere.

The challenge has been to ensure that systemic risk can be adequately measured and monitored in real time. With recent developments along this line of research, several approaches of quantifying systemic risk have been suggested that emphasize the need to pay greater attention to individual institutions that are systemically important. While systemic importance is usually closely linked to the "too big to fail" paradigm, the recently proposed initiatives also emphasize the increasing importance of a bank's inter-linkages with other banks and aim to lessen the risk of institutions becoming "too interconnected to fail". For example, since 2011 the Financial Stability Board has published the annual list of global systemically important banks (G-SIBs) that are required to hold an additional capital buffer based on a range of criteria, including their global activity and interconnectednedness with other financial institutions.[1] Accordingly, the global systemic relevance appears to be specific to European and U.S. banks, as only 6 out of 30 banks outside the U.S. and Europe were classified as G-SIBs in 2014.[2]

The growing interdependence between European and U.S. markets has facilitated much debate about the effect the European sovereign debt crisis could have on the U.S. banking system. As some have argued in much the same way as the U.S. Lehman crisis severely impacted the European economy through financial market dislocation, a European banking crisis would materially impact the U.S. economy both through the financial market

[1] Financial institutions are assessed based on the individual factors, such as the size of institutions, the lack of readily available substitutes or bank infrastructure, the global activity, the complexity as well as their interconnectedness. The total score for each institution is calculated as a simple average of its five category scores and institutions whose overall score exceeds a cutoff level set by the Basel Committee are allocated into different equally-sized buckets according to their score rankings. The amount of additional capital requirement is then determined for each bucket (Financial Stability Board (2011, 2012, 2013, 2014)).

[2] The updated list for 2014 includes 3 Chinese and 3 Japanese banks.

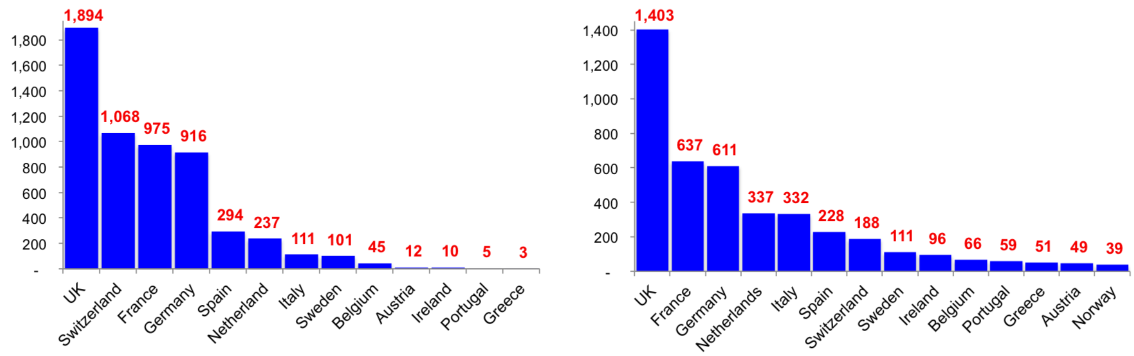
channel and through a generalized increase in global economic risk aversion. The concern has been that if a European bank were to fail, some U.S. banks might be exposed to big losses.

The U.S. financial system is highly exposed to the European banking system, which in turn is directly exposed to the European periphery. Sovereign debt defaults in the European periphery would have a major impact on the balance sheet position of the European banking system. The Bank for International Settlements (BIS) reports that the U.S. banks have exposure to the German and French economies, the largest bank lenders to Greece, in excess of 1.2 trillion USD and U.S. banks have written derivative contracts on the sovereign debt of the peripheral Europe over 400 billion USD. Direct exposure of U.S. banks to GIPSI (Greece, Ireland, Portugal, Spain, Italy) countries alone was about 765 billion USD in December 2011 (Figure 2.1). According to the Fitch rating agency, short-term loans by U.S. money market funds to the European banking system still total over 1 trillion USD or more than 40% of their total overall assets.

Furthermore, several structural changes in the financial systems of both economic regions have made it particularly important to track inter-linkages over time. In the U.S, increasing consolidation as well as the removal of regulatory barriers to universal and cross-state banking has led to the emergence of large and complex banking organizations, whose activities and interconnections are particularly difficult to follow. In Europe, gradual integration of financial systems under a common currency increased cross-border relationships and, therefore, risk dependence between banks across borders. The outbreak of the sovereign debt crisis in the Euro zone and, consequently, greater demand for economic and regulatory

Figure 2.1 – International Bank Exposures

(a) European banks' exposure to U.S. banks **(b)** U.S. banks' exposure to European banks



Notes: The figure shows international claims of European banks vis-a-vis U.S. banks (left panel) and claims of U.S. banks vis-a-vis Europe (right panel) as of December, 2011. The numbers include foreign claims (private sector, bank and non-bank sector) plus other potential exposures (derivative contracts, guarantees and credit commitments). Source: BIS.

convergence has made the issue more acute.

Henceforth, approaches toward measuring and monitoring financial linkages between these two key economic regions should constitute an integral part of global systemic risk regulation. The quantification of risk co-dependencies can serve as an additional stress-testing tool for supervisors in designing appropriate policies regarding bank regulation and supervision, especially when the banks that are considered "too-interconnected-to-fail". This exercise would also allow banks to analyze how they are connected to their peer banks and help them better determine the causes of such linkages and enhance risk management policies.

So, how do we quantify the risk spillovers between banks? The literature discusses two main channels through which spillover effects operate: i) direct exposures between financial institutions through the interbank claims and counterparty relations and ii) indirect exposure to common risk factors, such as reliance on wholesale markets for funding and feedback effects from market volatility due to the adoption of similar risk management and accounting practices. Hence, if, for example, banks hold similar portfolios, a common shock may simultaneously affect all banks and also lead to joint default of multiple banks. A suitable measure of risk interconnectedness should capture both direct and indirect spillover (or contagion) effects from one institution to another. Another problem that arises in assessing financial linkages is that the degree of interbank connectedness, the location of banks within the interbank network or the correlations between portfolios are often difficult to monitor and measure. Therefore, a majority of the empirical studies have focused on measures that utilize publicly available information. Generally, the only data required for the calculation of this type of measures are market prices for the financial firms, such as equity or CDS, combined with the balance sheet information. These so called "market information-based" approaches have two main advantages over alternative approaches. First, they allow consistent assessment of systemic importance for financial institutions that operate in different countries and banking systems. Second, by using high-frequency market data they help detect systemic vulnerabilities in a more timely fashion than alternative methods. In addition, provided market efficiency holds, market data are forward looking in general and capture market expectations on changes in the risk and performance of financial institutions. This makes the market-based approaches more attractive and potentially useful for macroprudential regulation.

Against this background, this chapter aims to empirically investigate the degree of cross-border linkages between European and U.S. financial institutions using market information. More specifically, I compute a pairwise risk measure, conditional Value-at-Risk, to quantify the impact of a financial institution in one region on an institution across the Atlantic. Conditional Value-at-Risk (CoVaR) is originally proposed by Adrian and Brunnermeier (2011) and defined as a Value-at-Risk (VaR) of a bank conditional on another bank being in a distress state. This approach has two major advantages. First, CoVaR is based on the well-known concept in banking and securities industries, VaR. Second, it captures systemic importance of an institution alongside the individual risk of this institution and allows mapping all pairwise measures across the banks. My focus is on what are widely acknowledged to be the most important systemic actors - large and internationally active commercial and investment banking institutions.

The analysis consists of two main steps. First, I quantify spillover effects between 30 European and 17 U.S. banks by estimating each bank's cross-border risk exposure measure for the period from 3 January 2000 to 31 December 2011. More specifically, I use daily data on stock prices to estimate $\Delta\text{CoVaR}^{j|i}$ as the difference between CoVaR of European financial institution j when U.S. institution i is in distress and this European institution's unconditional VaR. Hence, $\Delta\text{CoVaR}^{j|i}$ captures the increase in European bank's risk when U.S. bank falls into trouble. By reversing the conditioning institution I can measure the risk exposure of the U.S. bank to the European bank. To assess the cross-border importance of each institution I calculate the indicator of the overall risk exposure, denoted eRISK, which aggregates the risk that each bank faces from all of its cross-Atlantic counterparts. I also analyze the total impact of an institution on all of the other institutions across the Atlantic by calculating the indicator of individual bank's cross-border risk contribution. Using these indicators I can rank banks according to their overall risk exposure or risk contribution. The results based on the rankings suggest that the pairwise CoVaR measure brings additional information over VaR to determine the cross-border importance of financial institutions. The main conclusion is that institutions may have a low VaR but a high CoVaR. Banks with the highest risk exposure (contribution) are not necessarily individually risky banks, as measured by their VaR. The findings have important regulatory implications suggesting that capital requirements imposed based on an institution's VaR could be significantly different from capital requirements determined based on a institution's ΔCoVaR. The results also provide some insights regarding the bailout of Bear Stearns and the bankruptcy of Lehman Brothers. The spillover effects estimated using market prices suggest that prior to the crisis both banks had been equally globally important in terms of their riskiness, which does not seem to support the policy decision to bailout Bear Stearns instead of Lehman Brothers.

In the second part of this chapter I empirically investigate the inter-linkages between European and U.S. banks to unveil the possible bank-specific factors that explain how banks in the two economic regions are connected to each other. More specifically, I use fixed effects panel regressions to examine the association between the estimated pair-wise ΔCoVaR, and a set of bank characteristics, such as size, leverage, short-term borrowing and VaR, over time. The empirical findings suggest that leverage, size and VaR are all important in explaining institution's cross-border importance. However, within the set of institutions in my sample a relevant difference emerges between U.S. and European banks as to bank's size as a dominant factor in explaining institution's cross-border importance.

The remainder of Chapter 2 is structured as follows. Section 2.2 provides a review of recent empirical literature on quantifying systemic risk and assessing financial interlinkages.

Section 2.3 defines the co-risk pairwise measure, ΔCoVaR, and describes its estimation procedure via quantile regression. Section 2.4 presents data and estimation results of the risk measures for the European and U.S. samples. Section 2.5 analyzes the bank-specific determinants of cross-border ΔCoVaR and section 2.6 discusses the several robustness checks. Finally, section 2.7 summarizes the main findings and concludes.

2.2 Related Literature

This paper builds on the growing literature on measuring and assessing systemic importance of individual financial institutions that incorporates market and accounting information. The underlying theoretical framework refers to interlinkages among financial institutions that could spread both through negative externalities or fundamental shocks, as well as liquidity and volatility spirals, or network effects. This line of research investigates the systemic impact resulting from the problems of an institution or a market, and emphasizes the role of size, interconnectedness and the availability of substitutes. These studies propose measures that allow identifying systemically important financial institutions and allocating macro-prudential capital requirements on individual banks.[3]

In their seminal paper Adrian and Brunnermeier (2011) introduce the concept of CoVaR to quantify the contribution of an individual financial institution to the risk of the financial system. The authors focus on the U.S. financial system, where the system consists of a portfolio of 1,226 publicly traded financial institutions. In their setting CoVaR is defined as the Value-at-Risk of the financial system conditioned on individual institution

[3]Bisias et al. (2012) provide a comprehensive survey of systemic risk literature.

experiencing a loss in its asset value. Using CoVaR the authors estimate the marginal contribution of a U.S. institution to the risk of the financial system, denoted ΔCoVaR, as an increase in the system-wide risk when a particular firm falls into a distress condition. In addition to considering the contribution of an institution to the stability of the entire system, Adrian and Brunnermeier (2011) also take into account the systemic interconnectedness of institutions and the effects they have on each other.

A growing number of studies further builds up on the ΔCoVaR as a measure of systemic importance. Some examples include Hautsch et al. (2011), Lopez-Espinoza et al. (2012), Lee et al.(2012), Girardi and Ergun (2013), Sedunov (2013), Rodriguez-Moreno and Pena (2013), Benoit et al. (2013a), Cao (2013), and Castro and Ferrari (2014). For example, Lopez-Espinoza et al. (2012) use the CoVaR approach to investigate the determinants of systemic in a global framework. They consider 54 large international financial institutions in 18 countries over the period from 2001 to 2009. Girardi and Ergun (2013) generalize the CoVaR by defining financial distress as the returns of a financial firm being at most at its VaR level as opposed to being exactly at its VaR. This change allows analyzing more severe distress conditions and backtesting the computed CoVaR measure via standard tests. Sedunov (2013) modifies the definition of ΔCoVaR as the change in financial institution's VaR in case of a financial crisis. This measure, called *adapted exposure* ΔCoVaR, captures the systemic risk exposures of an individual institution. Rodriguez-Moreno and Pena (2013) estimate two distinct groups of high-frequency market-based systemic risk measures, which includes ΔCoVaR, for a set of European and U.S. banks. They further compare the best performing measures within each group using Granger causality test and Gonzalo and

Franger metric. Benoit at al. (2013a) compare ΔCoVaR with other two widely-cited systemic risk measures, Marginal Expected Shortfall and SRISK under the common theoretical and empirical framework. Using Shapley values Cao (2013) decomposes the system-wide risk among the financial institutions in a CoVaR setting. Castro and Ferrari (2014) develop a test of significance of ΔCoVaR to determine whether a financial institution can be classified as a systemically important institution and a test of dominance to test whether one financial institution is more systemically important than another according to the estimated ΔCoVaR.

A related strand of literature begins from a notion of systemic risk and then identifies how much each financial institution adds to it. For example, Acharya et al. (2010) propose the Marginal Expected Shortfall (MES) as the expected losses of an institution when the system as a whole is in distress. MES can be interpreted as the per dollar systemic risk contribution of this particular institution. Using MES Acharya et al. (2010) calculate Systemic Expected Shortfall (SES) as the weighted average of the institution's MES and its leverage. Brownlees and Engle (2012) expand on the MES by constructing the SRISK index, which captures the expected capital shortage of a financial firm given its MES and leverage. In contrast to Acharya et al. (2010), who compute time-invariant MES, Brownlees and Engle (2012) estimate time-varying MES using a bivariate GARCH model and non-parametric tail estimators. Tarashev et al. (2009, 2010) and Drehman and Tarashev (2011a, 2011b) use the Shapley value decomposition approach to measure systemic importance of individual institution. This approach defines a bank's risk contribution as a weighted average of its add-on effect to each subsystem that includes this bank.

The third line of research specifically aims at measuring the degree of connectivity among financial firms and assessing how risk profiles of these institutions can generate systemic risk. The analysis is not meant to be directly applicable to determining optimal bank capital requirements or taxation but merely serve as early warning signals of potential market dislocation and may be used to detect systemically important institutions and linkages. The most widely used method that belongs to this group of literature is the network analysis. Network analysis considers the financial system as a complex dynamic network of players that are connected directly through mutual exposures in the interbank market and indirectly through holding similar portfolios or sharing the same mass of depositors. If an institution is a part of the financial network it bears network risk, which it cannot effectively defend itself against. Then, simulating shocks, network analysis can track the reverberation of a credit event or liquidity squeeze through the system and provide important measures of institutions resilience to the domino effect triggered by financial distress. More recent examples include Van Lelyveld (2006), Degryse and Nguyen (2007), Allen and Babus (2008), Cocco et al. (2009). Van Lelyveld and Liedorp (2006), for instance, investigate contagion risk in the Dutch interbank market by estimating the extent of bilateral and foreign exposures. The results suggest that the Dutch interbank market only seems to carry systemic risk if a large bank failed, and even in this extreme event not all of the remaining banks were impacted.

The major problem with constructing a matrix of inter-institution exposures, and especially cross-border exposure matrix, is that data may only be available for national supervisors and that some information is not collected on a systematic basis. For this reason, studies mainly focus on their respective banking system or use alternative available data and study cross-country bilateral exposures. Cihak et al. (2011) incorporate country-level cross-border banking data to answer the following question: Does a country's banking system get more or less prone to a banking crisis when it is more linked to the global banking network? This approach is attractive as it helps determine the degree of exposure of one country's financial system to the risk of other countries. However, the method focuses on aggregate data and does not allow us to detect the sources of vulnerabilities and identify which financial institutions are possibly a threat to the overall systemic stability. It provides little information about inter-linkages among financial institutions, which may be important given that systemic risk materializes through transmission of stress from one institution to many others.

Alternative methods include the work of Billio et al. (2012) which focuses on measuring the degree of interconnectedness among market returns of various financial industries and their impact on systemic risk based on principal components analysis and Granger-causality tests. Their analysis considers four sectors: hedge funds, commercial banks, broker-dealers and insurance companies, and shows that all four sectors have become highly interrelated and less liquid, possibly increasing the level of systemic risk over the past decade. Hedge funds seem to provide early indications of market dislocation. Lehar (2005) estimates correlations between bank-asset portfolios and uses default probabilities of financial institutions as a measure of systemic risk. More specifically, the author's proposed measure is based on the probability that banks with total assets of more than a certain percentage of all banks' assets default within a short period of time. Following a similar approach, Segoviano and Goodhart (2009) suggest a set of banking stability indicators according to distress dependence, and Huang et al. (2010, 2012) introduce a risk-neutral-based pricing measure based on Merton's (1974) model for individual firm default.

Applications of ΔCoVaR that specifically focus on assessing interdependencies among financial institutions include International Monetary Fund (2009), Adams et al. (2011), and Roengpitya and Rungcharoenkitkul (2011). International Monetary Fund (2009) proposes a co-risk methodology based on CDS prices to assess risk dependences between financial institutions. Adams et al. (2011) estimate a state-dependent sensitivity VaR (SVAR) to quantify the spillover effects among systemically important financial institutions accounting for the effects of different market states on the magnitude of risk spillovers. Roengpitya and Rungcharoenkitkul (2011) apply the ΔCoVaR approach for the analysis of financial linkages in the Thai banking sector.

The current analysis contributes to the latter strand of literature by incorporating the CoVaR approach into the measurement of international financial linkages. The next section introduces the methodology in more detail.

2.3 CoVaR Methodology

2.3.1 Definition

CoVaR is based on the concept of Value-at-Risk (VaR), a measure defined as the worst expected loss in the value of a risky asset or portfolio for a given probability and time horizon. Given the returns of institution i, r_t^i, the VaR^i is defined as:

$$Pr(r_t^i \leq VaR_{\alpha,t}^i) = \alpha \tag{2.3.1}$$

The definition states that for a confidence level of, for example, $(1-\alpha) = 0.95$, there is only a 5 percent chance that losses will be greater than the estimated VaR over the chosen risk period. So, VaR$_{0.05}$ represents the 5^{th} quantile of the firm's return distribution.[4]

Adrian and Brunnermeier (2011) propose CoVaR as a way to gauge the severity of distress in one institution, given the distress in another institution. More formally, CoVaR$_\alpha^{j|i}$ is defined as the VaR of institution j conditional on some tail event for institution i. If we define a conditioning event as firm's return being at its VaR level, $r_t^i = VaR_{\alpha,t}^i$, then CoVaR$_\alpha^{j|i}$ is simply the α-quantile of the following conditional distribution:[5]

$$Pr(r_t^j \leq CoVaR_{\alpha,t}^{j|i} | r_t^i = VaR_{\alpha,t}^i) = \alpha \tag{2.3.2}$$

To capture the marginal contribution of institution i to the risk of institution j they define ΔCoVaR as the difference between the VaR of institution j conditional upon insti-

[4]VaR specified by Equation (2.3.1) assumes a negative value when α is small. A common practice is to report the estimates of VaR in positive values. I will follow this convention.

[5]Alternatively, one can specify the distress event more generally as losses exceeding VaR, i.e. $r_t^i \leq VaR_{\alpha,t}^i$. Girardi and Ergun (2013) use this conditioning event for the estimation of CoVaR using a multivariate GARCH model. Their empirical findings show that the impact of institution-specific characteristics, such as size, leverage and VaR, on ΔCoVaR estimated under this more general conditioning event, $r_t^i \leq VaR_{\alpha,t}^i$, is not significantly different from that on the ΔCoVaR estimated given the condition of $r_t^i = VaR_{\alpha,t}^i$.

tution i being in a distress state and the unconditional level institution i's VaR:[6]

$$\Delta CoVaR_{\alpha,t}^{j|i} = CoVaR_{\alpha,t}^{j|i} - VaR_{\alpha,t}^{j} \tag{2.3.3}$$

This measure shows the extent of institutions' risk codependence: when two banks' risks are dependent, $\Delta\text{CoVaR}_{\alpha}^{j|i}$ will be different from zero. It, therefore, reflects the externalities not captured by an institution's stand-alone VaR and allows assessing the spillover effects across the financial network by computing marginal contribution of each bank to the risk of another bank.

In their application Adrian and Brunnermeier (2011) consider the situation in which j represents the U.S. financial system. Their estimated $\text{CoVaR}^{system|i}$ measures the risk of the whole U.S. financial system given the stand-alone risk of U.S. institution i. For the current analysis I study the case where j corresponds to a European bank, $\{j = EU\}$, and i corresponds to a U.S. bank, $\{i = US\}$. Accordingly, $\Delta\text{CoVaR}^{EU|US}$ represents the additional amount of a European bank's VaR, apart from its institution-alone VaR, caused by a troubled U.S. bank. Likewise, $\Delta\text{CoVaR}^{US|EU}$ captures the risk exposure of a U.S. bank to its European counterpart. As Adrian and Brunnermeier (2011) emphasize $\Delta\text{CoVaR}^{j|i}$ does not have to be symmetric. That is, it is possible that a distressed U.S. institution may impose a high risk on a European institution whereas the European institution in a distress condition may cause small risk spillovers on the U.S. bank. So, it is quite possible that $\Delta\text{CoVaR}^{EU|US}$ significantly may differ from $\Delta\text{CoVaR}^{US|EU}$.

[6]This definition is used in the earlier version of Adrian and Brunnermeier (2009). The updated version defines $\Delta\text{CoVaR}_{\alpha}^{j|i}$ as the difference between the VaR of the system conditional on firm i being at its VaR level and the VaR of the system conditional on the normal (median) state of firm i. As a robustness check I also re-estimate $\Delta\text{CoVaR}_{\alpha}^{j|i}$ using this later specification.

2.3.2 Estimation Procedure

There are several ways to calculate CoVaR empirically. The estimation amounts to modeling the tail risk taking into account that dependence between stock prices is not linear. The co-movement in the financial institutions' equity return tends to increase more proportionately during distress times. Quantile regression is a simple technique that estimates the functional relationship among variables at a specific quantile of the distribution rather than at the mean, as is normally done through ordinary least squares estimation. As such, quantile regression is well suited to capture nonlinear relationships in stock returns and leads to a more accurate estimation of the tail dependency. Extreme-value method can be also used for capturing dependence between institutions. However, since extreme value measures focus only on the tail realizations of the series they ignore a significant amount of information from the whole data sample. This creates a problem when sample size is small. Consider the model:

$$y_t = x_t'\beta + \varepsilon_t$$

The α quantile estimator $\hat{\beta}(\alpha)$ minimizes:

$$\min_{\beta} \sum_{i}^{N} \rho_\alpha \Big(y_i - \eta(x_i, \beta) \Big) \tag{2.3.4}$$

where $\rho_\alpha(.)$ is a function that assigns weights to each observation depending on the given quantile. More specifically, the function assigns a weight equal to the quantileα if the residual is positive and a weight of α-1 if the residual is negative. The minimization problem can be solved using the standard linear methods and the covariance matrices can be estimated using bootstrap techniques.

The estimation of CoVaR with the quantile regression includes the following steps:[7]

Step 1. VaR for each U.S. institution i is estimated by running the following α-quantile regression:[8]

$$r_t^i = \delta_\alpha^i + \gamma_\alpha^i M_{t-1}^{U.S.} \tag{2.3.5}$$

where r^i denotes the demeaned daily equity return[9], $M_{t-1}^{U.S.}$ is the vector of lagged exogenous macroeconomic and financial variables that are widely used in the literature to capture the expected part of returns. The detailed discussion of these conditioning factors is provided in Section 2.4.1.

Individual VaRs are obtained using the predicted values from Equation (2.3.5) according to:

$$VaR_{\alpha,t}^i = \hat{\delta}_\alpha^i + \hat{\gamma}_\alpha^i M_{t-1}^{U.S.} \tag{2.3.6}$$

Step 2. By the same analogy, CoVaR$^{j|i}$ of each European-U.S. bank pair is estimated by regressing European bank j's returns on U.S. bank i's return and a set of macroeconomic indicators related to the European region:

$$r_t^j = \delta_\alpha^j + \beta_\alpha^j r_t^i + \gamma_\alpha^j M_{t-1}^{EUR} \tag{2.3.7}$$

[7]Studies that utilize the quantile regression for the estimation of CoVaR include Lopez-Espinoza et al. (2012), Sedunov (2013) and Rodriguez-Moreno and Pena (2013), Benoit et al. (2013a).

[8]See also Engle and Manganelli (2004) on modelling VaR via quantile regression.

[9]The common practice in analyzing inter-institution exposures and linkages is to employ interbank exposure data. Similarly, the availability of prices for Credit Default Swaps (CDS) can be used to construct a default probability-based measure of systemic risk. However, as previously mentioned, data on inter-bank exposures is usually not publicly available and while the CDS approach provides an important assessment of the default dependencies between financial institutions, it can capture only one type of risk, namely, credit risk. Following a large strand of literature on stock price co-movements I use equity return in order to account for general market risk.

whose fitted values evaluated at $\{r_t^i = VaR_{\alpha,t}^i\}$ correspond to the definition of CoVaR$_{\alpha,t}^{j|i}$ as follows:

$$CoVaR_{\alpha,t}^{j|i} = \hat{\delta}_{\alpha}^{j} + \hat{\beta}_{\alpha}^{j} VaR_{\alpha,t}^{i} + \hat{\gamma}_{\alpha}^{j} M_{t-1}^{EUR} \tag{2.3.8}$$

The spillover coefficient, $\hat{\beta}_{\alpha}^{j}$, measures the risk sensitivity of a European bank at the α^{th} quantile. So, the larger the estimated CoVaR$^{j|i}$ in absolute value, the larger is the spillover effect and, consequently, the more vulnerable is the European bank to the U.S. bank.[10]

Step 3. To quantify the degree of European bank's risk exposure to a U.S. bank (or how much a U.S. institution adds to the VaR of a European institution) I calculate ΔCoVaR$^{j|i}$ according to Equation (2.3.3).

Step 4. To assess the impact of each U.S. bank on all of the European peer banks I construct the aggregate risk indicator as a weighted sum of its ΔCoVaR$^{j|i}$s:

$$CoRISK_t^i = \sum_{j=1}^{30} \omega_t^j \Delta CoVaR_{\alpha,t}^{j|i} \qquad i = 1, ..., 17. \tag{2.3.9}$$

where weights, ω_t^j, are assigned according to each European bank's book value of liabilities.

The CoRISK$_t^i$ indicator summarizes the overall impact of a particular U.S. institution on all European banks in the sample.[11] I select the liabilities as a weighting variable in order to more accurately capture the degree of bank's risk exposure. For example, due to deteriorating market conditions a bank in the U.S. can be considered risky for a bank in Europe in terms of ΔCoVaR. However, the *impacted* European bank might have enough

[10] Under this methodology the estimated slope coefficient, $\hat{\beta}_{\alpha}^{j}$, is time invariant meaning that the effect of VaR on CoVaR is constant over time.

[11] This indicator can not be viewed as the total risk contribution of a particular U.S. bank to all European banks in the sample. Since CoVaR is based on VaR it lacks the additive property and summing up ΔCoVaRs will not produce the aggregate measure of risk.

capacity to issue additional debt to finance its assets, thereby, limiting the spillover effect and withstanding overall risk it faces from the U.S. counterpart.

While CoRISK helps identify the riskiest U.S. banks in terms of their cross border risk contribution, from the regulatory perspective it might be very useful to know which European institutions are most vulnerable to the U.S. financial system. One option is to compute the indicator of an individual bank's risk exposure as follows:

$$eRISK_t^j = \sum_{i=1}^{17} \Delta CoVaR_{\alpha,t}^{j|i} \qquad j = 1, ..., 30. \tag{2.3.10}$$

Using the eRISK indicator I can rank European institutions according to their overall cross-border risk exposure and identify which banks are particularly vulnerable to the risk stemming from their cross-Atlantic counterparts. This measure can potentially serve as a stress-testing tool in identifying most risk exposed financial institutions that should be subject to stricter regulation.

I replicate the above procedure for European banks to obtain their respective daily risk measures.

2.4 Data and Estimation

2.4.1 Data

The analysis utilizes daily data for the sample of 30 European and 17 U.S. globally active banks and covers the period spanning from 01/03/2000 to 12/31/2011. There are 3020 observations for each institution. The sample is constructed according to the following criteria. First, I consider all 8 U.S. and 15 European banks that were identified as G-SIBs by the Financial Stability Board in November 2011 and 2012.[12] I add to this list large banks with market capitalization greater than USD15 bln as of 06/30/2007. About 60% of the European sample is represented by the banks from the following 5 countries: the UK (5), France (4), Sweden (4), Spain (3), and Italy (3). Appendix A1 lists all banks by their respective countries, ticker symbols, asset size and market value of equity.

The time-varying VaR and CoVaR measures are estimated using individual stock prices and a set of macro-financial variables. These conditioning risk factors are specific to the geographic region, either U.S. or Europe, each bank belongs to. In particular, U.S. state variables consist of the VIX index which captures the implied volatility in the S&P 500 stock market, liquidity spread defined as the difference between the 3-month U.S. repo rate and the 3-month U.S. T-bill rate, the change in the 3-month Treasury bill, the change in the slope of the U.S. yield curve measured as the yield spread between the U.S. 10-year Treasury bond and the 3-month Treasury bill rates, the credit spread constructed as the yield spread between the 10-year Moody's seasoned BAA corporate bond and 10-year Treasury bond, and the market index return. The European counterparts of these predictors include the VDAX, the spread between the 3-month EURIBOR and the 3-month German government bond yield, the change in the 3-month German government bond, the change in the slope of the yield curve defined as the difference between the 10-year and 3-month German government bond yield, and the FTSE European stock index return. Tables (2.1a) and Table (2.1b) provide the summary statistics for the U.S. and European state variables, respectively.

[12]The sample excludes French Groupe BPCE which was formed only in 2009.

For the second part of the paper, which investigates of the bank-specific determinants of the estimated ΔCoVaR measures, I use individual balance sheet data from Compustat and Bloomberg. Balance sheet information is at semiannual frequency and covers the period between 07/01/2002 and 12/31/2011.

Equity price and accounting data are obtained in U.S. dollars in order to minimize a bias that may result from foreign exchange risk. All risk measures are estimated at the $\alpha = 5\%$ risk threshold and at daily frequency. Appendix A2 presents the definitions of all variables used in the analysis and sources of data.

Table 2.1a – Summary Statistics for U.S. State Variables

	Mean	Median	St.Dev	Min	Max	Skewness	Kurtosis
VIX	22.33	20.74	9.4761	9.89	80.86	1.8077	5.3564
Liquidity Spread	0.1552	0.0700	0.2047	-0.3300	1.8500	1.8016	4.7986
3-month Treasury Change	-0.0015	0.0000	0.0575	-0.8100	0.7400	-0.5390	45.9560
Term Spread Change	0.0001	0.0000	0.0773	-0.5100	0.7400	0.2828	9.0744
Credit Spread Change	0.0004	0.0000	0.0341	-0.1600	0.3800	1.4476	14.1930
Equity Market Return	0.0001	0.0006	0.0139	-0.0898	0.1148	-0.0528	6.4792

Notes: The table reports the descriptive statistics for the U.S. state variables used in the estimation of ΔCoVaR for the sample of U.S. banks. The variables are the VIX index, liquidity spread computed as the difference between the 3-month U.S. repo rate and the 3-month U.S. T-bill rate, the change in the 3-month Treasury bill, the change in the slope of the U.S. yield curve defined as the yield spread between the U.S. 10-year Treasury bond and the 3-month Treasury bill rates, credit spread measured as the yield spread between the 10-year Moody's seasoned BAA corporate bond and 10-year Treasury bond, and the market index return. Data are daily covering the period between 01/03/2000 and 12/31/2011.

2.4.2 Results

There are a few points worth comment from the quantile regression estimation. The estimates from the regressions of the VaR processes (Equation (**??**)) show that, the market volatility index and liquidity spread is statistically significant in terms of predicting one-step ahead VaR. An increase in the volatility and the widening of the spread in the previous day

Table 2.1b – Summary Statistics for European State Variables

	Mean	Median	St.Dev	Min	Max	Skewness	Kurtosis
VDAX	23.84	21.30	9.4782	10.98	74.00	1.3902	1.8831
Liquidity Spread	0.4383	0.2480	0.4855	-0.5890	3.4780	2.6807	10.0332
3-month Treasury Change	-0.0013	0.0000	0.0677	-1.2010	0.7710	-1.9162	62.2088
Term Spread Change	0.0003	-0.0010	0.0804	-0.7910	1.2260	0.8296	34.4200
FTSE return	0.0000	0.0000	0.0131	-0.0885	0.0984	0.0697	5.9104

Notes: The table presents the descriptive statistics for the European state variables used in the estimation of ΔCoVaR for European banks. The variable are the VDAX index, liquidity spread defined as the spread between the 3-month EURIBOR and the 3-month German government bond yield, the change in the 3-month German government bond, the change in the slope of the yield curve computed as the difference between the 10-year and 3-month German government bond yield, and the FTSE European stock index return. Data are daily covering the period between 01/03/2000 and 12/31/2011.

are associated with larger expected losses for both U.S. and European banks. Similar results hold for the regressions of the CoVaR processes (Equation (3.2.1)) with market volatility and liquidity spread exhibiting the strongest predictive power. Moreover, the coefficient on cross-border bank returns is significant across all CoVaR regressions suggesting a strong spillover effect running from the *source* foreign institutions onto *impacted* domestic institutions.

Figure (2.2) plots the daily estimates of VaR and CoVaR risk measures for the two specific institutions - Bank of America and Deutsche Bank. Figure (2.2a) illustrates Bank of America's stand-alone VaR and its risk exposure to Deutsche Bank, as measured by $CoVaR^{BAC|DBK}$, and Figure 2.2b depicts Deutsche Bank's daily VaR and $CoVaR^{DBK|BAC}$. In both figures the CoVaR line always lies above the VaR line suggesting that the bank's equity losses conditioned on its international peer bank in a distress state are larger compared to its unconditional VaR. Financial distress of Deutsche Bank (when its equity return equals the 5 percent VaR), on average, increases the equity losses of Bank of America by 50 percent compared to Bank of America's corresponding VaR. Similarly, an average increase in Deutsche Bank's loss conditional on Bank of America's return being at its $VaR_{5\%}$

increases by 20 percent over Deutsche bank's unconditional VaR.

The CoVaR methodology can be further used to assess inter-linkages between banks by measuring the percentage increase in each bank's risk should another bank fall into distress. More specifically, I calculate the $\%\Delta\text{CoVaR}^{j|i}$ as the percentage difference of a European institution's VaR if its U.S. peer bank i were at it 95% VaR level from the stand-alone VaR of this European institution as follows:

$$\%\Delta CoVaR^{j|i} = \frac{CoVaR^{j|i} - VaR^{j}}{VaR^{j}} \tag{2.4.11}$$

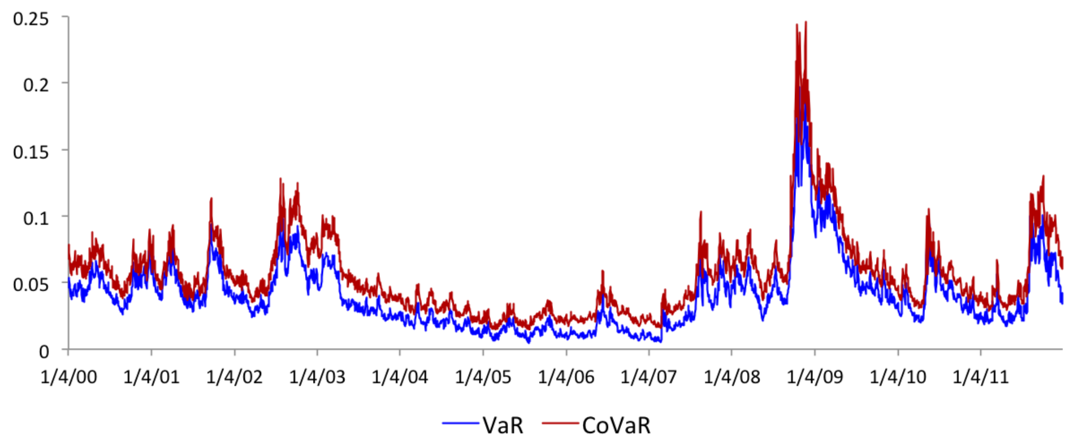
I define the distress state of a bank when it observed the VaR at 95% quantile of its VaR distribution during the sample period.[13]

Figure 2.3 provides a graphical depiction of the estimated pairwise %ΔCoVaR risk measures between Lehman Brothers and each of the four largest European investment banks. Numbers accompanying the red arrows outgoing from Lehman Brothers represent $\%\Delta\text{CoVaR}^{j|LEH}$ computed as the percentage change between VaR of the European bank conditional on the distress state of Lehman Brothers and this European bank's unconditional VaR. For example, the percentage increase in Deutsche Bank's VaR induced by Lehman Brothers being at its 95 percent VaR level is 38%. Similarly, the numbers associated with arrows originating from each European bank show the percentage change in Lehman Brothers' VaR should its European counterpart fall into distress. Accordingly, the risk of Lehman Brothers conditional on the 95% VaR of Deutsche Bank would have been 28% higher than Lehman Brothers' risk in isolation, as measured by its VaR and so on.

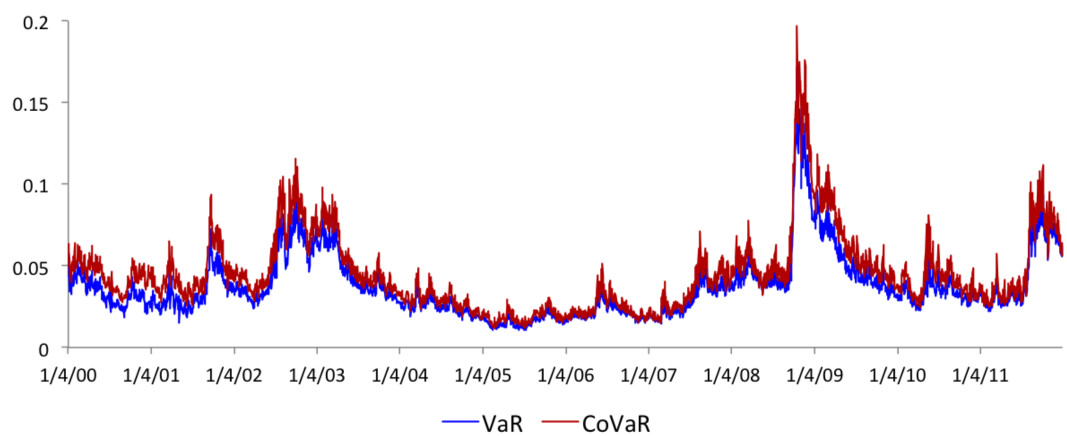
[13] The 95th percentile corresponds to the value of the observed VaR such that 95 percent of the observations have lower values and 5 percent of the observations have higher values.

Figure 2.2 – VaR and CoVaR

(a) VaR^{BAC} and $\text{CoVaR}^{BAC|DBK}$

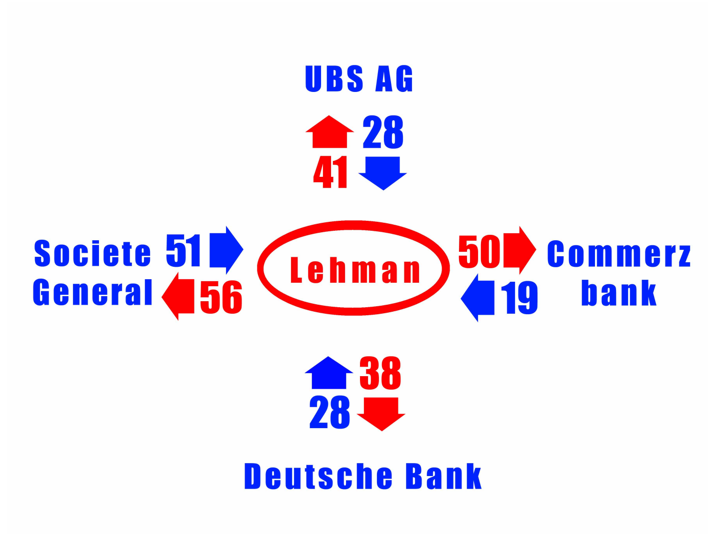


(b) VaR^{DBK} and $\text{CoVaR}^{DBK|BAC}$



Notes: The top panel plots Bank of America's VaR and its exposure to the risk of Deutsche Bank, as measured by $\text{CoVaR}^{BAC|DBK}$. The bottom panel plots Deutsche Bank's VaR and its risk exposure to Bank of America, as measured by $\text{CoVaR}^{DBK|BAC}$. Estimations are for the period 07/01/2000 - 12/31/2011.

Figure 2.3 – %ΔCoVaR for Lehman Brothers



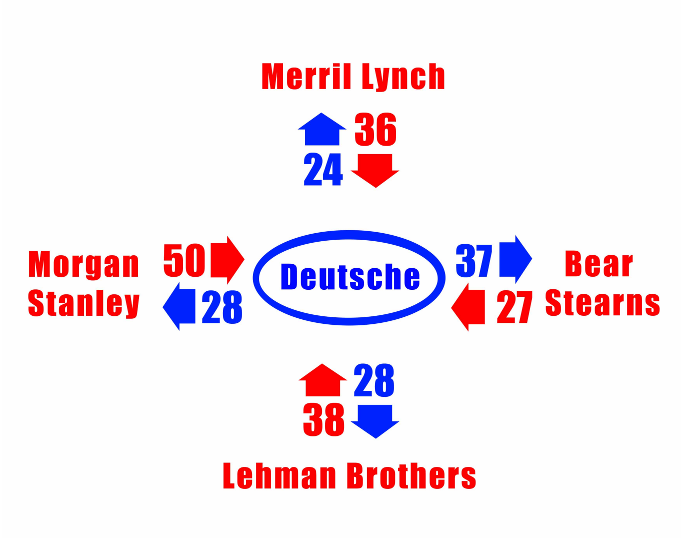
Notes: The figure presents the %ΔCoVaR between Lehman Brothers and four European investment banks. Numbers in red represent the percentage increase in each European bank's VaR conditional on Lehman Brothers' VaR at 95% level from its unconditional VaR. Numbers in blue correspond to the percentage increase in Lehman Brother's VaR induced by each European bank in distress condition. Estimations are for the period 01/03/2000-07/01/2007.

The figure shows that prior to the crisis Lehman Brothers had the largest risk exposure to French Societe General (the estimated $\%\Delta\text{CoVaR}^{GLE|LEH}$ is 51%) and it also imposed the highest risk onto Societe General (the estimated $\%\Delta\text{CoVaR}^{LEH|GLE}$ is 56%).

The co-risk estimates for the Deutsche Bank-U.S.investment bank pairs are presented in Figure 2.4 and suggest that Deutsche Bank was very sensitive to the risk spillovers from U.S. institutions during the pre-crisis period of 2000-2007. For instance, Deutsche Bank's VaR given the distress condition of Bear Stearns was 27% higher than its unconditional VaR. Likewise, it had the highest risk contribution to Bear Stearns when compared to the risk it imposed on four other U.S. institutions. When Deutsche Bank's VaR was at 95% quantile, this would have resulted in an increase of 37% in Bear Stearns' VaR.

As mentioned above, this type of analysis represents a useful tool for bank supervision,

Figure 2.4 – %ΔCoVaR for Deutsche Bank



Notes: The figure presents the %ΔCoVaR between Deutsche Bank and four U.S. investment banks. Numbers in red represent the percentage increase in each U.S. bank's VaR conditional on Deutsche bank's VaR being at 95% VaR level from its unconditional VaR. Numbers in blue correspond to the percentage increase in Deutsche bank's VaR induced by each U.S. bank peer in distress condition. Estimations are for the period 01/03/2000-07/01/2007.

as it reveals which institutions are perceived to be more connected to each other by market participants.

Table 2.3 presents the average ranking of top five riskiest banks according to three estimated risk measures - VaR, eRISK and CoRISK, for the period of 01/03/2000 to 06/29/2007. Panel A contains the rankings for U.S. banks and shows that all five largest U.S. investment banks in my sample were the most risky banks according to their VaR estimates (column 1). Similarly, four out of five top risky European banks are investment banks, with the two key players being German banks. More importantly, the table shows an interesting result in light of the rescue of Bear Stearns and the bankruptcy of Lehman Brothers. First, both institutions were ranked among the top five individually risky banks (column 1). Furthermore, not only were they also among the top riskiest banks according to their cross-border risk exposure, as the eRISK-based rankings suggest (column 3), but they also imposed a risk of similar magnitude to European banks as measured by their CoRISK indicator (column 2). These results indicate that both institutions were perceived to be equally globally risky and suggest that the government should have provided financial support to both institutions rather than preferring one to another. Of course, one should be cautious in deducing a definite conclusion. The current analysis is based on the assumption that markets are fully efficient. Obviously, market prices may not incorporate all relevant private information. Also the information content of market prices may be affected by factors unrelated to an institution's risk. Hence, conclusions based on market information may not be sufficient to support or oppose any policy decisions made using private information available to policymakers and regulators only.

Panel B of the table provides the corresponding rankings of European banks. It confirms that German banks were the most risky banks among their European counterparts. In particular, Deutsche Bank appears as the top riskiest bank based on all three risk measures. It has the highest ranking in terms of its overall impact on U.S. banks (column 2) and ranked as the second most vulnerable institution (column 3) among all European banks in the sample.

Table 2.4 contains the descriptive statistics of the estimated risk measures for all U.S. and European banks across the 2000-2011 sample period as well as their mean values segmented into pre-crisis and post-crisis periods. The table shows that all risk measures increased after the global crisis both for U.S. and for European samples. However, the growth rates of the measures were quite different. While the average VaR equally doubled

Table 2.3 – Rankings of Financial Institutions, 2000-2007

Panel A: U.S. Banks

Rank	VaR^{US}	CoRISK^{US}	eRISK^{US}
1	MS	MER	MS
2	**LEH**	NCC	BK
3	MER	**LEH**	STT
4	GS	**BSC**	**BSC**
5	**BSC**	BAC	**LEH**

Panel B: European Banks

Rank	VaR^{EU}	CoRISK^{EU}	eRISK^{EU}
1	**CBK**	**DBK**	**CBK**
2	GLE	UBSN	**DBK**
3	CSGN	SAN	UBSN
4	NDA	CSGN	DEXB
5	**DBK**	UCG	INGA

Notes: The table reports the list of U.S. institutions (Panel A) and the list of European institutions (Panel B) ranked according to their estimated risk measures from most to least risky. Average rankings for 01/03/2000-06/29/2007.

for banks in both regions, the percentage increase of the mean CoRISK indicator for U.S. banks was more than twice as much as that for European banks. Compared to the pre-crisis period the additional risk of European banks imposed by U.S. banks more than doubled after June 2009 whereas the additional risk imposed by European banks onto their U.S. peers grew by roughly 45%. During the same period the overall risk exposure of U.S. banks increased by 52% and the exposure of European banks to U.S banks grew by 64%.

Table 2.4 – Summary Statistics for Estimated Risk Measures

	U.S. Banks			**European Banks**		
	VaR^{US}	CoRISK^{US}	eRISK^{US}	VaR^{EU}	CoRISK^{EU}	eRISK^{EU}
Mean	0.0384	0.0072	0.2987	0.0368	0.0117	0.1160
St.Dev	0.0228	0.0051	0.1562	0.0224	0.0062	0.0717
Min	0.0028	-0.0030	-0.1394	-0.0159	-0.0015	-0.0992
Max	0.2508	0.0581	1.8381	0.3457	0.0850	0.7728
Pre-crisis	0.0195	0.0037	0.2212	0.0211	0.0084	0.0600
Post-crisis	0.0391	0.0080	0.3358	0.0421	0.0121	0.0982

Notes: The table contains men, standard deviation, maximum and minimum values of the daily estimates of VaR, eRISK and CoRISK measures for U.S. and European banks. Sample period is from 01/03/2000 to 12/31/2011. The bottom two rows report the average values for the pre crisis (07/01/2005-06/29/2007) and post crisis (07/01/2009-12/31/2011) periods.

Table 2.5 and 2.6 contain the complete rankings for the whole sample period for all U.S. and European institutions, respectively. They reveal that, indeed, the rankings of firms based on their stand-alone VaR are not necessarily the same as their rankings according to their two co-risk measures. For example, the list of U.S. banks in Table 2.5 shows that two large institutions, Citibank and Morgan Stanley, and two smaller institutions, BBT and US Bancorp have very similar rankings according to all measures. The first two are ranked among top three riskiest firms based on VaR and CoRISK, whereas the latter are perceived to be the least risky banks in terms of all risk measures. In contrast, Bank of America, which leads the U.S. bank ranking according to the eRISK indicator is not listed among the top riskiest banks according to its cross-border risk contribution as measured by CoRISK. Similarly, Regions Financial with the second highest VaR has one of the lowest ranking in terms of CoRISK.

Table 2.5 – Rankings of U.S. Banks

Rank	VaR^{US}	CoRISK^{US}	eRISK^{US}	Size
1	MS	BK	BAC	JPM
2	RF	MS	C	BAC
3	C	C	STI	C
4	BAC	JPM	RF	WFC
5	STT	GS	JPM	GS
6	STI	STI	MS	MS
7	BK	PNC	WFC	USB
8	JPM	BAC	STT	BK
9	GS	WFC	BK	PNC
10	WFC	RF	GS	STT
11	USB	BBT	BBT	STI
12	BBT	STT	PNC	BBT
13	PNC	USB	USB	RF

Notes: The table reports the average ranking of U.S. institutions according to their estimated risk measures from most to least risky for the period 01/03/2000-12/31/2011. The last column ranks banks based on their asset size for 12/31/2011.

A similar picture can be observed when one compares the risk rankings obtained for European banks. First, Table 2.6 suggests that banks that are most likely to transfer the risk to other banks in terms of their cross-border risk contribution are not necessarily the individually riskiest banks (banks with the highest VaR). Allied Irish Bank with the highest VaR is, at the same time, ranked the least risky bank according to its CoRISK indicator, whereas HSBC with the lowest average VaR estimate is among top five risky institutions in the European CoRISK-based ranking. Second, there does not seem to be a very strong

Table 2.6 – Rankings of European Banks

Rank	VaR^{EU}	CoRISK^{EU}	eRISK^{EU}	Size
1	ALBK	SAN	DEXB	DBK
2	CBK	DBK	INGA	HSBA
3	BARC	UBSN	RBS	BNP
4	GLE	GLE	CBK	BARC
5	KBC	HSBA	GLE	RBS
6	INGA	ACA	LLOY	ACA
7	LLOY	BBVA	ISP	INGA
8	RBS	CSGN	ALBK	SAN
9	EBS	UCG	BARC	GLE
10	DBK	BNP	ACA	UBSN
11	EBS	STAN	UBSN	LLOY
12	SAN	INGA	KBC	UCG
13	SWEDA	NDA	SEBA	CSGN
14	SEBA	SWEDA	DBK	NDA
15	CSGN	SEBA	KN	CBK
16	DEXB	CBK	BNP	ISP
17	ACA	RBS	CSGN	BBVA
18	SAN	DANSKE	UCG	KN
19	NDA	KBC	SWEDA	STAN
20	KN	ISP	BBVA	DANSKE
21	BNP	EBS	STAN	DEXB
22	UBSN	SHBA	EBS	KBC
23	BMPS	DNBNOR	SAN	SHBA
24	UCG	POP	NDA	DNBNOR
25	BBVA	LLOY	DNBNOR	SEBA
26	DNBNOR	BMPS	POP	BMPS
27	DANSKE	BARC	HSBA	EBS
28	SHBA	DEXB	BMPS	SWEDA
29	POP	KN	DANSKE	ALBK
30	HSBA	ALBK	SHBA	POP

Notes: The table reports the list of U.S. institutions (Panel A) and the list of European institutions (Panel B) ranked according to their estimated VaR and CoRISK measures from most to least risky. Rankings are for 12/31/2011.

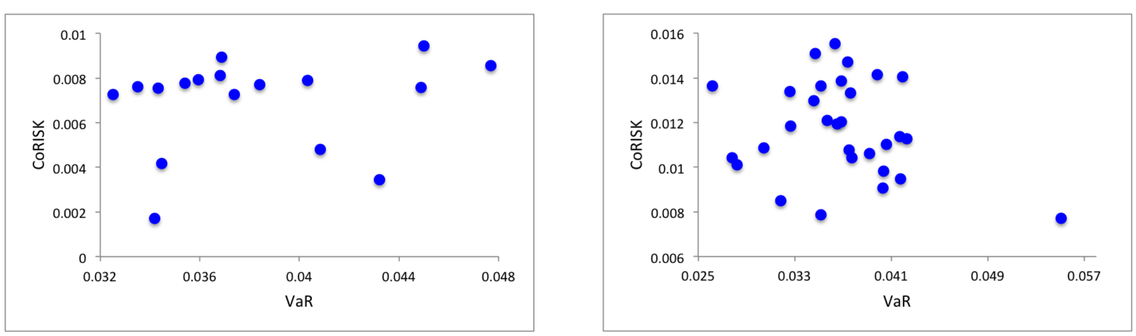
relationship between an institution's size and its risk. For example, the two largest U.K banks, Barclays and Royal Bank of Scotland, have relatively low rankings in terms of their riskiness for U.S. banks.

The sample contains 8 U.S. and 15 European banks that were identified as G-SIBs in 2012 based on their performance in 2011. The risk rankings of institutions suggest that CoRISK is generally better suited to identify G-SIBs than is VaR. For instance, if we consider top 15 risky European institutions the CoRISK-based ranking identifies 12 European G-SIBs whereas the VaR-based rankings contains only 6 G-SIBs.

The analysis of the relationship between VaR and ΔCoVaR indicates that these two measures have a very weak relation in cross-section. The results are summarized graphically in Figure 2.5. It plots the cross-time mean of VaRs against the cross-time mean of CoRISKs separately for the panel of U.S. institutions and separately for the panel of European institutions. Notice that CoRISK is simply the sum of individual ΔCoVaRs.

Figure 2.5 – Cross-Sectional Relation between VaR and CoRISK

(a) U.S. Banks **(b)** European Banks



Notes: The scatter plots display the relationship between the cross-time mean of CoRISK and the cross-time mean of VaR for each (a) U.S. institution and (b) European institution. Estimates are daily for the period 07/01/2000-12/31/2011.

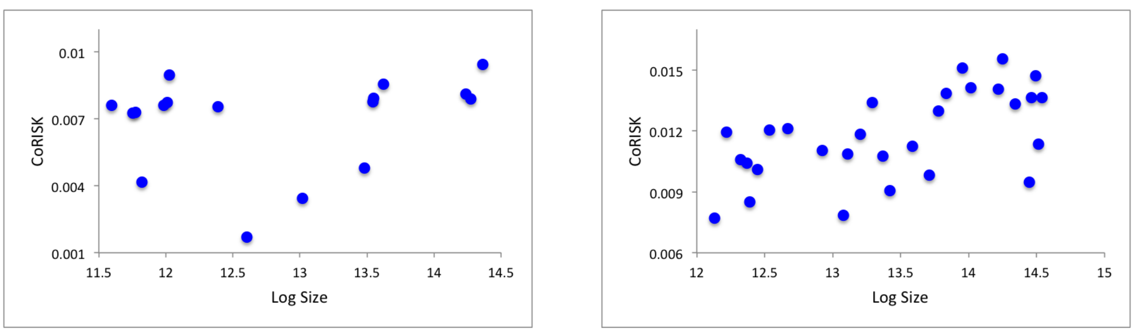
These two scatter plots suggest that there is, indeed, a weak cross-sectional link between bank's VaR and CoRISK. An institution's risk in isolation is not equivalent to the risk it imposes on another institution (or a group of institutions) The implication of this result is that banks can reduce their risk contribution by altering their returns distribution.

Given the recent discussion that size does matter we should expect that larger banks have greater impact on other banks compared to banks of smaller size. To assess the relation between the size of an institution and its cross-border risk Figures 2.6 shows the link between the log of banks' total assets and CoRISK. There seems to be weak but somewhat positive correlation between the log of institutions' size and their cross-border riskiness.

Figure 2.6 – Cross-Sectional Relation between Size and CoRISK

(a) U.S. Banks

(b) European Banks



Notes: The figure plots the CoRISK against log assets for each (a) U.S. institution and (b) European institution. Daily estimates for 07/01/2000-12/31/2011.

In the next stage of the analysis I examine the relation between estimates of $\Delta\text{CoVaR}^{j|i}$ and individual institution characteristics in more detail.

2.5 Bank-Specific Determinants of Cross-Border Linkages

2.5.1 Empirical Specification

In this section I turn to the identification of empirical drivers of the estimated pair-wise ΔCoVaR measures. More specifically, I investigate whether a set of bank-specific characteristics can predict the differences in international linkages and explain how banks in the two geographic regions are connected to each other.

The empirical strategy relies on the fixed effects regression model. The dependent variable in the estimations is $\Delta\text{CoVaR}^{j|i}$ - the additional risk domestic bank j faces from cross-Atlantic bank i on top of its stand-alone risk at time t. Since balance sheet data are at semiannual frequency and my estimates of $\Delta\text{CoVaR}^{j|i}$ are daily, I time-aggregate the latter by computing the simple average of daily ΔCoVaRs within each half a year period.

The baseline model for the *impacted* European banks takes the following form:

$$\Delta CoVaR_{\alpha,t}^{j|i} = \alpha + \beta Size_t^i + \gamma Size_t^j + \delta Bank_t^i + \eta_t + \varepsilon_t^{ij} \qquad (2.5.12)$$

where $\Delta CoVaR_{\alpha,t}^{j|i}$, is the additional risk of European bank (j = 1,...,29) conditional on a distress state of U.S. bank (i = 1,...,13) in period t (t = 2002H2 - 2011H2)[14], $Size_t^i$ is a U.S. bank's size, $Size_t^j$ is a European bank's size, $Bank_t^i$ is a vector of time-varying U.S. bank-specific characteristics, δ_t are time fixed effects, and ε_t^{ij} captures unobservable time-varying bank-pair effects.

Following a number of recent studies that confirm the relationship between institu-

[14] Four U.S. banks and one European bank that disappeared or were absorbed by other financial institution were excluded from the estimation.

tion's risk contribution and its balance sheet characteristics I consider the following bank-specific variables:[15]

- Size^i, defined as the log of U.S. institution's total assets. Larger foreign banks are expected be more risky for domestic banks, so one can expect a positive relation between bank's size and it's risk contribution. However, it can be argued that banks with a more concentrated home market might be less dependent on business in international markets, so the relationship can be negative. The sign of the coefficient on U.S. bank size therefore has to be determined empirically. The size of an *impacted* bank may also influence the degree of bank's risk exposure. Therefore, I include the log of European banks' assets as regressors to control for the European bank size effect. The larger the *affected* domestic bank the greater must be its risk exposure. Arguably, larger banks could be less risk sensitive compared to smaller banks suggesting a negative relationship between the *impacted* bank's size and its cross-border risk exposure measure, $\Delta\text{CoVaR}^{j|i}$.

- Leverage, defined as the ratio of U.S. bank's total assets to its equity in book values. This measure reflects the solvency of an institution: the higher an institution's leverage, the lower its solvency. Less solvent banks impose more risk on their peers, so I conjecture a positive relation between leverage and dependent variable.

- Short-term borrowing, defined as the ratio of short-term debt to total assets. Short-term debt represents the amount of short-term notes including repos and commercial papers and the current portion of long-term debt that is due within twelve months. This ratio is a proxy for balance sheet interconnectedness among financial institutions and captures a bank's

[15] See, for instance, Adrian and Brunnemeier (2011), Lopez-Espinoza et al.(2012), and Girardi and Ergun (2013).

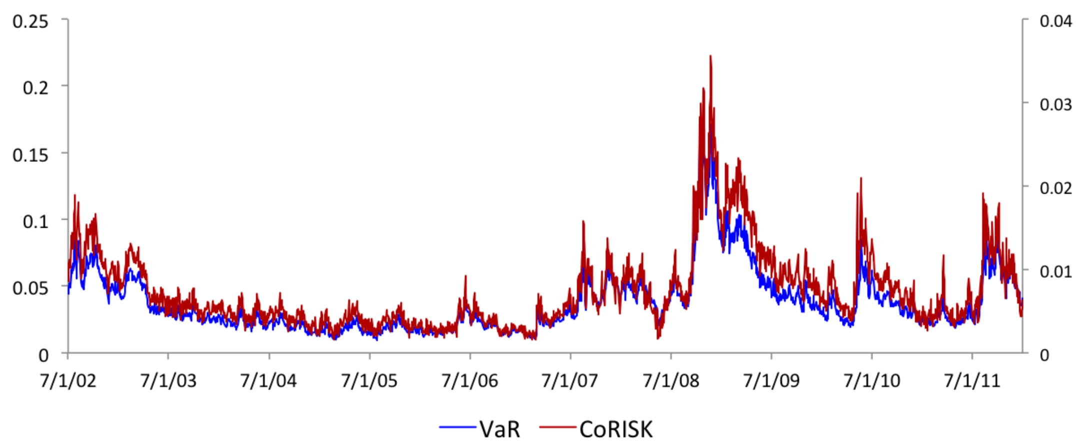
exposure to liquidity risk. One can expect that banks with a larger proportion of short-term debt in total assets contribute more to the risk of their cross-Atlantic counterparts. For example, Lopez-Espinoza et al.(2012) and show that banks that were more dependent on short-term funding contributed more to systemic risk in the global financial market. Brunneimeier and Pedersen (2009) also argue that heavy reliance of banks on short-term funding exposed these institutions to liquidity risk during the recent crisis leading to an increase in systemic risk.

- VaR of U.S. banks is also included as an explanatory variable since the estimation results show that an institution's VaR is closely related to its risk contribution, ΔCoVaR, in the time-series (Figure 2.7). This is in line with some previous findings that confirm a strong relationship between financial firms' VaR and ΔCoVaR. (Adrian and Brunnermeier, 2011 and Benoit et al., 2013a).

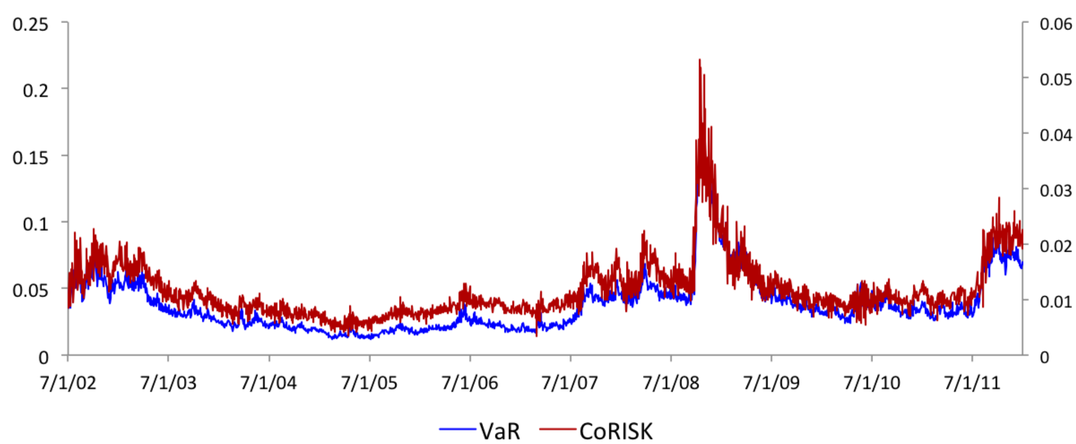
Table 2.7 contains the summary statistics of the bank specific variables for U.S. and European financial institutions over the sample period. The table reveals that European banks in my sample are much more leveraged than their U.S. counterparts. Although compared with the before-crisis period the average semiannual leverage was lower for both European and U.S. banks after the crisis, the former group remains twice as much leveraged as the latter. Looking at the short-term borrowing ratio it is apparent that U.S. institutions have used less short-term debt financing over the sample period. This can also confirmed by comparing the mean dollar value of firms' short-term debt, which declined from $151 million two years before the crisis to $137 million after the crisis for U.S. banks and increased from $169 million in pre-crisis times to $189 million in post-crisis period for European banks.

Figure 2.7 – Time Series Relation between VaR and CoRISK

(a) U.S. Banks



(b) European Banks



Notes: The top panel time plots the average VaR (blue line, left vertical axis) and the average CoRISK (red line, right vertical axis) for the sample of U.S. institutions. The bottom panel plots the average VaR (blue line, left vertical axis) and the average CoRISK(red line, right vertical axis) for the sample of European institutions. Estimations are for the period 07/01/2000 - 12/31/2011.

The numbers reflect differences between the funding structure of the U.S. and European banking systems. U.S. banks finance a far higher proportion of the loan books by deposits: a loan to deposit ratio in U.S. market is 78% compared to more than 110% in Europe.[16] Consequently, European banks have to rely on the wholesale markets to fill in their funding gap.

Table 2.7 – Summary Statistics for Bank-Specific Characteristics

	U.S. Banks				European Banks			
	Assets	Leverage	ST Debt	VaR	Assets	Leverage	ST Debt	VaR
Mean	637	13.28	0.16	0.037	906	24.84	0.19	0.038
St.Dev	651	5.36	0.14	0.020	761	10.07	0.12	0.021
Min	48	6.72	0.01	0.013	44	9.45	0.01	0.010
Max	2,364	34.65	0.54	0.111	3,745	69.01	0.62	0.170
Pre-crisis	608	14.07	0.17	0.018	869	25.81	0.20	0.021
Post-crisis	825	11.07	0.13	0.039	1,142	22.45	0.16	0.042

Notes: The table reports the descriptive statistics of balance sheet variables for the sample of U.S. banks in the top panel and for the sample of European banks in the bottom panel. Column 1 gives the total number of observations, columns 2 to 4 contain the panel mean, standard deviation the minimum and maximum values, respectively, and the last three columns report mean values for the pre- and post-crisis periods. Total assets are in billion USD; Leverage is the ratio of total assets to total equity; and Short-term borrowing is defined as the ratio of short-term debt to total assets. Sample period is from 01/07/2002 to 12/31/2011.

Because of the quantitative importance of the empirical analysis, a robust estimation procedure, particularly to the possible presence of unit roots, is critical. And with non-stationary panel data, the specter of spurious regressions comes to fore in the absence of cointegration. Finally, even with cointegrating variables, fixed effects estimates of Equation (4.5.3) may lead to biased point estimates and non-standard t-statistics, impairing statistical inference. To check for the stationarity of variables in the panel I run the Fisher-ADF unit root test. The null hypothesis of the test is that all panels contain a unit root. The results of the test indicate that the dependent and explanatory variables in both panels are

[16] Sources: Federal Reserve Bank of Saint Louis and European Central Bank, 2012.

nonstationary. All variables in first differences pass the stationarity test at 1% significance level.[17]

Consequently, I estimate the transformed model with bilateral (bank-pair) fixed-effects. All specifications include time fixed effects. Standard errors are panel-clustered using each bank-pair as a cluster.[18] I first run the regressions without the lagged dependent variable and subsequently include it to account for time persistence in the dynamics of ΔCoVaR estimates.

2.5.2 Estimation Results

Tables 2.8 and 2.9 summarize the estimation results for European and U.S. bank samples, respectively. Columns (1) and (2) in Table 2.8 present the fixed effects regression outputs with the European banks' risk exposure measure $\Delta \text{CoVaR}^{EU|US}$ as the dependent variable and U.S. banks-specific indicators as predictors. Column (3) includes the size of the European bank as an independent variable and column (4) reports the results when the lag of the dependent variable is also included as regressor in the estimation. The results across all specifications show that the effect of the leverage is positive and statistically significant, which may suggest that less solvent banks impose more of a risk on their cross-border counterparts. The effect of the (growth rate of) U.S. banks' size is positive and significant as well indicating that the higher the growth rate of a U.S. bank, the more risky it might be to a European bank. The size of *impacted* European banks appears as an important factor in terms of explaining their risk exposure to U.S. banks (columns (3)-(4)). As expected, the

[17]The panel unit root tests of Peasaran and Shin (2003) and the ADF test of Maddala and Wu (1999) confirm the Fisher test results.

[18]Since the assumption of homoskedasticity of the error term is likely to be violated it is quite important to use panel-corrected standard errors.

sign of the Size^{EU} coefficient is positive which may suggest that banks with higher asset growth rates are more risk exposed. Short-term borrowing is not statistically significant across all specifications. There is no evidence indicating that banks with relatively higher dependence on short-term liquidity impose more risk on their peers across the border. Finally, the effect of VaR is positive and highly significant confirming strong time-series relationship between an institution's risk in isolation, as measured by VaR, and its risk contribution, as measured by ΔCoVaR. The last column contains the results with the lagged value of ΔCovaR$^{EU|US}$ added as independent variable. All coefficients retain their original signs and significance levels under this specification as well.

Table 2.8 – Fixed Effect Estimation Results for European Banks

	Dependent variable: ΔCoVaR$^{EU\|US}$			
	(1)	(2)	(3)	(4)
	in x10^{-2} units	in x10^{-2} units	in x10^{-2} units	in x10^{-2} units
Size^{US}	-0.0524	0.0957***	0.0957***	0.1021***
	(0.0354)	(0.0258)	(0.0258)	(0.0264)
LEV^{US}	0.0115***	0.0055***	0.0055***	0.0056***
	(0.0025)	(0.0019)	(0.0019)	(0.0019)
STB^{US}	-0.0589	-0.0594	-0.0594	-0.0407
	(0.0799)	(0.0747)	(0.0747)	(0.0780)
VaR^{US}		16.2396***	16.2396***	15.9937***
		(1.8453)	(1.8453)	(1.8522)
Size^{EU}			0.0363**	0.0380**
			(0.0161)	(0.0173)
ΔCoVaR$^{EU\|US}$ (-1)				2.4010**
				(0.9390)
Constant	0.8412***	0.0989	0.1018	0.0983***
	(0.0182)	(0.0820)	(0.0820)	(0.0268)
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	6,786	6,786	6,786	6,409
Number of bank pairs	377	377	377	377
Adjusted R^2	0.826	0.847	0.847	0.842

Notes: The table reports the results from fixed-effects regressions for the European bank sample. All variables are in first-differences. Clustered standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Estimation results for U.S. banks in Table 2.9 are broadly consistent with those for European banks. The coefficient on LEV^{EU} is significantly positive implying that less solvent European banks have a higher spillover effect on their U.S. counterparts. The results also confirm that an institution's VaR is strongly related to its cross-border risk contribution: the coefficient on VaR^{EU} is statistically significant across all regression specifications. In contrast to the findings of Table 2.8 the size of a European bank does not appear as statistically significant in explaining its risk importance for U.S. peer banks. However, the size of *impacted* U.S. banks turns out to be statistically significant. Moreover, the relationship between Size^{US} and $\Delta\text{CoVaR}^{US|EU}$ is negative which may suggest that faster growing U.S.

Table 2.9 – Fixed Effect Estimation Results for U.S. Banks

	Dependent variable: $\Delta\text{CoVaR}^{US\|EU}$			
	(1)	(2)	(3)	(4)
	in x10^{-2} units	in x10^{-2} units	in x10^{-2} units	in x10^{-2} units
Size^{EU}	-0.0066	-0.0003	-0.0003	0.0031
	(0.0190)	(0.0176)	(0.0174)	(0.0183)
LEV^{EU}	0.0043***	0.0033***	0.0033***	0.0034***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
STB^{EU}	0.0766***	0.0333	0.0333	0.0474
	(0.0291)	(0.0280)	(0.0281)	(0.0316)
VaR^{EU}		10.2565***	10.2565***	10.1405***
		(1.6840)	(1.6810)	(1.6818)
Size^{US}			-0.0908***	-0.1068***
			(0.0322)	(0.0326)
$\Delta\text{CoVaR}^{US\|EU}$ (-1)				0.9864
				(1.3751)
Constant	0.7716***	0.3919***	0.4031***	-0.4109***
	(0.0173)	(0.0598)	(0.0598)	(0.0371)
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	6,747	6,747	6,747	6,370
Number of bank pairs	377	377	377	377
Adjusted R^2	0.835	0.854	0.855	0.857

Notes: The table reports the results from fixed-effects regressions for the U.S. bank sample. All variables are in first-differences. Clustered standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

banks are less risk exposed to European banks. Similar to the regression outputs of Table 2.8, short-term debt to asset ratio is not found to be important in explaining European banks' risk contribution.

Overall, empirical results are in line with other related studies. I find that leverage, size and VaR are all important in explaining systemic linkages between financial institutions. However, within the set of institutions in my sample a relevant difference emerges between U.S. and European banks as to bank's size as a dominant factor in explaining institution's cross-border importance. Moreover, the effect of balance sheet variables seems to be very small in magnitude. Given that most of the bank activities are conducted through the interbank market more granular data on actual interlinkages between financial institutions is necessary in order to assess more deeply and dynamically the interdependences that may generate cross-border spillovers among institutions.

2.6 Robustness Checks

To gauge the robustness of the main conclusions of the study I perform the following series of checks.

Definition of ΔCoVaR

Adrian and Brunnermeier (2011) introduce an alternative definition of $\Delta CoVaR^{j|i}$ as the difference between firm j's VaR conditional on another firm i being at its VaR level and the VaR of firm j conditional on the normal state of firm i:

$$\Delta CoVaR_{\alpha,t}^{j|i} = CoVaR_{\alpha,t}^{j|r_t^i=VaR_\alpha} - CoVaR_{\alpha,t}^{j|r_t^i=VaR_{0.5}}$$

I obtain each bank's $\Delta CoVaR^{j|i}$ based on this definition and used them to reestimate the fixed effects model (2.5.12). The findings are robust with respect to the previous specification of $\Delta CoVaR^{j|i}$.

VaR estimation and Risk Threshold

I estimate conditional VaRs using a GJR-GARCH model (Glosten et al. 1993) which accounts for asymmetries in the returns correlation and produces time-varying volatilities. Assuming that the marginal distribution of the standardized returns of a financial institution is a location-scale distribution, the conditional VaR can be expressed as follows:

$$VaR_{it}^i(\alpha) = \sigma_{it} F^{-1}(\alpha) \tag{2.6.13}$$

where σ_{it} is the conditional volatility for each firm i and F (.) denotes the true distribution of the standardized returns r_{it}/σ_{it}. Conditional variances are obtained using quasi maximum likelihood estimation in the GJR-GARCH model. Since the quantile $F^{-1}(\alpha)$ is unknown I replace it by its empirical counterpart.

I also estimate all risk measures at the α=1% risk threshold in order to analyze more severe distress events by focusing on further left tail of the bank's return distribution. The empirical results are robust to the results of the baseline model.

Alternative Regression Models

I also consider two other traditional panel data estimators: pooled-OLS and random-effects models. The random-effect model is specified to control for bank-specific heterogeneity. The results are presented in Tables 2.10 and 2.11 and are robust to the fixed effect estimation outputs. In both models I consider the industry group dummy that takes on the value one when both U.S. and European banks belong to the same industry, either commercial banks or broker-dealers, and zero otherwise. The coefficient on the dummy variable is not statistically significant in both sample panels - there is no evidence suggesting that banks within the same industry group are more connected to one another.

Table 2.10 – Estimation Results for European Banks

	Dependent variable: ΔCoVaR$^{EU\|US}$							
	Pooled OLS				Random Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size^{US}	0.000957***	0.000957***	0.001024***	0.001022***	0.000957***	0.000957***	0.001021***	0.001021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LEV^{US}	0.000056***	0.000056***	0.000057***	0.000056***	0.000055***	0.000055***	0.000056***	0.000056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
STB^{US}	-0.000572	-0.000572	-0.000232	-0.000239	-0.000594	-0.000594	-0.000390	-0.000390
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VaR^{US}	0.162464***	0.162464***	0.159439***	0.159439***	0.162396***	0.162396***	0.159859***	0.159859***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
SIze^{EU}		0.000411***	0.000385**	0.000384**		0.000363**	0.000378**	0.000378**
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
ΔCoVaR$^{EU\|US}$ (-1)			0.035763***	0.035729***			0.027190***	0.027184***
			(0.010)	(0.010)			(0.009)	(0.009)
Industry				0.000017				-0.000008
				(0.000)				(0.000)
Constant	0.000985	0.001018	0.000880***	0.000869***	0.000811***	0.000818***	0.000771	0.000773
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects					Yes	Yes	Yes	Yes
Number of observations	6,786	6,786	6,409	6,409	6,786	6,786	6,409	6,409
Number of bank pairs					377	377	377	377
Adjusted R^2	0.844	0.844	0.839	0.839	0.847	0.847	0.842	0.842

Notes: The table reports the regression results for the European bank sample. All variables are in first-differences. Clustered standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.11 – Estimation Results for U.S. Banks

	Dependent variable: $\Delta\text{CoVaR}^{US\|EU}$							
	Pooled OLS				Random Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size^{EU}	0.000030	0.000030	0.000049	0.000047	-0.000003	-0.000003	0.000031	0.000031
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LEV^{EU}	0.000032***	0.000032***	0.000033***	0.000033***	0.000033***	0.000033***	0.000034***	0.000034***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
STB^{EU}	0.000339	0.000339	0.000500*	0.000501*	0.000333	0.000333	0.000474	0.000474
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VaR^{EU}	0.105265***	0.105265***	0.103212***	0.103180***	0.102565***	0.102565***	0.101399***	0.101399***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Size^{US}		-0.000898***	-0.001050***	-0.001052***		-0.000906***	-0.001066***	-0.001066***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
$\Delta\text{CoVaR}^{US\|EU}$ (-1)			0.017960	0.017687			0.010093	0.010094
			(0.014)	(0.014)			(0.014)	(0.014)
Industry				0.000022				0.000002
				(0.000)				(0.000)
Constant	0.003821***	0.003931***	-0.004141***	-0.004153***	0.004243***	0.004367***	0.004450***	-0.003741***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects					Yes	Yes	Yes	Yes
Number of observations	6,747	6,747	6,370	6,370	6,747	6,747	6,370	6,370
Number of bank pairs					377	377	377	377
Adjusted R^2	0.853	0.854	0.856	0.856	0.855	0.856	0.858	0.858

Notes: The table reports the regression results for the U.S. bank sample. All variables are in first-differences. Clustered standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2.7 Conclusion

In this study I examine how ΔCoVaR can be used in assessing risk dependence between European and U.S. banks. The focus on international linkages between financial firms is very important given that systemic risk materializes through transmission of stress from one institution to another causing disruption in global markets. The quantification of risk dependences can be used as a complementary stress-testing tool to identify "too-connected-to-fail" financial institutions. Banks can also apply this approach to measure their degree of interconnectedness with other peer banks to help them improve their risk management policies.

Using daily stock return data for the sample of U.S. and European banks I estimate $\Delta \text{CoVaR}^{j|i}$ measure which captures the additional risk of an institution conditional on another institution across the border being in distress. Based on this measure I construct the CoRISK indicator which helps to assess the impact of individual bank on its foreign counterparts. I also use the eRISK measure to analyze the overall risk exposure of each institution. The estimates show that the pairwise CoVaR measure brings added-value over VaR to determine the global importance of financial institutions.

I further investigate the determinants of the ΔCoVaR measures separately for European and separately for U.S. banks. The empirical findings are broadly in line with the literature and suggest that leverage, size and VaR are important in explaining interlinkages between financial institutions. However, within the set of institutions in my sample a relevant difference emerges between U.S. and European banks as to bank's size as significant factor.

Indeed, approaches based on market information also have their shortcomings, especially when it relates to the information content of market prices. The underlying assumption is that markets are efficient which may not necessarily be the case. A second issue related to the adoption of "market-based' approaches is that they are not able to take into account domino effects or feedback loops in the assessment of systemic impact of an institution. The cross-border network analysis could be a suitable approach to map the interbank exposures across institutions in the network and capture cascade or domino effects in order to assess more deeply and dynamically the interdependences that may generate cross-border spillovers among institutions. The implementation of this method greatly depends on availability of granular information, including the interbank data, needed as input to estimate systemic linkages. In practice, this type of information is not always available to the general public. Hence, it is crucial that national and global regulators integrate quantitative and qualitative data carefully in the assessment, surveilance and monitoring of systemically relevant financial firms and communicate it clearly to the general public.

In spite of some noted shortcomings, the availability, frequency and the forward-looking nature of the market data utilized in the market approaches may make them potentially useful when designing macro-prudential policy, especially in the absence of timely confident information. Further research should aim to incorporate additional detailed information, consider other key actors in the financial markets and strengthen estimation techniques in order to improve our understanding of the nature of international financial linkages.

Chapter 3

Identifying Systemically Important Financial Institutions: Toward a Simpler Approach

3.1 Introduction

A growing number of recent studies on systemic has proposed various measures which would allow regulators to identify systemically important financial institutions (SIFIs) and allocate macro-prudential capital requirements in order to reduce their risk.[1] Among widely-cited systemic risk measures are the measures of tail dependence in financial institutions' equity returns such as the Delta Conditional Value-at-Risk ($\Delta CoVaR$) of Adrian and Brunnermeier (2011), the Marginal Expected Shortfall (*MES*) of Acharya et al. (2010) and the

[1]See Bisias et al. (2012) for a survey of systemic risk measures.

Systemic Risk Measure *SRISK* of Brownlees and Engle (2012). $\Delta CoVaR$ focuses on market losses conditional on a particular institution being in distress whereas *MES* and *SRISK* define the systemic risk contribution of an institution as the expected losses of this institution given a negative market shock. These three measures aim to evaluate the contribution of an institution to system-wide risk and have been widely discussed in terms of their ability to predict systemic risk ranking of financial institutions.

The key step in the estimation of $\Delta CoVaR$ and *MES* is modeling the joint distribution of individual firm's and market returns taking into account nonlinear dependence between returns. Indeed, markets may be more dependent during extreme downward movements then when they are moving upwards.[2] To account for this property of stock returns, studies that build on the $\Delta CoVaR$ and *MES* propose different estimation methods to account for any possible nonlinear dependence structure of returns. In other words, they try to model the relationship between firm's and market returns during extreme events as accurately as possible in order to obtain a precise measure of the firm's systemic risk contribution. The approach usually involves relatively complicated estimation procedures. For example, Adrian and Brunnermeier (2011) model the tail dependence using quantile regression, Brownlees and Engle (2012) apply nonparametric tail estimator of Scaillet (2005) and Engle et al. (2012) use *Student t* copula. Chuanliang (2012) also suggest various copula functions to more accurately estimate the $\Delta CoVaR$, the *MES* and the *SRISK* whereas Straetmans and Chaudhry (2013) and Balla et al. (2012) use extreme value theory for assessing systemic risk. Yet, the key question is whether or not these attempts are justified given the objectives

[2] This is related to the notion of a financial contagion discussed, for example, in King and Wadhwani (1990), Rigobon (2001), Forbes and Rigobon (2002) and, Bekaert and Harvey (2003).

of the current macro-prudential regulation.

Banking regulation, so far, has focused on individual risk measure, like Value-at-Risk (*VaR*), as a way to determine the minimum capital a financial institution is required to put aside to cover the self-imposed risk. In this regard, it might be important that a financial firm estimates an accurate risk measure utilizing its internal risk model. In contrast, the recent improvements in the Basel III accord envision that capital surcharges be imposed on institutions that are identified as systemically risky according to their systemic relevance [BCBS (2011)].[3] More specifically, the percentage of additional capital that a firm is required to hold is determined by the systemic risk ranking of this institution and is not directly linked to the magnitude of its systemic risk contribution. As such the sufficient requirement for a systemic risk measure should be its ability to accurately identify and rank SIFIs.

This study investigates the impact of nonlinear and linear methods of estimating the Δ*CoVaR*, the *MES* and the *SRISK* on the identification of SIFIs. First, we use quantile regression and nonparametric tail estimator to capture the nonlinear dependence of returns in the calculation of these measures. Second, we model dependence in a linear fashion by assuming that dependence is fully captured by the correlation coefficient. This allows us to simplify our estimations of systemic risk measures. We use two metrics - Kendal rank order correlation and percentage of concordant pairs - to compare the rankings of financial firms according to the estimated risk measures. Our results show that estimation methods that

[3] Financial institutions are assessed based on the indicator-based measurement approach, which considers the individual factors such as the size of institutions, their interconnectedness, the lack of readily available substitutes or bank infrastructure, the global activity and the complexity. Using this methodology the total score for each institution is calculated as a simple average of its five category scores. Next, institutions whose overall score exceeds a cutoff level set by the Basel Committee are allocated into different equally-sized buckets according to their score rankings. The amount of additional capital requirement is then determined for each bucket [Financial Stability Board (2011), Financial Stability Board (2012)].

account for nonlinear dependence structure in returns provides very similar results as the methods that model the dependence structure linearly in terms of their ability to identify SIFIs. The linear estimation methods appear to be sufficient to rank systemically important financial firms according to their systemic risk measures. The advantage of these techniques is the ease of computation and lower estimation errors. Our results support a growing discussion about the simplicity in the systemic risk regulation and estimation. For example, Haldane (2011) highlights the three key principles of a good regulation: (i) simplicity, (ii) robustness and (iii) timeliness. Drehmann and Tarashev (2011), Drehmann (2013) and Rodríguez-Moreno and Pena (2013) argue that the regulation should focus on simple indicator(s) of monitoring systemic risk. Finally, our findings are also in line with Patro et al. (2013) suggesting that daily stock returns correlation is a simple and a sufficiently informative indicator for assessing systemic importance of institutions and monitoring systemic risk.

The remainder of the chapter is structured as follows. Section 3.2 introduces the $\Delta CoVaR$, *MES* and *SRISK* measures and their nonlinear and linear estimation methods. Section 3.3 describes the data used in this paper and presents estimation results. Section 3.4 provides comparative analysis of the rankings of financial institutions obtained using the two estimation methods at different levels of risk. Section 3.5 concludes.

3.2 Measures of Systemic risk

In this section we outline the framework and estimation methods of $\Delta CoVaR$, *MES* and *SRISK* introduced in the seminal papers of Adrian and Brunnermeier (2011), Acharya et al. (2010) and Brownlees and Engle (2012). Based on this framework we present the linear estimation approaches to the computation of these two measures by assuming that dependence is fully captured by correlations.

3.2.1 Definitions

Conditional Value at Risk

Conditional Value at Risk (*CoVaR*) is defined as the *VaR* of the financial system conditional on particular institution i being in financial distress. Given a distress event that the return of institution i is at its α percent *VaR* level, *CoVaR* of the system is given by:

$$Pr\Big(r_{mt} \leq CoVaR_{it}(q,\alpha) | r_{it} = VaR_{it}(\alpha)\Big) = q, \tag{3.2.1}$$

where r_{mt} denotes market return, r_{it} is the return of firm i and q is the conditional probability of market financial distress when firm i is under stress.

The contribution of firm i to system-wide risk, denoted by $\Delta CoVaR_{it}(q,\alpha)$, is then defined as the difference between *VaR* of the system given that institution i is in distress and *VaR* of the system given normal state of institution i:

$$\Delta CoVaR_{it}(q,\alpha) = CoVaR_{it}(q,\alpha) - CoVaR_{it}(q,0.5). \tag{3.2.2}$$

Hence, the $\Delta CoVaR$ measures additional risk that an individual institution imposes on the whole system. Adrian and Brunnermeier (2011) emphasize that a regulation based only on the risk of institutions in isolation can lead to an excessive risk-taking along systemic risk dimensions. We can consider two financial firms that have the same *VaR*s but different Δ*CoVaR*s, and therefore, different level of contribution to the risk of the system. According to the Basel II regulation both firms would be subject to the same capital requirements based on their *VaR*s. However, capital surcharges should be higher for firms that are systemically risky as measured by their Δ*CoVaR*. Using this approach would force firms to limit activities that impose additional risk on the system.

Marginal Expected Shortfall

Marginal Expected Shortfall (*MES*) is defined as the expected equity loss of an institution conditional on the market return falling below some threshold value, C. For a given threshold equal to the conditional VaR of the market, $C = VaR_{mt}(\tau)$, we can express the *MES* of financial firm i at time t as:

$$MES_{it}(\tau) = E_{t-1}\Big(r_{it}|r_{mt} < VaR_{mt}(\tau)\Big) \tag{3.2.3}$$

In contrast to *CoVaR*, which captures market losses when a particular financial firm experiences turmoil, *MES* focuses on the institution's loss when market as a whole is in distress. *MES* can also be interpreted as a measure of the firm's sensitivity to a financial shock. More specifically, *MES* shows the sensitivity of a firm to the exceptionally bad returns of the financial system that it belongs to, which may not be necessarily attributed to a systemic event.

SRISK Measure

SRISK is defined as the expected capital shortfall of a given financial institution conditional on a shock to the financial system:

$$SRISK_{it} = E_{t-1}\Big(Capital\ Shortfall_i | Crisis\Big) \tag{3.2.4}$$

Acharya et al. (2012) further express *SRISK* as follows:

$$SRISK_{it} = max[0; kD_{it} - (1-k)W_{it}(1 - LRMES_{it})] \tag{3.2.5}$$

where $0 < k < 1$ is the prudential capital ratio, D_{it} is the quarterly book value of the bank's total liabilities, W_{it} is the bank's daily market capitalization or market value of its equity and *LRMES* is the long-run *MES*.

Notice that *SRISK* is an increasing function of the liabilities and a decreasing function of the market capitalization. So, *SRISK* can be viewed as an increasing function of the quasi-leverage (leverage hereafter) defined as the ratio of the book value of total liabilities to the market value of equity. The *SRISK* also considers a firm's interconnection with the rest of the system through the *LRMES*. *LRMES* corresponds to the expected drop in the equity value of a firm should the market fall by more than a given threshold within the next six months. Acharya et al. (2012) propose to approximate it as $LRMES \simeq 1 - exp(18 \times MES)$ where *MES* is the expected daily loss if market returns are less than 2%, as defined in Equation (3.2.3).

3.2.2 Estimations

Estimations of the systemic risk measures involve modeling the joint distribution of asset returns. The most common measure for dependency - correlation - can be efficiently used to model the dependence structure of returns when the distribution follows the strict assumptions of normality and constant dependency across quantiles. Existing empirical evidence suggests that asset prices exhibit skewed and heavy tail marginal distributions. Extreme co-movements also occur in multivariate distributions given by asymmetric dependence, which suggests that assets follow different levels of correlation during extreme downward market movements than during upward movements. Conclusions made by simply looking at linear correlation can be misleading for distributions that are not normally distributed due to outliers or strong nonlinear relationship. With these considerations, Δ*CoVaR* and *MES* are usually estimated accounting for possible nonlinear dependence between financial returns.

ΔCoVaR

Adrian and Brunnermeier (2011) propose to estimate *CoVaR* via quantile regression (Koenker and Bassett (1978a)). Quantile regression models the nonlinear relationship between institution's and market returns for different quantiles of the return distribution.

The estimation of ΔCoVaR that accounts for non-linear dependence in returns includes the following step:

First, we run the quantile regression on the following relationship:

$$r_{mt} = \delta_i^q + \gamma_i^q r_{it} + \epsilon_{it} \tag{3.2.6}$$

where r_{mt} is market stock return and r_{it} is financial institution's equity return, and q is the q^{th} quantile of the returns distribution.

Second, the predicted values from Equation (3.2.11) are used to compute *CoVaR* as follows:

$$CoVaR_{it}(q,\alpha) = \hat{\delta}_i^q + \hat{\gamma}_i^q \, VaR_{it}(\alpha) \tag{3.2.7}$$

As in Chapter (2.6) $VaR_{it}(\alpha)$ in Equation (3.2.7) is calculated according to:

$$VaR_{it}^i(\alpha) = \sigma_{it} F^{-1}(\alpha) \tag{3.2.8}$$

where σ_{it} are time-varying volatilities for each firm i. Assuming that $r_{it} \sim F$ a location-scale distribution and the estimation of σ_{it} is done using a GJR-GARCH model (Glosten et al., 1993).

Finally, to examine sensitivity of the system to a distressed institution i, $\Delta CoVaR_{it}$ is estimated as follows:

$$\begin{aligned} \Delta CoVaR_{it}(q,\alpha) &= CoVaR_{it}(q,\alpha) - CoVaR_{it}(q,0.5) \\ &= \hat{\gamma}_i^q \Big(VaR_{it}(\alpha) - VaR_{it}(0.5) \Big) \end{aligned} \tag{3.2.9}$$

Δ*CoVaR* in Equation (3.2.9) is dynamic given that the estimated *VaR*s are time-varying.

The linear version of Δ*CoVaR* can be estimated using standard ordinary least squares (OLS) regression. Given its focus on mean response of the dependent variable OLS does not reflect the extreme quantile relationship between equity returns.

Using the OLS method we can express $\Delta CoVaR_{it}$ as follows:

$$\Delta CoVaR_{it}(\alpha) = \hat{\gamma}_i \Big(VaR_{it}(\alpha) - VaR_{it}(0.5) \Big), \tag{3.2.10}$$

where $\hat{\gamma}_i$ is the estimated slope coefficient comes from the OLS regression of the market return, r_{mt} on firm i's return, r_{it}:

$$r_{mt} = \delta_i + \gamma_i r_{it} + \epsilon_{it} \tag{3.2.11}$$

MES

Our methodological framework of estimating *MES* is based on the linear market model defined by Brownlees and Engle (2012) as follows:

$$r_{mt} = \sigma_{mt}\,\varepsilon_{mt} \tag{3.2.12}$$

$$r_{it} = \sigma_{it}\,\rho_{it}\,\varepsilon_{mt} + \sigma_{it}\,\sqrt{1-\rho_{it}^2}\,\xi_{it} \tag{3.2.13}$$

$$(\varepsilon_{it}, \xi_{it}) \sim F \tag{3.2.14}$$

where ρ_{it} is the correlation between r_{mt} and r_{it}, σ_{mt} and σ_{it} are the volatilities of the market and the firm, respectively, and $(\varepsilon_{mt}, \xi_{it})$ are disturbances that follow an *i.i.d.* process with zero mean vector and identity covariance matrix. $F(.)$ is the bivariate distribution of the standardized innovations, which is assumed to be unknown. Notice that $(\varepsilon_{mt}, \xi_{it})$ are not independent of each other at time t. This assumption of dependence between the innovations is valid given that extreme values of these distributions can happen simultaneously for systemically risky firms.

Given Equations (3.2.12) and (3.2.13) the MES can be expressed as a function of the firm return volatility, its correlation with the market return, and the comovement of the tail of the distribution as follows:

$$\begin{aligned} MES_{it}(\tau) &= \sigma_{it}\ \rho_{it}\ E_{t-1}\Big(\varepsilon_{mt}|\varepsilon_{mt} < VaR_{mt}(\tau)/\sigma_{mt}\Big) \\ &\quad + \sigma_{it}\ \sqrt{(1-\rho_{it}^2)}\ E_{t-1}\Big(\xi_{it}|\varepsilon_{mt} < VaR_{mt}(\tau)/\sigma_{mt}\Big) \end{aligned} \tag{3.2.15}$$

where σ_{it} and σ_{mt} are estimated using GJR-GARCH model Glosten et al. (1993), ρ_{it} is calculated using the asymmetric Dynamic Conditional Correlation (DCC) GARCH model of Engle (2002) and the tail expectation of the standardized market residual, ε_{mt}, and the tail expectation of the standardized idiosyncratic residual, ξ_{it}, are computed using a nonparametric kernel estimator as in Scaillet (2003). The conditional tail expectation in the second term of Equation (3.2.15) capture the tail-spillover effects from the financial system to the financial firm that are not captured by the correlation. Since both marginal distributions of standardized returns are unknown, the conditional expectation in the first term of Equation (3.2.15) is also unknown. If the standardized innovations, ε_{mt} and ξ_{it} are *i.i.d*, the nonparametric estimates of these tail expectations are given by:

$$\hat{E}_{t-1}\Big(\varepsilon_{mt}|\varepsilon_{mt} < \kappa\Big) = \frac{\sum_{t=1}^{T} K(\frac{\kappa-\varepsilon_{mt}}{h})\varepsilon_{mt}}{\sum_{t=1}^{T} K(\frac{\kappa-\varepsilon_{mt}}{h})} \tag{3.2.16}$$

$$\hat{E}_{t-1}\Big(\xi_{it}|\varepsilon_{mt} < \kappa\Big) = \frac{\sum_{t=1}^{T} K(\frac{\kappa-\varepsilon_{mt}}{h})\xi_{it}}{\sum_{t=1}^{T} K(\frac{\kappa-\varepsilon_{mt}}{h})} \tag{3.2.17}$$

where $\kappa = VaR_m(\alpha)/\sigma_{mt}$, $K(x) = \int_{-\infty}^{x/h} k(u)du$, $k(u)$ is a kernel function, and h is a positive bandwidth parameter. Following Scaillet (2005), we fix the bandwidth at $T^{-1/5}$ and select the standard normal probability distribution function as a kernel function.

MES given by Equation (3.2.15) is dynamic given that estimated correlations, ρ_{it}, and volatilities, σ_{it} and σ_{mt} vary over time. Notice that any possible nonlinear dependence between market and firm returns is captured by the second term of Equation (3.2.15).

Under assumption that the dependence between firm and market returns is fully captured by the time-varying correlation Equation (3.2.15) for *MES* reduces to:

$$\begin{aligned} MES_{it}(\tau) &= \sigma_{it}\ \rho_{it}\ E_{t-1}\Big(\varepsilon_{mt}|\varepsilon_{mt} < VaR_{mt}(\tau)/\sigma_{mt}\Big) \\ &= \beta_{it}\ E_{t-1}\Big(r_{mt}|r_{mt} < VaR_{mt}(\tau)\Big) \\ &= \beta_{it}\ ES_{mt}(\tau) \end{aligned} \tag{3.2.18}$$

where $\beta_{it} = \frac{cov(r_{it}, r_{mt})}{var(r_{mt})} = \rho_{it}\ \frac{\sigma_{it}}{\sigma_{mt}}$ is the conditional *beta* of firm i and $ES_{mt} = E_{t-1}\Big(r_{mt}|r_{mt} < VaR_{mt}(\tau)\Big)$ is the expected shortfall of the market. Hence, the "linear" version of *MES* is directly related to the market's expected shortfall.

SRISK

The estimation of *SRISK* is based on the same framework as that of *MES*. According to Engle et al. (2012) the capital shortfall of a given financial firm i is defined as:

$$CS_{it} = k\ D_{it}\ - (1-k)\ (1 - LRMES_{it})\ W_{it}\ , \tag{3.2.19}$$

where D_{it} and W_{it} denote the value of the book value of total liabilities and equity of firm i and k is a prudential capital ratio of equity to assets, and *LRMES* is given by the following equation:

$$\mathit{LRMES}_{it} = \mathit{LRMES}_{i,t:t+T} = -\mathbb{E}_{t-1}\Big(R_{i,t:t+T} | \, R_{m,t:t+T} \leq -40\% \Big) \ , \tag{3.2.20}$$

where $R_{i,t:t+T}$ and $R_{i,t:t+T}$ are cumulative returns defined as:

$$R_{i,t:t+T} = \exp\Big(\sum_{j=1}^{T} r_{i,t+j}\Big) - 1 \quad \text{and} \quad R_{m,t:t+T} = \exp\Big(\sum_{j=1}^{T} r_{m,t+j}\Big) - 1 \ ,$$

LRMES is estimated at a time horizon of six-month and T sets at 126 trading days. Then, the *LRMES* is approximated without simulation by:

$$\mathit{LRMES}_{it} = -\Big(\exp(18 \times \mathit{MES}_{it}(\tau)) - 1\Big) = 1 - \exp(18 \times \mathit{MES}_{it}(\tau)). \tag{3.2.21}$$

Finally, the *SRISK* contribution of a given firm to the risk of the system is given by:

$$\begin{aligned} \mathit{SRISK}_{it} &= \max\Big(0 \, ; CS_{it}\Big) \\ &= \max\Big(0 \, ; k \ D_{i,t} \ - (1-k) \ \exp\Big(18 \times \mathit{MES}_{it}(\tau)\Big) \ W_{i,t}\Big) \ . \end{aligned} \tag{3.2.22}$$

Since SRISK is by construction a function of the MES, possible nonlinear dependence in returns is accounted for in the computation of nonlinear *MES* as given by Equation (3.2.15). Consequently, the linear version of *SRISK* is calculated by using *MES*, as given by Equation (3.2.18), in the definition of *SRISK*.

3.3 Data and Estimation Results

Our sample comprises 94 U.S. financial institutions with equity market capitalization greater than 5 bln USD as of June 30, 2007. We extract daily data on equity return and market value of equity from CRSP and quarterly book value of liabilities from COMPUSTAT spanning the period from 01/03/2000 to 12/31/2011. Out of all financial firms 60 had continuously traded over the sample period. Appendix A4 provides the list of institutions in the sample categorized by industry groups.

All risk measures are estimated at the $q = \alpha = \tau = 5\%$ risk threshold. In accordance with the regulatory standards we set the prudential capital ratio, k, to 8% in the calculation of the $SRISK$.

We first, replicate the estimations of systemic risk measures used in the seminal papers that allow capturing the nonlinear dependence. To simplify estimations, we next model the dependence in returns linearly. We do so in order to compare the rankings of financial firms according to each of the three systemic risk measures, computed using both nonlinear and linear estimation methods.

Table 3.1 provides summary statistics for the estimated systemic risk measures discussed in Section 3.2.2. The first two columns report estimates of $\Delta CoVaR$ obtained via quantile regression (denoted $\Delta CoVaR_{NL}$) and OLS regression (denoted $\Delta CoVaR_{L}$), respectively. Column 3 presents estimates of the MES measure that account for nonlinear dependence (denoted MES_{NL}) and column 4 contains the linear estimates of MES (denoted MES_{L}). The last two columns report estimates of nonlinear and linear $SRISK$ (denoted $SRISK_{NL}$ and $SRISK_{L}$, respectively). As evident from Table 3.1 the standard statistics of the estimated measures that account for nonlinear dependence are very close to those that do not capture nonlinear dependence features in the data. The only exception are the maximum values of two Δ*CoVaR*s, suggesting that nonlinear dependence structure might be better suited to capture extreme events in this case.

Table 3.1 also presents the within standard deviations (across time) and between standard deviations (across financial firms). For the Δ*CoVaR*s and *MES*s the volatility is larger in time series and for the *SRISK* the volatility is larger in cross section due to the strong dispersion across firms' liabilities. The estimated Pearson correlation coefficient between the two Δ*CoVaR*s, $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$, is always equal to 1 and the average correlation coefficients are equal to 0.98 and 0.99 for *MES* and *SRISK*, respectively.

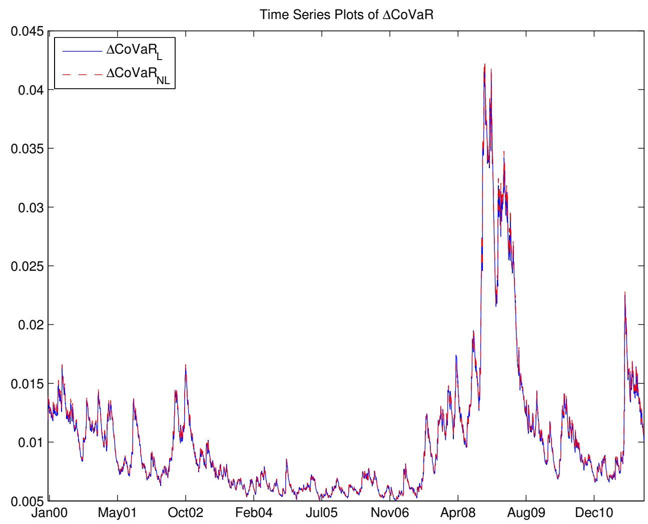
Table 3.1 – Summary Statistics for the Estimated Systemic Risk Measures

	$\Delta CoVaR_{NL}$	$\Delta CoVaR_{L}$	MES_{NL}	MES_{L}	$SRISK_{NL}$	$SRISK_{L}$
Mean	0.0101	0.0103	0.0283	0.0262	-1.2768	-1.6548
Min	0.0007	0.0008	-0.0154	-0.0178	-159.22	-168.51
Max	0.1620	0.1052	0.5625	0.5522	164.73	164.28
Std.Dev	0.0074	0.0074	0.0252	0.0236	18.958	19.209
Between Std.Dev	0.0028	0.0028	0.0080	0.0075	9.652	9.837
Within Std.Dev	0.0060	0.0061	0.0203	0.0191	5.807	5.839

Notes: The table contains descriptive statistics for the estimated systemic risk measures for all firms in the sample. Within standard deviation is computed as the standard deviation of the time-series mean of individual Δ*CoVaR*s, *MES*s and *SRISK*s. Between standard deviation is the standard deviation of the cross-sectional average of Δ*CoVaR*, *MES* and *SRISK* over time. Δ*CoVaR*s and *MES*s are in percentages and *SRISK*s are in billion USD. Sample period is from 01/03/2000 to 12/31/2011.

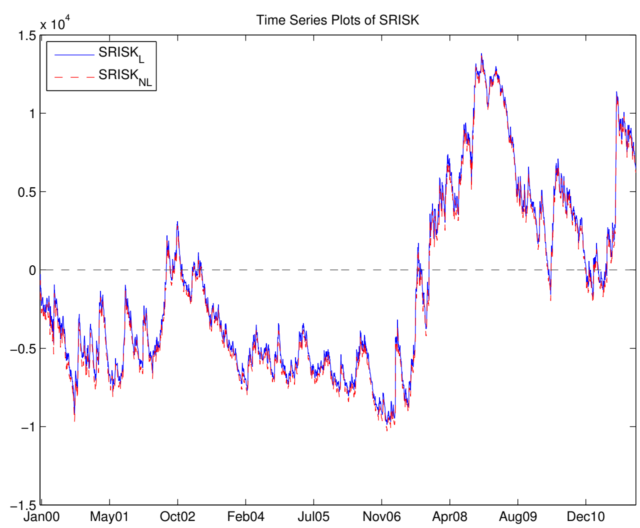
Next we analyze the dynamics of the estimated measures over time. Figure 3.1 time plots $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ averaged over all financial firms, Figure 3.2 displays the time plot of the mean MES_{NL} and MES_{L} measures and Figure 3.3 displays the time plot of the mean $SRISK_{NL}$ and $SRISK_{L}$ measures. In all graphs we observe a very close time-series dynamics of the each measure-pair over the sample period.

Figure 3.1 – Time Series Plots of $\Delta CoVaR$



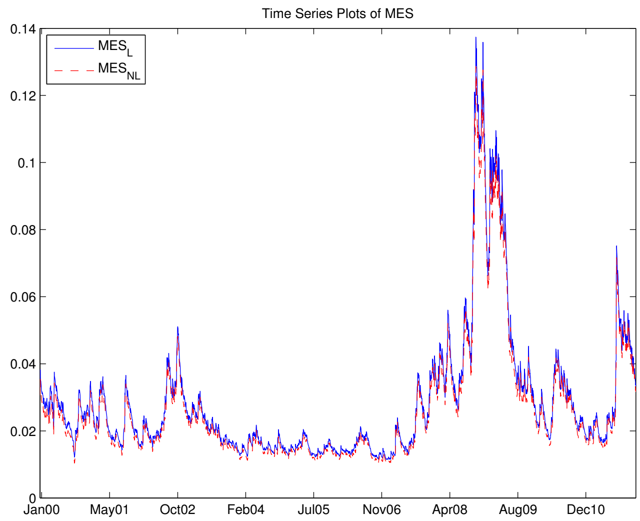
Notes: This figure displays the mean values of $\Delta CoVaR_L$ (blue solid line) and the $\Delta CoVaR_{NL}$ (red dashed line). The estimation period is from 01/03/2000 to 12/30/2011.

Figure 3.3 – Time Series Plots of *SRISK*



Note: This figure displays the mean values of $SRISK_L$ (blue solid line) and the $SRISK_{NL}$ (red dashed line). The estimation period is from 01/03/2000 to 12/30/2011.

Figure 3.2 – Time Series Plots of *MES*



Note: This figure displays the mean values of MES_L (blue solid line) and the MES_{NL} (red dashed line). The estimation period is from 01/03/2000 to 12/30/2011.

3.4 Comparison of Systemic Risk Rankings

In this section, we compare the daily rankings of financial institutions in our sample according to the three systemic risk measures that are computed using nonlinear and linear estimation techniques described in Section 3.2.2. The key objective is to determine whether the two contrasting methods of estimating systemic risk measures lead to the same conclusion.

We use two metrics to compare the systemic risk rankings: the Kendal rank order correlation and the percentage of concordant pairs.

3.4.1 Nonlinearity versus Linearity

Table 3.2 presents the rankings of financial institutions based on their contribution to systemic risk, as measured by $\Delta CoVaR$, *MES* and *SRISK*, for September 15, 2008. This date corresponds to one day before the collapse of Lehman Brothers. We report the results only for top 10 SIFIs for convenience.[4] The first two columns rank firms based on their $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$, respectively. Column 3 reports the ranking based on MES_{NL} and column 4 contains the ranking based on MES_{L}. The last two columns show the ranking based on $SRISK_{NL}$ (column 5) and $SRISK_{L}$ (column 6). We observe that the ranking of SIFIs based on the nonlinear systemic risk measures are very close to their ranking based on the same measures estimated linearly. The percentage of concordant pairs between the $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ is 8, which means that eight SIFIs out of ten are identified by both measures. This number is even higher for the *MES*-pair and for the *SRISK*-pair. $\Delta CoVaR$ and *MES* rank Lehman Brothers as the most systemically risky firm on the date of its bankruptcy. AIG was ranked among top five riskiest financial firms the day before it was rescued by the Federal Reserve. Overall, financial institutions with large systemic risk contribution are identified by all systemic risk measures regardless of the methods we use to estimate them. The mean of the absolute difference in the rankings between nonlinear and linear versions of $\Delta CoVaR$ and *MES* is only 3 and less than 1 for the *SRISK*.

To analyze the dynamics of systemic risk rankings over time we, first, examine the rankings obtained for Bank of America (BAC), the institution that has been continuously traded over the sample period. Figure 3.4 presents the time plot of the absolute daily

[4] Results for all firms are available upon request.

Table 3.2 – Systemic Risk Rankings

Rank	$\Delta CoVaR_{NL}$	$\Delta CoVaR_{L}$	MES_{NL}	MES_{L}	$SRISK_{NL}$	$SRISK_{L}$
1	LEH	LEH	LEH	LEH	C	C
2	MER	MER	AIG	AIG	BAC	BAC
3	AIG	AIG	WM	WM	JPM	JPM
4	WM	BBT	ABK	MER	AIG	AIG
5	NYX	NYX	MER	ABK	MER	MER
6	EV	CMA	MBI	MBI	MS	MS
7	LM	LM	NYX	NYX	GS	GS
8	JNS	EV	CIT	LM	LEH	LEH
9	CMA	JNS	LM	BAC	PRU	MET
10	BEN	WM	SLM	JNS	MET	PRU

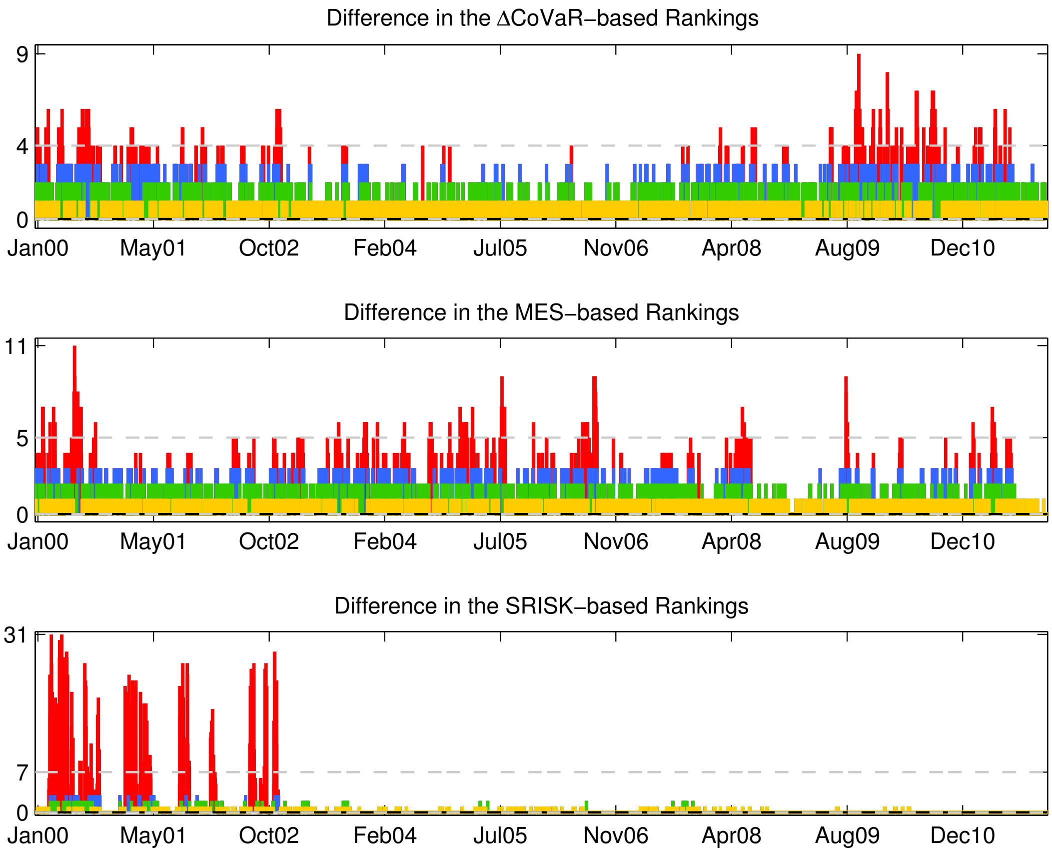
Pairs	$\Delta CoVaR_{NL}$	$\Delta CoVaR_{L}$	MES_{NL}	MES_{L}	$SRISK_{NL}$	$SRISK_{L}$
$\Delta CoVaR_{L}$	8					
MES_{L}			9			
$SRISK_{L}$					10	

Notes: In the upper panel, the column labeled $\Delta CoVaR_{NL}$ displays the ranking of the top 10 financial institutions in terms of $\Delta CoVaR_{NL}$, listed from most to least risky. The following 5 columns display the top 10 financial institutions based on $\Delta CoVaR_{L}$, MES_{NL}, MES_{L}, $SRISK_{NL}$, and $SRISK_{L}$ respectively. In the lower panel, we report the number of concordant pairs between rankings based on systemic risk measures. Rankings are for September 15, 2008.

differences between $\Delta CoVaR_{NL}$-based rankings and $\Delta CoVaR_{L}$-based rankings, MES_{NL} and MES_{L}-based rankings as well as $SRISK_{NL}$ and $SRISK_{L}$-based rankings for BAC. On most days the difference between the rankings of BAC obtained using nonlinear estimation methods and linear estimation methods equals 0 or 1. More specifically, the ranking of BAC based on $\Delta CoVaR_{NL}$ is the same as its ranking based on $\Delta CoVaR_{L}$ on 28% of days over the sample period. Similar results are obtained when we consider the MES-based rankings with the two rankings matching exactly on 26% of the days. $SRISK_{NL}$ and $SRISK_{L}$ produce the same rankings of financial firms on 77% of the days. During some periods the difference between the rankings based on nonlinear measures and the rankings based on linear measures is large. These events are, however, rare. The difference in the ranking greater than 3 (shown by the red line) is observed on only 7%, 10% and 6% of the days for the $\Delta CoVaR$-pair, *MES*-pair and *SRISK*-pair rankings, respectively. The average difference in the rankings for BAC is 1.4 for the $\Delta CoVaR$-based rankings, 1.5 for the *MES*-based rankings and 1.1 for the *SRISK*-based rankings. Moreover, large differences in the *MES*-based rankings are usually observed in calm periods (from 10/2002 to 11/2006 and after 09/2009) when the nonlinear dependence in returns is less pronounced. This suggests that accounting for nonlinear dependence in calm periods may result in the overestimation of institution's systemic risk contribution and, consequently, to the inaccurate identification of SIFIs. The bottom panel of Figure 3.4 shows that there are large differences in the *SRISK*-based rankings before the end of 2002. Indeed, at this period and based on *SRISK*, financial institutions are closely ranked. As a consequence, a very small variation in the values of the *SRISK* may induce a large difference in terms of ranking. However, after October 2002 the *SRISK* had been mainly driven by the leverage and then by the total amount of liabilities resulting in relatively stable rankings, almost without difference between linear and nonlinear estimation methods as can be observed in Figure 3.5 because those quantities are clearly different from one firm to another.

We further examine the rankings for all financial institutions in the sample. Figure 3.6 reports the time series evolution of the Kendall rank order correlation coefficient between the rankings based on nonlinear and linear systemic risk measures. Kendall rank correlation coefficient is a statistic used to measure the association between two measured quantities. Specifically, it measures the similarity of the orderings of the data when ranked by each of the quantities. The figure shows that this coefficient is always greater than 74% for each measure-pair implying a high similarity in the two rankings. On average, the Kendall

Figure 3.4 – Difference in Daily Rankings, Bank of America



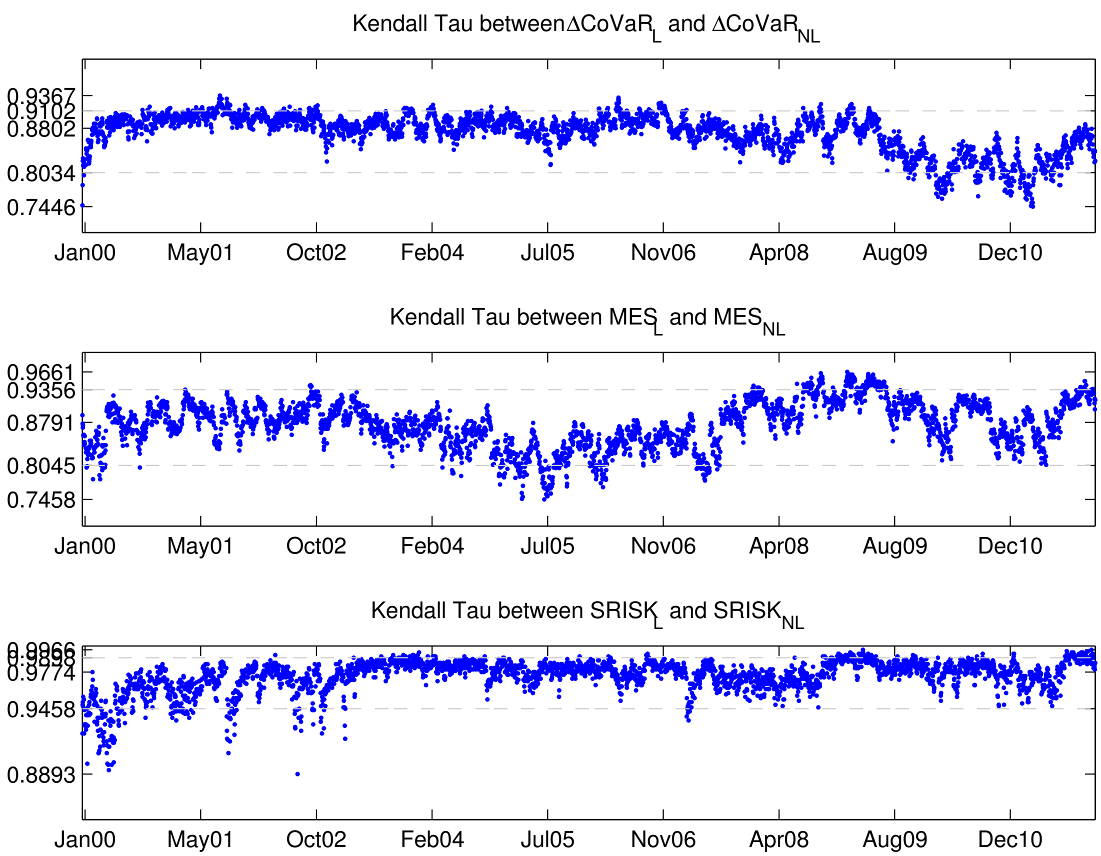
The top figure shows the daily difference between the $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$-based rankings for Bank of America (BAC). The middle figure shows the daily difference in the MES_{NL} and MES_{L}-based rankings for BAC. The bottom figure plots the daily difference between $SRISK_{NL}$ and $SRISK_{L}$-based rankings for this institution. The 0, 1, 2, 3, and >3 differences in the rankings are plotted with black, yellow, green, blue and red lines, respectively. The estimation period is from 01/03/2000 to 12/30/2011.

Figure 3.5 – Rankings of Bank of America

The top panel time plots the daily ranking of Bank of America (BAC) based on $\Delta CoVaR_L$ (blue line) and $\Delta CoVaR_{NL}$ (red line), the middle panel displays the daily ranking of this institution based on its MES_L (blue line) and MES_{NL} (red line) and the bottom panel presents daily ranking based on its $SRISK_L$ (blue line) and $SRISK_{NL}$ (red line). The estimation period is from 01/03/2000 to 12/30/2011.

correlation is 87.18% between $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ rankings, 87.55% between MES_{NL} and MES_{L} rankings, and 97.39% between $SRISK_{NL}$ and $SRISK_{L}$ rankings. These results suggest the relevance of computing systemic risk measures using simpler linear estimation methods for the identification of SIFIs. Although nonlinear techniques are better suited to estimate a more accurate magnitude of an institution's systemic risk importance, they produce the rankings of financial firms very similar to the rankings obtained using simpler estimation methods.

Figure 3.6 – Kendall Rank-Order Correlations



The top figure shows the daily time-varying Kendall rank-order correlation coefficient difference between the $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ whereas the middle figure shows the daily time-varying Kendall rank-order correlation coefficient difference between the MES_{NL} and MES_{L}, obtained for the 60 financial institutions which are continuously trading over the whole period. Finally, the bottom figure plots the results for the *SRISK*. The estimation period is from 01/03/2000 to 12/30/2011.

Next, we estimate the percentage of concordant pairs between the rankings based on systemic risk measures estimated using nonlinear methods and the rankings based on systemic risk measures obtained using the linear methods. The percentage of concordant pairs equals 100 if the ranking of a financial institution according to the "nonlinear" systemic risk measure exactly matches its ranking according "linear" systemic risk measure. For example, concordance is 100% if both $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ produce the same ranking for a given institution. This would suggest that the nonlinear estimation of an institution's systemic risk measure has no value added over its linear estimation with respect to the ranking of this institution.

Figure 3.7 provides some insights to the $\Delta CoVaR$-based rankings analysis. The yellow line plots the percentage of concordant pairs between $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ for top 10 SIFIs, top 20 SIFIs and all 60 financial institutions that had continuously traded over the sample period. Table 3.3 further shows that the average percentage of concordance equals 18% when we consider all firms. In other words, the rankings based on $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ are exactly the same for 10 financial firms. Next we compare the rankings allowing for the deviations from full concordance in terms of one, two or three position changes in the ranking for each firm. Figure 3.7 shows the time plot of the percentage of concordance for these deviations. As given by Table 3.3 the percentage of concordant pairs more than doubles reaching 42% when we allow for one position change in the ranking. On average, the percentage increases by around 20 basis points for every additional difference in the position allowed for. Moreover, the percentage is much higher if we focus on top 10 riskiest firms, ranging from 37% when each institution's ranking is the same, to over 80%

when we allow for two position changes in the ranking. These results indicate that there is no large difference in the identification and ranking of SIFIs between $\Delta CoVaR$ estimated using nonlinear method and $\Delta CoVaR$ computed linearly. The identification of SIFIs is not greatly affected by the methodology of estimating their systemic risk contribution.

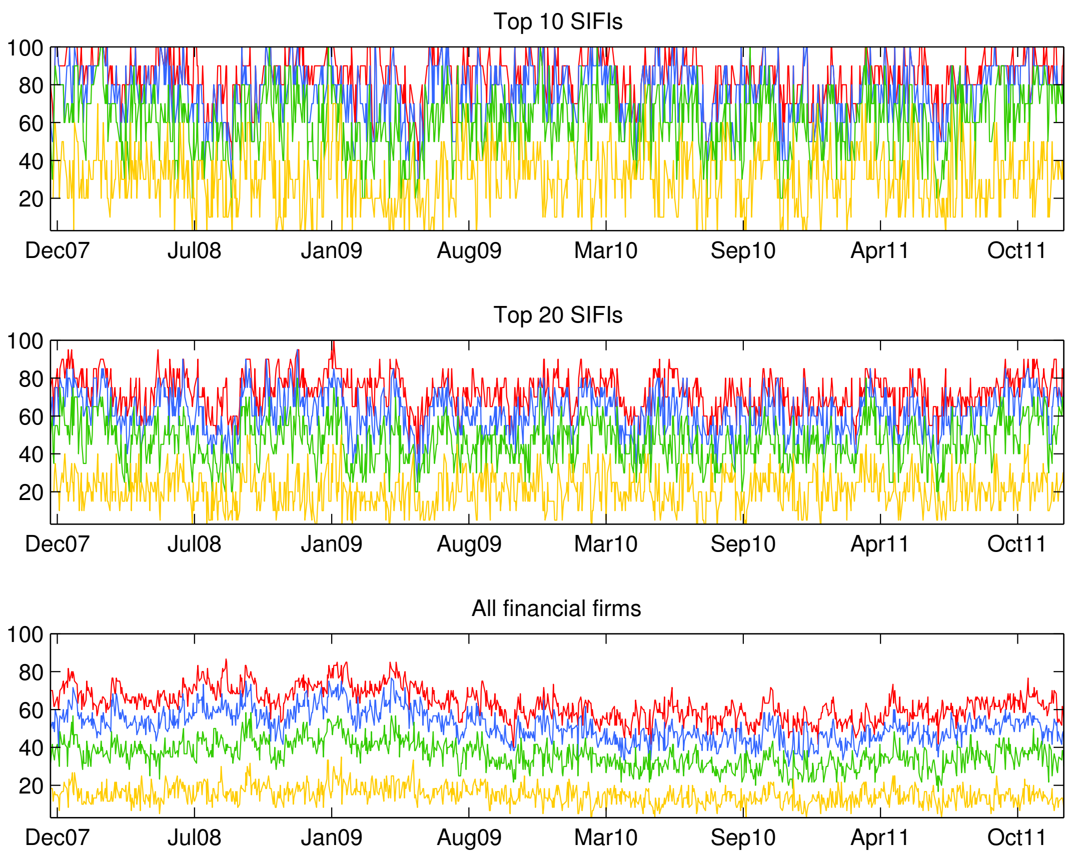
Table 3.3 – Percentage of Concordance for the $\Delta CoVaR$-based Rankings

	Rank Diff.	Mean	Std.Dev	Min	Max
Top 10 SIFIs	3	89	11	30	100
	2	82	14	30	100
	1	68	17	10	100
	0	37	19	0	100
Top 20 SIFIs	3	79	10	35	100
	2	69	12	25	100
	1	53	13	15	95
	0	26	11	0	70
All Firms	3	70	8	40	92
	2	58	8	30	82
	1	42	8	17	65
	0	18	6	3	40

Notes: This table presents descriptive statistics (mean, standard deviation, minimum and maximum values) of the percentage of concordant pairs for the rankings of financial institutions based on $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ for top 10 SIFIs, top 20 SIFIs and all financial institutions which had continuously traded over the sample period. The column labeled Rank Diff. shows the deviations from concordance in terms of 0, 1, 2 or 3 position changes in the ranking of each firm.

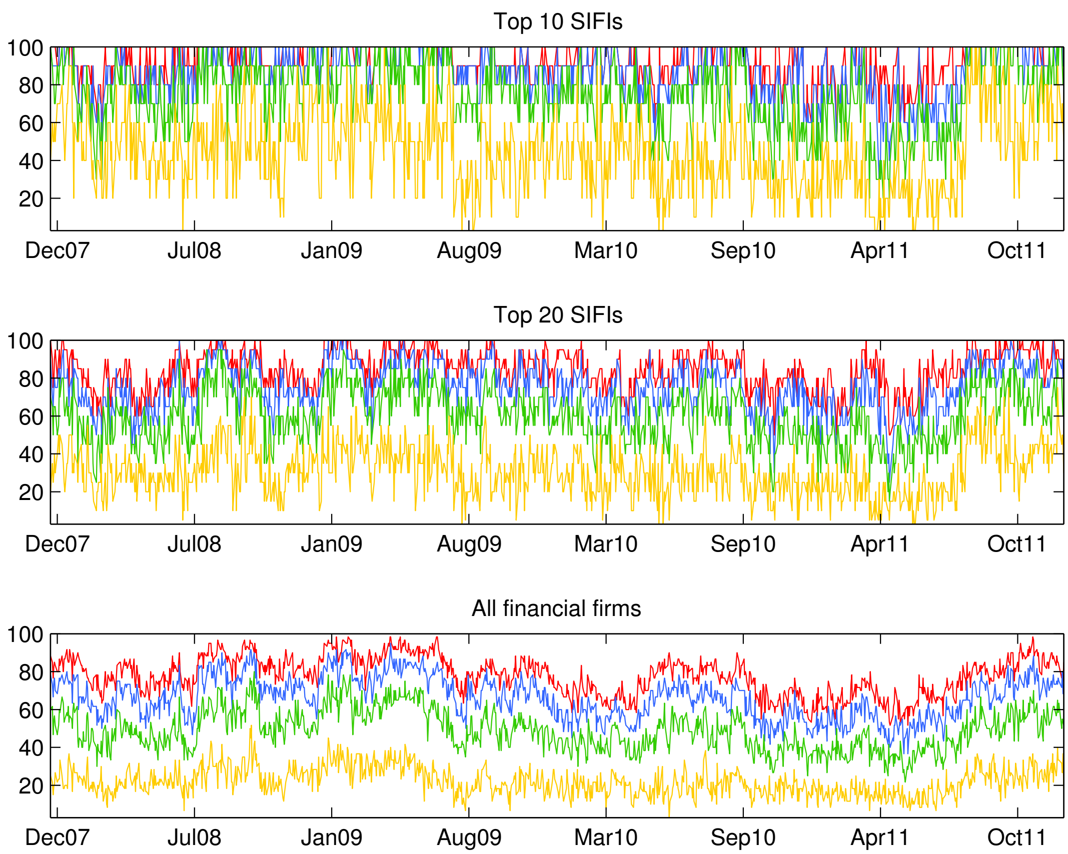
Figure 3.8 time plots the percentage of concordant pairs between MES_{NL} and MES_{L}-based rankings. As in the $\Delta CoVaR$ case we observe a large increase in the percentage when the deviation from concordance increases from 1 to 3 changes in institution's position in the overall ranking. Table 3.4 summarizes the results across the sample period and shows that on average the percentage of concordant pairs is equal to 19%. When we allow for 1, 2 or 3 differences in the ranking the percentage almost doubles growing from 43% to 71%. On average, the percentage growth is close to 20 basis points per additional difference in the position allowed. As shown above the percentage of concordant pairs is much higher for

Figure 3.7 – Percentage of Concordant Pairs for $\Delta CoVaR$-based Rankings



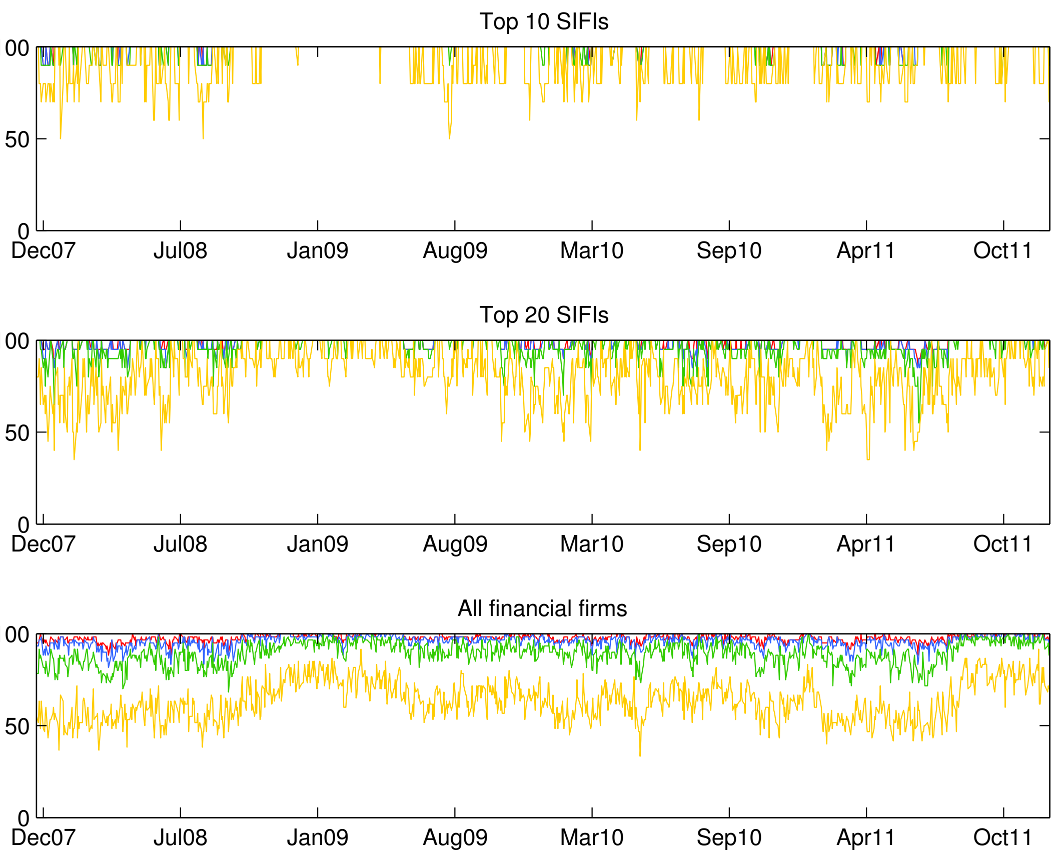
The figure time plots the percentage of concordant pairs between $\Delta CoVaR_{NL}$ and $\Delta CoVaR_{L}$ (yellow line). It also shows the percentage of concordance for deviations allowed in terms of 1 position change in the ranking (green line), 2 positions change in the ranking (blue line) and 3 positions change in the ranking (red line). The top panel considers the top 10 SIFIs, the middle panel focuses on the top 20 SIFIs and the bottom panel considers all 60 financial institutions that had continuously traded over the sample period. The estimation period is from 01/03/2000 to 12/30/2011.

Figure 3.8 – Percentage of Concordant Pairs for *MES*-based Rankings



The figure time plots the percentage of concordant pairs between MES_{NL} and MES_L (yellow line). It also shows the percentage of concordance for deviations allowed in terms of 1 position change in the ranking (green line), 2 positions change in the ranking (blue line) and 3 positions change in the ranking (red line). The top panel considers the top 10 SIFIs, the middle panel focuses on the top 20 SIFIs and the bottom panel considers all 60 financial institutions that had continuously traded over the sample period. The estimation period is from 01/03/2000 to 12/30/2011.

Figure 3.9 – Percentage of Concordant Pairs for *SRISK*-based Rankings



The figure time plots the percentage of concordant pairs between $SRISK_{NL}$ and $SRISK_{L}$ (yellow line). It also shows the percentage of concordance for deviations allowed in terms of 1 position change in the ranking (green line), 2 positions change in the ranking (blue line) and 3 positions change in the ranking (red line). The top panel considers the top 10 SIFIs, the middle panel focuses on the top 20 SIFIs and the bottom panel considers all 60 financial institutions that had continuously traded over the sample period. The estimation period is from 01/03/2000 to 12/30/2011.

top 10 and top 20 SIFIs. On some dates, the percentage of concordant pairs reaches 100% for the top 10, and 90% for the top 20 SIFIs. Furthermore, when we allow for 3 position changes in the ranking, the percentage reaches 77% for the top 20 SIFIs and increases further to 87% for the top 10 SIFIs. This implies that despite the difference in the values of the MES_{NL} and MES_L, the rankings based on MES_{NL} are very close to those based on MES_L.

Table 3.4 – Percentage of Concordance for the *MES*-based Rankings

	Rank Diff	Mean	Std.Dev	Min	Max
Top 10 SIFIs	3	87	13	30	100
	2	81	17	20	100
	1	69	21	0	100
	0	39	21	0	100
Top 20 SIFIs	3	77	15	30	100
	2	68	17	15	100
	1	53	18	5	95
	0	26	14	0	90
All Firms	3	71	11	40	98
	2	59	12	27	95
	1	43	11	15	80
	0	19	7	3	52

Notes: This table presents descriptive statistics (mean, standard deviation, minimum and maximum values) in terms of the percentage of concordant pairs for the rankings of financial institutions based on nonlinear and linear *MES*s for top the 10 SIFIs, top 20 SIFIs and all financial institutions which had continuously traded over the sample period. The column labeled Rank Diff. shows the deviations from concordance in terms of 0, 1, 2 or 3 position changes in the ranking of each firm.

Table 3.5 presents the descriptive statistics for the percentage of concordant pairs between $SRISK_{NL}$ and $SRISK_L$-based rankings. The results show that the two *SRISK*s produce very similar rankings. On average, the percentage of concordant pairs equals 83%, which is twice as much as the percentage of full concordance obtained for the $\Delta CoVaR$ and *MES*-based rankings. This number increases to 99% for the top 10 SIFIs when we allow for 3 position changes in each firm's ranking. The percentage of concordance remains high when we add more firms to the analysis. In particular, it equals 67% for the top 20 risky firms and 59% for all 60 firms, and increases to 97% when we allow for 3 position changes in the rankings. Figure 3.9 further shows that the dynamics of concordance is pretty stable over time. The yellow line time plots the percentage of concordant pairs for the top 10 SIFIs. On almost all days the concordance is greater than 75% and is close to 100%. It does not drop below a 50% mark on 84.03% and 80.39% of days when we consider the top 20 SIFIs and all financial firms.

Table 3.5 – Percentage of Concordance for the *SRISK*-based Rankings

	Rank Diff	Mean	Std.Dev	Min	Max
Top 10 SIFIs	3	99	4	60	100
	2	98	5	50	100
	1	96	8	40	100
	0	83	18	10	100
Top 20 SIFIs	3	97	5	50	100
	2	95	7	40	100
	1	89	12	25	100
	0	67	19	5	100
All Firms	3	97	3	77	100
	2	95	5	62	100
	1	86	8	47	100
	0	59	11	23	92

Notes: This table presents descriptive statistics (mean, standard deviation, minimum and maximum values) in terms of the percentage of concordant pairs for the rankings of financial institutions based on nonlinear and linear *SRISK*s for the top 10 SIFIs, top 20 SIFIs and all financial institutions which had continuously traded over the sample period. The column labeled Rank Diff. shows the deviations from concordance in terms of 0, 1, 2 or 3 position changes in the ranking of each firm.

3.5 Conclusion

In this study we compare nonlinear and linear approaches to the estimation of the three market-based systemic risk measures, *MES*, Δ*CoVaR* and *SRISK*. Our results show that estimation methods that account for nonlinear dependence structure in return series do not greatly improve in terms of identifying SIFIs compared to those that model the dependence structure linearly in a standard framework. However, the choice of the risk threshold has an impact on the results. We show that *SRISK*-based rankings do not change when we use the 1% threshold in the estimation of the systemic risk measures. Given the focus of the current regulation modeling the dependence structure of returns linearly appears to be sufficient to identify and rank SIFIs. These findings are similar to those of Patro et al. (2013) and suggest that the market-based systemic risk measures are mainly driven by stock return correlations.

Chapter 4

Determinants of Credit Risk in Transition Europe

4.1 Introduction

The boom-bust cycle of the recent years has left a legacy of high non-performing loans (NPLs) in many countries in Central, Eastern and Southeastern Europe (CESEE) and the Commonwealth of Independent States (CIS).[1] Rapid growth of credit during 2003-2007 gave rise to an unsustainable boom that came to an abrupt halt with the global financial crisis of 2008. The deep recession that followed after the era of easy foreign-funded credit revealed many of the accumulated underlying problems, including poor quality of loans on banks' books. Since the crisis began the NPL ratios in the region have risen sharply from an average of 3 percent in 2007 to 12 percent in 2013 (Figure 4.1).

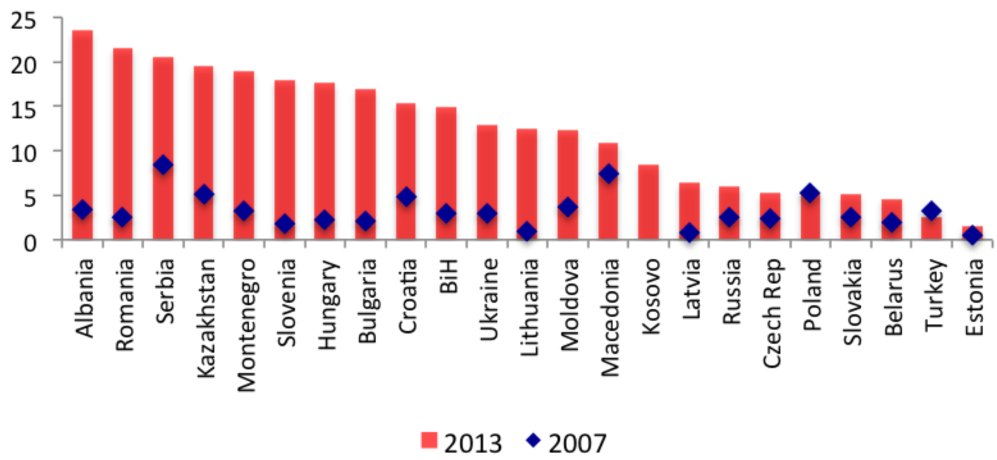
[1] CESEE: Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Kosovo, Latvia, Lithuania, Macedonia, Montenegro, Poland, Romania, Slovak Republic, Slovenia, and Serbia; and CIS: Belarus, Kazakhstan, Moldova, Russia, and Ukraine.

NPL problems became most acute in those countries where the GDP contraction has been significant and where the pre-crisis credit boom had been the most extreme. In Latvia, the real GDP shrank by a stunning 18 percent in 2009 whereas NPLs spiked to 14 percent from about 2 percent recorded in 2008. NPL ratios reached 20 percent in Lithuania, Romania, and Serbia. In contrast, countries that avoided recession, such as Poland, or overcame it quickly, such as Turkey, experienced a more modest rise of NPLs to peak of 5 percent. Loan quality continues to deteriorate in Southeastern Europe, where the economic recovery has been weak, and in Hungary, where in addition to very modest growth a large share of mortgages is denominated in strongly-appreciated Swiss francs. According to Raiffeisen Research, the high level of NPLs in Hungary and Slovenia have a significant negative impact on the entire Central and Eastern region, overshadowing the stable or declining NPL ratios in the Czech and Slovak banking sectors. Elsewhere, NPL ratio seem to have peaked but any reduction tends to be small and is bound to face headwinds from the renewed slowdown of the global economy. In the CIS region, for instance, the average share of NPLs more than doubled from 4 percent in 2008 to 9 percent in 2009 and was on a slight downtrend, from the peak of 9.5 percent in 2010 to 8.3 percent at year-end 2013. However, the distribution of NPL ratio has been uneven across countries ranging between 0.6 percent in Uzbekistan and 20 percent in Kazakhstan[2]. Due to data deficiencies and possible under-reporting of bad loans in some countries the true NPL problem may be even bigger than official statistics suggest.

Poor quality of bank loans is an issue of utmost importance for regulatory authorities concerned with financial stability. As Kaminsky and Reinhart (1999) point out, a large

[2]Source: IMF Financial Stability Indicators and International Financial Statistics.

Figure 4.1 – Nonperforming Loans in Transition Europe



Sources: World Bank World Development Indicators and IMF Financial Stability Indicators.

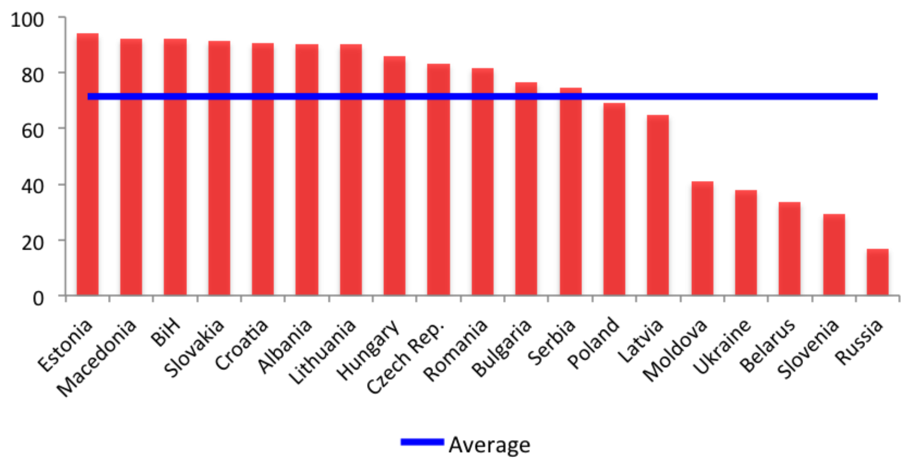
increase in NPLs can signal the onset of a banking crisis. Rising NPLs are particularly dangerous for the financial stability of the CESEE and CIS region, where banks use mainly a traditional business model based on accepting deposits and granting loans. Significant losses that are associated with the deterioration of asset quality can weaken banks' capital base, potentially giving rise to illiquidity or insolvency. Overall financial stability would be at risk if such problems were to arise in a substantial part of the banking system. Furthermore, there is greater concern that persistent weakness in banks' loan portfolios could hamper economic growth. Lessons learned from past financial crises suggest that lasting economic recovery requires a clean-up of the financial sector, and in particular, a reduction of NPLs. Indeed, bad loans on banks' balance sheets create uncertainty and limit their ability to resume lending, thereby imposing downward pressure on aggregate demand and investment.

Another distinguishing feature of the banking systems in the CESEE and CIS region is a dominant presence of foreign banks, mainly from Western Europe. Large western banks have taken strong positions in CESEE since early 2000, bringing to the region expertise, modern business practices and fresh capital. Foreign banks helped improve access to credit and introduced very important banking products that were largely absent in these economies until 2000, like mortgages. They also introduced state-of-the-art risk management practices, good marketing and a customer oriented service culture. Since early 2000 the incidence of banking crises in the region has declined sharply. The few systemic crises that did occur, e.g. in Turkey in 2001 and in Latvia and Ukraine in 2008-09, involved domestic banks only. With the large inflow of foreign banks and foreign funding, credit grew rapidly during the 2002-2007 period with the large share denominated in foreign currency.

BIS data suggest that assets owned by BIS-reporting banks currently exceed 50 percent of GDP in most CESEE countries, with the exception of Macedonia, Turkey, and the European CIS countries. According to EBRD data asset share of foreign banks exceeeds 60 percent in 15 out of 20 countries in CESEE and the European CIS countries. In many countries it surpassed 80 percent in 2011 resulting in an average of 70 percent for the whole region. This number was lower than 40 percent only in Slovenia and the European CIS countries (Figure 4.2). Since 2000 foreign banks' asset share has grown most rapidly in Serbia, Belarus, Ukraine and Albania.

Bank ownership may impact the level of credit risk. Indeed, foreign-owned banks may differ in terms of management, experience, and risk taking behavior and especially in terms of the ways they assess and monitor loans. As such, regulators in the region may need to place greater emphasis on banks' risk management practices in order to detect banks with

Figure 4.2 – Asset Share of Foreign Banks, as % of total assets, 2011



Sources: EBRD Banking Survey and IMF Global Financial Stability Report.

potential NPLs increases and to limit the sources of systemic risk in the future.

Against this background, this study aims to investigate the determinants of credit risk in the transition economies of Europe. The major research topics covered by the analysis are summarized in two strongly interlinked questions, as follows: i) What have been the main drivers of the deterioration in banks' asset quality since early 2000? and ii) Given that foreign banks play an important role in the banking system of these countries, was an increase in credit risk different for foreign banks than for domestic banks?

The study contributes to the literature and ongoing concern about banks' loan quality in two main ways. First, I investigate two distinct types of the determinants of credit risk: macroeconomic and bank-specific for the transition economies of Europe and CIS. This is different from the previous studies on NPLs that focus on the countries of CESEE region, which utilize mainly aggregate, country-level data. Few studies that use bank-level data on problem loans are based on country-specific examples only. The study aims to identify the most significant bank-specific determinants, after controlling for the macroeconomic condition for a large set of countries. These countries are: i) in Central Europe and Baltic States: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic, and Slovenia; ii) in South-Eastern Europe: Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Macedonia, Romania, and Serbia; and iii) in Commonwealth of Independent States: Belarus, Kazakhstan, Moldova, Russia, and Ukraine. They all have gone through the transition from a single bank (state savings bank) system, where banking activities were entirely subservient to central planning, to a market-oriented banking sector.

The empirical methodology focuses on estimating a baseline model with general macroeconomic variables as regressors and then examine if the addition of bank-specific variables increases the explanatory power of the model. The choice of the bank-specific variables is based on hypotheses on credit risk which have been discussed in the literature. Under the assumption that the macroeconomic environment and the business cycle constitute fundamental determinants of NPLs, this methodology allows me to isolate the bank-specific drivers that impact banks' NPLs in transition Europe.

Second, the study examines the differences in NPLs of foreign and domestic banks. This is important given the high reliance of the banking sectors in the region on Western European banks and in view of the recent European crisis. I compare the drivers of NPLs separately for foreign and domestic banks using the dataset from Claessens and van Horen (2013), which tracks the ownership of individual banks over time. The results are helpful in assessing on the pros and cons of foreign bank presence in CESEE and CIS and how to prevent financial crisis by applying more effective monitoring actions.

The analysis uses individual bank information available in the BankScope database. This allows me to obtain a detailed picture of the financial structure of individual banks and to study the determinants of credit risk at the bank level. My sample contains 1287 banks in 15 CESEE and 5 CIS countries for which data on the share of non-performing loans are available. There is no standard approach to analyzing the drivers of NPLs in the literature. Data availability poses a major limitation, constraining the methodological options. My empirical methodology is based on dynamic panel regressions that link each bank's NPL to macroeconomic conditions and the bank's own fundamentals.

The results from the suggest the following. Macroeconomic environment appears to be a key factor that drives banks' credit risk. Rising unemployment rate, nominal exchange rate depreciation and higher inflation contribute to higher NPLs while higher GDP growth lowers the NPL ratio. I also find that banks' own fundamentals influence their asset quality. In particular the credit risk is likely to increase for less solvent and less profitable banks. Larger banks do not appear to have more problem loans than do smaller banks. The results also show that there are both qualitative and quantitative differences among the effects of these variables on the NPL ratio. Although the key bank-level factors impact NPLs, their overall explanatory power is found to be low.

More importantly, my findings show that foreign ownership, after controlling other factors, is associated with higher level of NPLs. The estimation results indicate that foreign ownership increases banks' annual NPLs by 0.2 to 0.6 percentage points. These results highlight the relevance of a bank's ownership in credit risk.

The remainder of the chapter is structured as follows. Section 4.2 provides a literature review on both the macroeconomic and bank-level determinants of NPLs. Section 4.3 describes the data that are used in the analysis. Section 4.4 presents the empirical methodology and the hypotheses that are tested. Section 4.5 discusses the estimation results. The last section concludes and offers some policy implications.

4.2 Literature Review

Existing literature that examines the determinants of credit risk differentiates between macroeconomic and bank-specific factors that influence nonperforming loans.

4.2.1 Macroeconomic Factors

There is rich theoretical literature that discusses the interactions between the financial system and macroeconomic activity. The financial accelerator theory, discussed in Bernanke and Gertler (1989), Bernanke, Gertler and Gilchrist (1999), and Kiyotaki and Moore (1997), has become the most prominent theoretical framework for thinking about macrofinancial linkages. Bernanke and Gertler (1989) and Bernanke, Gertler and Gilchrist (1999) discuss the procyclicality of credit markets and show that asymmetric information between lenders and borrowers as well as the balance sheet channel amplify and propagate credit shocks to the wider economy. Kiyotaki and Moore (1997)'s model demonstrates that in the presence of credit market imperfection even small shocks might be sufficient to explain business cycle fluctuations.

Many studies empirically confirm that the quality of loans is closely linked to the economic cycle. These empirical regularities include the cyclical nature of bank credit, NPLs, and loan loss provisions. In particular, in upturns, contemporaneous NPL ratios tend to be low as borrower enjoy a sufficient stream of income, which improves their debt servicing capacity. Furthermore, during lending booms, banks engage in excessive risk taking by extending loans to lower-quality customers. This later results in the increase in the share of NPLs during the recession period. Hence, in downturns, as unemployment rises and incomes fall, higher-than-expected NPL ratios, coupled with the decline in the value of collateral, engender greater caution among lenders and lead to a tightening of credit extension with adverse impact on domestic aggregate demand.

The set of macroeconomic variables used varies across studies, but broad indicators of macroeconomic performance, such as GDP growth and unemployment, are generally considered as the principle determinants of NPLs. A negative relationship between NPLs and economic growth is a common finding among studies. (Blaschke and Jones, 2001; Gerlach et al., 2005; Baboucek and Jancar (2005); Quagliarello, 2007; Mannasoo and Mayes, 2009; Kattai, 2010; Festic et al. 2011). For example, Baboucek and Jancar (2005) investigate the macroeconomic determinants of loan quality for the Czech banking system and find evidence of a positive correlation between NPLs and unemployment rate and negative correlation between GDP growth and the NPL ratio. Quagliarello (2007) finds that the business cycle affected NPLs for a large set of Italian banks over the 1985-2002 period. Kattai (2010) analyzes the banking system of the three Baltic states and shows that credit risk is associated with economic growth, unemployment and long-term interest rates. Some studies also find a positive relationship between the growth of credit and NPLs. For instance, Festic et al. (2011) demonstrates that the combination of economic slowdown and deterioration in the growth of credit have been negatively associated with the dynamics of bad loans in five EU member countries: Bulgaria, Estonia, Latvia, Lithuania, and Romania. Kauko (2012) examines the macroeconomic drivers of NPLs for 34 advanced and emerging EU countries in the cross-sectional setting. His results show that the deterioration of credit was mainly attributed to the combination of a current account deficit and rapid growth of credit during the pre-crisis period.

Other macroeconomic variables, which were found to affect banks' asset quality, include the exchange rate, interest rate, and inflation. Accordingly, exchange rate depreciation might have a negative impact on loan quality, particularly in countries with a large amount of lending in foreign currency to unhedged borrowers. Rising interest rates worsen the borrowers' ability to pay back the debt, especially in case of variable rate loans. The impact of inflation is ambiguous. On one hand, higher inflation can improve the borrowers' debt servicing capacity by reducing the real value of their outstanding loan, but on the other hand, it can also reduce the borrowers' real income. Baboucek and Jancar (2005) find that the real effective exchange rate appreciation does not exacerbate the NPL ratio but that consumer price inflation is positively correlated with the level of NPLs. In a study covering the nine largest banks in Greece during 2003 - 2009 Vouldis and Metaxas (2012) find a positive relationship between NPLs and real lending rates. Beck et al. (2013) analyze the drivers of NPL development for a global panel covering 75 countries by using annual data on nonperforming loans and find that the real GDP growth, exchange rate and lending rates are all important variables that impact the NPL dynamics.

4.2.2 Bank-specific Factors

The second group of literature looks more at the variability of NPLs across banks and attributes the level of non-performing loans to bank-level factors. This line of research investigates the impact resulting from the problems of an institution and emphasizes the role of bank's management, ownership structure and cost efficiency.

The prominent paper of Berger and DeYoung (1997) examines the causal relationship between credit quality, cost efficiency and bank capital. The authors consider three hypotheses concerning the flow of causality between these variables: i) "bad management" hypothesis, ii) "skimping" hypothesis and iii) "moral hazard" hypothesis. The "bad management" hypothesis postulates that low cost efficiency, as a result of poor skills in collateral appraisal and credit evaluation and monitoring, leads to an increase in NPLs. Berger and DeYoung (1997) find evidence for this hypothesis for U.S. commercial banks for the period between 1985 and 1994. Podpiera and Weill (2008), who analyze Czech banking sector between 1994 and 2005, also find a negative impact of cost-efficiency on the share of banks' NPLs. In their analysis of the determinants of NPLs in the Greek banking sector broken down by three types of loans - business, consumer, and mortgages - Vouldis and Metaxas (2012) show that management inefficiency, proxied by a higher ratio of operating expenses-to-operating income, is positively associated with NPLs.

The "skimping hypothesis" suggests a possible positive causality between high cost efficiency and NPLs. According to this view banks with high level of cost efficiency are likely to be the banks that allocate few resources to credit risk management and monitoring, and, therefore may face the deterioration in their asset quality in the long run. Rossi et al.

(2005), who investigate the relationships between loan quality, cost and profit efficiency, and capitalization, find support for this hypothesis for a sample of 278 banks in nine transition countries - Czech Republic, Estonia, Hungary, Latvia, Lithuania Poland, Romania, Slovakia and Slovenia - during the period from 1995 to 2002.

Finally, the "moral hazard" hypothesis projects that low-capitalization of banks is associated with higher credit risk. Bank managers tend to take on more risk in times when their institutions are not well capitalized. This leads to a higher number of nonperforming loans in the future. Keeton and Morris (1987) demonstrate that indeed excess loss rates were prominent among banks that had relatively low equity-to-assets ratio. The negative relationship between the capital ratio and NPLs was also found in Berger and DeYoung (1997) and Salas and Saurina (2002). More specifically, Salas and Saurina (2002) compare the determinants of problem loans of Spanish commercial and savings banks, taking into account both the macroeconomic and bank-specific variables. They find that in addition to branch expansion, inefficiency, portfolio composition, size, net interest margin, and market power, capital ratio is an important factor that explains bank's credit risk.

Salas and Saurina (2002) further discuss the "product diversification" hypothesis which links the bank's diversification opportunities to the quality of loans extended to customers. According to this hypothesis large banks have more diversified sources of income and, therefore, are less prone to credit risk. There is another channel through which size can affect the level of NPLs. Large banks may have a comparative advantage in processing the information and assessing the creditworthiness of customers. They have better capacity of lending to large customers as they can exploit scale economies in evaluating the hard information that is available on such customers. Salas and Saurina (2002) report a negative relation between bank size and NPLs for a sample of Spanish banks. Rajan and Dhal (2003) find similar empirical evidence for Indian banks.

Credit growth is also found to impact the current level of problem loans. As discussed in Keeton and Morris (1987) rapid credit growth sustained over several years can often signal a credit boom, which is typically followed by an increase in NPL ratios as banks take on too much risk during good times. Above-average credit growth implies that a bank loosening its credit standards or somehow encouraging borrowers to move over their business. It can also mean that the bank has targeted new markets at a low-cost capital base that allows this bank to charge less for its loans. Jimenez and Saurina (2005), who examine the Spanish banking sector from 1984 to 2003 provide evidence of a positive relationship between NPLs and past credit growth.

In summary, the brief review of the empirical studies reveals that both macroeconomic and bank-specific variables may influence banks' credit risk.

4.3 Data

The data used in estimations cover annual statistics for the period 2000 - 2012 and come from several sources. The macroeconomic variables are retrieved from the IMF's International Financial Statistics and World Economic Outlook. They include real GDP growth, unemployment, inflation, nominal effective exchange rate, and lending rate. The data source of nonperforming loans and other bank-specific variables is the Bankscope database. I use unconsolidated balance sheet statements whenever possible, and rely on consolidated statements when unconsolidated information is not available. The definitions and sources of all macroeconomic and bank-level variables are presented in Appendix A4.

The final sample contains 1287 banks operating in 20 CESEE and CIS countries for which data on NPLs are available. I consider only commercial and savings banks, and exclude investment, micro-finance and development banks from the sample. Merged banks are treated as two entities before the merger and one entity after the merger. The countries in the sample are: Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Kazakhstan, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russia, Slovak Republic, Slovenia, Serbia, and Ukraine.[3]

There are two potential concerns with respect to the bank-level data. First, several studies have raised some suspicions regarding the selectivity bias that might be present in the Bankscope database. For example, Bhattacharya (2003) states that two major Indian bank categories, regional rural and foreign, are almost absent from Bankscope. As a consequence, some categories of banks, and more particularly small banks, are likely to be underrepresented. To check whether my sample is exhaustive and covers substantial portion of each country's banking sector, I compare my subset of banks with the full banking population in each country both in terms of the number of banks and their asset share. In general, the Bankscope dataset covers most banks operating in the region, but for a significant fraction of banks the NPLs data are not reported. Nevertheless, my restricted sample of banks accounts on average for about 75 percent of all banks and over 80 percent of total bank assets in the respective banking sectors. The number of banks varies from

[3] I exclude Montenegro from the analysis because Bankscope contains the NPL series for only 1 out of 14 banks reported in the dataset.

6 in Estonia to 911 in Russia and the sample covers between 65 and 97 percent of bank assets. Table 4.1 summarizes information on the number and asset share of banks in their respective countries.

Table 4.1 – Sample Coverage

Country	**Number of Banks**		**Asset Share of Sample**
	Total	Sample	**to Total Bank Assets**
Albania	16	12	80
Belarus	31	16	73
Bosnia and Herzegovina	30	16	85
Bulgaria	30	20	87
Croatia	32	26	90
Czech Republic	43	23	90
Estonia	17	6	65
Hungary	38	13	70
Kazakhstan	39	26	85
Latvia	27	20	86
Lithuania	17	9	84
Macedonia	18	14	96
Moldova	15	14	97
Poland	67	32	71
Romania	31	23	84
Russia	1058	911	68
Serbia	34	20	80
Slovak Republic	26	16	91
Slovenia	25	16	83
Ukraine	182	54	71

Note: Assets are in percent of the total bank assets of that country.
Sources: EBRD Transition Indicators, 2009; European Banking Sector Facts and Figures, 2012; BIS Consolidated Banking Statistics.

The second issue is related to the classification of nonperforming loans. First, there is no internationally accepted standard for NPL measurement. The universal definition of NPLs as specified in the IMF Financial Soundness Indicators Compilation Guide is "the principle or interest that is more than 90 days past due" (IMF, 2006). This definition is used mainly for regulatory purposes. Bankscope contains information on "impaired loans", which is an accounting concept and may differ from the IMF's definition of NPLs. Impaired loans are defined as the total value of the loans that have a specific impairment against them.

Loans can be classified as "impaired" if the lender has doubts that the full amount of the loan as specified in the loan agreement can be collected.

Second, the definitions of "impaired" loans may significantly vary since there is no conformity to classifying impaired loans, both cross country and intra country.[4] The main reason for this is variation in accounting approaches, which are vague in their definition of when a loan is impaired. As a result, national supervisors follow different definitions for loan classification. Barisitz (2011) discusses the differences in the national classification of NPLs across ten Central, Eastern and Southeastern European countries. The conclusion is that NPL definitions seem to be largely comparable across the participating countries as they are based on the "90-days-past-due criterion" and the majority report the total amount of defaulted loans as nonperforming. However, practices regarding the treatment of collateral, restructured loans, criteria other than the overdue period, and multiple loans by the same defaulted borrower vary widely. With this caveat in mind, I use the Bankscope reported series on the share of impaired loans to total gross loans as a measure of credit risk.

4.4 Empirical Specification and Hypotheses

My empirical strategy relies on the dynamic panel regression method in order to account for the time persistence in the growth of nonperforming loans.[5]

[4]For some banks impaired loans will be all non-accrual loans, restructured loans, watchlist loans, and any loan 90+ days overdue. Other banks may opt not to include all or any of the restructured and watchlist loans, and some banks do not include all 90+ overdue loans. Some banks designate loans that are in none of these categories as impared. For example, some banks, where a borrower of an impaired loan is sufficiently linked to the borrower of a normal loan, then the normal loan will also be impaired.

[5]Studies that adopt this methodology to investigate the determinants of problem loans include Salas and Saurina (2002), Louzis et al. (2012), Beck et al. (2013), and Castro (2013) among others.

The dependent variable in the estimations is the ratio of (aggregate) impaired loans to total (gross) loans of a reporting bank i ($i = 1, ..., 1287$) in country j ($j = 1, ..., 20$) at time t ($t = 2000 - 2012$). As in Salas and Saurina (2002) the dependent variable is expressed in terms of a logistic transformation to ensure it spans over the interval of $(-\infty, +\infty)$ and is distributed symmetrically.[6]

The baseline model takes the following form:

$$NPL_{i,j,t} = \alpha NPL_{i,j,t-1} + \beta Macro_{j,t} + \gamma Bank_{i,j,t-1} + \delta Crisis_t + \eta_i + \varepsilon_{i,j,t} \qquad (4.4.1)$$

where $Macro_{i,t}$ is a vector of country-specific macroeconomic variables, $Bank_{i,j,t-1}$ is a vector of time-varying bank-specific variables, $Crisis_t$ is a dummy variable to control for the crisis effect, δ_i are the time-constant bank-specific effects, and $\varepsilon_{i,j,t}$ is a vector of disturbances.

Following the aforementioned literature that confirms the transmission from the macroeconomy to the banking sector, I consider the following set of macroeconomic variables: real GDP growth, change in unemployment rate, inflation, lending rate, and nominal effective exchange rate.

The growth rate of GDP and unemployment rate are used as general indicators of the economic environment. The negative relationship between economic activity and asset quality may reflect the impact of cyclical output downturns on the banking system, the finding that has been highlighted in the literature. The underlying hypothesis is supported by the fact that during the booming phase of the economic cycle NPLs are low, while recession de-

[6]The transformed dependent variable is $ln(NPL_{i,j,t}) - ln(100 - NPL_{i,j,t})$.

presses debtors' reimbursing capacity, pushing NPLs up. An increase in unemployment rate is expected to have a negative impact on the cash flow streams of households and increase the debt burden. Rising unemployment rates also decreases demand forcing firms to cut back production. This is likely to decrease revenues and worsen debt conditions of firms. Hence, I conjecture a negative relation between GDP growth and NPLs and a positive link between the change in unemployment rate and NPLs.

Price inflation is another macroeconomic indicator that influences loan quality. The unexpected rise in inflation under the cyclical downturns is likely to hurt the performance of banks and recovery of loans. Theoretically, it can weaken the ability of borrowers to repay the debt by reducing their real incomes when wages are sticky. On the other hand, it can improve the debt servicing capacity of borrowers by reducing the real value of outstanding loans. The impact of inflation on credit risk, therefore, must be determined empirically. The sample period includes some hyper-inflation country episodes which may drive the results. As a robustness check exercise I also estimate the model without inflation.

Depreciation of the local currency can have mixed implications. On the one hand, it can expose unhedged borrowers, whose income is denominated in local currency, to foreign exchange risk. In this sense, depreciation can contribute to the deterioration of loan quality. On the other hand, exchange rate appreciation may limit firms' growth prospects by squeezing profit margins, especially in export-oriented industries and adversely affect their debt-servicing capacity (Kaminsky and Reinhart, 1996). So, the sign of the relationship between nominal exchange rate and NPLs is indeterminate.[7]

Lending rate is also an important factor that may impact banks' credit risk. Rising

[7] Many countries in the region experienced large exchange rate fluctuations during the sample period.

interest rates increase the debt servicing costs for borrowers, especially if the loan rates are variable. This implies that the effect of loan lending rate on credit risk is expected to be positive. I use nominal rather than real interest rate because when granting loans banks calculate their expected profits and losses in terms of nominal rates. To account for the lag effect the lending rate enters the regression model with a one-year lag.

The impact of crisis is measured in two ways. First, I include a crisis dummy in the regressions for the period 2008 - 2011 to capture the overall difference in banks' performance between before crisis and crisis periods. Alternatively, the crisis dummy is interacted with other right-hand-side variables to analyse how banks change their response to the macroeconomic conditions and their own financial fundamentals.

The empirical model also includes a set of the following bank-specific variables. Return on equity measures bank's profitability and is included to test for the "bad management" hypothesis discussed in Section 4.2. Accordingly, since more profitable banks are better managed and more prudent in credit extension, higher profitability in the past leads to a lower NPL ratio.[8] The equity to asset ratio is another variable considered in the estimations to test for the "moral hazard" hypothesis. It is defined as the proportion of shareholders' equity used to finance a company's assets and measures the capital adequacy of a bank. The ratio is a very common financial indicator used in the region and reflects the solvency of an institution. Since lower solvency is associated with higher risk, the ratio is expected to have a negative relationship with the dependent variable. The growth rate of loans is also included as a regressor. As discussed in Section 4.2, rapid credit expansion during the

[8]For the sake of clarity, it must be stated that, in addition, there may well be an impact of the NPL ratio on banks' profitability in later periods, in particular via net creation of loan loss provisions, with the calculation of impairment charges usually taking more time.

boom periods is associated with a decrease in the quality of extended loans as banks tend to engage in excessive risk taking in good times. I expect a positive sign on the loan growth coefficient.

The size of a bank may also influence its customer profile. Large banks may have a comparative advantage in processing the information and assessing the creditworthiness of their customers, mainly because they have better capacity to allocate additional resources to loan evaluation and monitoring. Moreover, banks of larger size may lend more to large companies, whose hard information is more transparent and easier to evaluate, whereas smaller banks tend to service smaller businesses because of regulatory lending limits. Finally, larger size is associated with more diversification opportunities. So, one can expect a negative relation between diversification and NPLs, since the diversification lowers credit risk.

Tables 4.2a and 4.2b provide the summary statistics for the macroeconomic and bank-specific variables. Table 4.2a reflects the deterioration of the macroeconomic conditions in the region after 2007, as shown by a significant fall in the average growth rates of output and an increase in unemployment. The growth of GDP fell from an average of 6 percent during the pre-crisis period to an average of 1 percent during the crisis period ranging between -18 percent in Latvia and 10 percent in Belarus in 2008. The lowest and highest unemployment rates were also recorded in 2008 ranging from 0.8 percent in Belarus to 34 percent in Macedonia. High double digit inflation rates were observed mainly in Russia, Serbia, Romania, and Belarus in early 2000, whereas negative inflation rates were prominent in Latvia, Macedonia, and Bosnia and Herzegovina during the crisis period.

Table 4.2a – Summary Statistics for Macroeconomic Variables

	Obs.	Mean	St.Dev	Min	Max	Pre-Crisis	Crisis
$GGDP$	260	4.09	4.46	-17.73	13.50	5.99	1.09
ΔUR	240	-0.13	1.80	-5.61	9.37	-0.58	0.63
INF	259	7.61	10.32	-1.22	80.60	8.36	6.43
$NEER$	195	100.09	14.07	62.32	191.66	100.58	100.04
LR	231	13.01	8.32	4.93	67.67	14.05	11.15

Notes: The table reports the descriptive statistics for the macroeconomic variables used in the estimations. The last two columns report the average values for the before (2000-2007) and crises (2008-2011) periods. Sample period is from 2000 to 2012.

Table 4.2b further reveals that the crisis has also significantly affected the overall performance of banks in the region. Compared to the pre-crisis period the average ratio of NPLs almost doubled during the crisis growing from 4 percent to 7 percent, whereas banks' profitability, as measured by the return to equity ratio, dropped from about 12 percent to 5 percent over the same period. Likewise, the average growth rate of loans decreased by almost 50 percent, from 51 percent in 2000 - 2007 to 27 percent in 2008-2001.

Table 4.2b – Summary Statistics for Bank-Specific Variables

	Obs.	Mean	St.Dev	Min	Max	Pre-Crisis	Crisis
NPL	8669	5.84	10.80	0.00	100.00	3.97	6.99
$Size$	10957	2.37	6.57	0.00	81.63	3.17	1.68
EA	10957	19.86	15.64	-43.42	100.00	19.03	20.78
RoE	10936	8.32	21.78	-292.12	662.11	11.72	5.01
LG	9654	36.59	74.30	-100.00	988.29	50.65	26.86

Notes: The table contains the descriptive statistics for the bank-specific variables. NPL is the ratio of impaired loans to total loans. $Size$ is calculated as a ratio of bank's assets to total assets of all sample banks in a particular country. EA is the equity to asset ratio;RoE is the return to equity defined as the ratio of profits to total shareholders' equity; and LG denotes the growth rate of gross loans. The last two columns report the average values for the before (2000-2007) and crises (2008-2011) periods. All variables are in percentage points. Sample period is from 2000 to 2012.

Table 4.4 presents the correlation matrix of all variables included in the estimations. Cross-correlations between macroeconomic variables broadly confirm the expected signs.

GDP growth, inflation rate and nominal exchange rate appreciation are negatively correlated with the level of NPLs, whereas the change in unemployment and lending rate exhibit positive correlations with the dependent variable. As for the bank-level indicators, only the return to equity ratio has an expected sign and exhibits a negative correlation with the dependent variable. Size and equity to asset ratio are positively correlated with the level of NPLs. The negative correlation of NPLs with the loan growth results from the contemporaneous effect of the volume of loans in the denominator of the NPL ratio.

Table 4.4 – Correlation Matrix

	NPL	$GGDP$	ΔUR	INF	LR	$NEER$	$Size$	EA	RoE	LG
NPL	1									
$GGDP$	-0.18	1								
ΔUR	0.16	-0.80	1							
INF	-0.15	-0.03	0.17	1						
LR	0.11	-0.37	0.42	0.51	1					
$NEER$	-0.26	0.49	-0.17	0.37	-0.03	1				
$Size$	0.11	0.01	0.03	-0.23	-0.02	-0.12	1			
EA	0.03	-0.04	0.01	0.10	0.04	0.02	-0.18	1		
RoE	-0.21	0.19	-0.16	0.03	-0.08	0.15	0.05	-0.09	1	
LG	-0.17	0.17	-0.15	0.04	-0.04	0.09	-0.04	-0.04	0.09	1

Notes: The table reports the correlation matrix for all variables included in the estimations.

To test for the stationarity of the variables I run the Fisher-ADF unit root test, which assumes that individual unit root processes across banks are included in the panel. The test shows that all panels are stationary at the conventional 5 percent significance level.

4.5 Estimation and Results

4.5.1 Estimation

I begin the empirical data exploration by running fixed effect regression on Equation (4.5.3) which allows me to control for the unobserved bank heterogeneity.[9] However, the fixed-effect estimation may give rise to a "dynamic panel bias" because the lagged dependent variable in Equation (4.5.3) is correlated with bank-specific effects (Roodman, 2009).[10]

Taking the first-difference of Equation (4.5.3) leads to the elimination of bank-specific effects since they do not vary over time:

$$\Delta NPL_{i,j,t} = \alpha \Delta NPL_{i,j,t-1} + \beta \Delta Macro_{i,j,t} + \gamma \Delta Bank_{i,t-1} + \delta \Delta Crisis_t + \Delta \varepsilon_{i,j,t} \quad (4.5.2)$$

However, the transformed model contains two sources of bias. First, by construction the lagged dependent variable, $NPL_{i,j,t-1}$, in $\Delta NPL_{i,j,t-1}$ is still correlated with the lagged error term, $\varepsilon_{i,j,t-1}$ in $\Delta\varepsilon_{i,j,t}$. Second, in the presence of a reverse causality any regressors that are not strictly exogenous become potentially endogenous with respect to $\varepsilon_{i,j,t-1}$.[11] Therefore, one still needs to instrument for $NPL_{i,j,t-1}$.

To work around this problem, Arellano and Bond (1991) propose the generalized method of moments (GMM) approach, known as the "difference GMM estimator". The method uses longer lags of the regressors, which remain orthogonal to the error, as suitable

[9] Standard errors are cluster-corrected using each bank as a cluster.

[10] The random effects estimator is also biased in a dynamic panel data setting. To check the robustness of my results I reestimate the models using a random effect estimator. The Hausman test favors the use of the fixed effects model.

[11] The strict exogeneity assumption requires that the error term is uncorrelated with all past, current and future values of each independent variable (Wooldridge, 2006).

instruments in the estimation of Equation (4.5.2). More specifically, in the one-step GMM the first-differenced lagged dependent and predetermined variables are instrumented with their past levels and the strictly exogenous variables are instrumented with themselves. Under the assumption of independent and homoscedastic residuals the one-step GMM estimation produces consistent parameter estimates.

The major weakness of the first-difference transformation method is that it magnifies gaps in the unbalanced panel. This may lead to significant data losses when the number of time series observations is limited. An alternative to differencing is the "orthogonal deviations" approach of Arellano and Bover (1995) that preserves sample size in panels with gaps. Instead of taking the difference between the current and lagged observation this method subtracts the average of all future available observations of a variable from the contemporaneous observation, thereby, minimizing data loss. Moreover, lagged observations are now available as instruments. I use this approach to estimate the model via one-step GMM.

Another drawback of the "difference GMM" is that the lagged levels of regressors can be poor instruments for the first-differenced regressors if the series exhibit high level of persistence. Arellano and Bover (1995) and Blundell and Bond (1998) suggest the "system GMM" estimator that augments Arellano-Bond by making an additional assumption that the first differences of instrument variables are uncorrelated with the fixed effects. Essentially, the system GMM estimator uses the level Equation (4.5.3) to obtain a system of two equations: one differenced equation and one equation in levels. This allows introducing more instruments and can dramatically improve efficiency. Thus, the bank-specific variables are treated as predetermined and instrumented with their own first differences in the level equation. The macroeconomic variables are assumed to be strictly exogenous and instrumented by themselves as IV style instruments.[12]

According to the Arellano-Bond methodology the following two procedures must be completed to ensure the consistency of the GMM estimates. First, I test the null hypothesis of no second-order autocorrelation in the transformed error term, $\Delta\varepsilon_{i,j,t}$ using the AR(1) and AR(2) Arellano-Bond tests for first and second order autocorrelations of the residuals (Arellano and Bond, 1991).[13] Next, I check for the overall validity of the instruments using the Hansen test of overidentifying restrictions discussed in Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998). The Arellano-Bond tests rejects the hypothesis that errors are not correlated in the first order and fails to reject the null hypothesis of no autocorrelation in the second order. The Hansen test suggests that the instruments are not correlated with the residuals.

4.5.2 Results

Table 4 reports the baseline results for the fixed-effect (FE), Difference GMM and System GMM estimators, respectively. Column (1) of each estimated model contains the output with only macroeconomic variables as regressors. Bank-specific variables are added in the second column, and columns (3) and (4) report the results for the specifications that include the interaction of the crisis dummy with the core regressors in each of the estimated models. For the GMM regressions, I also report the Hansen test results and the number of

[12] See Roodman (2009) for details.

[13] Note that estimates are still consistent in the presence of the first-order autocorrelation in the error term.

instruments at the bottom of the table.

Econometric results indicate that the macroeconomic indicators are the principle determinants of banks' loan quality. Unemployment has been found a leading indicator, suggesting that a rise in unemployment has a negative impact borrowers' ability to service their debts. The coefficient of the change in unemployment rate is statistically significant across all estimations. The regression results in the third and fourth columns for all models show that during the boom period of 2000 - 2007, a 10 percentage point increase in unemployment growth had led to about 1 percentage point decrease in the annual level of NPLs. The analysis also finds a significant negative effect of nominal exchange rate on NPLs.[14] A depreciation of domestic currency is associated with deterioration of banks' loan quality which confirms the hypothesis that depreciation exposes unhedged borrowers of foreign-currency denominated loans to foreign exchange risk. Moreover, GDP growth interest rate, inflation and exchange rate changes are also statistically relevant, as demonstrated by the System GMM estimator results. For all macroeconomic variables, the estimated coefficients are statistically significant and have the expected sign, compatible with the theoretical arguments surveyed in Section 4.2. Rising lending rates are found to increase the level of problem loans - the coefficients of the lending rate are positive as expected.

Columns (2) and (4) of Table 4 present the coefficients estimates when bank-specific variables are included in the model. The incorporation of bank-level indicators in the baseline model does not affect the quantitative effect of the macroeconomic fundamentals. All coefficients of the macro-variables retain their sign and economic and statistical significance across different models with the bank-specific variables. However, the impact of bank-level

[14] An increase of nominal effective exchange rate ($NEER$) represents an appreciation of the home currency.

financial indicators is somewhat less clear. First, the coefficient of the lagged dependent variable is positive and statistically significant. The implication is that NPLs are likely to rise when they have increased in the previous year. The diversification hypothesis is clearly rejected for the set of banks in my sample. When the size variable is used as a proxy for diversification, the corresponding coefficients are not statistically significant across the FE and Difference GMM models. The size effect is significant in the System GMM model but does not have the expected sign. These results suggest that size may not fully capture diversification or that there may be countertendencies to the degree of risk-taking from increasing size, e.g.large banks may engage in more risky activities compared to the activities of smaller banks. The System GMM estimations also suggest that while larger banks exhibited higher level of NPLs during the boom period of 2000 - 2007, such positive relationship dropped after 2008 (Column 4). As for other bank-specific indicators, both the return on equity and solvency ratios do not appear as important factors that explain the NPL dynamics. Although the coefficients of both variables have the expected sign they are significant only in few specifications and at 10 percent significance level only. In particular, the System GMM estimations show that these two financial indicators were somewhat significant before the crisis. Interestingly, past loan growth has a negative relationship with NPLs although its economic significance is also very low.

Table 4 – Baseline Regression Results, All Banks in the Sample

	Fixed Effects				Difference GMM				System GMM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
NPL (-1)	0.361***	0.330***	0.357***	0.325***	0.427***	0.408***	0.417***	0.417***	0.578***	0.553***	0.573***	0.558***
	(0.020)	(0.021)	(0.021)	(0.021)	(0.061)	(0.056)	(0.062)	(0.056)	(0.040)	(0.039)	(0.0409)	(0.038)
GGDP	-0.017	-0.020	-0.039*	-0.043**	-0.015	-0.017	-0.033	-0.028	-0.066***	-0.040**	-0.078***	-0.068***
	(0.014)	(0.015)	(0.020)	(0.021)	(0.014)	(0.015)	(0.021)	(0.022)	(0.012)	(0.016)	(0.018)	(0.019)
x *Crisis*			0.031	0.037			0.0234	0.010			0.018	0.026
			(0.022)	(0.025)			(0.024)	(0.027)			(0.024)	(0.029)
ΔUR	0.110***	0.102***	0.158***	0.142***	0.111***	0.106***	0.158***	0.154***	0.099***	0.106***	0.107***	0.103***
	(0.021)	(0.022)	(0.025)	(0.027)	(0.021)	(0.022)	(0.025)	(0.027)	(0.019)	(0.021)	(0.027)	(0.030)
x *Crisis*			-0.052	-0.039			-0.056	-0.056			-0.016	0.013
			(0.036)	(0.036)			(0.036)	(0.037)			(0.038)	(0.043)
INF	0.001	-0.003	-0.008	-0.021*	0.003	-0.000	-0.005	-0.014	-0.042***	-0.017	-0.027***	-0.027***
	(0.008)	(0.008)	(0.011)	(0.012)	(0.008)	(0.008)	(0.011)	(0.012)	(0.007)	(0.012)	(0.009)	(0.010)
x *Crisis*			0.003	0.028**			0.001	0.013			-0.042***	-0.034***
			(0.012)	(0.014)			(0.011)	(0.014)			(0.010)	(0.012)
NEER	-0.009***	-0.010***	-0.001	-0.002	-0.008**	-0.008**	-0.000	0.000	-0.015***	-0.014***	-0.013***	-0.009***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
x *Crisis*			-0.008*	-0.006			-0.007	-0.009*			-0.010***	-0.016***
			(0.004)	(0.005)			(0.004)	(0.005)			(0.004)	(0.004)
LR (-1)	-0.004	0.001	-0.010	-0.002	-0.005	-0.002	-0.011	-0.006	0.032***	0.036***	0.021***	0.024***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)	(0.010)	(0.011)	(0.011)	(0.005)	(0.008)	(0.005)	(0.005)
x *Crisis*			0.040***	0.031**			0.038***	0.021			0.028**	0.016
			(0.015)	(0.013)			(0.014)	(0.013)			(0.012)	(0.012)
Size		-0.007		-0.006		0.013		-0.016		0.048**		0.021***
		(0.015)		(0.016)		(0.035)		(0.030)		(0.020)		(0.008)
x *Crisis*				0.010***				-0.002				-0.019**
				(0.004)				(0.007)				(0.007)
EA (-1)		-0.006*		-0.006		-0.004		-0.011		-0.002		-0.009*
		(0.003)		(0.005)		(0.012)		(0.014)		(0.005)		(0.005)
x *Crisis*				-0.001				0.012				0.007
				(0.004)				(0.009)				(0.006)
RoE (-1)		-0.002*		-0.003		-0.001		-0.000		-0.001		-0.003*
		(0.001)		(0.002)		(0.001)		(0.002)		(0.001)		(0.001)
x *Crisis*				0.001				-0.000				0.002
				(0.002)				(0.002)				(0.002)
LG (-1)		-0.001*		-0.000		-0.002***		-0.000		-0.002***		-0.000
		(0.000)		(0.001)		(0.001)		(0.002)		(0.000)		(0.001)
x *Crisis*				-0.001*				-0.001				-0.001
				(0.001)				(0.002)				(0.001)
Crisis	0.760***	0.841***			0.673***	0.195			-0.216	-0.557*		
	(0.114)	(0.131)			(0.202)	(0.224)			(0.224)	(0.319)		
Constant	-1.953***	-1.856***	-1.853***	-1.737***								
	(0.339)	(0.348)	(0.374)	(0.623)								
Number of observations	6,284	5,545	6,284	5,545	5,190	4,489	5,190	4,489	6,284	5,545	6,284	5,545
Number of banks	1,094	1,056	1,094	1,056	1,006	973	1,006	973	1,094	1,056	1,094	1,056
Adjusted R-squared	0.317	0.317	0.319	0.319								
Number of instruments					50	186	55	231	68	273	73	326
Hansen, p-value					0.21	0.43	0.28	0.53	0.1	0.35	0.15	0.3
AR(1), p-value					0	0	0	0	0	0	0	0
AR(2), p-value					0.31	0.57	0.26	0.48	0.67	0.86	0.6	0.67

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

To check the robustness of the estimations I also run the regressions excluding inflation as independent variable. I perform this exercise because many countries of the region exhibited periods of very high inflation during the sample period covered in the analysis. Table 4.6 contains the estimation results for all three models, which are very similar to the results presented in the previous table. All coefficients retain their sign and explanatory power.

Given that Russian banks account for over 70 percent of the sample, their inclusion in the estimations are likely to drive the results. Moreover, as emphasized in Beck et al. (2013) the definition of NPLs in Russia does not conform with the international practices to account for the total amount of troubled loan and includes only the due installments and interest. This underestimation of the NPLs can distort the results for the whole region.[15] To check for the significance of my findings I run alternative regressions by excluding Russian banks from the sample. Table 4.7 reports the estimation results for the sample restricted to banks in 19 countries. The results are broadly in line with the full sample results. All macroeconomic variables have the same sign. Change in unemployment and lending rate have a positive relation with NPLs whereas GDP growth, inflation rate and nominal effective exchange rate are negatively correlated with banks' credit risk. Compared to the full sample result the explanatory power of the return on equity and capital ratio coefficients is higher in the restricted sample. Higher profitability and lower leverage are associated with lower NPLs, lending support to the "bad management" and "moral hazard" hypotheses. This is consistent with the findings of Berger and DeYoung (1997), Podpiera and Weill (2008) and

[15]This might be one of the reasons why the ratio of NPLs on average is smaller compared with that in other countries in the sample.

Louzis et al. (2012). As before, the “diversification” hypothesis does not find support for the CESEE and CIS banking systems. Furthermore, the “countercyclical lending” hypothesis is rejected, as it implies a positive relation between past credit and current NPLs.

Table 4.6 – Regression Results for the Model without Inflation, All Banks in the Sample

	Fixed Effects				Difference GMM				System GMM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
NPL (-1)	0.361***	0.330***	0.358***	0.327***	0.428***	0.407***	0.418***	0.414***	0.575***	0.550***	0.580***	0.547***
	(0.020)	(0.021)	(0.021)	(0.021)	-0.061	-0.057	(0.062)	(0.057)	(0.041)	(0.040)	(0.042)	(0.040)
$GGDP$	-0.017	-0.018	-0.036*	-0.044**	-0.016	-0.017	-0.031*	-0.026	-0.069***	-0.041**	-0.080***	-0.070***
	(0.013)	(0.014)	(0.018)	(0.020)	-0.013	-0.014	(0.019)	(0.021)	(0.013)	(0.016)	(0.019)	(0.020)
x $Crisis$			0.030	0.038			0.023	0.009			0.029	0.035
			(0.022)	(0.025)			(0.024)	(0.026)			(0.025)	(0.029)
ΔUR	0.110***	0.103***	0.158***	0.138***	0.110***	0.106***	0.158***	0.152***	0.104***	0.109***	0.099***	0.096***
	(0.021)	(0.022)	(0.025)	(0.027)	-0.021	-0.022	(0.025)	(0.028)	(0.019)	(0.021)	(0.027)	(0.030)
x $Crisis$			-0.050	-0.036			-0.054	-0.054			0.026	0.036
			(0.036)	(0.037)			(0.036)	(0.037)			(0.039)	(0.043)
$NEER$	-0.009***	-0.010***	-0.001	-0.005	-0.008**	-0.008**	-0.001	-0.001	-0.018***	-0.014***	-0.017***	-0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	-0.004	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
x $Crisis$			-0.006*	-0.004			-0.006	-0.007			-0.004	-0.008**
			(0.004)	(0.004)			(0.004)	(0.004)			(0.003)	(0.004)
LR (-1)	-0.004	0.000	-0.012	-0.007	-0.005	-0.002	-0.012	-0.009	0.012***	0.028***	0.014***	0.0173***
	(0.011)	(0.012)	(0.012)	(0.012)	-0.011	(0.011)	(0.011)	(0.011)	(0.004)	(0.008)	(0.004)	(0.005)
x $Crisis$			0.042***	0.041***			0.039***	0.026**			-0.011	-0.009
			(0.014)	(0.013)			(0.014)	(0.013)			(0.014)	(0.014)
$Size$		-0.007		-0.006		0.013		-0.011		0.048***		0.024***
		(0.015)		(0.015)		(0.035)		(0.029)		(0.018)		(0.008)
x $Crisis$				0.008**				-0.003				-0.012*
				(0.004)				(0.007)				(0.006)
EA (-1)		-0.006*		-0.006		-0.004		-0.012		-0.002		-0.009**
		(0.003)		(0.005)		(0.011)		(0.014)		(0.005)		(0.005)
x $Crisis$				-0.000				0.013				0.007
				(0.004)				(0.009)				(0.007)
RoE (-1)		-0.002*		-0.003*		-0.000		-0.000		-0.001		-0.003*
		(0.001)		(0.002)		(0.001)		(0.002)		(0.001)		(0.002)
				0.001				0.000				0.002
				(0.002)				(0.002)				(0.002)
LG		-0.001*		-0.000		-0.002***		-0.001		-0.002***		-0.000
		(0.000)		(0.001)		(0.001)		(0.002)		(0.000)		(0.001)
x $Crisis$				-0.001				-0.001				-0.001
				(0.001)				(0.002)				(0.001)
$Crisis$	0.763***	0.829***			0.761***	0.199			-0.229	-0.603*		
	(0.113)	(0.129)			(0.112)	(0.214)			(0.220)	(0.311)		
Constant	-1.940***	-1.903***	-2.053***	-1.675***								
	(0.332)	(0.341)	(0.404)	(0.569)								
Number of observations	6,284	5,545	6,284	5,545	5,190	4,489	5,190	4,489	6,284	5,545	6,284	5,545
Number of banks	1,094	1,056	1,094	1,056	1,006	973	1,006	973	1,094	1,056	1,094	1,056
Adjusted R-squared	0.317	0.317	0.319	0.319								
Number of instruments					49	185	53	229	67	272	65	324
Hansen, p-value					0.20	0.42	0.27	0.55	0.10	0.30	0.10	0.18
AR(1), p-value					0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2), p-value					0.31	0.56	0.27	0.49	0.77	0.90	0.81	0.86

Notes: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4.7 – Baseline Regression Results, Restricted Sample

	Fixed Effects				Difference GMM				System GMM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
NPL (-1)	0.408***	0.401***	0.403***	0.396***	0.149	0.317***	0.111	0.246***	0.470***	0.431***	0.463***	0.443***
	(0.039)	(0.035)	(0.040)	(0.036)	(0.136)	(0.087)	(0.137)	(0.080)	(0.090)	(0.077)	(0.092)	(0.065)
GGDP	-0.023	-0.026*	-0.027	-0.030	-0.0299**	-0.025*	-0.050**	-0.036	-0.047***	-0.055***	-0.049**	-0.066***
	(0.014)	(0.014)	(0.020)	(0.021)	(0.014)	(0.014)	(0.025)	(0.022)	(0.013)	(0.013)	(0.023)	(0.021)
x *Crisis*			0.008	0.007			0.039	0.013			0.003	0.032
			(0.027)	(0.030)			(0.034)	(0.029)			(0.031)	(0.032)
ΔUR	0.054***	0.053***	0.077***	0.072**	0.0394**	0.057***	0.042	0.065**	0.030	0.024	0.087***	0.075**
	(0.019)	(0.020)	(0.026)	(0.028)	(0.020)	(0.020)	(0.032)	(0.031)	(0.020)	(0.021)	(0.029)	(0.032)
x *Crisis*			-0.034	-0.028			0.008	-0.023			-0.078*	-0.034
			(0.037)	(0.042)			(0.043)	(0.042)			(0.040)	(0.046)
INF	-0.003	-0.002	-0.017	-0.020	-0.013	-0.001	-0.032**	-0.032**	-0.008	-0.012	-0.024**	-0.028**
	(0.009)	(0.008)	(0.013)	(0.013)	(0.010)	(0.008)	(0.015)	(0.015)	(0.008)	(0.008)	(0.012)	(0.012)
x *Crisis*			0.034**	0.044**			0.044**	0.051**			0.033**	0.047***
			(0.016)	(0.017)			(0.018)	(0.021)			(0.015)	(0.018)
NEER	-0.019***	-0.017***	-0.017***	-0.016***	-0.026***	-0.017***	-0.024***	-0.018***	-0.011***	-0.014***	-0.010***	-0.010**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)
x *Crisis*			0.008*	0.004			0.008	0.005			0.008*	0.007
			(0.005)	(0.005)			(0.005)	(0.005)			(0.005)	(0.005)
LR (-1)	0.012	0.015	0.018	0.022*	0.021	0.014	0.030*	0.033**	0.013**	0.033***	0.012**	0.024***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.012)	(0.016)	(0.016)	(0.005)	(0.010)	(0.006)	(0.009)
x *Crisis*			0.018	0.004				-0.012			0.023*	0.003
			(0.015)	(0.013)				(0.019)			(0.012)	(0.014)
Size		-0.010		-0.010		-0.020		-0.015		0.016		0.009
		(0.013)		(0.013)		(0.043)		(0.038)		(0.013)		(0.007)
x *Crisis*				0.006				0.000				-0.013*
				(0.005)				(0.008)				(0.008)
EA (-1)		-0.019**		-0.020**		-0.024		-0.028		-0.030**		-0.019
		(0.009)		(0.010)		(0.028)		(0.032)		(0.014)		(0.012)
x *Crisis*				0.006				0.029				0.010
				(0.007)				(0.023)				(0.017)
RoE (-1)		-0.002***		-0.002		-0.004***		-0.001		-0.004***		-0.006***
		(0.001)		(0.002)		(0.001)		(0.003)		(0.001)		(0.002)
x *Crisis*				-0.000				-0.002				0.002
				(0.002)				(0.003)				(0.002)
LG (-1)		-0.001		-0.000		-0.004**		-0.003		-0.002*		-0.001
		(0.001)		(0.001)		(0.002)		(0.002)		(0.001)		(0.001)
x *Crisis*				-0.002				0.001				-0.001
				(0.002)				(0.003)				(0.002)
Crisis	-0.374***	0.092			-0.692***	-0.320*			-0.394	0.207		
	(0.139)	(0.089)			(0.222)	(0.166)			(0.298)	(0.289)		
Constant	0.644**	0.789***	-1.219*	-0.671								
	(0.279)	(0.261)	(0.632)	(0.577)								
Observations	1,441	1,356	1,441	1,356	1,176	1,110	1,176	1,110	1,441	1,356	1,441	1,356
Number of id	265	246	265	246	227	212	227	212	265	246	265	246
Adjusted R-squared	0.602	0.613	0.605	0.616								
Number of instruments					26	66	31	87	38	123	43	152
Hansen, p-value					0.83	0.52	0.81	0.62	0.27	0.57	0.23	0.60
AR(1), p-value					0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2), p-value					0.93	0.18	0.95	0.28	0.32	0.18	0.34	0.30

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.5.3 Foreign Ownership

Does bank ownership impact NPLs? To answer this question I investigate the differences in the performance of foreign and domestic banks using bank ownership information. I utilize the ownership dataset from Claessens and Van Horen (2013) which allows me to track the ownership of individual banks over time. This is different from most other studies where a bank's ownership is often defined only based on its most recent status. Time varying ownership information is important to gauging the ownership effect on NPLs in Central, Eastern and Southeastern Europe and CIS - a region that has seen many bank ownership changes since 2000.

The database contains bank ownership information for 5,324 banks in 137 countries for the period 1995-2009. For each bank it reports the year of its establishment, the year of inactivity, its ownership status (foreign or domestic) and the home country of the majority shareholder, if foreign-owned. A bank is defined as foreign-owned when over 50 percent of its shares are held directly by foreigners.[16]

I am able to match 315 banks from the Bankscope database with those included in the ownership dataset for the period from 2000 to 2009. The last observation of the ownership data is 2009, which may not allow for capturing the differences in banks' response during the crisis period as accurately as possible. The estimations capture the foreign ownership effect in the following way. Some regressions include foreign ownership related dummies, to gauge the average difference between domestic and foreign banks. Next, I consider the interaction of the foreign ownership dummy with the crisis dummy in order to further explore the

[16]For detailed description of the dataset see Claessens and Van Horen (2013).

variations among foreign banks.

The revised baseline model takes the following specification:

$$NPL_{i,j,t} = \alpha NPL_{i,j,t-1} + \beta Macro_{j,t} + \gamma Bank_{i,j,t-1} + \delta Crisis_t + \eta_i + \theta Own_{i,j,t} + \sigma COwn_{i,j,t} + \varepsilon_{i,j,t} \tag{4.5.3}$$

where $Own_{i,j,t}$ controls for foreign ownership and $COwn_{i,j,t}$ are the variables controlling for the joint effect of crisis and foreign ownership.

Table 4.8 reports the estimates of the foreign ownership effect. In column (1) of each model, FE, Difference GMM and System GMM, respectively, the crisis and foreign ownership effects are captured by the crisis dummy, the foreign ownership dummy, and their interaction term. In Column (2), rather than including the crisis dummy, the model interacts the core regressors with the crisis dummy and contains a separate dummy to account for the ownership effect. This provides a better understanding of the reasons for the changes between the performance of foreign and domestic banks during the crisis period.

Foreign ownership per se, after controlling all other factors, appears to be associated with higher level of NPLs. The coefficient of the foreign ownership dummy is statistically significant across all regression models. The System GMM results show that foreign ownership increases banks' annual NPLs by 0.5 to 0.6 percentage points. The coefficient of the ownership in the second column of each model is also significant, which suggests that NPLs had increased more for foreign banks than for domestic banks during the pre-crisis period. There is no evidence suggesting that NPLs grew more for foreign banks during the crisis. The coefficient of the foreign ownership-crisis interaction terms is positive but insignificant.

Table 4.8 – Bank Ownership Regression Results

	Fixed Effects		Difference GMM		System GMM	
	(1)	(2)	(1)	(2)	(1)	(2))
NPL (-1)	0.283***	0.259***	0.345***	0.287***	0.522***	0.523***
	(0.049)	(0.048)	(0.112)	(0.109)	(0.097)	(0.094)
GGDP	-0.033*	-0.023	-0.03	-0.018	-0.049**	-0.058**
	(0.018)	(0.025)	-0.021	(0.026)	(0.020)	(0.028)
x *Crisis*		-0.052		-0.067		-0.029
		(0.042)		(0.044)		(0.047)
ΔUR	0.103***	0.074**	0.096***	0.072*	0.059*	0.083**
	(0.026)	(0.034)	-0.03	(0.037)	(0.031)	(0.039)
x *Crisis*		-0.028		-0.059		-0.091
		(0.060)		(0.070)		(0.072)
INF	0.000	0.002	0.004	0.002	-0.009	-0.015
	(0.010)	(0.013)	-0.009	(0.013)	(0.012)	(0.015)
x *Crisis*		0.047**		0.036*		0.013
		(0.019)		(0.011)		(0.018)
NEER	-0.015***	-0.008	-0.012**	-0.007	-0.007	-0.0094**
	(0.005)	(0.006)	(0.005)	(0.007)	(0.004)	(0.004)
x *Crisis*		0.029***		0.030***		0.023**
		(0.008)		(0.010)		(0.011)
LR (-1)	0.018	0.015	0.016	0.016	0.023**	0.021**
	(0.013)	(0.013)	(0.012)	(0.014)	(0.009)	(0.001)
x *Crisis*		0.069***		0.046		0.010
		(0.023)		(0.030)		(0.021)
Size	0.017	0.017	0.033	0.0301	0.016	0.011
	(0.019)	(0.018)	(0.050)	(0.054)	(0.015)	(0.015)
x *Crisis*		0.012**		0.011		-0.023
		(0.006)		(0.017)		(0.018)
EA (-1)	-0.012	-0.008	-0.030	-0.012	-0.018	-0.004
	(0.010)	(0.010)	(0.027)	(0.031)	(0.014)	(0.024)
x *Crisis*		-0.029***		-0.002		-0.015
		(0.008)		(0.029)		(0.026)
RoE (-1)	-0.002	-0.002	-0.002	-0.003	-0.003	-0.001
	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.003)
x *Crisis*		-0.002		-0.000		-0.006
		(0.004)		(0.001)		(0.005)
LG (-1)	0.001	0.001	-0.002	-0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
x *Crisis*		-0.001		0.006**		0.001
		(0.002)		(0.003)		(0.002)
Crisis	-0.089		-0.076			
	(0.287)		(0.347)			
Own	0.258**	0.268**	0.223*	0.404**	0.538**	0.603***
	(0.169)	(0.170)	(0.419)	(0.439)	(0.249)	(0.204)
COwn	0.090		0.079		0.365	
	(0.131)		(0.265)		(0.231)	
Constant	-0.953*	-5.601***				
	(0.519)	(1.119)				
Number of observations	1,327	1,327	1,012	1,012	1,327	1,327
Number of banks	315	315	277	277	315	315
Adjusted R-squared	0.412	0.430				
Number of instruments			92	100	144	155
Hansen, p-value			0.60	0.66	0.48	0.21
AR(1), p-value			0.00	0.01	0.02	0.03
AR(2), p-value			0.72	0.76	0.64	0.54

Notes: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

However, as noted before, the crisis dummy captures only the first two years of crisis, which may not be sufficient to fully assess the effect of the crisis on banks' performance. It is also important to note that when a foreign ownership dummy is added as an explanatory variable other core bank-specific variables become statistically insignificant. All macroeconomic variables are significant and have the expected sign except the inflation rate which is now insignificant across all models.

4.6 Conclusion

In this study I use dynamic panel methods to investigate the empirical determinants of NPLs in the CESEE and CIS regions. My results show that macroeconomic variables are important drivers of banks' credit risk. The real GDP growth, the change in unemployment rate, inflation and exchange rate have a strong effect on the level of NPLs. The coefficient of these explanatory variables is significant, proving that the slowdown in the economic activity has greatly affected the financial stability of the region. Moreover, bank-specific variables such as performance and solvency possess additional explanatory power when added into the baseline model thus lending support to the "bad management" and "moral hazard" hypotheses linking these indicators to the quality of management.

More importantly, my findings show that bank ownership has been a significant factor in explaining the rising NPL ratios in the region. Increase in NPLs is larger for foreign banks than for domestic banks.

High levels of NPLs across the region are a legacy of the recent crisis. As economic recovery came to the countries of the region relatively late and remains weak, NPL ratios are still expected to cause problems undermining the financial stability of the region. The findings of the study have several implications in terms of regulation and policy. Specifically, there is evidence that performance measures may serve as leading indicators for future problem loans. This suggests that regulatory authorities should focus on managerial performance in order to detect banks with potential NPLs increases. In addition, macroeconomic and bank-level indicators can be used for forecasting and stress testing purposes for both regulators and banks. Such tests are widely applied by the regulatory authorities the EU, US and UK.

In general, the solution to the problem of NPLs would be a proactive and cooperative approach of creditors, debtors and the regulatory system. This kind of comprehensive approach is particularly important in the region, given that any restructuring would help spur economic recovery, thereby also helping lift the value of collateral backing other loans. Further research would require a longer time series for non-performing loans for each country, which would enable exploring the determinants of NPLs in more detail. This in turn would help policy makers to get a clearer image of the steps necessary to stabilize their banking systems in the post-crisis period.

Appendices

A1 – List of Financial Institutions

Country	Bank	Ticker	Total Assets	Market Value
Austria	Erste Group Bank	EBS	267.18	24.75
Belgium	KBC Group SA	KBC	465.94	46.68
	Dexia SA	DEXB	781.62	36.61
Denmark	Danske Bank A/S	DANSKE	558.83	28.12
France	BNP Paribas* †	BNP	2,252.20	107.63
	Credit Agricole SA†	ACA	1,884.30	66.80
	Societe General* †	GLE	1,519.40	80.00
	Natixis	KN	729.04	29.86
Germany	Commerzbank AG*	CBK	863.97	31.34
	Deutsche Bank AG* †	DBK	2,623,90	72.49
Great Britain	Barclays Bank Plc* †	BARC	2,324.70	91.43
	HSBC Holdings Plc* †	HSBA	2,150.40	215.09
	Lloyds Banking Group	LLOY	708.70	62.98
	Royal Bank of Scotland†	RBC	2,029.70	120.48
	Standard Chartered†	STAN	297.49	45.87
Ireland	Allied Irish Banks	ALBK	239.92	24.00
Italy	Banca Monte dei Paschi	BMPS	231.70	20.38
	Intesa SanPaolo SpA	ISP	816.48	95.64
	UniCredit SpA†	UCG	1,176.00	92.96
Netherlands	ING Groep NV†	INGA	1,786.20	95.47
Norway	DnB NOR Bank ASA†	DNBNOR	244.05	17.26
Spain	Banco Bilbao Vizcaya†	BBVA	631.47	87.52
	Banco Popular Espanol†	POP	132.65	22.74
	Banko Santander SA†	SAN	1,198.90	115.91
Sweden	Nordea Bank AB	NDA	507.68	40.70
	Skandinaviska Enskilda	SEBA	319.89	22.31
	Svenska Handelsbanken	SHBA	287.37	17.46
	Swedbank AB	SWEDA	218.59	18.76
Switzerland	Credit Swiss Group AG* †	CSGN	1,158.40	74.82
	UBS AG* †	UBSN	2,078.90	116.25
United States	Bank of America†	BAC	1,534.36	216.92
	BB&T	BBT	127.58	22.45
	Bank of New York Mellon†	BK	126.33	31.50
	Bear Stearns*	BSC	423.30	17.72
	Citigroup†	C	2,220.87	255.14
	Goldman Sachs* †	GS	943.20	100.38
	JP Morgan Chase†	JPM	1,458.04	164.66
	Lehman Brothers*	LEH	605.86	38.90
	Merill Lynch*	MER	1,076.32	71.83
	Morgan Stanley* †	MS	1,199.99	89.44
	National City Corp	NCC	140.64	18.87
	PNC Financial Services	PNC	125.65	24.48
	Regions Financial	RF	137.62	23.32
	Suntrust Banks	STI	180.31	29.93
	State Street†	STT	112.27	23.03
	US Bancorp	USB	222.53	56.93
	Wells Fargo & Co†	WFC	539.87	118.25

Notes: * denotes broker-dealers and † denotes global systemically important banks (G-SIBs). Assets and market value of equity are in billion USD as of 06/30/2007.

A2 – Description of the Variables for Chapter 2

Variable	Definition	Source
I. Macro-financial Variables		
a) *U.S.*		
VIX	Implied Volatility on the S&P 500 Index	Bloomberg
Liquidity Spread	3month U.S. repo rate - 3month T-bill rate	Bloomberg, FED's H.15 Release
Change in T-bill	3month T-bill rate, change	FED's H.15 Release
Term Spread Change	U.S. 10year Treasury bond - 3month T-bill, change	FED's H.15 Release
Credit Spread Change	Moody's BAA corporate bond - 10year Treasury bond, change	FED's H.15 Release
Market Return	Equity Market Return	CRSP
b) *Europe*		
VDAX	Implied Volatility on German DAX Index	Bloomberg
Liquidity Spread	3month EURIBOR - 3month German government bond	Bloomberg
Change in T-bill	3month German government bond, change	Bloomberg
Term Spread Change	10year German gov.bond - 3month German gov.bond, change	Bloomberg
Equity Market Return	FTSE Stock Index Return	Bloomberg
II. Bank-Specific Variables		
Return	Equity Return, daily closing share prices	CRSP, Bloomberg
Assets	Total assets, in billion USD	COMPUSTAT, Bloomberg
Leverage	Ratio of Total Assets to Total Equity	COMPUSTAT, Bloomberg
Short-term Borrowing	Ratio of Short-term Debt to Total Assets	COMPUSTAT, Bloomberg

A3 – Tickers and Company Names by Industry Groups

Depositories (29)		Insurance (32)	
BAC	Bank of America Corp.	ABK	Ambac Financial Group
BBT	BB&T Corp.	AET	Aetna
BK	Bank of New York Mellon Corp.	AFL	AFLAC Inc.
C	Citigroup Inc.	AIG	American International Group Inc.
CBH	Commerce Bancorp	AIZ	Assurant
CMA	Comerica Inc.	ALL	Allstate Corp.
HBAN	Huntington Bancshares Inc.	AOC	Aon Corp.
HCBK	Hudson City Bankshares Inc.	BKLY	W.R. Berkley Corp.
JPM	JP Morgan Chase & Co.	BRK	Berkshire Hathaway Inc.
KEY	Keycorp New	CB	Chubb Corp.
MI	Marshall & Ilsley Corp.	CFC	Countrywide Financial
MTB	M&T Bank Corp.	CI	CIGNA Corp.
NCC	National City Corp.	CINF	Cincinnati financial Corp.
NTRS	Northern trust Corp.	CNA	CNA Financial Corp.
NYB	New York Community Bancorp Inc.	CVH	Coventry health Care Inc.
PBCT	Peoples United Financial Inc.	FNF	Fidelity National Financial
PNC	PNC Financial Services Grp Inc.	GNW	Genworth Financial
RF	Regions Financial Corp.	HIG	Hartford financial Svcs Grp Inc.
SNV	Synovus Financial Corp.	HNT	Health Net Inc.
SOV	Sovereign Bancorp	HUM	Humana Inc.
STI	Suntrust Banks Inc.	LNC	Lincoln National Corp.
STT	State Street Corp.	MBI	MBIA Inc.
UB	Unionbancal Corp.	MET	MetLife
USB	US Bancorp	MMC	Marsh & McLennan Cos Inc.
WB	Wachovia	PFG	Principal Financial Group
WFC	Wells Fargo & Co	PGR	Progressive Corp.
WM	Washington Mutual	PRU	Prudential Financial
WU	Western Union	SAF	Safeco
ZION	Zions Bancorp	TMK	Torchmark Corp.
		TRV	Travelers companies Inc.
		UNH	United Health Group Inc.
		UNM	Unum Group

Broker-Dealers (10)		Others (23)	
AGE	A.G. Edwards	ACAS	American Capital Ltd
BSC	Bear Stearns	AMP	Ameriprise Financial
ETFC	E*Trade Financial Corp.	AMTD	TD Ameritrade Holding Corp.
GS	Goldman Sachs group Inc.	AXP	American Express Co.
LEH	Lehman Brothers	BEN	Franklin Resources Inc.
MER	Merill Lynch	BLK	BlackRock Inc.
MS	Morgan Stanley Dean Witter & Co	BOT	CBOT Holdings
NMX	Nymex Holdings	CBG	C.B. Richard Ellis Group
SCHW	Schwab Charles Corp.	CBSS	Compass Bancshares
TROW	T. Rowe Price Group Inc.	CIT	CIT Group
		CME	CME Group
		COF	Capital One Financial Corp.
		EV	Eaton Vance Corp.
		FITB	Fifth Third Bancorp
		FNM	Fannie Mae
		FRE	Freddie Mac
		HRB	H&R Block
		ICE	Intercontinental Exchange
		JNS	Janus Capital
		LM	Legg Mason Inc.
		NYX	NYSE Euronext
		SEIC	SEI Investment Company
		SLM	SLM Corp.

A4 – Description of the Variables for Chapter 4

Variable		Definition	Source
I. Macroeconomic Variables			
GDP growth	$GGDP$	Growth rate of real gross domestic product, in percent	IMF WEO
Change in Unemployment	ΔUR	Change in unemployment rate, in percent of labor force	IMF WEO
Lending Rate	LR	Lending interest rate, in percent	IMF IFS
Exchange Rate	$NEER$	Nominal effective exchange rate index	BIS, IMF IFS
Inflation	INF	Consumer price inflation, average, in percent	IMF, WEO
Financial Crisis	$Crisis$	Dummy variable =1 for the 2008-2011 period, =0 otherwise	
II. Bank-Specific Variables			
Nonperforming Loans	NPL	Ratio of non-performing (impaired) loans to total gross loans, in percent	Bankscope
Asset size	$Size$	Ratio of bank's assets to total assets of the country's banking system	Bankscope
Equity to Asset	EA	Equity to Asset Ratio	Bankscope
Return on Equity	RoE	Ratio of bank's profits to shareholders' equity	Bankscope
Loan growth	LG	Growth rate of credit, in percent	Bankscope
Foreign Ownership	Own	Dummy variable =1 if more than 50\% of bank ownership is in foreign hands =0 otherwise	Claessens and Van Horen (2013)

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