UNIVERSITY OF LJUBLJANA
FACULTY OF ECONOMICS

MASTER'S THESIS

MEASURING SYSTEMIC RISK IN BANKING: THE CASE OF THE EUROZONE

Ljubljana, February 2015 NIKO ČIČAK

AUTHORSHIP STATEMENT

The undersigned Niko Čičak, a student at the University of Ljubljana, Faculty of Economics, (hereafter: FELU), declare that I am the author of the master's thesis entitled *Measuring Systemic Risk in Banking: The Case of the Eurozone*, written under supervision of prof.dr. Marko Košak.

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INTRODUCTION

Issues pertaining to financial stability have once again become the focus of interest among academics and regulators following the global financial crisis of 2007/08. The crisis unveiled a series of inadequacies in the financial regulatory system, like the problem of procyclicality and the shortcomings of a microprudential approach to regulation. In the aftermath of the crisis, regulatory reform efforts have focused primarily on establishing a more comprehensive, macroprudential alternative (see Borio, 2003, for an early analysis of macroprudential regulation; De Nicolò, Favara & Ratnovski, 2012, provide a post-crisis assessment).The ultimate aim of this post-crisis shift in attitude is the development of a regulatory system with a capacity to detect build-ups in systemic risk *ex-ante* that would enable regulators to act preemptively.

Systemic risk and financial stability are often used interchangeably and have become somewhat of a catch phrase following the global financial crisis. Despite the apparent ubiquity of the term, however, systemic risk has no unified definition to date. Nonetheless, the scope of the literature dealing with the problem of systemic risk has been steadily growing in the years prior to the global financial crisis and has received additional impetus in its aftermath. Early theoretical models of bank runs and contagion that are based on general equilibrium theory (see Diamond & Dybvig, 1983) have been subsequently upgraded to accommodate more complex financial structures and simulate empirically observable phenomena, like liquidity spirals (see, for example, Brunnermeier & Pedersen, 2009). At the same time, systemic risk literature has been increasingly branching out, incorporating various alternative methodological frameworks. The contribution of Eisenberg and Noe (2001), for example, has been influential in the development of contagion models that are based on network theory.

A growing number of empirical and theoretical papers seek to address the issue of proper systemic risk measurement in particular. Recently proposed methods that aim to quantify the contribution of individual financial institutions to systemic risk include: Adrian and Brunnermeier’s (2011) delta CoVaR (henceforth ΔCoVaR) approach that is an extension of the Value-at-Risk (henceforth VaR) methodology, Acharya, Pedersen, Philippon and Richardson (2010) propose the systemic expected shortfall approach (henceforth SES) that is based on the marginal expected shortfall (MES) methodology. The latter features as one of the variables in Brownlees and Engle’s (2012) systemic risk index (henceforth SRISK), while Huang, Zhou and Zhu (2009) propose the distressed insurance premium (henceforth DIP) approach that utilizes data on credit default swap (CDS) premia to determine systemic riskiness of financial institutions.

Empirical methods listed above have so far mostly been applied to the US financial system. Gauthier, Lehar and Souissi (2012) use various systemic risk measuring methodologies to analyze the Canadian financial system. Lopez-Espinosa et al. (2012) employ the CoVaR and MES methods to analyze systemic risk drivers of large international banks. Despite the fact that some European economies experienced profound build-ups in systemic risk in the pre-2008 period, the scope of quantitative inquiries into systemic risk contributions of Eurozone banks is fairly limited. Acharya and Steffen (2013) analyze the European banking sector using the MES methodology. Engle, Jondeau and Rockinger (2012), on the other hand, focus on the broader European financial system, which includes banks, insurance companies, real-estate companies and financial services companies, and employ the SRISK approach.

Given the severity of the problem in some Eurozone countries, where threat of systemic failure prompted state interventions on an unprecedented scale, the issue of financial institutions' contributions to systemic risk thus remains relevant. I use a combined theoretical-empirical approach to provide a broad overview of the key issues pertaining to financial stability and systemic risk management and analyze systemic risk contributions of banks in the Eurozone. The aim of the master's thesis is therefore twofold. First, I present the pertinence of the ongoing, post-crisis shift to a macroprudential regulatory regime, by analyzing the major flaws of the microprudential approach and reviewing the extensive literature on systemic risk measurement. Second, I produce an empirical analysis of systemic risk contributions of Eurozone banks using the ΔCoVaR method of Adrian and Brunnermeier (2011). Specifically, I analyze the time-dependent evolution of VaR and ΔCoVaR of 46 Eurozone banks using the DCC GARCH (1,1) model proposed by Engle (2002) and construct a systemic risk ranking of Eurozone banks. To this end, I use daily bank stock return data spanning January 5th to December 31st from the Datastream database. In addition, I incorporate quarterly balance sheet data for 44 Eurozone banks form the Bloomberg database and analyze the effect of VaR, beta, size, and leverage on ΔCoVaR using fixed and random effects panel data models. I test three hypotheses:

- **Hypothesis 1:** Bigger Eurozone banks, measured by total assets, have higher ΔCoVaR
- **Hypothesis 2:** Eurozone banks with higher leverage have higher ΔCoVaR
- **Hypothesis 3:** Eurozone banks with higher stock beta have higher ΔCoVaR

The master's thesis is structured as follows. In the first part, I briefly review the concept of financial instability. I discuss the pitfalls of the pre-crisis regulatory approach, specifically the issues of procyclicality of bank capital regulation and the shortcomings of the microprudential regulatory framework. In the second part, I present various definitions of systemic risk and review the literature on systemic risk measurement. I subdivide the literature into four categories: 1) models of bank runs and contagion, 2) network models, 3) models of individual contribution to systemic risk, and 4) alterative models. In the third part, I perform an empirical analysis of systemic risk contributions of Eurozone banks and systemic risk factors. I briefly summarize my findings in concluding remarks.

1 FINANCIAL INSTABILITY

The shockwaves unleashed by the global financial crisis and the European debt crisis that followed in 2010 uprooted many commonly held beliefs regarding global systemic fragility. In the few years that separated the bursting of the dot-com bubble and the onslaught of the 2007/08 crisis, systemic risk in developed economies appeared permanently subdued. The threat of a major systemic event on a global scale was deemed remote. IMF (2007), for example, concluded that significant spillover effects from the deteriorating US subprime mortgage market were unlikely mere months before the market began to fully unravel. Similarly, Bertram, Brown and Hund (2007) estimated that pre-crisis global systemic financial risk was low.

A general revival of interest in financial stability normally follows major financial calamities as individuals seek to explain the causes and implications of the latest crisis. An abundance of historical post-crisis responses (see, for example, Ferguson, 2009) indicates that financial instability continues to pose somewhat of an epistemological challenge to researchers. The debate on what causes financial systems to swing from periods of exuberant optimism to near implosion is yet to be definitively settled. Furthermore, financial theory is divided on the issue of whether the question of financial instability is at all relevant. Orthodox financial theory (see, for example, Malkiel, 2007) posits that financial markets are inherently efficient. Significant aberrations in such a framework, like asset price bubbles that eventually burst during the crisis of 2007/08, are therefore highly improbable, if not impossible. On the other hand, alternative theoretical frameworks, like behavioral economics (see, for example, Shiller, 2005), suggest that financial markets are generally not efficient. They attribute financial instability to bounded rationality of market participants, whose sometimes erratic behavior can lead to increased market volatility and asset price bubbles.

The severity of the 2007/08 crisis dispelled the myth that the financial sectors of the world's most developed economies were inherently robust. This widely held belief (a prominent example is Greenspan, 2004) was partly predicated on banks' ability to reduce their overall riskiness by transferring some of the risk to other financial institutions. These novel risk management practices were made possible by a variety of new instruments, including credit derivatives. The negative side-effects of this development, most notably the dramatic increase in bank leverage and the proliferation of opaque securitized instruments, however, went largely undetected. The ensuing collapse therefore raised a series of issues regarding the adequacy of pre-crisis financial regulation that falls in the microprudential domain. Furthermore, the crisis revealed that regulators failed to detect massive build-ups in systemic risk and were overall unwilling to impose more stringent limitations on banks' aggressive risk taking policies (see Admati & Hellwig, 2013, for a critique of common misconceptions regarding pre-crisis banking regulation).

The highly volatile nature of finance has intrigued researchers since the dawn of modern capitalism. Bagehot (1873) was a pioneer in identifying the underlying causes of financial instability as both endogenous and exogenous phenomena. In his view, liquidity panics and consequent banks runs were caused either by bank failures or by unfavorable events like poor harvests and political turbulence that undermined the quality of credit, i.e., the public's trust that banks would be able to meet the demand for currency. In order to prevent liquidity panics from evolving into full-blown financial crises, Bagehot (1873) proposed that central banks should assume the role of the lender of last resort.

The main body of research on financial instability was produced following the Great Depression. The key contribution is Fisher's (1933) *Debt-Deflation Theory of Great Depressions* that centers on over-indebtedness as the main trigger of depressions. A combination of falling asset prices and mass deleveraging stoke the panic and serve as a propagation channel that fuels the depression. According to Fisher (1933), chronic over-indebtedness that eventually unravels in a downward spiral of deleveraging and deflation is usually the result of new investment opportunities. He stipulates that business ventures that promise above average rates of return but eventually go bad are made possible by low interest rates and easily available credit.

Building on Fisher's theory of great depressions in a Keynesian framework, Minsky (1982) develops the financial instability hypothesis. The key insight of the hypothesis is the decreasing sustainability of credit financing during a period of economic expansion. According to Minsky (1982), capitalist economies exhibit upward instability. The cycle begins with businesses increasing the amount of debt to finance investments during an economic boom. This development is accommodated by the loosening of lending standards, as past financial commitments are invariably met during the boom phase of the business cycle[1]. The structure of businesses' financial arrangements consequently evolves from conservative, where firms' cash flows exceed their debt payment obligations, to speculative. In the final stage of the cycle, financial arrangements become reminiscent of Ponzi schemes, as firms can only continue to make their debt payments by acquiring more debt. By this point, a credit fueled expansion is no longer sustainable and eventually ends in a debt deflation as debtors become unable to meet their commitments and banks restrict lending.

Mainstream economic theory treats the amplifying effect of bank credit activity on economic cyclicality as a particular feature of information asymmetries in credit markets. The theoretical framework that has since emerged is also known as the financial

[1] Berger and Udell (2003) provide empirical support for the assumption (the institutional memory hypothesis) that bank lending behavior is highly procyclical, i.e., that banks lend too much during a boom and constrict lending during a downturn, effectively amplifying business cycle fluctuations.

accelerator approach. Bernanke and Gertler (1989), for example, construct an overlapping generations model in which borrowers' net worth amplifies business fluctuations. Frictions in the model are introduced through auditing costs that are imposed on a group of borrowers. The ensuing model dynamics produce the accelerator effect. Kashyap, Stein and Wilcox (1993) investigate the significance of the bank lending channel in the transmission of monetary policy and focus on the overreaction of the financial system to monetary shocks. They identify the imperfect substitutability of bank assets (loans and securities) and corporate liabilities (bank loans and non-bank sources of funding) as necessary conditions for monetary policy to have an impact on economic activity through the credit channel.

Similarly, Bernanke and Gertler (1995) find that both the bank lending and the credit channel play a significant role in explaining the effect of monetary policy on real economic activity. Kiyotaki and Moore (1997), on the other hand, introduce endogenous credit constraints into a dynamic equilibrium model, where land is the main asset as well as a source of collateral. By imposing a credit constraint on some firms, exogenous shocks to the model that cause net worth of firms and the price of land to fall, become amplified and more persistent. The latter suggests that credit market frictions produce a dynamic multiplicative effect that spills over to the real economy.

The main drawback of financial accelerator models discussed above is the fact that the underlying drivers of financial distress are still extraneous to the models themselves. The models focus primarily on the amplification role of financial systems following exogenous shocks, rather than modeling financial instability endogenously. To Cecchetti, Disyatat and Kohler (2009), the absence of properly modeled financial instability and financial crises is one of the major problems of modern macroeconomics. In terms of their macroeconomic effects, financial crises are far from benign. Major financial turmoil has been shown to have a considerable negative effect on economic performance[2] and tends to undermine the stability of public finances[3]. Given that financial crises occur too regularly to be dismissed as unimportant or unlikely, Cechetti et al. (2009) conclude that incorporating endogenous financial instability into the modern macroeconomic modeling and policy framework is essential going forward.

Overall, the fragility of financial systems is evident from the tumultuous history of modern finance, which is replete with episodes of severe financial distress. Despite the diverse array of periods and regions that have experienced financial calamities in the past, Kindleberger and Aliber (2011) argue that the principal cause of all financial crises can be

[2] According to Hoggarth, Reis and Saporta (2002), banking crises are particularly costly, resulting in an average annual output loss ranging from 15-20% of GDP in both developed and developing economies.

[3] The European Commission (2012a) estimates that the total amount of state aid committed to bailing out financial institutions in the EU between October 2008 and October 2011 reached 4.5 trillion EUR, which is equivalent to 37% of EU GDP.

traced back to the unstable nature of credit financing. In their view, most financial crises unfold as self-fulfilling prophecies. Invariably, every financial crisis has essentially the same common denominator. A crisis is triggered when a large number of debtors in an economy become unable to meet outstanding financial commitments following an unsustainable credit expansion. A similar view is provided by Reinhart and Rogoff (2009), who argue that historically, all financial crises are fundamentally the same. Specifically, excessive growth of either sovereign or private sector debt represents the underlying cause of an overwhelming majority of financial crises.

The accumulation of debt during the boom phase of the business cycle is therefore the main driver of systemic risk. Significant debt overhangs eventually become the biggest threat to financial stability, once an economy enters the bust phase of the cycle. Jorda, Schularick and Taylor (2012) provide empirical evidence that crises tend to be more severe following periods of fast credit expansion. Furthermore, they show that recessions tend to last longer and are generally deeper the higher the rates of pre-recession credit growth. Borio, Furfine and Lowe (2001) also hold that the increase in the risk premium following a transition from an economic expansion to recession is simply a realization of accumulated risks. Increased systemic risk that is manifested in systemic events, like numerous bank failures, is therefore primarily the result of *ex-ante* developments in financial markets and the macro economy.

In the two decades predating the outbreak of the global financial crisis of 2007/08, most empirical work on the subject of financial stability and systemic risk focused on developing economies (see, for example, Kaminsky & Reinhart, 1999; Bertram, Brown & Hund, 2007). The interest in developing economies reflects the fact that they were particularly susceptible to severe financial crises (e.g. the Latin American crises in the 80's and 90's, the East Asian crisis of 1997, the Russian crisis of 1998, and the Argentinean crisis of 2001). During the same period, most developed economies of the world, excluding Scandinavian countries and Japan, were experiencing a prolonged period of reduced output and inflation volatility with only a few short-lived recessions.

The period from the mid 1980's to 2007 eventually became known as the Great Moderation in the USA (Bernanke, 2004). At the same time, innovations in credit risk management ostensibly improved the risk bearing capacity of individual banks, but global financial regulators failed to detect the contemporaneous build-up in systemic risk. According to Nijskens and Wagner (2011), new credit risk transfer instruments in the form of credit default swaps (CDS) and collateralized loan obligations (CLO) did enable individual institutions, mostly banks, to reduce their individual risk. Nonetheless, new risk management tools simultaneously increased the overall risk of the financial system by providing incentives for unbridled growth of leverage.

The financial crisis of 2007/08 therefore played a catalytic role in revealing the fault lines within the global financial regulatory framework that proved highly procyclical and had a significant impact on the depth of the recession. Two particularly contentious regulatory mechanisms that had a negative systemic effect are international bank capital adequacy standards that are colloquially referred to as Basel standards and the microprudential approach to financial regulation that was ubiquitous prior to the crisis (I analyze the difference between microprudential and macroprudential policies in chapter 1.2). The severity of the 2007/08 downturn was additionally amplified by a credit crunch, as banks restricted lending in order to maintain adequate capital ratios. In an environment of falling asset prices and rising default rates, such a response increased the strain on the macro economy and further eroded the capital base of banks.

The Basel Committee on banking Supervision (2010a, 2010b) introduced the new Basel III international capital accord in 2010 that is to be fully implemented by 2019. The new standard includes provisions aimed specifically at limiting excessive leverage and increasing minimum capital requirements for banks. The Basel Committee on banking Supervision (2011b) also issued an assessment methodology for quantifying and managing systemic risk by imposing additional capital requirements on global systemically important banks. Simultaneously, financial regulation is becoming increasingly macroprudentialy oriented, i.e., shifting towards more rigorous systemic risk management practices that aim to stabilize the entire financial system. This signifies a departure from the microprudential approach that focuses primarily on individual institutions. The shift to a more comprehensive regulatory framework has been accompanied by the development of new quantitative tools that enable regulators to assess contributions of individual financial institutions to systemic risk.

1.1 Procyclicality of bank capital regulation

The procyclical behavior of financial systems can have a considerable effect on financial stability due to positive feedback effects. Procyclicality is usually manifested as excessive risk-taking during economic booms that results in steeper downturns. A strong link between macroeconomic and financial activity does appear to exist and is empirically observable. Borio et al. (2001), for example, show that developed economies exhibit strong positive correlation between economic activity, measured by the output gap, and financial indicators like private credit growth and asset prices. Bank provisioning, on the other hand, is strongly negatively correlated with the output gap, since provisions tend to increase during recessions.

The procyclicality of financial systems is driven by a mixture of exogenous factors, like current macroeconomic trends, and endogenous factors, like excessive optimism or pessimism of financial institutions (institutional memory hypothesis) and financial market frictions (financial accelerator theory). An additional endogenous source of procyclicality is the international capital adequacy framework that has been shown to encourage the procyclical behavior of banks in particular.

In an effort to consolidate international capital adequacy rules and improve the stability of the global banking system, the Basel Committee on Banking Supervision released the International Convergence of Capital Measurement and Capital Standards in 1988. The Basel I standard introduced three key components for assessing capital adequacy of banks: 1) definition of tier 1 and tier 2 (or supplementary) capital, 2) determination of the appropriate level of capital for different asset categories using the risk-weighting approach, and 3) setting a minimum capital adequacy ratio of 8% for total risk-weighted assets, with a minimum core capital ratio requirement of 4%.

The risk-weighting framework of the Basel I standard includes five risk-weights (0, 10, 20, 50 and 100%) that are applied to various types of assets based on their perceived credit risk. Such methodological simplicity of Basel I was primarily motivated by the desire to create a level playing field for banks. This entailed designing international capital adequacy standards that would transcend specific national regulatory and accounting practices in order to limit regulatory arbitrage[4].

A risk based approach to capital adequacy regulation of banks was deemed preferable to simple uniform capital ratios on an individual firm level (see, for example, Rochet, 1992). Nonetheless, system-wide implications of new capital adequacy standards were less clear. Using a simple macroeconomic model, Blum and Hellwig (1995) show that a rigid application of capital adequacy standards can result in increased procyclical behavior of banks' lending policies. This in turn makes credit activity highly dependent on banks' equity levels. Blum and Hellwig (1995) further argue that capital adequacy standards can force banks to mitigate the impact of low asset returns by restricting credit activity. The result is a self-reinforcing cycle of falling investment demand and rising default rates that further undermine banks' equity levels. A scramble to meet capital adequacy requirements by a large number of banks in a depressed economic environment can therefore amplify the magnitude of initial shocks and produce a procyclical effect.

Potential procyclical effects of the Basel I standard were therefore already an issue by the time it was fully implemented. Still, the comprehensive revision of the standard that followed in 2004 did not directly address the question of bank capital regulation's impact on business cyclicality. By making the risk-weighting methodology more dependent on

[4] Jones (2000) notes that the transition to the *originate-to-distribute* model of banking, made possible by financial innovations like securitization, enabled banks to engage in regulatory capital arbitrage, following the introduction of Basel I. Securitization enables banks to lower the regulatory measures of risk of their portfolios without reducing their actual exposures.

procyclical parameters, like external credit ratings, the problem became further exacerbated. The Basel II standard of 2004 (Basel Committee on Banking Supervision, 2004) significantly expanded the scope and scale of regulatory oversight. It introduced the supervisory review process (second pillar) and market discipline (third pillar) in addition to upgrading minimum capital requirements (first pillar) of Basel I to include market and operational risk (see Table 1). The minimum capital requirement remained unchanged at 8% of risk-weighted assets. An important methodological change involved the credit risk-weighting approach of Basel I being superseded by the Standardized and the Internal Ratings Based (IRB) approach. The Basel II standard had been gradually phased-in on a global level following its launch in 2004.

Table 1: *The Basel II framework*

<table>
<tr><td colspan="3">The first pillar:
Minimum capital requirements</td></tr>
<tr><td>Credit risk</td><td>Market risk</td><td>Operational risk</td></tr>
<tr><td>• The Standardized Approach
• The Internal Ratings Based Approach (IRB):
o foundational
o advanced</td><td>• The Standardized Approach
• The Internal Models Approach (VaR)</td><td>• The Basic Indicator Approach
• The Standardized Approach
• Advanced Measurement Approaches</td></tr>
<tr><td colspan="3">The second pillar:
Supervisory review process</td></tr>
<tr><td colspan="3">The third pillar:
Market discipline (disclosure requirements)</td></tr>
</table>

Source: Basel Committee on Banking Supervision International Convergence of Capital Measurement and Capital Standards, 2004.

The arrangement under Basel II provides banks with the option to choose the credit risk weighting methodology that best corresponds to their asset portfolio structure and complexity. The Standardized Approach, which is an upgrade of the Basel I standard, includes 6 risk-weights or buckets for different categories of assets. Individual weights depend on counterparties' credit ratings that are provided by external credit assessment institutions, like credit rating agencies. This makes the Standardized approach more risk sensitive than Basel I, according to the Basel Committee on Banking Supervision (2006), because risk buckets are redefined to reflect long-term credit quality of counterparties.

According to Altman and Rijken (2005), credit rating agencies mostly employ the through-the-cycle (TTC) method for determining credit ratings, because it provides both rating stability and a fairly accurate estimate of future default probabilities at the cost of neglecting short-term changes in credit risk. An alternative to the TTC method is the point-in-time (PIT) method that is timelier and overall a more accurate short-term predictor of default probabilities. Altman and Rijken (2005) report that credit rating agencies rationalize their preference for the TTC method as: 1) catering to investors, who are reluctant to rebalance their portfolios following incremental changes in risk, 2) catering to regulators that aim to maintain financial stability, and 3) reputational considerations, since a highly volatile rating regime would compromise credit rating agencies' credibility.

Despite the inherent countercyclical design of the TTC method, the severe downward pressure on credit ratings during the worst of the financial crisis revealed that TTC-based credit rankings are not impervious to sudden dramatic changes. As shown by Kiff, Kisser and Schumacher (2013), wide-spread use of the TTC method can result in rating cliff effects. A gradual adjustment of credit ratings becomes untenable during a deep financial crisis and can force credit rating agencies to downgrade by multiple notches at a time. By doing so, credit rating agencies using the TTC method failed to meet any of their own criteria outlined by Altman and Rijken (2005) during the crisis of 2007/08. On the other hand, banks estimating probabilities of default (PD) based on the TTC method failed to keep their lending activity stable. Ultimately, large-scale credit rating downgrades had a pronounced procyclical effect. They were usually followed by asset price declines and forced Basel II compliant banks to increase their capital base during a period of unprecedented market turmoil.

As an alternative to the Standardized approach, banks can opt for the IRB approach under Basel II. Minimum capital adequacy under the IRB methodology is defined as the capital level needed to cover extreme losses that are estimated using VaR. Total losses are comprised of expected (EL) and unexpected (UL) losses. According to the Basel Committee on Banking Supervision (2004, 2005), banks are required to adequately manage expected losses (EL) with appropriate provisioning and reserve policies. Unexpected losses (UL) are managed using credit risk weighting that is based on four risk parameters: probability of default (PD), exposure at default (EAD), loss given default (LGD) and maturity (M). Under the foundation IRB approach, banks asses PD using their own internal models, while data on other risk parameters is provided by regulators. Under the advanced IRB approach, banks are required to provide their own estimates of all 4 risk parameters, subject to regulatory approval.

The Basel Committee on Banking Supervision (2010a), acknowledged the problem of procyclicality of the Basel II standard. Yet this downside was deemed unavoidable within a framework of risk-sensitive capital adequacy requirements. As a remedy, Basel II does include provisions that are designed to mitigate its procyclical effects. Key measures include the requirement that banks provide estimates of their PDs using the TTC rather than the PIT method, the introduction of the concept of down-turn LGD that exhibits greater stability over the business cycle, and a requirement for banks to perform regular stress tests.

One of the main drawbacks of the IRB approach is the fact that appropriate capitalization of banks is determined based on a single confidence level. A setup of this kind stimulates procyclical behavior of banks. As argued by Kashyap and Stein (2004), an adverse event that is more extreme than the chosen confidence level implies, can result in a significant risk increase in the credit portfolio. Higher credit risk directly relates to higher capital charges, which can force banks to lower their exposures and tighten the credit supply.

The IRB approach is therefore rather inflexible. During recessions banks are likely to meet the capital ratio requirement by limiting the size of their risk-weighted assets (RWA). The alternative, raising additional equity, is usually far more cumbersome during economic downturns. Consequently, credit activity is likely to contract, producing a procyclical effect. As a potential remedy, Kashyap and Stein (2004) promote the use of a greater number of risk curves as a more suitable alternative to the single-risk-curve method of the IRB approach. They also suggest greater flexibility of the minimum capital adequacy standard. Such an arrangement would enable banks to lower their capital ratios during economic downturns and dampen the procyclical effect.

Altman, Brady, Resti and Sironi (2005) identify the empirically observable and significant negative correlation of default rates (realized PDs) and recovery rates (LGD and recovery rate of an asset, a loan for example, sum to 1) as an additional source of procyclicality under the IRB approach. The cycle-amplifying mechanism works through banks' PD estimates that increase during recessions, while recovery rates tend to decrease. Banks' credit losses consequently swell-up and their capital requirements increase. Due to the lack of flexibility of the IRB approach, banks respond by limiting credit activity, in order to maintain adequate capital ratios, which further depresses economic growth. Reciprocally, as a result of falling capital requirements and low default rates (high recovery rates), banks tend to oversupply credit during periods of high economic growth. This in turn provides additional stimulus to the economy and can lead to sizeable debt build-ups.

Depending on the model banks use to estimate their EL and UL under the IRB approach, Altman et al. (2005) find that the severity of potential stress events can be underestimated by as much as 30%. This discrepancy stems from the fact that correlation of recovery rates and default rates is usually neglected in a credit VaR model. Using an inappropriate model to determine capital adequacy can therefore result in significant undercapitalization of banks. Along with inducing procyclicality, the IRB approach can also result in insufficient capital levels due to the misjudgment of the scale and probability of extreme events.

The latest revamp of international capital adequacy standards, in the form of Basel III, is designed to address the main drawbacks of preceding accords. In addition, it seeks to improve the resilience of the banking sector in light of the deficiencies revealed during the global financial crisis. The main issues addressed by the Basel Committee on Banking Supervision (2010a, 2010b) pertain to the problems of procyclicality of risk-based capital measures, excessive bank leverage, and inadequate liquidity provisioning. The latter in particular became one of the main sources of contagion that turned the collapse of the US mortgage market into a global financial crisis (see, for example, Brunnermeier, 2009).

The problem of liquidity provisioning prompted the launch of a new framework for liquidity management parallel to the upgrade of the three-pillar approach of Basel II. The new liquidity management framework consists of the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). According to the Basel Committee on Banking Supervision (2010b), the aim of the LCR is to ensure that banks hold an adequate reserve of highly liquid securities in order to withstand a liquidity crunch lasting up to 30 days. Under the NSFR, banks are required to better match the liquidity profiles of their liabilities and their assets in order to limit their reliance on short-term wholesale financing.

Under the new regime, the problem of undercapitalization of banks and the quality of their capital base has been tackled threefold. First, the share of tier 1 capital in the minimum capital adequacy ratio of 8% has increased to 6% and the share of tier 2 decreased to 2%, while the core tier 1 (or common equity) capital requirement has increased from 2% to 4.5% of RWA. Second, addressing the issue of excessive bank leverage, a non-risk based leverage ratio of a minimum of 3% of core tier 1 capital to total assets has been imposed. Third, the Basel III has introduced two additional capital buffers: the capital conservation buffer and the countercyclical buffer on top of the minimum capital requirement.

The capital conservation buffer imposes an additional capital requirement of 2.5% core tier 1 above the mandated minimum of 4.5%. The additional buffer is intended to function as a safeguard that prevents banks from falling below the minimum requirement in an event of a crisis. Furthermore, banks are prohibited from distributing their earnings over abundantly and are required to retain a portion of earnings, as long as their total core tier 1 capital is below 7% RWA. The enforcement of the countercyclical buffer is slightly more ambiguous, since regulators are given discretion to demand that banks add up to 2.5% of core tier 1 capital to existing capital buffers. Criteria for determining the level of countercyclical buffers depend on credit growth levels and perceived systemic risk (Basel Committee on Banking Supervision, 2010a). The Basel III standard does not specify a methodology for the assessment of systemic risk that would add a degree of consistency to the imposition of the countercyclical buffer across different countries.

The impact of Basel III on global lending activity and financial stability has become a contentious issue following its release. A higher required common equity ratio and the capital conservation buffer are expected to force banks to acquire additional equity. Cosimano and Hakura (2011) estimate that higher capital requirements of Basel III could result in a 1.3% long-term decrease in lending activity of the world's largest banks. Their findings do, however, reveal considerable variations in the cost of additional equity and lending volumes across different countries. In the case of American banks, Kashyap, Stein and Hanson (2010) find that the impact of higher capital requirements on lending to households and firms would be rather minuscule. Nonetheless, given the highly competitive nature of the banking industry, Kashyap et al. (2010) argue that higher capital requirements under Basel III can potentially stimulate regulatory capital arbitrage. Side effects of this development could involve increased flow of assets into the shadow banking sector.

Despite the seemingly extensive upgrade of the capital adequacy standard, methodological issues that plagued its predecessors are still ingrained in the Basel III framework. The addition of the countercyclical buffer to the existing minimum capital requirement deals with the problem of procyclicality and systemic risk management only part wise. It also lacks a comprehensive systemic risk management methodology. Furthermore, the methodological issues of the Standardized and the IRB approach that have been shown to be inherently procyclical remain unresolved. A considerable improvement of the overall stability of the banking system due to higher capital requirements of Basel III is also questionable. Admati and Hellwig (2013), for example, are among a group of leading academics calling for a much higher capital ratio of 25 to 30% than the ratio currently prescribed in Basel III. An additional concern regards the fact that global systemically important banks have been steadily reducing their RWA to total assets from 70% in 1991 to 35% in 2007, according to Slovik (2012). Given that a considerable portion of risk does not figure in the calculation of the capital level, risk-based capital adequacy regulation may be suboptimal overall. Even though the Basel standards have become a global benchmark for capital adequacy regulation, the world's biggest banks, which were at the center of the latest global financial crisis, have been able to consistently circumvent existing rules.

1.2 Micro- and macroprudential regulatory policies

The term macroprudential, as a definition of a specific regulatory policy, has been in use since the mid 1970's (see Borio, 2003). It is, however, yet to be developed into a comprehensive framework with clearly defined objectives and operational tools. Galati and

Moessner (2011), for example, contrast the current state of the macroprudential policy debate to that of macroeconomic policies. They focus on monetary policy that has established itself as an effective mechanism for maintaining price stability using a diverse assortment of policy instruments. By conducting highly expansive monetary policy, central banks were largely successful in preventing severe deflationary risks from materializing during the global financial crisis.

Galati and Moessner (2011) find the macroprudential concept to still be in its infancy compared to almost apodictic tenets of modern monetary policy. The macroprudential approach therefore still needs to be properly defined as a separate regulatory policy. Bank of England (2009) argues in favor of a clear separation of macroprudential and monetary policy mandates. Conventional monetary policy instruments are generally ill-suited for managing financial stability (see, for example, Dale, 2009). The short-term policy rate, in particular, can be ineffective in guiding behavior of market participants during periods of high volatility. There exists therefore a prescient need for a separate, macroprudential regulatory mechanism that would focus exclusively on financial stability. As a consequence, such an arrangement could effectively lessen the burden of monetary policy that would be free to pursue the goal of price stability.

Table 2: *Comparison of the macro- and microprudential approach to regulation*

	Macroprudential	Microprudential
Proximate objective	Limit financial system-wide distress	Limit distress of individual institutions
Ultimate objective	Avoid output (GDP) costs linked to financial stability	Consumer (investor/depositor) protection
Characterization of risk	Seen as dependent on collective behavior (endogenous)	Seen as independent of individual agents' behavior (exogenous)
Correlation and common exposures across institutions	Important	Irrelevant
Calibration of prudential controls	In terms of system-wide risk (top down)	In terms of individual institutions' risk (bottom up)

Source: C. Borio, Towards a Macroprudential Framework for Financial Supervision and Regulation, 2003, p. 2.

Consensus regarding a clear delineation between microprudential and macroprudential policies and their respective role within a comprehensive regulatory framework is slowly emerging. Summary of an early contribution by Borio (2003) is given in table 2. According to Borio (2003), the difference between the two sets of policies lies in their objectives and models used to estimate risk. The objective of the microprudential approach is protecting investors and depositors from losses by ensuring that individual financial institutions are fundamentally sound. With such an atomistic approach, individual financial institution's risk is modeled as an exogenous phenomenon, where intra-institutional dynamics do not play a significant role. The macroprudential approach, on the other hand, focuses on minimizing macroeconomic losses by limiting systemic risk. Consequently, risk is modeled endogenously, with a strong emphasis on interaction between financial institutions, specifically their common exposures and interdependence.

Strong focus on the soundness of individual financial institutions had been the cornerstone of the regulatory framework in the years preceding the crisis of 2007/08. This regulatory frame of mind is overtly reflected in Basel I and II. Given the absence of truly systemic banking crises during this period, such microprudential regulatory policy was considered adequate. The backbone of pre-crisis regulatory policy consisted of measures instituted following the Great Depression, like deposit insurance schemes that had been shown to significantly reduce the risk of bank runs (see, for example, Diamond & Dybvig, 1983).

The reasoning behind capital adequacy requirements that eventually became Basel I and II, on the other hand, was primarily related to the moral hazard problem. According to De Nicolò et al. (2012), the problem mostly relates to potentially risky behavior of banks that traditionally operate with high leverage. Such an arrangement gives rise to hazardous risk-seeking behavior, as bank shareholders seek to appropriate gains from highly leveraged investments, while passing the risk of loss to depositors and creditors. Imposing mandatory capital requirements therefore diminishes the shareholder's moral hazard problem and improves the stability of individual banks.

The failure of microprudential regulatory policies during the financial meltdown of 2007/08 is attributable to the specific causes and the subsequent development of the crisis. According to Gorton (2009), large scale bank failures of 2007/08 were different from comparable historical episodes in that this time banks generally did not experience runs from depositors[5], but runs from other banks. After the extent of losses on US mortgage-related securities became apparent in the summer of 2007, and particularly following the collapse of Lehman Brothers in the fall of 2008, banks became unwilling to lend to one another. Longstaff (2010), for example, provides empirical evidence that structured credit

[5] Bank runs in the classical sense played a minor role in the crisis of 2007/08. The UK bank Northern Rock experienced a depositors' run in 2007, after it had already negotiated an emergency funding injection with the Bank of England due to its dire liquidity situation (see Shin, 2009). A depositors' run on the US bank Washington Mutual took place in September 2008. The bank was subsequently sent into receivership and was sold to JP Morgan (see Brunnermeier, 2009).

products linked to the US subprime mortgage market played a significant role in propagating the distress across the US financial system.

In response to mounting losses and shrinking liquidity, banks began withdrawing liquid assets from other banks. As recounted by Brunnermeier (2009), the ensuing panic resulted in a liquidity crunch that was manifested by the drying-up of short-term funding sources. These consisted mostly of repo contracts and money market funds. The withdrawals eventually led to steep asset price declines, as banks began to sell assets at depressed prices in order to maintain adequate liquidity. Consequently, market failures played a significant role in the propagation of the crisis and made conventional microprudential policy tools highly ineffective.

Microprudential tools, like deposit insurance and capital requirements, helped mitigate the fallout from the meltdown, but were overall inadequate in preventing distress from spreading across institutions and national jurisdictions. The global financial crisis revealed that an overreliance on microprudential regulation leads to the fallacy of composition[6], i.e., the problem of equating the soundness of individual financial institutions to the robustness of the entire financial system. De Nicolò et al. (2012) therefore emphasize the need for a complementary, macroprudential set of tools that would tackle the issue of market failures or externalities related to: strategic complementarities (procyclical behavior of financial institutions), fire sales (wide-spread deterioration of financial institutions' balance sheet quality), and interconnectedness of financial institutions (financial contagion).

Even though the basic goals of macroprudential policy are rather straightforward, maintaining financial stability being the key objective, their implementation remains problematic. Arnold, Borio, Ellis and Moshirian (2012) point to the lack of relevant theoretical work on the subject as the main reason macroprudential approach to regulation does not have a conclusive set of instruments and a clearly defined policy path. They argue that simple replication of good practices in different jurisdictions, without understanding country-specific institutional factors, can be counterproductive. Nonetheless, a host of recent papers have proposed specific instruments designed to help manage systemic risk (for a list of examples see table 1 in appendix 2). Some of these instruments, like countercyclical capital buffers, have already been formalized within the Basel III framework.

Time-varying capital surcharges, in particular, have been a recurring theme in the debate regarding macroprudential policy instruments. Bank of England (2009), for example, outlines a two-tiered methodology for managing system-wide or aggregate risk and

[6] Kindleberger & Aliber (2011), for example, employ the concept of the fallacy of composition to explain speculative manias in financial markets, namely that rational behavior of investors can lead to irrational behavior of markets, or the fact that competitive devaluations can improve the current account balance of individual countries, while worsening the balance of other countries in the group.

systemic risk of individual banks or network risk. Both methodologies consist of assigning a dynamic capital surcharge over banks' existing microprudential capital requirements. Under the aggregate risk approach, the extent of the additional systemic capital requirement is defined by linking exuberance in various subsectors of the financial system to estimates of banks' PDs and is uniformly enforced. Under the network approach, the additional dynamic capital surcharge is designed to reflect individual banks' contribution to system LGD and is enforced on an individual basis.

Hanson, Kashyap and Stein (2010) stress the importance of introducing time-variability into capital adequacy regulation, in particular the need for greater flexibility of capital ratios as a distinct macroprudential measure. They argue in favor of banks being required to increase capital buffers during periods of economic expansion and allowing them to lower their regulatory capital ratios during recessions. Such a framework could dampen the volatility of banks' credit activity, especially during recessions, since banks would no longer be compelled to meet capital requirements by reducing the supply of credit.

As a corollary, Hanson et al. (2010) propose that prompt corrective action of regulators, usually executed when banks fail to meet capital requirements or come close to falling below the regulatory minimum, should focus specifically on bolstering bank equity rather than merely improving their capital ratios. Removing the option that is implicit in existing capital regulation and gives banks the freedom to meet regulatory capital requirements during recessions either by issuing additional equity or reducing their credit activity, would therefore also contribute to financial stability.

Dynamic loan loss provisioning is usually included in the time-varying macroprudential toolbox and was already in use prior to the outbreak of the crisis. Dynamic provisions function similarly to dynamic capital requirements, whereby banks are required to increase their provisions during upswings, creating an additional reserve of funds that can be depleted during downturns. Spain is the first country to have made dynamic provisioning for banks mandatory in 2000, in an attempt to reduce the procyclicality of bank lending (see, for example, Saurina, 2009). In hindsight, dynamic provisioning in Spain failed to restrain excessive credit growth, while provisions that were made during the run-up to the crisis were insufficient to help Spanish banks cope with extensive losses, mostly on their mortgage portfolios. In the end, the Spanish banking system had to be recapitalized with funds from the European Financial Stability Fund (EFSF) in 2012 (details of the agreement are given in European Commission, 2012b).

According to the Bank of England (2009), the failure of the Spanish dynamic provisioning model is primarily due to its backward-looking nature. By calibrating the model using historical data, Spanish banks ended up underestimating the severity of subsequent losses. Bank of England (2009) therefore proposes forward looking provisioning as a more suitable alternative to the Spanish model. Encouraging the use of forward looking provisions and transitioning from incurred to expected loss (EL) accounting has subsequently become one of the priorities of the Basel III standard. According to the Basel Committee on Banking Supervision (2010a), a more rigorous application of the EL approach and forward looking provisioning can play an important stabilizing role by diminishing the procyclicality problem and making actual bank losses more transparent.

Overall, building a comprehensive regulatory framework with a clear macroprudential component has become the goal of regulators across the globe. In order to bolster the systemic risk management framework, the European Union has established the European Systemic Risk Board (ESRB) as part of the European System of Financial Supervisors that has issued a detailed framework for implementing macroprudential oversight of banks in the Eurozone (see, ESRB, 2014). In the USA this function has been assigned to the Financial Stability Oversight Counsel (FSOC) that was established by the Dodd-Frank Wall Street Reform and Consumer Protection Act, as part of the post-crisis regulatory response. On a global level, the Financial Stability Board (FSB) has been entrusted with the responsibility of coordinating international efforts for improving financial stability.

A series of proposed macroprudential instruments and policy objectives have also been integrated into the new capital accords. Nonetheless, due to the gradual phasing-in of Basel III from January 2013 to January 2019, the full impact of these new measures is yet to be empirically validated. An additional challenge for a full implementation of a macroprudential regulatory mechanism is the absence of a consistent systemic risk management framework that is also evident in the Basel III standard. Even though the mitigation of systemic risk is the quintessential macroprudential policy goal, there is still no universally accepted definition of systemic risk and methodologies to estimate it vary considerably.

2 SYSTEMIC RISK

2.1 Defining systemic risk

General consensus on a proper definition of systemic risk is yet to emerge. Part of the problem of clearly delineating systemic risk is attributable to the ambiguity of the concept itself. Sheldon and Maurer (1998), for example, argue that even though the threat of highly adverse developments in financial markets due to systemic risk is ever-present, the risk itself is largely unperceivable *ex-ante*. This problem is further exacerbated by the fact that systemic risk and systemic financial crises have not yet been fully integrated into prevailing macroeconomic models. Consequently, systemic risk does not explicitly feature in models that are used to forecast economic trends and guide policy decisions. According to Brunnermeier, Gorton and Krishnamurty (2011), simply measuring *ex-post* losses due to systemic events does little to elucidate the nature of systemic risk. Understanding the dynamics of systemic risk entails properly incorporating endogenous shocks that precipitate systemic events into macroeconomic models[7].

Kaufman and Scott (2003) define systemic risk in broad terms as the probability that disruptions occur on a systemic level rather than affecting only particular parts of the system, while systemic risk in banking is characterized by high correlation of banks' asset returns and numerous banks failures. Brunnermeier et al. (2011) define systemic risk more narrowly as the risk that shocks to the financial system lead to endogenous self-reinforcing feedback loops that amplify the initial shock, increase the distress of the financial system, and have a negative effect on economic output. A more succinct definition by Borio (2003) interprets systemic risk as an event or a process, by which an initial distress of a financial institution (endogenous event) or a macroeconomic shock (exogenous event) spreads throughout the financial system via specific transmission channels that include balance sheet links and overreaction to bad news by individual institutions and investors.

De Bandt and Hartmann (2000) base their definition of systemic risk on a more rigorous definition of systemic events, summary of which is given in table 3. They classify systemic events as either single, pertaining to an individual institution or a single market, and wide, affecting numerous financial institutions or markets. Systemic events are further differentiated, based on the severity of their impact, as either weak, not resulting in institution or market failure, and strong, resulting in institutional and market failures as well as exhibiting contagion effects. De Bandt and Hartmann (2000) further subdivide systemic events according to the type of shock. Events that result from either idiosyncratic or limited systemic shocks, i.e., when a single institution or market is in distress, are defined as systemic events in the narrow sense, while shocks that affect numerous institutions and markets simultaneously give a broad definition of systemic events.

De Bandt and Hartmann (2000) consequently define systemic risk as the risk of strong systemic events materializing. Systemic risk thus defined is more nuanced compared to alternative definitions, since it differentiates between varying systemic events based on their overall impact on the financial system. Consequently, systemic events are a necessary but not always a sufficient condition for systemic crises to occur. The criterion delineating generally innocuous, limited systemic events from potentially calamitous events is the transmission of the initial shock across the financial system or contagion. In the absence of contagion, systemic events due to weak narrow shocks do not result in systemic crises.

[7] For a recent example of a macroeconomic model with a financial sector, see Brunnermeier and Sannikov (2012). By allowing endogenous risk-taking behavior, they are able to model a common trait of systemic risk - the volatility paradox, i.e., the phenomenon of increasing endogenous risk, due to the swelling-up of agents' leverage, even as aggregate risk is decreasing.

Table 3: *Definition of systemic events and systemic crises*

Type of initial shock	**Single systemic events** (affect only one institution or one market)		**Wide systemic events** (affect many institutions or markets)	
	Weak (no failure or crash)	**Strong** (failure of one institution or crash of one market)	**Weak** (no failure or crash)	**Strong** (failure of many institutions or crashes of many markets)
Narrow shock				
• Idiosyncratic shock	Systemic event	Systemic event and contagion	Systemic event	Systemic event and contagion leading to a systemic crisis
• Limited systemic shock	Systemic event	Systemic event and contagion	Systemic event	Systemic event and contagion leading to a systemic crisis
Systemic shock			Systemic event	Systemic event leading to a systemic crisis

Note: The bold bracket contains a broad definition of systemic events, the shaded area within the bracket contains a narrow definition of systemic events

Source: O. De Bandt, & P. Hartmann, Systemic Risk: A Survey, 2000, p. 12.

Common traits of the definitions of systemic risk given above can be crudely distilled into three key components: 1) a trigger or systemic event that disrupts part of the financial system, 2) a contagion mechanism that enables the initial disruption to spread across the financial system, and 3) a subsequent failure of a number of financial institutions, which inhibits the normal functioning of the financial system and has an adverse impact on the macro economy. Early research on systemic risk focused primarily on the problem of contagion and was, to a large extent, motivated by serial bank failures in emerging markets during the 1990s. Rochet and Tirole (1996), for example, define systemic risk as essentially contagion, or the risk of financial distress spreading from financial institution to institution.

According to Kaufman (1994), one of the main arguments in favor of stricter banking regulation following the Great Depression is based on the fact that banks, unlike other sectors of the economy, appear to exhibit a higher degree of contagion risk. Analyzing past episodes of banking crises in the US, Kaufman (1994, p. 126) identifies the following five "*stylized facts*" of bank contagion:

- Bank contagion occurs faster,
- Contagion spreads more broadly within the banking sector,
- Contagion leads to a higher number of bank failures,
- Contagion results in higher losses to creditors and depositors,
- Contagion spreads beyond the financial system and has a negative effect on the macro economy as well.

Early theoretical models of systemic risk therefore deal mostly with identifying and analyzing various interbank links that function as propagation channels for adverse shocks. Empirical research, however, failed to provide conclusive evidence that contagion in developed financial systems is highly probable. Upper (2011) attributes sparse empirical evidence in support of the contagion hypothesis to insufficient data. Regulators generally prefer to bail-out banks, rather than letting them fail, which is usually sufficient to prevent distress of individual institutions from spreading across the system, especially following single systemic events. Consequently, quantifying the damage due to contagion, in the absence of unambiguous contagious episodes, like defaults of financial institutions, is rather difficult.

Nonetheless, the events during the financial crisis of 2007/08 have shown contagion risk to continue to pose a credible threat to financial stability. The high degree of global interconnectedness and the systemic importance of the biggest financial institutions that are classified as "*too big to fail*" (TBTF) made the problem particularly severe. The threat of potential spill-over effects due to financial institutions' failures was the main motivation for unprecedented state interventions. These were mostly aimed at propping-up individual institutions and preventing a major disruption in global financial markets. Potentially devastating implications of allowing systemically important financial institutions to fail were showcased by events following the collapse of the US investment bank Lehman Brothers in September 2008. The ensuing increase in volatility and a massive liquidity crunch, which crippled international financial markets, exemplify the difficulty of containing the spread of distress, once a highly interconnected financial institution has failed.

The ongoing debate on the need to establish a macroprudential policy regime has focused on the importance of ameliorating the robustness of financial systems *ex-ante* rather than having to manage unforeseeable consequences of wide systemic events *ex-post*. The need for coherent systemic risk measures that would enable regulators to prevent adverse developments in financial systems by acting in a preemptive fashion has spurred the development of a new strand within the systemic risk literature. Measures of individual institutions' contribution to systemic risk, like the MES metric by Acharya et al. (2010) and the *ΔCoVaR* method of Adrian and Brunnermeier (2011), for example, have shifted from a highly stylized, theoretical analysis of the contagion mechanism, to a more pragmatic, empirically-driven approach. Overall, the post-crisis literature on systemic risk has become more concerned with the issue of properly quantifying systemic risk. Specifically, imposing additional requirements on financial institutions that are deemed systemically important and whose failure could result in a systemic crisis.

2.2 Measuring systemic risk

Operational macroprudential regulation requires systemic risk to be adequately quantified, which entails not only measuring potential costs associated with failures of institutions but also understanding the dynamics within the financial system, i.e., contagion mechanisms, which can amplify adverse shocks. Comprehensive systemic risk measures should therefore combine practicality, in order to be applicable as macroprudential instruments, and theoretical underpinnings of the systemic risk and contagion literature. Given the post-crisis proliferation of various new methodologies of systemic risk measurement and increasing complexity of theoretical models of contagion, systemic risk models can be subdivided into four broad categories: 1) theoretical models of bank runs and various channels of contagion, 2) network models of contagion, 3) models of individual institutions' contribution to systemic risk, and 4) alterative models that include contingent claims analysis (CCA) of systemic risk and the indicator-based systemic risk measurement approach proposed by the Basel Committee on Banking Supervision (2011).

2.2.1 Models of bank runs and contagion

Attempts to describe the propagation process of financial crises, the reasons behind bank runs and the nature of systemic risk are as old as financial crises themselves. Fisher (1933), for example, in his theory of Debt Deflations, effectively describes a potential contagion channel, corresponding to the process of over-indebted individuals and firms being forced to deleverage and by doing so trigger a deflationary spiral. The bulk of contemporary literature on systemic risk, however, is rooted in the early formalized models of bank runs that were developed in the 1980s, particularly the multiple equilibria model of Diamond and Dybvig (1983). Subsequent research identified various contagion mechanisms that can lead to simultaneous bank runs and address both the liability and the asset side of bank's balance sheets (see table 4). In general terms, according to de Bandt and Hartmann (2000), contagion operates through two distinct channels: 1) direct links between banks due to common exposures and 2) the information channel or fear of bank failures due to asymmetric information.

Table 4: *Possible channels of contagion in the banking system*

Asset Side	Liability Side
Direct effects	Bank runs
• Interbank lending	• Multiple equilibria/fear of other withdrawals
• Payment system	• Common pool of liquidity
• Security settlement	• Information about asset quality
• FX settlement	• Portfolio rebalancing
• Derivative exposures	• Fear of direct effects
• Equity cross-holdings	• Strategic behavior by potential lenders
Indirect effects	
• Asset prices	

Source: C. Upper, Simulation Methods to Asses the Danger of Contagion in Interbank Markets, 2011, p. 112.

Bryant (1980) develops a simple and highly stylized overlapping-generations model of borrowing and lending, in which bank reserves and deposit insurance play a beneficial role in limiting the losses due to the behavior of individual agents. Within the framework of the model, financial intermediaries provide liquidity to deposit-holders at a cost advantage that makes direct borrowing highly prohibitive. By making assets of intermediaries risky and distributing the knowledge of impending losses among agents in a random fashion, Bryant (1980) models deposit runs as loss-avoiding behavior of more knowledgeable individuals due to asymmetric information. Given that intermediaries are fairly restricted in mitigating the adverse consequences of runs, government deposit insurance schemes are preferable because they are generally less costly for managing runs once they occur, even though they cannot prevent deposit runs from taking place in such a framework. The exact form of government deposit insurance, however, is not specified by Bryant (1980), and the broader, risk redistribution implications of various deposit insurance schemes remain opaque.

Diamond and Dybvig (1983), in their seminal paper, employ a more realistic framework for modeling individual bank runs, in which banks engage in qualitative asset transformation, i.e., converting illiquid assets into highly liquid deposits. They model the illiquidity of a homogeneous asset by using technological constraints that make returns of short-term investments lower than those of long-term investments. Bank liabilities are introduced as alternative contracts to private assets that provide greater liquidity over their life-cycle. Demand for liquidity arises because some agents are more eager to consume immediately, while others prefer postponing consumption, which makes bank deposits essentially a form of insurance that enables both groups of agents to consume when they desire to do so. Liquidity demand in the model of Diamond and Dybvig (1983) is therefore explicitly driven by asymmetric information of agents. Illiquid assets in this framework provide a rationale for bank deposits as well as bank runs, which are among the possible equilibrium states of the model and occur when all agents decide to withdraw their deposits at the same time. In doing so, agents face a sequential service constraint, i.e., those that are quick to withdraw their deposits incur lower losses than late withdrawers.

Bank runs in the Diamond and Dybvig (1983) model are random or sunspot events, which occur due to shifts in agents' expectations regarding the soundness of banks and their exposure to the sequential service constraint. A bank run in such a framework can therefore be triggered by a multitude of reasons. This is a departure from earlier models that mostly focused on individual aspects of agents' behavior as run-inducing events. Furthermore, the model provides a more rigorous treatment of measures that can prevent bank runs from taking place. First, by allowing banks to suspend deposit convertibility, essentially introducing bank holidays, less impatient agents are deterred from withdrawing their deposits early, which significantly reduces the risk of a run. Second, by instituting a government-sponsored deposit insurance scheme, agents no longer face the sequential service constraint, which makes bank runs disadvantageous for all agents.

By definition (see Bhattacharya & Thakor, 1993) a bank run pertains to an event that affects an individual bank, whereas banking panics result from multiple simultaneous bank runs. The difference between individual bank runs and banking panics is the presence of contagion in the latter case. Since the model of Diamond and Dybvig (1983) deals exclusively with individual bank runs, Gorton (1988) provides an empirical test of the model's key assumptions. The time horizon covers banking panics in the USA up to and including the Great Depression. His results suggest that the information channel of contagion played a significant role in exacerbating banking panics in pre-deposit insurance USA. Unlike the theoretical assumption of the original model that bank runs are sunspot phenomena, Gorton (1988) concludes that based on US historical data, banking panics are determined by the business cycle. According to this view, depositors' expectations regarding the soundness of banks are highly dependent on changes in the macro economy. The business cycle hypothesis therefore explains high correlation of macroeconomic downturns and banking panics in the pre-deposit insurance period.

The concept of banking panics being caused by business cycle fluctuations is further developed by Allen and Gale (1998). They upgrade the fundamental framework of Diamond and Dybvig to accommodate the influence of business cycles on banking panics by differentiating between a safe asset that provides a fixed amount of the consumption good at expiration, and a risky asset, whose return is random and depends on the value of a generic economic indicator. Since banks enjoy an information advantage over depositors regarding the riskiness of assets in the model, the risky asset is held mostly by banks as consumers acquiring the risky asset face an adverse selection problem.

Bank runs in the Allen and Gale (1998) model are retail lending phenomena, which occur due to exogenous shocks that depress the value of the economic indicator and make depositors realize that returns on risky assets of banks are going to be low. The ensuing withdrawals lead to banks being forced to sell assets at fire sale prices and face liquidation in the event that their assets are insufficient to cover their liabilities. Allen and Gale (1998) show that in the event of a fire sale, the price of the risky asset can fall below its fundamental value. As long as the return of the safe asset is the same for banks and outside investors, bank runs still represent an optimal allocation of risk in the model. By introducing a tradable market for the risky asset, bank runs become suboptimal even when returns on the safe asset are identical, because the liquidation value of the risky asset is generally too low to cover outstanding liabilities. Bank losses due to fire sales in this scenario can be mitigated by central bank intervention.

Allen and Gale (2000) further upgrade the original framework to incorporate wholesale funding contagion due to liquidity preference shocks. Similarly to the preceding model, banking panics are assumed to be the result of macroeconomic cyclicality. The alternative assumption that banking panics are random occurrences does not lend itself to modeling contagion effects directly. Contagion between different regions in the model is therefore possible due to common macroeconomic fundamentals. Each region in the model contains a random distribution of early and late consumers, while aggregate liquidity demand is constant. An interbank liquidity exchange system enables banks to manage their regional liquidity demand by trading deposits with other banks. Consequently, as long as the interbank network is complete and all banks are connected to all other banks in the network, the risk of contagion is low. Highly diversified risk-sharing therefore improves the robustness of the banking network. In the event of incomplete deposit markets, however, Allen and Gale (2000) find that risk of contagion is significantly higher. Banks in this setup are more heavily exposed to a smaller number of other banks. Liquidity shocks that depress the value of other banks' assets have a greater impact on the soundness of individual banks.

Rochet and Tirole (1996) analyze the significance of the interbank lending channel by developing an autarkic model of banking. Interbank monitoring provides a rationale for a decentralized lending market and serves as a mechanism for attenuating the moral hazard problem among banks. Within the framework, stability of individual banks depends on their commercial lending activities as well as the quality of their monitoring of borrowing banks. All banks are exposed to random liquidity shocks, which makes lending banks that perform inadequate peer-monitoring of borrowing banks prone to suffering significant losses. These in turn can jeopardize their solvency.

A key feature of the Rochet and Tirole (1996) model is the treatment of the TBTF policy. It arises as a special form of a soft budget constraint, when a central bank decides to assist a nearly insolvent lending bank by bailing out the borrowing bank instead. The TBTF policy is made possible by banks' economies of scope that include returns from their lending and monitoring activities. Given that banks exhibit a high degree of interconnectedness in the presence of TBTF, Rochet and Tirole (1996) find that relatively modest liquidity shocks can have a profound impact on the stability of the banking sector. Consequently, a small increase in the liquidity shock of a single bank can lead to a meltdown of the entire banking sector due to contagion.

Partly inspired by emerging market financial crises of the 1990's, Freixas, Parigi and Rochet (2000) approach modeling contagion risk by introducing numerous regions with varying degrees of investment returns and a single bank operating in each region. They modify the methodology of Diamond and Dybvig so that consumers are no longer differentiated based on when they consume but in which region they consume and define the homogeneous good as cash issued by the central bank. Due to the regional division of banks, an interbank credit market arises as a more efficient alternative to depositors moving their cash across regions in pursuit of desired consumption opportunities. By forming a network of credit lines, the banking system becomes more resilient to failures of individual banks as a result of diversification.

Nonetheless, the broad availability of credit in the model of Freixas et al. (2000) can result in diminished market discipline as defunct banks can be allowed to continue to operate. Banking panics in the model can therefore occur due to a synchronized bank run of a large number of depositors who fear that a failure of the interbank credit system is imminent. Alternatively, banking panics result from contagion through the interbank market after a single bank becomes insolvent. In the latter case, the central bank can intervene by either winding down the insolvent bank or bailing it out, if the insolvent bank is classified as too important or too interconnected to fail. An appropriate policy response, according to Freixas et al. (2000), to an orderly closure of the insolvent bank should include a liquidity injection by the central bank. Such a course of action prevents contagion and mitigates the moral hazard problem.

Kodres and Pritsker (2002) develop a short-term horizon, rational expectations model in which adverse asset price movements due to shocks are propagated across different regions that share common macroeconomic factors. The contagion mechanism is based on the process of portfolio rebalancing by agents in different regions as a response to exogenous asset price shocks. The two-period setup includes informed investors, uninformed investors and noise traders that trade the risky asset in the first period and consume the liquidation value of the asset in the second period. Unlike comparable models of contagion, Kodres and Pritsker (2002) do not use common macroeconomic developments as factors of systemic risk but rather focus on macroeconomic variables as conveyers that enable contagion to spread across different regions.

The model of Kodres and Pritsker (2002) contains two traditional channels of contagion: 1) liquidity shocks that are driven by liquidity demand of noise traders, and 2) information shocks that result from informed investors acquiring new information regarding the liquidation value of the risky asset. Contagion is therefore possible as long as the proportion of informed investors in the model is small enough, so that the overreaction of uninformed investors to bad news leads to cross-market adjustments in prices and portfolios. Furthermore, Kodres and Pritsker (2002) show that a higher degree of information asymmetry between investors in a particular region directly relates to that region being more prone to contagion from other regions due to an over commensurate response to exogenous asset price shocks that are mistakenly regarded as domestic information shocks by uninformed investors.

A majority of papers on bank contagion deal with direct liability and asset side channels of distress transmission. Cifuentes, Ferrucci and Shin (2005), however, develop a model that centers on the indirect contagion channel of asset price volatility. Banks in this framework hold a mixture of a liquid asset that has a uniform price and an illiquid asset that is priced based on market supply and demand. Banks also engage in interbank lending, they are required to mark-to-market the value of their assets, and are subject to a regulatory minimum capital requirement. Following a liquidity shock, banks that fall below the minimum capital ratio must meet the requirement by selling part of their asset portfolio. Since the price of the illiquid asset is determined by the market, a significant downward pressure on the asset price due to fire sales of a single bank can lead to contagion. Eventually, other banks are forced to follow suit.

Similarly to Allen and Gale (2000), Cifuentes et al. (2005) find that highly interconnected banking systems are generally safer. Still, the benefits of a diversified banking system become fairly limited once contagion is allowed to spread through asset prices. Their model simulations reveal that system-wide asset sales increase in a nonlinear fashion following a liquidity shock as the number of banks in the system increases. Furthermore, in the event that the liquidity shock is particularly strong, a minimum capital requirement can be ineffectual in preventing contagion from spreading across the banking system as the capital buffer is quickly depleted. Regulatory implications of Cifuentes et al. (2005) model results are twofold. First, a prudent regulatory policy should combine a minimum capital requirement and an appropriate liquidity buffer, requiring banks to invest a greater share of their portfolio in liquid assets to be better able to withstand massive liquidity shocks.

Second, there exists a trade-off between a minimum capital adequacy requirement and a liquidity requirement, namely that a higher capital ratio relates to a lower liquidity reserve needed to bolster banks' resilience to systemic risk.

Diamond and Rajan (2005) analyze the impact of common liquidity pools on interbank contagion. Their model includes investors endowed with investment assets, entrepreneurs with short- and long-term investment projects lacking appropriate funding and banks that collect deposits from investors and lend to entrepreneurs. Investment goods as well as loans in this framework are illiquid due to the inalienability of human capital constraint (see Hart & Moore, 1994), i.e., the fact that entrepreneurs can decide at any time to withdraw from an investment project, which puts an upper bound on the extent of entrepreneurs' debt financing. Unlike comparable models, e.g. Allen and Gale (2000) that simulate bank contagion as a response to liability-side liquidity shocks due to deposit withdrawals, Diamond and Rajan (2005) include asset-side liquidity effects that result from underperforming investment projects. Contagion in their model is therefore a possible outcome of either a classical banking panic or a general liquidity crunch after a bank in the system has become insolvent as a result of low investment returns. In the latter case, adverse shocks can spread across the system because banks share an exposure to a common pool of liquidity, without having explicitly modeled interbank links.

Regulatory intervention by infusing additional liquidity in the common pool in the Diamond and Rajan (2005) model can prevent bank failures and contagion when aggregate liquidity supply no longer meets the demand. Conversely, when a single bank is at risk of failing due to idiosyncratic factors, a direct recapitalization of the struggling bank is preferable for staving off a bank run and possibly contagion. The precise form of intervention in such a framework is, however, not clear-cut. Recapitalizing weak banks, whose failure would otherwise increase aggregate liquidity due to the release of invested assets, can augment liquidity demand by investors, exacerbating the problem of inadequate aggregate liquidity and eventually leading to contagion and serial bank failures. According to Diamond and Rajan (2005), liquidity provisioning is generally less harmful then recapitalization of weak banks, especially when the regulator does not have adequate information on the state of individual banks, but is potentially less effective in preventing individual bank failures.

Brunnermeier and Pedersen (2009) employ an empirically driven model of tradable asset liquidity. The model includes three types of agents and a market for trading a risky asset with a random payoff and an ARCH-type volatility process. Risk-averse customers trade the risky asset and simultaneously reduce its liquidity due to order imbalance, i.e., they engage in trading in a sequential manner. Risk-neutral speculators provide market liquidity by trading the risky asset with borrowed funds. Banks lend to speculators and manage their exposures by charging a margin that reflects their VaR. Instability in the Brunnermeier and

Pedersen (2009) framework arises due to the structure of bank margins. As long as banks are well informed about the value of the risky asset, their margins are inversely related to the illiquidity of the risky asset, because the ultimate payoff of the asset is known. In the event that banks are ill-informed, their margins increase along with the illiquidity of the risky asset, which leads to greater market fragility and can induce liquidity spirals.

Acharya, Shin and Yorulmazer (2009) analyze the effects of agents' strategic behavior on the *ex-ante* portfolio structure of banks, consisting of safe liquid assets and risky illiquid assets. The two-period, four-date model includes four types of agents: bank shareholders, banks, depositors, and a regulator. Illiquidity of the risky asset is modeled as an outcome of the banks' moral hazard problem, specifically the bank shareholders' costs of monitoring loan performance that are subject to the inalienability of human capital constraint. Furthermore, poor performing banks in the model are liquidated, while their remaining assets are auctioned-off to sound banks by the regulator. The fact that the prices of liquidated banks' assets are determined endogenously is the defining characteristic of the Acharya et al. (2009) framework. The structure of banks' liquidity holdings is therefore not simply a result of an optimal portfolio choice, as with earlier models, but reflects strategic *ex-ante* positioning of banks.

The level of bank liquidity in the Acharya et al. (2009) model is affected by return prospects associated with bank failures, business cyclicality and asset purchases of liquidated banks by non-bank investors. During periods of economic expansion returns on the risky asset are high and only a small number of banks fail. As a consequence, the selling price of liquidated banks' assets is too low to provide a considerable return, which relates to a lower willingness of banks to hold liquid assets. Conversely, since during recessions more banks end up being liquidated and potential returns of remaining assets are higher, banks are induced to increase the share of the liquid asset in their portfolios. Non-bank investors tend to have a negative effect on the price of failed banks' assets as long as their pool of funds is insufficient to cover the aggregate liquidity gap. Additionally, non-bank investors' returns on remaining assets are lower than comparable bank returns. The function of non-bank investors in the Acharya et al. (2009) framework is mostly motivated by the empirically observable discrepancy in the profitability of liquidated bank assets when managed by non-bank entities as opposed to banks (see, for example, Acharya, Bharath & Srinivasan, 2007).

2.2.2 Models based on network theory

An increasing body of literature on financial contagion employs advanced network theory to model the structure of inter-institutional exposures and analyze its overall fragility (for a general overview of the application of networks in economics and social studies see, for example, Jackson, 2008). The models of Allen and Gale (2000) and Freixas et al. (2000) are early examples of simple network frameworks for analyzing financial contagion, in which the degree of completeness of interbank exposures determines the overall robustness of the network. These early models are, however, rooted in general equilibrium theory and do not make use of network theory explicitly. More recently, various models based on network theory have grown to encompass a vast number of connections between nodes, or individual institutions, that more closely resemble highly complex financial systems.

The clearing mechanism developed by Eisenberg and Noe (2001) is an influential early reference. The basic setup involves *n* financial nodes, equivalent in function to firms, which are interlinked through outstanding liabilities and receive operating cash flows from outside of the network. Liabilities and operating cash flows constitute the financial linkages in the model, whereas the equity of an individual node is determined as the cash inflows that exceed its liability payments. Given these basic contours of the model, the system-wide clearing mechanism of the Eisenberg and Noe (2001) network is designed to meet the following criteria: 1) limited liability (equity cannot fall below zero), 2) debt seniority (dividends to node shareholders are only available after all liabilities have been paid), and 3) proportionality (liabilities of a defaulted node are settled in proportion to the size of the liability).

Eisenberg and Noe (2001) simulate the exposures of individual nodes to systemic risk by introducing the concept of a fictitious default algorithm. The algorithm performs an iterative check of whether an individual node can meet its obligations given that all other liabilities in the network are settled. Consequently, nodes can be differentiated based on their robustness, i.e., early defaulting nodes are more fragile than nodes that default at a later stage of the iterative process. The extent to which an individual node's financial distress is driven by losses of previously defaulted nodes defines the susceptibility of that node to systemic risk. Implications of the Eisenberg and Noe (2001) specification of a network model on systemic risk and firm valuation are twofold. First, if markets are assumed to be complete, the value of an individual node in the network is simply a discounted value of all future cash flows, which implies that an increase in risk lowers the value of all nodes. Second, even in the absence of market frictions, higher volatility of cash flows in the network reduces the value of individual nodes.

Elsinger, Lehar and Summer (2006) extend the framework of Eisenberg and Noe (2001) by adding a rich macrofinancial part to the basic network model. Additionally, they introduce randomness and various degrees of liability seniority into the model. Such a setup enables them to define fundamental defaults, which occur in the first iteration of the fictitious default algorithm. They are the result of losses stemming from the structure of individual nodes' balance sheets, particularly their exposures to market and credit risk. Alternatively, contagious defaults occur during subsequent iterations of the algorithm, as nodes begin to default as a consequence of prior defaults of other nodes in the network. Because the value of nodes' equity is random and dependant on macrofinancial shocks, defaults and contagion have both an economic and a network dimension. Consequently, systemic risk is no longer modeled as depending solely on exposures between nodes. Losses stemming from exposures to market and credit risk contribute significantly to aggregate systemic risk in this framework.

Using a vast database on the structure of banks' balance sheets in the Austrian banking sector, Elsinger et al. (2006) provide an empirical application of their model. They first estimate extreme losses from market and credit risk exposures of banks in the sample with VaR and plug the results in the model to obtain default probabilities. Default and contagion dynamics are analyzed for a short-term horizon that corresponds to a clearing mechanism that suspends all payments following a bank default. Alternatively, a long-term horizon refers to a clearing mechanism that redistributes the liquidation value of a defaulted bank among remaining banks. Results of Elsinger et al. (2006) suggest that bank defaults due to contagion in the Austrian banking sector are more likely to occur over the short-term than the long-term. Furthermore, contagion is usually triggered by a relatively high number of fundamental defaults. Even though contagious defaults are less likely than fundamental defaults in the empirical exercise, Elsinger et al. (2006) find that contagion can nonetheless result in significant aggregate losses once it occurs.

Nier, Yang, Yorulmazer and Alentorn (2008) construct a random network model that is defined by five parameters: 1) the number of banks (nodes) in the network, 2) interbank links that have a uniform probability of occurring between two banks, 3) aggregate equity ratio, 4) aggregate interbank liability ratio, and 5) aggregate size of nonbank assets. Balance sheet structure of banks in the model is kept simple. Assets consist of commercial, or nonbank, and interbank loans, while liabilities include deposits, interbank debts and equity. Balance sheets of individual banks in the network are determined in a deductive fashion. Aggregate commercial loans are divided among banks according to a rule that ensures banks are of different sizes. Shocks in the Nier et al. (2008) framework are simulated as fundamental defaults. The basic procedure is largely reminiscent of the fictitious default algorithm of Eisenberg and Noe (2001). Individual banks are sequentially stressed until their equity is depleted. After individual banks default, their outstanding liabilities are imposed as losses among lending banks. Contagion in the network occurs, when lending banks become insolvent due to losses on their interbank portfolios.

Nier et al. (2008) perform a series of comparative statics simulations and analyze network response to changes in basic parameters. Their results suggest that the probability of contagion decreases as the aggregate equity of banks increases. The relationship is, however, not linear. Contagious defaults rise slowly as equity levels fall below 5% of aggregate assets. A drop of aggregate equity below the 2% threshold increases the incidence of contagious defaults significantly. Increased interconnectivity of banks, approximated by increasing the interbank liability ratio, also results in a higher number of contagious defaults. The number of defaults becomes asymptotically stable after the ratio of interbank loans reaches 30% of all assets due to the stabilizing effect of equity. Due to the specification of the model, equity increases along with interbank liabilities and offsets part of the effect.

A particularly interesting result of the model simulations by Nier et al. (2008) is the role that interbank links play in helping contagion spread across the network. Specifically, they look at whether an increase in the probability of interbank links forming improves the robustness of the network, which is suggested, for example, by Allen and Gale (2000). The results indicate that for low aggregate levels of equity, increasing interconnectivity increases the fragility of the network. Reciprocally, higher levels of aggregate equity imply that interbank links function more as buffers that attenuate rather than amplify adverse shocks.

The modeling approach of Allen, Babus and Carletti (2010) is a combination of a general equilibrium model and a network model with six nodes (banks). Banks in the model invest in projects that provide a random payoff at maturity and finance these projects with funds obtained from depositors. In exchange for funds, banks issue deposits with a fixed rate of return. Deposits that mature in the same period as investment projects approximate long-term finance, while those that mature one period prior to investment projects approximate short-term financial structures. The key difference between the two horizons, emphasized by Allen et al. (2010), is the presence of roll-over risk in the latter case. As the deposit contract matures and investors acquire new information regarding the soundness of banks, they make a decision on whether or not they shall reinvest their remaining funds.

In the event that the payoff of investment projects is low, so that an individual bank cannot settle the deposit contract at the specified rate, it defaults, triggering the default of all other banks in the network. The network structure of the model enables banks to exchange parts of their investment portfolio with other banks, which gives rise to monitoring costs. Diversification through assets sales improves the robustness of the network and lowers expected losses of bank defaults. Allen et al. (2010) analyze the concept of risk concentration in the banking sector by introducing two distinct market structures that reflect the composition of banks' portfolios. A clustered network is comprised of two independent groups of banks, in which all three banks are interconnected and therefore share the same risk profile. Alternatively, banks in a unclustered network are connected in a circular fashion, where each bank is linked with exactly two other banks. As a consequence, the risk profiles of individual banks in this network are unique.

Results of Allen et al. (2010) model simulations indicate that the structure of the banking network has no particular effect on contagion when deposit contracts are long-term. This result follows directly from the structure of the long-term model, in which banks are not exposed to roll-over risk as there is no maturity mismatch between assets and liabilities. The alternative, short-term model specification, however, results in significant aggregate welfare and network effects. In the presence of roll over risk, the unclustered network exhibits a higher degree of resilience to funding shocks. Banks in the clustered network, on the other hand, are at greater risk of defaulting due to withdrawals of funds. The latter result, in particular, highlights the potential problem of over diversification in banking. Allen et al. (2010) show that a banking system is generally more fragile, if the differences in the risk profiles of individual banks in the network are very small.

Battison, Gatti, Gallegati, Greenwald and Stiglitz (2012) propose a network model of complex interbank credit links that combines a banking system with a shadow banking component. Along with a network of credit liabilities the model also features CDS-type contracts that enable individual institutions to insure their exposures against losses due to defaults. Similarly to the approach of Nier et al. (2008), Battison et al. (2012) regard the aggregate ratio of bank equity to total assets as the aggregate robustness benchmark. They define individual institutions' robustness in terms of the distance to default, which is modeled using a jump-diffusion model. Interbank links are complete, i.e., every bank is linked to every other bank, and follow a model structure akin to the one in Eisenberg and Noe (2001). Furthermore, connections between banks are subject to the financial accelerator phenomenon that can undermine the equity position of borrowing banks through two distinct channels. First, a positive feedback loop that magnifies an adverse asset price shock, worsens the liquidity position of the bank, and leads to credit withdrawals of lending banks and potentially default. Second, lending banks compensate for higher risk of the borrowing bank, following a negative shock, by charging a higher interest rate, which lowers the robustness of the borrowing bank.

Model simulations of Battison et al. (2012) indicate that in the absence of accelerator effects, individual banks benefit from forming links in the network. In this case, risk sharing through diversification improves the loss-absorbing capacity of the individual bank. In the presence of accelerator effects, however, the implications for the resilience of individual banks are not as clear cut. As long as a particular bank in the network is relatively poorly interconnected, i.e., it is linked to approximately twenty other banks, the diversification effect dominates and the probability of default decreases sharply. Once the number of interbank links exceeds the twenty link threshold, the accelerator effect begins to hold sway and the probability of default increases. As a corollary, Battison et al. (2012) include an analysis of systemic dynamics by inverting the directionality of distress. In this scenario, default of a borrowing bank induces a series of lending bank defaults, following the iterative process of the fictitious default algorithm. Results for systemic robustness are similar to the individual default case. In the presence of strong accelerator effects, aggregate probability of default initially decreases, but begins to increase as the number of interbank links grows.

2.2.3 Models of individual contribution to systemic risk

Risk measurement methodologies that focus on quantifying financial institutions' contribution to systemic risk have become a major strand of the systemic risk literature following the crisis of 2007/08. This new field of research is rooted in the existing empirical and theoretical foundations of the systemic risk canon and seeks to provide a tractable methodology for evaluating systemic importance of financial institutions. Consequently, these new models represent an integral part of the post-crisis focal shift from microprudential to macroprudential regulatory policies. Furthermore, they enable regulators to assess systemic riskiness of individual financial institutions and provide a framework for assigning institution-specific capital surcharges. The defining characteristic of the individual contribution methodologies is their high degree of practicality. Most models utilize publicly available financial data on financial institutions' stock returns, size, CDS premia and measures of financial soundness like leverage and maturity mismatch.

The ΔCoVaR method developed by Adrian and Brunnermeier (2011) is a VaR-based measure of individual financial institutions' contribution to systemic risk. The VaR foundation relates to ΔCoVaR being a tail co-dependence[8] measure between an individual institution and the financial system. Specifically, ΔCoVaR is designed to capture the change in the conditional VaR of the financial system following a change in the VaR of an individual financial institution compared to that institution being at its normal or median state. ΔCoVaR can therefore also be interpreted as a marginal measure of systemic risk contribution that gauges the extent to which the distress of an individual institution, measured by its VaR, spills-over to the financial system.

Given that the CoVaR methodology is an extension of the VaR concept, a formal definition of VaR is warranted. According to Jorion (2007, p.106), VaR can be defined as "*the worst loss over a target horizon such that there is a low, prespecified probability that the actual loss will be larger*". An implicit definition of VaR is therefore analytically given as:

$$\Pr\left(R_{i,t} > VaR_{i,t}\right) \leq 1-c \tag{1}$$

[8] Adrian and Brunnermeier (2011) attribute the choice of the prefix *co-* to signify co-movement, conditional, contagion and covariance. All of these concepts are implied by the *CoVaR* measure.

where $R_{i,t}$ corresponds to the return series of institution i given the chosen low prespecified probability c (i.e., the confidence interval, henceforth CI). $VaR_{i,t}^{q}$ can also be expressed more directly in terms of the quantile function. For the q quantile (where $q = 1 - c$) of the institution i return distribution the quantile function equals:

$$\Pr\left(R_{i,t} \leq VaR_{i,t}^{q}\right) = q \tag{2}$$

Following this formulation of VaR, Adrian and Brunnermeier (2011, p.7) define $CoVaR_{q}^{j|i}$ as the VaR of the financial system conditional on institution i being at a particular state $Z\left(R_{t}^{i}\right)$. $CoVaR_{q}^{j|i}$[9] therefore equals the q quantile of the conditional probability distribution:

$$\Pr\left(R_{j,t} \leq CoVaR_{q,t}^{j|i} \middle| R_{i,t} = Z\left(R_{i,t}\right)\right) = q \tag{3}$$

The measure of institution i contribution to systemic risk or $\Delta CoVaR_{q,t}^{j|i}$ is consequently defined as the difference between $CoVaR_{q,t}^{j|i}$ of the financial system conditional on institution i being at its VaR and $CoVaR_{q,t}^{j|i}$ of the financial system conditional on institution i being at its median:

$$\Delta CoVaR_{q,t}^{j|i} = CoVaR_{q,t}^{R_{j,t}|R_{i,t}=VaR_{i,t}^{q}} - CoVaR_{q,t}^{R_{j,t}|R_{i,t}=Median} \tag{4}$$

$\Delta CoVaR_{q,t}^{j|i}$ therefore measures the percentage change in the VaR of the financial system, when the VaR of institution i changes by 1%. By inverting the conditionality of the CoVaR measure, so that $CoVaR_{q,t}^{i|j}$ becomes VaR of an institution i conditional on financial system being at its VaR, Adrian and Brunnermeier (2011) define a complementary systemic risk measure exposure *CoVaR*. Unlike the original definition, exposure CoVaR measures the sensitivity of individual institutions' returns to systemic shocks and falls in the same category as the MES measure of Acharya et al. (2010).

Adrian and Brunnermeier (2011) estimate ΔCoVaR for US financial institutions using quintile regressions, due to the straight-forward estimation procedure that requires no

[9] The superscript j can generally refer to any financial institution. Adrian and Brunnermeier (2011) define $CoVaR_{q}^{j|i}$ so that j represents the financial system, while the superscript i denotes a particular financial institution within said system. I follow this designation throughout the thesis.

distributional assumptions and is well suited for modeling tail risk. As a robustness check, they compute ΔCoVaR using a diagonal (DVECH) bivariate general autoregressive conditional heteroscedastic (GARCH) model, which, according to the authors, better captures time variability in model variables and the tail of the distribution. An empirical analysis by Benoit, Colletaz, Hurlin and Pérignon (2013) suggests that a GARCH model with dynamic second moments is a more suitable method for estimating ΔCoVaR than a quantile regression approach.

The overall appeal of CoVaR as a systemic risk measure, according to Adrian and Brunnermeier (2011, p. 9-11), is due to the following properties:

- Cloning property: financial institutions of different sizes that are otherwise identical have the same CoVaR.
- Causality: conditionality of CoVaR does not relate to causality, i.e., CoVaR does not explicitly convey whether systemic importance of a particular institution is due to a causal link or simply the result of exposure to common factors.
- Tail distribution: conditionality of CoVaR implies that it is a tail measure of risk and therefore a more extreme risk measure than unconditional VaR.
- Conditioning: CoVaR is conditioned on an individual financial institution being at a specific state (i.e., at its VaR) with probability q rather than a specific return level, which makes it an indiscriminate measure of systemic risk in terms of individual institutions' risk strategies.
- Endogeneity of systemic risk: CoVaR incorporates systemic risk as endogenous to the system and dependant on the risk taking behavior of financial institutions that operate in the system.
- Directionality: conditioning of CoVaR is not commutative, i.e., CoVaR conditioned on a particular institution being at its VaR does not equal CoVaR conditioned on financial system being at its VaR.
- Exposure CoVaR: inverting the directionality of $CoVaR_q^{j|i}$ to $CoVaR_q^{i|j}$ yields exposure CoVaR that is a measure conceptually analogous to stress test exercises on an individual institution level.
- Co-expected shortfall (CoES): CoVaR can also be defined as an expected shortfall (ES) measure of risk.

The systemic expected shortfall or SES model developed by Acharya et al. (2010) is a systemic risk measure based on the marginal expected shortfall (MES) methodology of quantifying risk. Authors provide two main reasons in favor of such a formulation of a systemic risk measure. First, they regard the VaR methodology as an inappropriate tool for analyzing aggregate systemic risk. VaR was developed and is primarily intended to be used as an internal risk management instrument by individual financial institutions. Second, there exists a gap between theoretical work on financial contagion and regulatory practice within the macroprudential domain. The SES model is therefore an attempt to construct a practical systemic risk measure that captures externalities associated with financial institution's failures or inadequate capitalization. The model itself is relatively sparsely defined, since systemic risk is assumed to be driven by individual institutions' capital shortfall measured by MES and their leverage.

According to Acharya et al. (2010), excessive risk within the financial system tends to build up as a consequence of a regulatory environment that fails to properly address the externality problem. Specifically, it relates to regulators' inability to induce financial institutions to bear part of the externality-related costs. The SES model can therefore be used as a macroprudential regulatory instrument in order to diminish the externality problem. By imposing a tax on financial institutions based on estimates of their contribution to systemic risk and their capital shortfalls, the regulator can effectively incentivize individual institutions to refrain from engaging in overly risky activities.

Unlike the basic VaR model that is used to produce quantile-based estimates of extreme losses given a certain CI, the ES methodology provides a framework for estimating extreme losses when VaR is exceeded. The ES methodology was first suggested by Artzner, Delbaen, Eber and Heath (1999) as a more comprehensive alternative to VaR. They define ES as the expected loss conditional on the loss exceeding VaR_i^q, which can be expressed analytically as:

$$ES_i^q = -E\left[R_i \middle| R_i \leq VaR_i^q\right] \tag{5}$$

An additional advantage of the ES methodology is the fact that it meets the Artzner et al. (1999, p. 208-210) criteria for coherent risk measures[10] that consist of:

- translation invariance: adding/removing assets from the existing position increases/decreases the risk of that position by the cash amount invested/received,
- subaditivity: aggregate risk of the portfolio of securities is equal to or smaller than the sum of risks of individual securities in that portfolio,
- positive homogeneity: risk of the multiple of a position equals the multiple of the risk of that position,
- monotonicity: the risk of the position with lower final net worth is smaller or equal to the risk of the position with higher final net worth,

[10] According to this definition, VaR is not a coherent risk measure, since it does not meet the subaditivity criterion, i.e., VaR of a portfolio can be greater than the sum of individual securities' VaR. As such, VaR can be a misleading risk measure if used as a benchmark for portfolio diversification (see Artzner et al., 1999).

- relevance: as long as the final net worth of the position is strictly negative, the corresponding risk of that position is greater than zero.

Acharya et al. (2010) expand the single institution definition of ES in equation 5 to include numerous institutions. They define ES as a weighted sum of expected losses of individual institutions conditional on the financial system exceeding its VaR:

$$ES^q = -\sum_{i=1}^{I} w_i E\left[R_i \middle| R_j \leq VaR_j^q\right] \tag{6}$$

where w_i are weights corresponding to the relative importance of each institution in the financial system. Acharya et al. (2010) further define the marginal effect of institution i being exposed to the financial system, or the marginal expected shortfall (MES), as:

$$MES_i^q = \frac{\partial ES^q}{\partial w_i} = -E\left[R_i \middle| R_j \leq VaR_j^q\right] \tag{7}$$

Unlike the Adrian and Brunnermeier (2011) CoVaR specification that is theoretically sparse, Acharya et al. (2010) propose the SES metric, which is a systemic risk measure based on estimates of MES, institution leverage and capital level, and also includes a concrete theoretical framework. Specifically, SES is defined as the capital shortfall of the financial system conditional on a macroeconomic shock materializing and is used to analyze aggregate welfare effects of bank defaults or undercapitalization.

Acharya et al. (2010) empirically test the performance of MES during the financial crisis of 2007/08 on a sample of US financial institutions. They analyze the effect of pre-crisis variable estimates on their cross-sectional variation during the crisis. Along with MES their model includes estimates of ES, leverage, annual volatility, realized SES and institutions' beta. Their results suggest that MES estimates appear to have a degree of predictive power in explaining subsequent realized returns of institutions in the sample, whereas ES and beta have not. Moreover, institution-specific risk measures (ES and volatility) and codependence measures (beta and MES) exhibit a high degree of correlation.

A potential drawback of such an approach to systemic risk estimation, according to Brownlees and Engle (2012), is the fact that financial institutions' contributions to systemic risk during severe financial crises can only be analyzed *ex-post*. They therefore propose SRISK as a more flexible upgrade of the SES methodology. The SRISK index of a single financial institution is comprised of its estimated MES, size and leverage. The sum of individual institutions' contribution to systemic risk, or aggregate SRISK, provides a system-wide estimate of potential capital shortfalls in the event of a systemic crisis. As such, aggregate SRISK can be used as a benchmark by regulators to estimate recapitalization needs of the financial system when market conditions deteriorate significantly.

Brownlees and Engle (2012) estimate individual institutions' MES by constructing a time series model of daily equity and market returns. The basic setup involves a bivariate GARCH model with dynamic conditional correlations (DCC), first proposed by Engle (2002), which is used to model both the conditional variances and conditional correlations of the return series. A model specification of this kind can be used to produce dynamic, out of sample forecasts of MES, which alleviates the problem of static, backward-looking analysis employed by Acharya et al. (2010). Furthermore, given the highly diverse and growing body of ARCH-type models (for an overview, see Bollerslev, 2008), a time series approach to estimating MES offers a variety of different volatility and correlation specifications.

By forecasting short-term expected capital shortfalls, the SRISK index can also be used as an early warning indicator by regulators. An empirical analysis of the US financial sector before and during the crisis of 2007/08 by Brownlees and Engle (2012) reveals that the capital shortfall of the US financial system, according to estimated aggregate SRISK, increased from 200 billion USD before the crisis to nearly 1000 billion USD during the crisis. Aggregate SRISK in this scenario is estimated assuming an 8% minimum capital requirement and a total market decline of 40%. Changing the parameters of the basic model yields alternative estimates of the capital shortfall under various regulatory scenarios. A comparative analysis of ΔCoVaR, SES and SRISK by Benoit et al. (2013) indicates that ΔCoVaR and SRISK are particularly suitable for constructing systemic risk rankings of financial institutions.

Huang et al. (2009) propose a systemic risk measure that is more parsimonious than the measures discussed so far but more timely. Their DIP method relies entirely on data that is available on a daily frequency, namely equity returns and CDS premia of financial institutions. They model systemic risk using a portfolio credit-risk approach and apply a two-step methodology. First, they estimate individual financial institutions' risk-neutral PDs using CDS spread data and make a quarterly forecast of default correlations using data on equity returns. Second, they define DIP as the price of insurance against expected losses of individual institutions within the specified portfolio in the event of a systemic crisis. A systemic event is defined as default of at least 15% of all financial institutions' liabilities.

Finally, Huang et al. (2009) use the estimates of financial institutions' PDs and DIP to perform two types of stress test exercises. The first stress test incorporates estimates of financial institutions' PDs in a vector autoregressive (VAR) model that also includes macro-level variables on market returns, market volatility and the structure of interest rates. The severity of the stress is determined based on adverse forecasts of the variables in the VAR model that are added to the existing time series and used to re-estimate the model. The second approach is a stress test based on a simulation of extreme historical market downturns. Both stress test exercises by Huang et al. (2009) produce distressed forecasts of the DIP measure that are comparable in magnitude to their estimated level of systemic risk during the crisis of 2007/08.

2.2.4 Alternative models

The three categories of systemic risk measurement methods discussed so far are characterized by a common theoretical or empirical foundation and include a multitude of varying techniques for analyzing systemic risk. The phenomenon of systemic risk is inherently complex and presents a wide scope for research, which partly explains the fact that different methodologies for measuring systemic risk frequently overlap. The proposed categorization is therefore merely an attempt to provide a straight-forward frame of reference. Along with these three broad categories of systemic risk measurement methodologies, important alternative methods have also been suggested. Methods that are particularly relevant include: the CCA approach to measuring systemic risk, systemic risk measures based on extreme value theory, econometric measures of systemic risk, and the regulatory proposal by The Basel Committee on Banking Supervision (2011).

Hartmann, Straetmans and De Vries (2004) use multivariate extreme value theory to model comovement in international financial markets during periods of financial crises. They approximate international asset market linkages with an international CAPM model structure that includes local inflation and market return variables along with the fundamental CAPM parameters. Systemic events on international asset markets are defined as either contagion or flight to quality. Contagion corresponds to a process of extreme, linked declines in stock prices, whereas flight to quality refers to extreme increases in government bond prices. Empirical results of the Hartmann et al. (2004) model for a sample of stock and government bond returns in G-5 countries indicate that stocks have generally fatter left tails, i.e., more extreme negative returns than bonds. Furthermore, based on a data set that covers major market downturns of the late 1980's and 1990's, Hartmann et al. (2004) find that a stock market crash is roughly twice as likely to result in contagion than a comparable episode in the bond market. Although systemic events of an extreme magnitude are not very common in the sample, negative effects of contagion on international financial markets can be considerable.

Lehar (2005) proposes a systemic risk index based on assets (or SIV index) that reflects default probabilities of banks in a particular banking sector. The basic framework for the estimation of default probabilities is based on contingent claims analysis. Input data for the SIV index consist of estimates of three key parameters: bank asset volatility, the level of bank equity and interbank asset value correlations. Lehar (2005) estimates the former two parameters using option pricing theory and obtains asset correlations by fitting an exponentially weighted moving average (EWMA) model. Furthermore, by using the CCA methodology, Lehar (2005) develops a measure of aggregate expected shortfall. The measure reflects the value of outstanding liabilities of a bank that exceed its equity level in the event that the bank defaults. It can therefore be used as an assessment of potential deposit insurance liabilities following bank defaults.

By combining the ES and the CCA approach, Gray and Jobst (2013) develop a forward-looking measure of systemic risk named System-CCA. They model systemic risk as a joint probability distribution of extreme losses, which they estimate from loss distributions of individual financial institutions in a specified portfolio. Loss functions of individual financial institutions are estimated using widely available data on daily stock and option prices. The key difference between the System-CCA measure and comparable systemic risk measures, according to Gray and Jobst (2013), is the fact that their specification includes both an idiosyncratic risk component and a systematic risk component. Specifically, the idiosyncratic component captures the risk of individual institutions that are reflected in their equity and option prices. The systematic component, on the other hand, captures risk from exposure to common macrofinancial factors. Consequently, systemic risk using the System-CCA approach can be analyzed on an aggregate as well as individual institution level simultaneously.

For a sample of US financial institution spanning the period from mid 2007 to early 2010, Gray and Jobst (2013) find that institutions that eventually required government assistance or defaulted also contributed the most to systemic risk measured by System-CCA. Given estimates of individual institutions' systemic riskiness, they asses additional equity needed to compensate for this risk at an average of 50 basis points per institution. For extreme risk realizations during the height of the financial crisis of 2007/08, total systemic risk-adjusted equity shortfall for US financial institutions exceeds 300 basis points on average.

Billio, Getmansky, Lo and Pelizzon (2012) develop a set of econometric measures of systemic risk, based on Granger causality tests and principal component analysis (PCA). The latter methodology is used to determine significant common factors among financial institutions that affect their systemic risk profiles. Granger causality tests are subsequently applied to determine statistically significant casual links between individual financial institutions. This setup enables the authors to analyze the empirical structure of links within a network of different financial institutions using five statistical measures of connectedness.

The five measures are (Billio et al., 2012, p. 540): 1) degree of Granger causality that measures the statistical significance of links, 2) number of connections of the individual institution defined as the difference between links to other institutions that are Granger caused by the institution and links to the institution that are Granger caused by other institutions, 3) sector-conditional connections that are defined as significant connections within a particular financial sector, 4) closeness that measures the smallest distance between a single institution and all other institutions in the network, and 5) eigenvector centrality that reflects the importance of a particular financial institution in the network.

Finally, following the release of the Basel III standard in 2010, the Basel Committee on Banking Supervision (2011) subsequently released a proposal of a regulatory measure of systemic risk. The proposed method is essentially an indicator-based systemic risk measure for global systemically important banks (G-SIBs), summary of which is given in table 5. According to the outlined methodology, systemic risk of individual financial institutions is measured based on estimates of their cross-jurisdictional activity, size, interconnectedness, substitutability, and complexity using individual indicators whose weights sum to 20% within each category.

Table 5*: Indicator-based systemic risk measurement approach*

Category and Weighting	**Individual indicator**
Cross-jurisdictional activity (20%)	• Cross-jurisdictional claims • Cross-jurisdictional liabilities
Size (20%)	• Total exposures as defined for use in the Basel III leverage ratio
Interconnectedness (20%)	• Intra-financial system assets • Intra-financial system liabilities • Wholesale funding ratio
Substitutability (20%)	• Assets under custody • Payments cleared and settled through payment systems • Values of underwritten transactions in debt and equity markets
Complexity (20%)	• OTC derivatives notional value • Level 3 assets • Trading book value and Available for Sale value

Source: Basel Committee on Banking Supervision, Global Systemically Important Banks: Assessment Methodology and the Additional Loss Absorbency Requirement, 2011, p. 5.

Systemic importance of individual G-SIBs is determined by assigning a score to individual indicators that reflects the importance of individual banks relative to the entire sample of G-SIBs (the Basel Committee on Banking Supervision, 2011, used a sample of 73 of the world's largest banks). Based on their estimated systemic importance, individual banks would be required to add up to 3.5% of common equity relative to RWA, in order to improve their loss-absorbing capacity and lower their probability of default. The indicator-based systemic risk measurement approach has been therefore developed specifically to address the issue of global SIBs and is primarily a regulatory attempt to improve the resilience of the world's largest banks that enjoy the TBTF status.

3 SYSTEMIC RISK CONTRIBUTIONS OF EUROZONE BANKS

Given the diverse array of techniques that have been proposed for measuring individual institutions' contributions to systemic risk, most empirical papers nonetheless focus on the US financial system. Engle et al. (2012) highlight some estimation and data issues that make systemic risk assessment of the European financial system somewhat more involved. Defining the exact location of the original adverse shock and its effects on individual countries or institutions is particularly problematic. Given the heterogeneous structure of the European national economies and financial systems, crises tend to have an asymmetric impact. Engle et al. (2012) attempt to alleviate these issues by introducing particular features into their SRISK index that account for country-, Europe-, and World-specific risk factors. They then use the augmented SRISK index to analyze systemic riskiness of the broader European financial system that includes banks, insurance companies, real-estate companies and financial services companies.

Acharya and Steffen (2013) focus on analyzing the systemic risk contributions within the European banking sector using the SES approach. Their sample covers banks that were part of the EBA stress test exercise in 2011 along with large banks from non-EU member states, like Switzerland. They use stock return data to obtain MES and add data on leverage and capital levels of banks to construct the SES index.

3.1 ΔCoVar of Eurozone banks

I use the CoVaR method of Adrian and Brunnermeier (2011) to perform an empirical assessment of systemic risk contributions of Eurozone banks in a Gaussian framework. In particular, I focus on comparing the systemic risk rankings of banks in the sample during the global financial crisis to the period that preceded the crisis. To this end, I subdivide the entire sample period that spans January 5th 2000 to December 31st 2012 (3330 observations in all) into two sub periods of equal length. First, the pre-crisis period spans December 27th 2002 to December 31st 2007. Second, the period encompassing both the global financial crisis and the beginning of the European debt crisis spans January 2nd 2008 to December 31st 2012. Both estimation periods consist of 1286 observations. I define the unit of observation as a publicly listed Eurozone bank with daily equity prices that are available for the entire sample period. Unlike other empirical analyses of systemic risk contributions that include various types of financial institutions, I focus solely on Eurozone banks. Given specific regulatory requirements for banks, the analysis of systemic risk factors that I perform in part 3.2 could result in omitted variable bias for a sample of different types of financial institutions.

Figure 1: *EUROSTOXX Banks Index daily log returns (in %), 2000-2012*

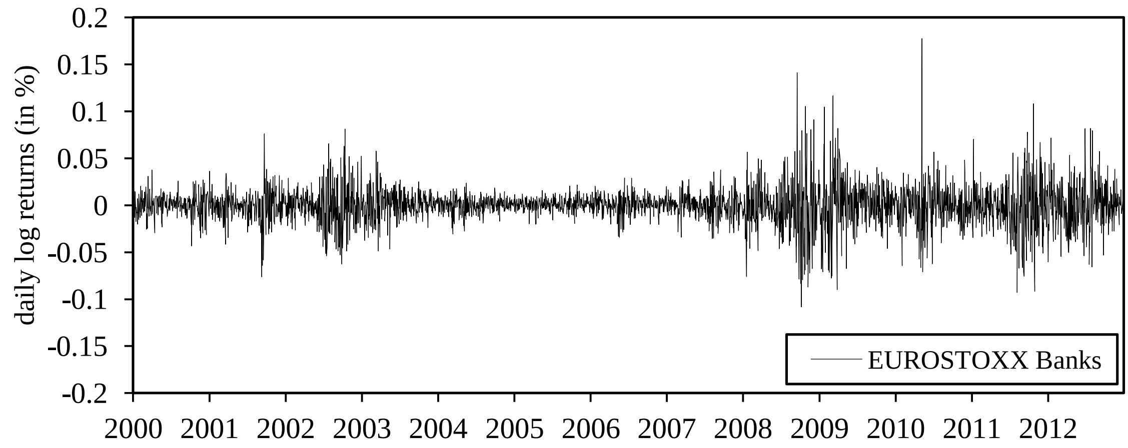
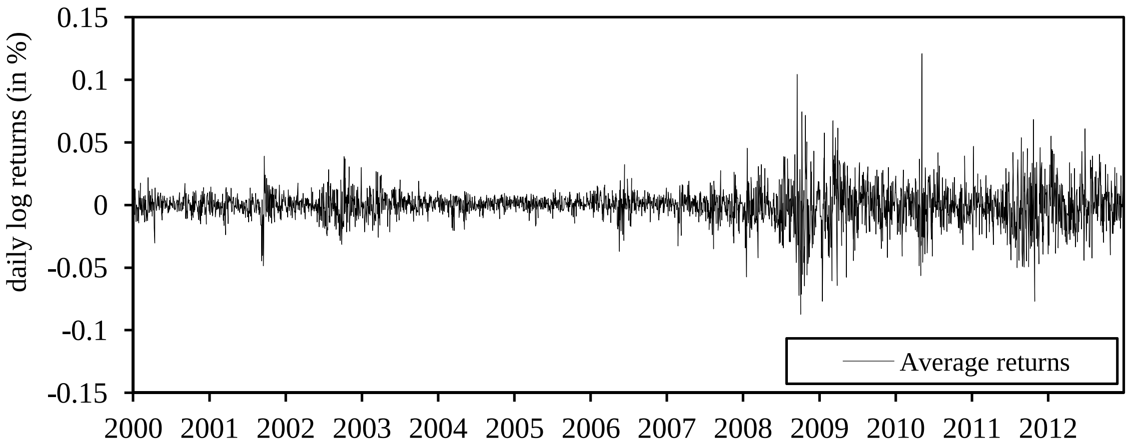


Figure 2: *Sample average daily log returns (in %), 2000-2012*



Following similar applications in the literature on VaR estimation (see, for example Engle, 2001; Tsay, 2010) and systemic risk measurement (see, for example, Brownlees & Engle, 2012; Benoit et al., 2013), I use ARCH-type models to obtain estimates of institutions' intertemporal VaR and CoVaR. Specifically, I employ a GARCH(1,1) model to estimate VaR and a bivariate GARCH DCC(1,1) model to estimate CoVaR. The latter specification is similar to the robustness check that Adrian and Brunnermeier (2011) perform in the original paper, in which they use a diagonal (DVECH) bivariate GARCH(1,1) model to estimate CoVaR. Given the specification of a multivariate GARCH(p,q) model with a DCC conditional correlation structure (see Engle, 2002), it appears better suited for estimating intertemporal correlations and hence CoVaR. The choice of ARCH-type models is further motivated by clear evidence of heteroscedastic effects and volatility clustering in the data series (see figure 1 and figure 2). In the presence of such effects, ARCH-type models provide a straightforward framework for analyzing time-dependent volatility.

3.1.1 Data

I use data on daily equity prices for a sample of 46 Eurozone banks from the Thomson Reuters Datastream database. Banks in the sample are chosen based on the availability and completes of their stock return time series covering the sample period January 5th 2000 to December 31st 2012 (only return series of banks that cover the entire sample period are included in the sample). Additionally, only highly liquid bank stocks are included in the sample (return series with more than 20% of all daily return observations equal to zero are excluded from the sample). I use data on the Euro Stoxx Banks index (symbol SX7E)[11] as a proxy for the financial system variable. For the purpose of the empirical analysis, I calculate daily log returns for the entire sample period. Descriptive statistics for daily log returns of individual banks in the sample are given in appendix 3, table 1.

The time series exhibit two pronounced intervals of increased volatility clustering (see figure 1 and figure 2). The first interval covers the period following the bursting of the dot-com bubble, the events of September 11th and the major US corporate scandals in 2002 and 2003. The second interval begins in late 2007 with volatility peaking following the Lehman collapse in September 2008. Throughout the 2008-2012 period, volatility of Eurozone bank stock returns remained significantly elevated, compared to the relatively low volatility environment of the years leading up to the crisis. The deepening of the European debt crisis in the fall of 2011 that prompted the ECB to launch the long-term refinancing operation (LTRO) in December 2011 is accompanied by another peak in bank stock return volatility.

[11] The Euro Stoxx Banks index is a capitalization-weighted sub index of the Euro Stoxx 600 index and is comprised of highly liquid stocks of large Eurozone banks.

3.1.2 Model

3.1.2.1 Time-dependent model of VaR

Following the definition in equation 2, $VaR_{i,t}^{q}$ corresponds to the q quantile of the return distribution of institution i. Assuming $R_{i,t}$ follows a normal distribution, $VaR_{i,t}^{q}$ can be expressed explicitly as:

$$VaR_{i,t}^{q} = \Phi^{-1}(q)\hat{\sigma}_{i,t} + \hat{\mu}_{i,t} \tag{8}$$

where $\Phi^{-1}(q)$ is the q quantile of the inverse of the probability density function of the standard normal distribution, $\hat{\sigma}_{i,t}$ is the estimated volatility of log returns, and $\hat{\mu}_{i,t}$ is the estimated mean of log returns at time t. I estimate the volatility of individual return series using the econometric approach outlined by Tsay (2010). The basic return specification follows:

$$R_{i,t} = \mu_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $\mu_{i,t}$ is the mean and $\varepsilon_{i,t}$ is the innovation at time t. In order to filter out autocorrelation in first lags from the return series, I model the mean process of $R_{i,t}$ using a simple auto regressive model with three lags – AR(3):

$$\mu_{i,t} = \alpha_0 + \alpha_1\mu_{i,t-1} + \alpha_2\mu_{i,t-2} + \alpha_3\mu_{i,t-3} + \varepsilon_{i,t} \tag{10}$$

The residual is specified as:

$$\varepsilon_{i,t} = z_t\sigma_{i,t} \tag{11}$$

where z_t is i.i.d. distributed with zero mean and unit variance, i.e., $\{z_t\} \sim i.i.d.(0,1)$. Conditional variance is modeled as a GARCH(p,q) process suggested by Bollerslev (1986), which is a generalized specification of the original ARCH(p) model first suggested in a seminal paper by Engle (1982). A GARCH(p,q) model of conditional variance is represented as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\alpha_i\varepsilon_{i,t-1}^2 + \sum_{j=1}^{q}\beta_j\sigma_{j,t-1}^2 \tag{12}$$

where α_0 is the constant, *p* term represents the ARCH component and *q* term the GARCH component in the model. Given that higher order GARCH(p,q) models are generally computationally intensive, I use a simple univariate GARCH(1,1) model to obtain intertemporal estimates of conditional variance in equation 12. The conditional variance process is consequently represented as:

$$\sigma_{i,t}^2 = \alpha_0 + \alpha\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2 \qquad (13)$$

The time-dependent estimator of conditional standard deviation for the return series of institution *i* from equation 8 therefore equals:

$$\hat{\sigma}_{i,t} = \sqrt{\sigma_{i,t}^2} \qquad (14)$$

I obtain time-dependent estimates of the mean process in equation 8 using the AR(3) specification in equation 10. Averages of intertemporal estimates of $VaR_{q,t}^i$ at the 99% CI for individual return series in the sample are given in appendix 4, table 1.

3.1.2.2 Time-dependent model of ΔCoVaR

According to Benoit et al. (2013) (see also Adrian & Brunnermeier, 2011), for symmetrical joint distributions of returns, ΔCoVaR can be expressed by a straightforward closed-form solution. Such a specification of ΔCoVaR is based on intertemporal estimates of conditional correlation between the residuals of the financial system and an individual institution.

The derivation of the closed-form solution for ΔCoVaR follows the approach outlined by Adrian and Brunnermeier (2011) and further elaborated by Benoit et al. (2013). I assume that the conditional distribution of each pair of market and individual bank returns follows a bivariate normal distribution that is represented by:

$$(R_{i,t}, R_{j,t}) \sim \mathrm{N}_2(\mu_{i,t}, \mu_{j,t}, \sigma_{i,t}^2, \sigma_{j,t}^2, \rho_{i,j,t}) \qquad (15)$$

where $R_{j,t}$, $\mu_{j,t}$, and $\sigma_{j,t}^2$ are the return series, the mean, and the variance of the financial system respectively. $R_{i,t}$, $\mu_{i,t}$, and $\sigma_{i,t}^2$ are the return series, the mean, and the variance of institution *i* and $\rho_{i,j,t}$ is the time-dependent conditional coefficient of correlation between returns of the financial system and returns of institution *i*.

According to the definition in equation 3, $CoVaR_q^{j|i}$ is a conditional distribution that represents VaR of the financial system, given that institution *i* is at a particular state. Following Alexander (2008), the conditional standard normal distribution is defined as:

$$R_{j,t} \mid R_{i,t} \sim \left(\mu_{\mathrm{j,t}} + \rho_{i,j,t}\sigma_{j,t}\left(\frac{R_{i,t}-\mu_{\mathrm{i,t}}}{\sigma_{i,t}}\right), \left(1-\rho_{i,j,t}^2\right)\sigma_{j,t}^2 \right) \tag{16}$$

where $\mu_{\mathrm{j,t}} + \rho_{i,j,t}\sigma_{j,t}\left(\frac{R_{i,t}-\mu_{\mathrm{i,t}}}{\sigma_{i,t}}\right)$ is the mean and $\left(1-\rho_{i,j,t}^2\right)\sigma_{j,t}^2$ is the variance of the standard normal conditional distribution. Standardizing the parameters in equation 3 when institution *i* is assumed to be at its p-level VaR therefore yields:

$$\Pr\left(\frac{R_{j,t}-\mu_{\mathrm{j,t}}-\rho_{i,j,t}\sigma_{j,t}\left(\frac{R_{i,t}-\mu_{\mathrm{i,t}}}{\sigma_{i,t}}\right)}{\sqrt{\left(1-\rho_{i,j,t}^2\right)\sigma_{j,t}^2}} < \frac{CoVaR_{i,t}(q,p)-\mu_{\mathrm{j,t}}-\rho_{i,j,t}\sigma_{j,t}\left(\frac{R_{i,t}-\mu_{\mathrm{i,t}}}{\sigma_{i,t}}\right)}{\sqrt{\left(1-\rho_{i,j,t}^2\right)\sigma_{j,t}^2}} \,\middle|\, R_{i,t}=VaR_{i,t}(p) \right) = q \tag{17}$$

where $\frac{R_{j,t}-\mu_{\mathrm{j,t}}-\rho_{i,j,t}\sigma_{j,t}\left(\frac{R_{i,t}-\mu_{\mathrm{i,t}}}{\sigma_{i,t}}\right)}{\sqrt{\left(1-\rho_{i,j,t}^2\right)\sigma_{j,t}^2}}$ has a standard normal distribution with zero mean and unit variance. The q-level CoVaR of the financial system when institution *i* is at its p-level VaR can now be written explicitly as:

$$CoVaR_{i,t}(q,p) = \Phi^{-1}(q)\sqrt{\left(1-\rho_{i,j,t}^2\right)\sigma_{j,t}^2} + \mu_{j,t} + \Phi^{-1}(p)\rho_{i,j,t}\sigma_{j,t} \tag{18}$$

When institution *i* is at its median state, i.e., when $p = 0.5$, then $\Phi^{-1}(p)\rho_{i,j,t}\sigma_{j,t} = 0$, which follows from the assumption that returns are distributed normally. Rewriting definition in equation 4, ΔCoVaR is expressed as:

$$\Delta CoVaR_{i,t}(q,q) = CoVaR_{i,t}(q,q) - CoVaR_{i,t}(q,p) \tag{19}$$

Consequently, the specification for ΔCoVaR simplifies to a closed-form solution:

$$\Delta CoVaR_{i,t}(q,q) = \Phi^{-1}(q)\hat{\rho}_{i,j,t}\hat{\sigma}_{j,t} \tag{20}$$

I estimate both the time-dependent volatility term and the time-dependent correlation term in equation 20 using a bivariate GARCH DCC(1,1) model. Following the specification by

Engle (2002), the conditional variance structures in a bivariate GARCH DCC(1,1) model are simple univariate GARCH(1,1) processes:

$$\begin{aligned}\sigma_{i,t}^2 &= \alpha_{i,0} + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \\ \sigma_{j,t}^2 &= \alpha_{j,0} + \alpha_j \varepsilon_{j,t-1}^2 + \beta_j \sigma_{j,t-1}^2\end{aligned} \tag{21}$$

Estimators of time-dependent conditional variance are therefore equivalent to the estimator in equation 14. Engle (2002) defines the estimators of the elements in the conditional variance-covariance matrix of the bivariate GARCH DCC model using two specifications. The first specification corresponds to:

$$\mathbf{Q_t} = \mathbf{D_t R_t D_t} \tag{22}$$

where $\mathbf{Q_t}$ is the conditional variance-covariance matrix and $\mathbf{D_t}$ is a diagonal normalization matrix of the form:

$$\mathbf{D_t} = diag\left\{\sqrt{\sigma_{i,t}^2}\right\} \tag{23}$$

The structure of the $\mathbf{D_t}$ matrix ensures that $\mathbf{R_t}$ is a conditional correlation matrix. Rewriting the definition in equation 22 by utilizing the definition of $\mathbf{D_t}$ in equation 23, Engle (2002) defines $\mathbf{R_t}$ explicitly as:

$$\mathbf{R_t} = diag\left(\sqrt{\mathbf{Q_t}^{-1}}\right)\mathbf{Q_t}\, diag\left(\sqrt{\mathbf{Q_t}^{-1}}\right) \tag{24}$$

Using matrix notation, the structure of $\mathbf{R_t}$ from equation 24 corresponds to:

$$\mathbf{R_t} = \begin{bmatrix} \sigma_{i,t} & 0 \\ 0 & \sigma_{j,t} \end{bmatrix}^{-1} \begin{bmatrix} \sigma_{i,t}^2 & \sigma_{i,j,t} \\ \sigma_{j,i,t} & \sigma_{j,t}^2 \end{bmatrix} \begin{bmatrix} \sigma_{i,t} & 0 \\ 0 & \sigma_{j,t} \end{bmatrix}^{-1} \tag{25}$$

Multiplying the matrices yields:

$$\mathbf{R_t} = \begin{bmatrix} 1 & \dfrac{\sigma_{i,j,t}}{\sigma_{i,t}\sigma_{j,t}} \\ \dfrac{\sigma_{j,i,t}}{\sigma_{j,t}\sigma_{i,t}} & 1 \end{bmatrix} \tag{26}$$

where $\sigma_{i,j,t} = \sigma_{j,i,t}$ is the conditional covariance of institution *i* and the financial system. The matrix in equation 26 can finally be rewritten as:

$$\mathbf{R_t} = \begin{bmatrix} 1 & \rho_{i,j,t} \\ \rho_{j,i,t} & 1 \end{bmatrix} \tag{27}$$

which confirms that the $\mathbf{R_t}$ matrix is indeed the time-dependent conditional correlation matrix. The second specification of the estimator of the conditional variance-covariance matrix by Engle (2002) corresponds to:

$$Q_{i,j,t} = (1-\alpha-\beta)\overline{R}_{i,j} + \alpha\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta Q_{i,j,t-1} \tag{28}$$

where $\overline{R}_{i,j}$ is the unconditional correlation matrix and the coefficients must satisfy $\alpha, \beta > 0$ and $\alpha + \beta < 1$, for the process to be weakly stationary. Given the structure of conditional variance estimators and conditional variance-covariance estimators, the time-dependent conditional correlation estimator is therefore defined as:

$$\hat{\rho}_{i,j,t} = \frac{\hat{\sigma}_{i,j,t}}{\sqrt{\hat{\sigma}^2_{i,t}\hat{\sigma}^2_{j,t}}} \tag{29}$$

Averages of intertemporal estimates of $\Delta CoVaR_{i,t}(q,q)$ at the 99% CI for individual return series in the sample are given in appendix 4, table 1.

3.1.3 Results

One of the major drawbacks of traditional, microprudential regulatory instruments, like VaR of individual financial institutions, is the fact that they do not entirely capture these institutions' systemic importance. Adrian and Brunnermeier (2011) developed the ΔCoVaR framework in order to address this flaw and provide a more comprehensive risk measure that reflects systemic riskiness of an individual institution. Analogous to the results in the original paper, I find that the cross-sectional relation between VaR and ΔCoVaR of Eurozone banks for the entire sample period lacks any particular regularity (see figure 3).

The cross-section for both sub-periods produces a similar outcome (see figures 1 and 2 in appendix 5). The plot of VaR and ΔCoVaR for the pre-crisis sample period is more concentrated, while the plot for the crisis period is more scattered. None of the plots, however, reveal strong cross-sectional association of VaR and ΔCoVaR. The latter suggests that VaR in isolation can be a misleading measure of systemic importance. Despite the fact that Irish and Greek banks in the sample exhibit highest VaR, select Spanish, French and Italian banks appear to contribute the most to systemic risk.

Figure 3: *VaR and ΔCoVaR (99% CI), 2000-2012 (in %)*

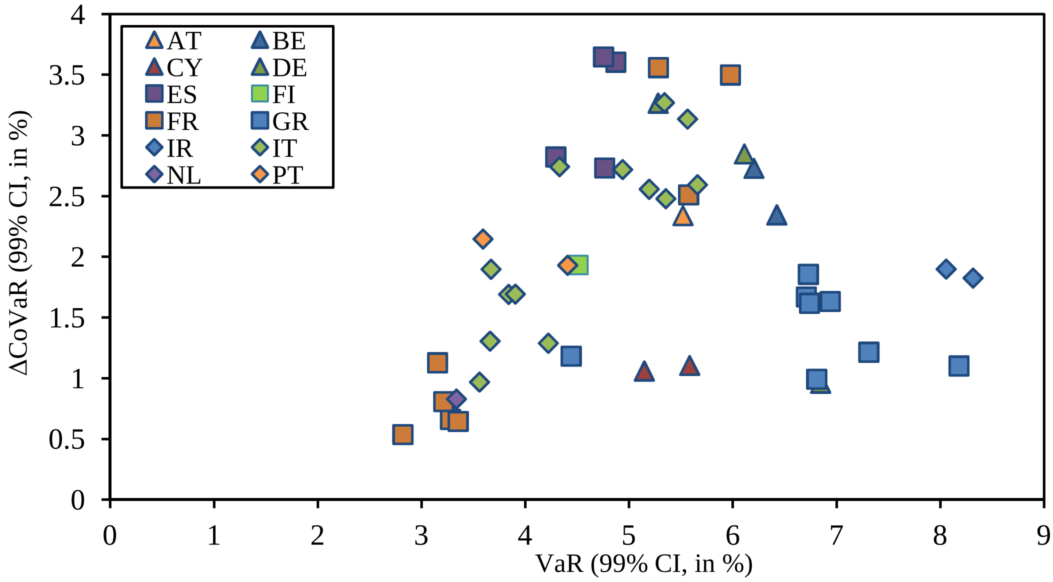
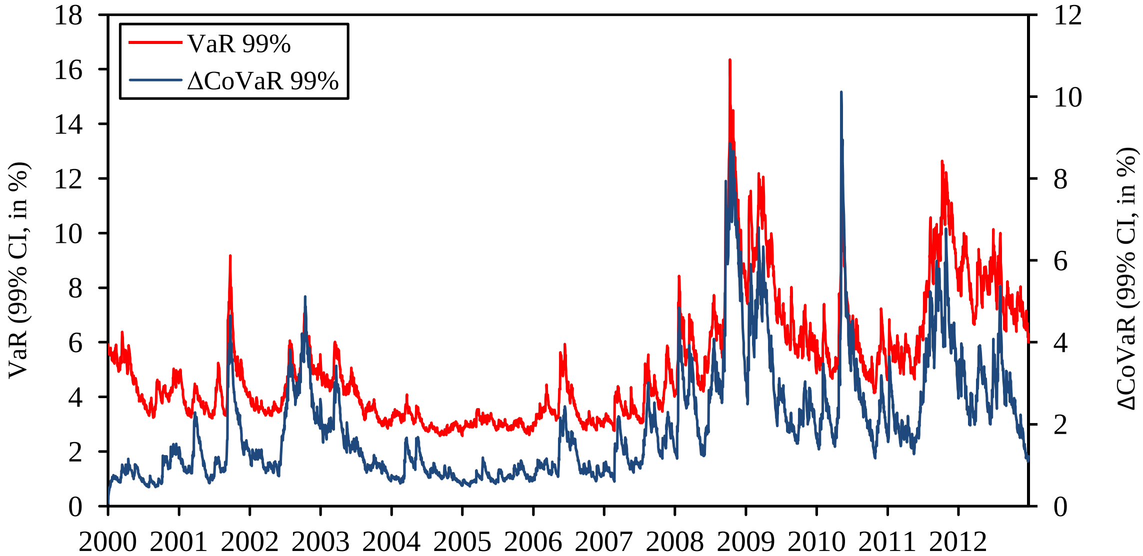


Figure 4: *Time-dependent estimates of VaR and ΔCoVaR (in %)*



Time-dependent estimates of VaR and ΔCoVaR averaged across all banks in the sample are given in figure 4. The figure indicates a high degree of synchronicity between estimated intertemporal VaR and ΔCoVaR. This result suggests considerable tail co-movement of individual bank returns in the sample and the financial system. The absence of a particular relationship structure in the cross section (figure 3) and apparently strong intertemporal codependence of VaR and ΔCoVaR is in line with the findings of Adrian and Brunnermeier (2011).

Both risk measures exhibit three pronounced peaks in the 2008-2012 period. The first peak follows the collapse of Lehman Brothers in late 2008, with average ΔCoVaR reaching 8.9% on October 14th 2008. The second peak takes place on May 11th 2010, with average ΔCoVaR reaching 10.1% following the agreement to establish the EFSF fund as a response to the deepening sovereign debt crisis in the Eurozone. The third peak occurs on November 2nd 2011, with average ΔCoVaR reaching 6.7%, which reflects the heightened uncertainty surrounding the second Greek financial aid package and financial stability issues of major Eurozone member countries.

Figure 5: *Time-dependent conditional correlation coefficient*

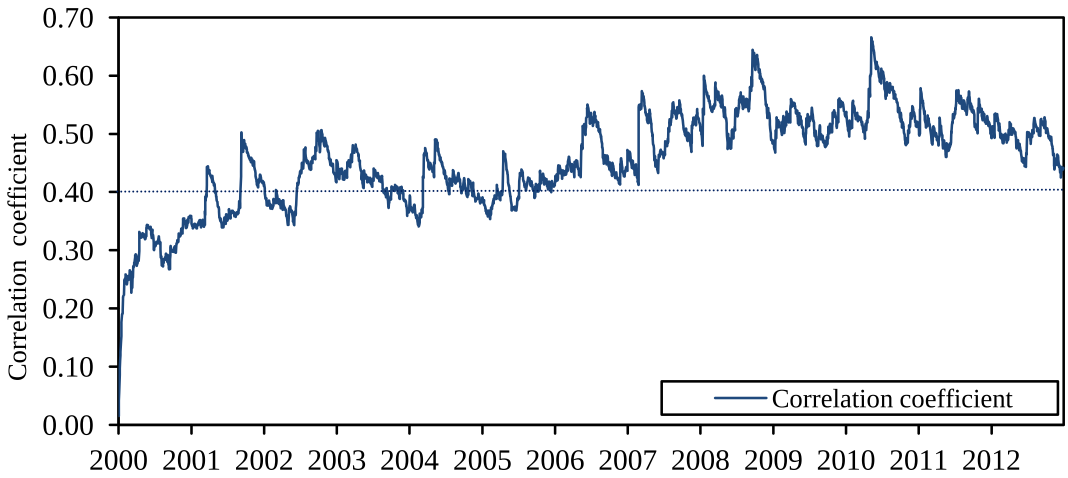
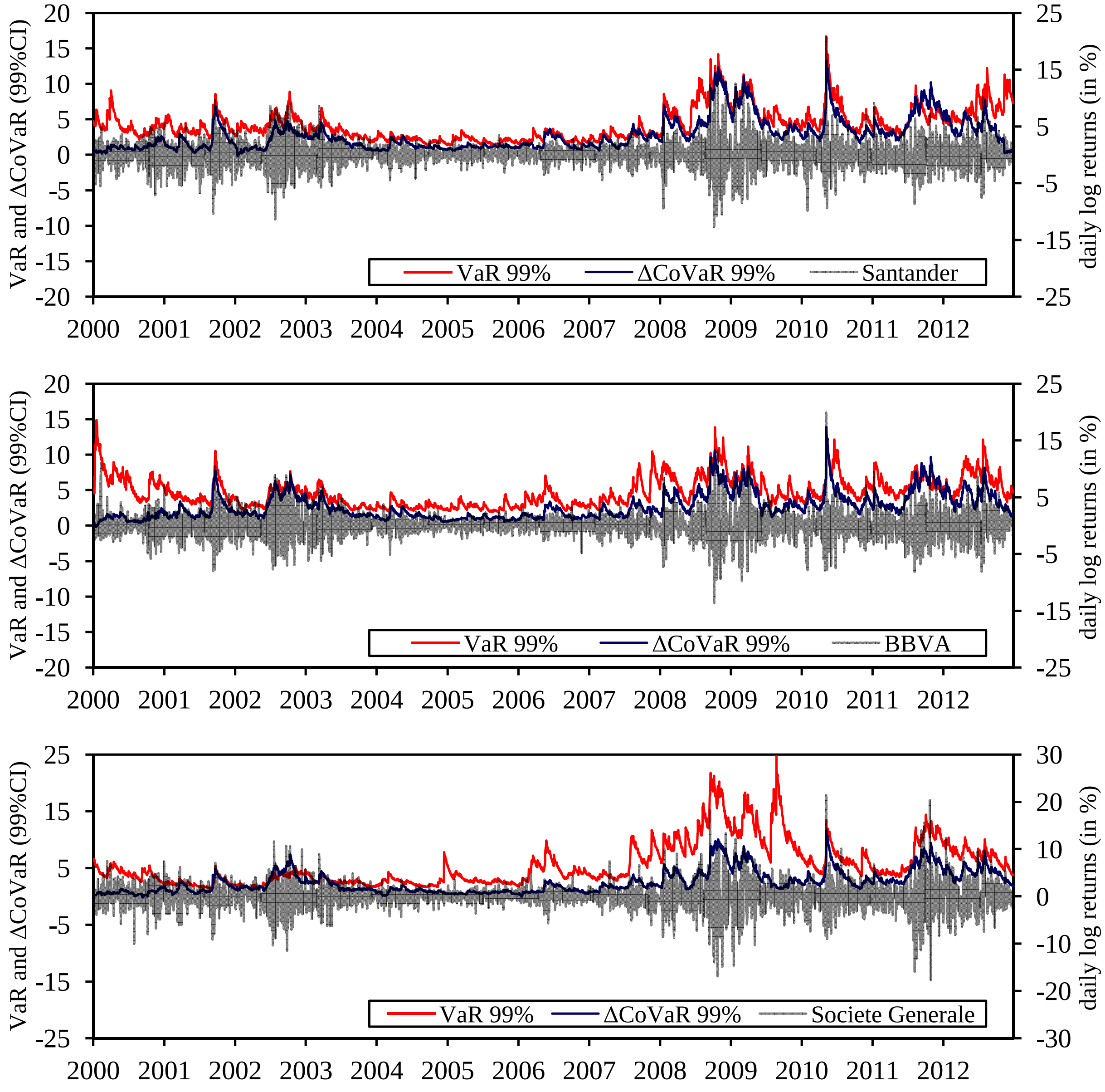


Figure 5 depicts the time-dependent estimate of the conditional correlation coefficient between bank and financial system returns averaged across all banks in the sample. The figure suggests that the average correlation had been steadily increasing from weakly positive at the beginning of the sample period, with the correlation coefficient in the 0.10 to 0.50 range, to strongly positive in the 2008-2012 period. The correlation coefficient in the latter period peaks on May 11th 2010 at 0.66, which coincides with the peak in average ΔCoVaR, and stays consistently above 0.40 throughout the period. This indicates that the correlation between financial system and individual bank returns increased in the period of significantly elevated volatility.

Figure 6: *Time-dependent VaR, ΔCoVaR and daily log returns for top-ranked banks*

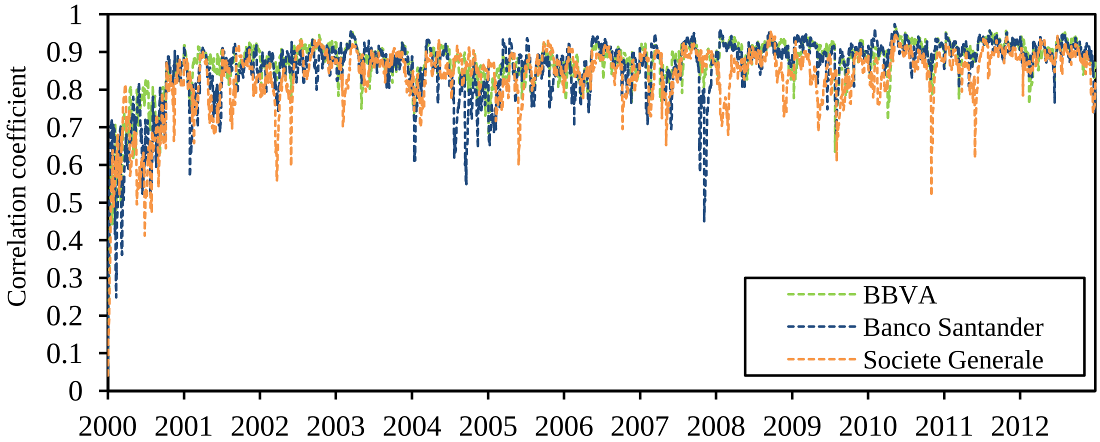


Systemic risk rankings of banks with highest ΔCoVaR within individual sample periods are given in appendix 6, tables 1-3. On an aggregate basis, an across-the-board increase in both stress, measured by VaR, and systemic riskiness, measured by ΔCoVaR, from the pre-crisis to the 2008-2012 period is observable for all banks in the sample. Employing the comparative statics approach, the rankings suggest that banks with the highest systemic risk contributions are fairly consistently ranked at the top throughout all three estimation periods. The banks that exhibit the highest increase in ΔCoVaR in the crisis period compared to the pre-crisis period are: Intesa Sanpaolo (IT) and Banco Santander (ES) with an increase of 3.6 p.p., Pohjola Pankki (FI), Unicredit (IT), and BBVA (ES) with an increase of 3.5 p.p., Erste Group Bank (AT) with an increase of 3.4 p.p., and Banca Popolare Emilia Romagna (IT) and Banco Popular Espanol (ES) both with an increase of 3.3 p.p (see table 1 in appendix 4).

Conversely, the banks in the sample that exhibit the highest jumps in their crisis-VaR compared to the pre-crisis period are banks from Eurozone countries that experienced severe turmoil in their banking sectors. The two Irish banks in the sample, in particular, display a considerable increase in distress. VaR of the Allied Irish Bank increased by 11.5 p.p., whereas VaR of Bank of Ireland increased by 11.3 p.p. These are followed by three Greek banks. Eurobank Ergasias experienced an increase in VaR of 7.9 p.p., VaR of Alpha Bank increased by 7.2 p.p., and VaR of Bank of Piraeus increased by 7.1 p.p. In addition, the two Belgian banks in the sample, Dexia and KBC, also experienced a sizeable upsurge in crisis-period distress with an increase in VaR of 7.0 p.p. (see table 1 in appendix 4).

Time-dependent estimates of VaR, ΔCoVaR and daily log returns for the three top-ranked systemically important banks in the 2008-2012 period are given in figure 6. The formulation of ΔCoVaR in equation 20 implies that the intertemporal correlation of returns plays a significant role in explaining potential spill-over effects to the financial system when individual banks are in distress. Consequently, a high degree of tail co-movement results in higher estimated ΔCoVaR of individual banks and hence their systemic risk. The latter is confirmed by estimated time-dependent correlation coefficients for top-ranked banks for the period 2008-2012 that are given in figure 7.

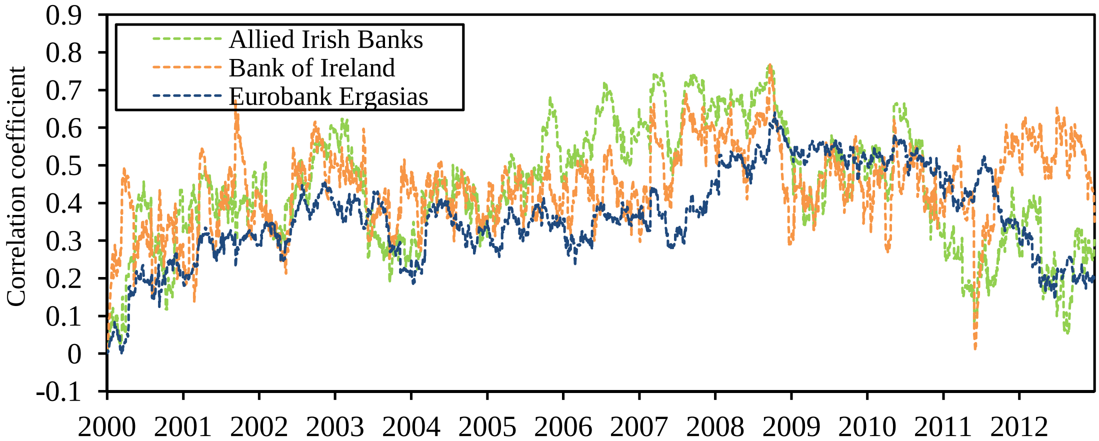
Figure 7: *Time-dependent correlation coefficients for top-ranked banks*



Throughout the sample period, but particularly during the 2008-2012 period, returns of all three banks that are ranked as highly systematically important exhibit a high degree of correlation with the financial system. The time-dependent conditional correlation coefficient for BBVA (ES), Banco Santander (ES) and Societe Generale (FR) in the 2008-2012 period is consistently within the 0.70 to 0.90 range, which relates to strong tail codependence of these banks and the financial system.

Conversely, the time-dependent conditional correlation coefficient for Eurozone banks that exhibit high levels of VaR but only moderate ΔCoVaR is far less consistent and generally lower. Time-dependent correlation coefficients for banks with highest VaR are given in figure 8. Results indicate that the conditional correlation coefficient for all three banks moved within the 0.20 to 0.70 range for most of the estimation period. Unlike the high ΔCoVaR banks, however, the conditional correlation coefficient of Allied Irish Banks (IR) and the Eurobank Ergasias (GR), in particular, declined significantly following the market turmoil of late 2008. The latter development suggests a decoupling from the financial system variable and hence lower ΔCoVaR despite increased volatility of these' banks stock returns.

Figure 8: *Time-dependent correlation coefficients for banks with high VaR and moderate ΔCoVaR*



3.2 Analysis of systemic risk factors

Common determinants of systemic risk that have been identified in the empirical literature include firm leverage, size (see, Brownlees & Engle, 2012, and Acharya et al., 2010), market beta, and VaR (see Adrian & Brunnermeier, 2011). I focus on the former three factors and also include VaR in the analysis, since it represents an important component of the ΔCoVaR framework. Furthermore, estimated intertemporal VaR exhibits a high degree of synchronicity with ΔCoVaR (see figure 4). I test the following three hypotheses regarding the codependence of systemic risk factors and ΔCoVaR:

- **Hypothesis 1:** Bigger Eurozone banks, measured by total assets, have higher ΔCoVaR
- **Hypothesis 2:** Eurozone banks with higher leverage have higher ΔCoVaR
- **Hypothesis 3:** Eurozone banks with higher stock beta have higher ΔCoVaR

3.2.1 Variables

In addition to the estimated VaR and ΔCoVaR that I average in order to obtain quarterly time series, I use quarterly and yearly balance-sheet data for 44 banks in the original sample from the Bloomberg database. Balance sheet data is not available for two Greek banks, Bank of Pireus and General Bank of Greece, while data for French, Irish and Dutch banks is only available on a yearly basis. The entire panel sample spans 2000 Q1 to 2012 Q4 and includes 1551 observations. I further subdivide the sample into two sub periods. The first period spans 2002 1Q to 2007 4Q and contains 714 observations, while the second period spans 2007 1Q to 2012 4Q and includes 727 observations. I obtain quarterly estimates of individual bank stock's beta using the CAPM formulation (see Brigham & Daves, 2004, p. 88):

$$\beta_{i,T} = \frac{\sigma_{i,j,T}}{\sigma_{j,T}^2} \tag{30}$$

where $\sigma_{i,j,T}$ is the unconditional covariance between individual bank and system returns and $\sigma_{j,T}^2$ is the unconditional variance of system returns in period T. I obtain estimates of quarterly leverage using the quasi-market value of assets to market value of equity approach, outlined in Acharya et al. (2010) that is computed as:

$$LEV_{i,T} = \frac{BA_{i,T} - BE_{i,T} + ME_{i,T}}{ME_{i,T}} \tag{31}$$

where $BA_{i,T}$ is book value of total assets, $BE_{i,T}$ is book value of total equity, and $ME_{i,T}$ is market value of equity of bank i in period T. Descriptive statistics for the panel data sample are given in table 1 in appendix 7. Due to the fact that balance sheet data for select banks is only available on a yearly basis, the overall sample is weakly balanced.

3.2.2 Model

Following the discussion by Greene (2012), a proper specification of a panel data model is predicated on an assumption regarding the correlation structure of omitted effects and estimated variables. In order to adequately specify the panel model, I run a fixed effects (FE) model using least squares dummy variable regression (LSDV) and a random effects (RE) model using the generalized least squares (GLS) method in order to perform the Hausman specification test.

The FE model is specified as follows:

$$DCVAR_{i,T} = \alpha_i + \beta_1 VAR_{i,T} + \beta_3 BETA_{i,T} + \beta_2 SIZE_{i,T} + \beta_4 LEV_{i,T} + \varepsilon_{i,T} \qquad (32)$$

where $DCVAR_{i,T}$ is ΔCoVaR, $VAR_{i,T}$ is VaR, $BETA_{i,T}$ is beta, $SIZE_{i,T}$ are total assets in bn EUR, and $LEV_{i,T}$ is leverage of bank *i* in period T. Furthermore, α_i is the regression intercept of bank *i*, and $\varepsilon_{i,T}$ is the residual.

The RE model is specified as follows

$$DCVAR_{i,T} = \alpha_0 + \beta_1 VAR_{i,T} + \beta_3 BETA_{i,T} + \beta_2 SIZE_{i,T} + \beta_4 LEV_{i,T} + \omega_{i,T} \qquad (33)$$

where $\omega_{i,T}$ is the composite error term, α_0 is the regression constant, and all other variables are the same as with the FE model. Both the FE and the RE models include bank-specific effects. Given that estimated ΔCoVaR exhibits a prolonged period of increased volatility following the global financial crisis of 2007/08, I incorporate time-specific effects in both panel models to control for this variation.

According to Wooldridge (2010), the Hausman specification test is designed to reveal, whether omitted effects and explanatory variables are correlated. Existence of a correlation structure is assumed by the specification of a FE model, while alternatively, omitted effects are assumed to be independent of explanatory variables and random in a RE model. Results of the Hausman test, given in table 1 in appendix 8, indicate that the covariance between an efficient estimator and its difference relative to an inefficient estimator is not significantly different from zero. This implies that the omitted effects and explanatory variables in the panel data sample are correlated, making the FE model a more appropriate choice for analyzing the effect of explanatory variables on ΔCoVaR.

3.2.3 Results for the 2000-2012 sample period

Results of both the FE and the RE panel regressions are given in table 1 in appendix 8. Both models produce similar results, R^2 of the FE model is higher than that of the RE model. The only major difference between both models is the statistically significant regression coefficient estimation at 95% CI for beta in the RE regression. The FE model, on the other hand, produces a statistically insignificant regression coefficient estimation for beta. Estimated coefficients for VaR, size and leverage are all highly statistically significant for both models, while the regression constant is statistically significant at the 90% CI for both models.

Results of the panel analysis for the entire sample period indicate that **Hypothesis 1**: Bigger Eurozone banks, measured by total assets, have higher ΔCoVaR, cannot be refuted at the 99% CI. The regression coefficient for *SIZE* for the FE model is highly statistically significant and positive. The coefficient is smaller than one, suggesting that an intertemporal increase in Eurozone bank size has an under commensurate positive effect on ΔCoVaR in the analyzed period. Specifically, a 1bn EUR increase in total bank assets results in a 22 b.p. increase in ΔCoVaR. Most banks in the sample have total assets within the 100 – 200 bn EUR range (see figure 3 in appendix 9), which could partially explain the size of the estimated coefficient. Nonetheless, the systemic risk rankings of Eurozone banks in tables 1-3 in appendix 6 indicate that the biggest Eurozone banks are fairly consistently ranked as the most systemically risky throughout the sample period.

Results of the panel analysis for the entire sample period further indicate that **Hypothesis 2:** Eurozone banks with higher leverage have higher ΔCoVaR, is refuted. The regression coefficient for *LEV* for the FE model is highly statistically significant and negative, suggesting that an increase is Eurozone bank leverage is accompanied by a decrease in ΔCoVaR. This outcome could be explained by the fact that high-leverage Eurozone banks do not generally exhibit high ΔCoVaR (see figure 5 in appendix 9). Furthermore, spikes in leverage and ΔCoVaR of Eurozone banks in the period up to 2011 occur with a time lag (see figure 6 in appendix 9). In both the 2003 and the 2008 period of heightened market distress, Eurozone bank leverage increases following a considerable increase in ΔCoVaR. The latter suggests that for Eurozone banks, an increase in leverage is an after effect of stressful periods, rather than their precursor.

A general increase in leverage of Eurozone banks is therefore likely to be the outcome of deteriorating asset quality due to falling asset prices and raising default rates following strong systemic events. The dramatic increase in bank leverage in year 2012 (see figure 5 in appendix 9), however, is mostly attributable to the significant increase in leverage ratio of Greek banks in the sample, following the debt swap agreement for Greek sovereign bonds in early spring of that year.

As already observed, results of the panel analysis for the entire sample indicate that **Hypothesis 3:** Eurozone banks with higher stock beta have higher ΔCoVaR, is inconclusive. The FE regression coefficient for *BETA* is statistically insignificant and exhibits considerable standard error. Despite the fact that cross-sectional average betas of individual Eurozone banks in the sample appear to be positively linearly related with ΔCoVaR (see figure 1 in appendix 9), the intertemporal dynamics of both variables do not show a considerable level of synchronicity (see figure 2 in appendix 9). The later is due to the FE model specification, which is suited for analyzing within group effects, i.e. intertemporal variation, rather than between group effects, i.e., cross-sectional variation. The RE model provides more insight regarding cross-sectional variation, since it can be interpreted as a weighted average of within and between group estimators (see Greene, 2012), which is why the regression coefficient for *BETA* is statistically significant at the 95% CI for the RE model. Even though beta and CoVaR share some conceptual similarities, as they are both designed to gauge the interdependence of market and individual stock returns, for the Eurozone bank sample, beta appears not to have any particular intertemporal explanatory power.

The regression coefficient for VaR is highly statistically significant, positive and smaller than one, suggesting that an intertemporal increase in VaR has an under commensurate positive effect on ΔCoVaR of Eurozone banks. Given the closed-from definition of ΔCoVaR in equation 20 that explicitly features VaR of a particular institution, the strong intertemporal positive association of VaR and ΔCoVaR is expected. The results of the panel model therefore suggest that even though VaR is a poor measure of relative systemic riskiness in the cross section or between different banks, it does provide a high degree of explanatory power for potential intertemporal tail spill-over effects that are captured by ΔCoVaR of individual banks.

Overall, the analysis of systemic risk factors for the sample of Eurozone banks reveals that size and VaR in particular play a significant role in explaining intertemporal systemic riskiness of Eurozone banks, measured by ΔCoVaR. Eurozone bank leverage, on the other hand, appears to be the result of increased systemic risk rather than one of contributing factors to ΔCoVaR. Lastly, stock beta does not appear to be of much significance in explaining the systemic riskiness of Eurozone banks in the 2000 1Q to 2012 Q4 period.

3.2.4 Results for the sub periods

Similar to the overall sample period, the results of the Hausman test for both sub periods suggests that the FE model is more suitable for analysis of both panel samples. For the pre-crisis period that encompasses 2002 1Q to 2007 Q4 estimated regression coefficients for size, leverage and the regression constant in the FE model are statistically insignificant, while the estimated regression coefficients for VaR and beta are both statistically significant at the 99% CI. Unlike the overall sample period, size and leverage of Eurozone banks have little intertemporal explanatory power in the FE model for the 2002 1Q to 2007 Q4 period, while the regression result for beta indicates that an increase in Eurozone banks' beta has an under commensurate negative intertemporal effect on their systemic riskiness measured by ΔCoVaR. Estimated regression coefficients for size and leverage in the RE model, on the other hand, are both strongly statistically significant, which suggests that both variables exhibit a degree of cross-sectional association with ΔCoVaR in the pre-crisis period.

Results for the crisis period that encompasses 2008 1Q to 2012 Q4 indicate that the FE model regression coefficients of all variables apart from size are statistically significant at the 99% CI. For the RE model, however, all estimated regression coefficients are statistically significant at the 99% CI. The estimated regression coefficient for beta in the FE model is statistically significant, negative and smaller than one but with considerably higher standard error than in the panel model for the pre-crisis period. The estimated regression coefficient for leverage is comparable to the estimation for the entire sample period, albeit with slightly higher standard error. The estimated regression coefficient for VaR is highly statistically significant, positive, and smaller compared to the overall period and the pre-crisis period.

Differences between estimated panel regressions for both sub periods and the overall period are in part attributable to fairly short time series that comprise both sub periods. The pre-crisis period includes 24 intertemporal observations, while the crisis-period includes 20 intertemporal observations, which could potentially give rise to small sample bias. Given the specifications of panel data models for all three estimation periods, estimates for the overall period provide the most tractable results.

CONCLUSION

The highly turbulent period in international finance that began with the global financial crisis of 2007/08 and led to the European debt crisis two years later resulted in a regulatory paradigm shift. The pre-crisis notion that unfavorable developments and asset price bubbles in the financial sector can be adequately dealt with using traditional instruments of economic policy was shown to be false. The depth of the turmoil forced central banks and fiscal authorities to engage in an unprecedented stimulus effort in order to prevent a considerable deterioration in financial stability and stave off a potential financial collapse. In the aftermath of these events, the approach to financial regulation fundamentally changed in favor of a more sustainable, forward-looking regulatory regime with a macroprudential mandate. Consequent changes of the international regulatory framework have sought to accommodate the highly complex and interwoven structure of modern financial systems and make the regulatory process more proactive.

Along with the shift of regulatory focus, the post-crisis response has been accompanied by a variety of new theoretical and empirical works on the issue of macroprudential instruments. More traditional methods of modeling systemic risk and financial contagion have been upgraded to include more realistic as well as complex scenarios, like liquidity spirals and network effects. The development of individual contribution methods of quantifying systemic risk, which include the MES, ΔCoVaR, SRISK and DIP approach, has become an important new subfield of systemic risk research.

An advantage of these methodologies is the fact that they rely on publicly available data and utilize insights from existing risk assessment methods, like VaR and ES. Consequently, they are particularly well suited for assessing the relative systemic riskiness of individual financial institutions. From a macroprudential point of view, these methodologies could be used for systemic risk management purposes, either by assigning institution-specific capital requirements or imposing a taxation scheme based on estimated contributions to systemic risk that would diminish the discrepancies in systemic riskiness between individual financial institutions.

In the master's thesis I analyze systemic risk contributions of 46 Eurozone banks in the period between 2000 and end of 2012 that encompasses both the global financial crisis and the first phase of the European debt crisis. In the first stage, I obtain intertemporal estimates of individual bank's ΔCoVaR and construct a ranking of systemically important Eurozone banks. The rankings for top ten Eurozone banks with highest ΔCoVaR include mostly large institutions and are fairly consistent over both sub-sample periods as well as the overall period. In the second stage, I analyze the association of ΔCoVaR to four systemic risk factors: VaR, size, leverage and beta, by running a panel data model with a quarterly frequency. Results suggest that VaR and size have a significant, positive effect on ΔCoVaR, whereas leverage has a significant negative effect on ΔCoVaR. The estimated regression coefficient for bank's stock beta is statistically not significant.

Results of the panel data model for the entire sample period corroborate the broadly accepted assumption that bigger banks are generally systemically riskier. Although the effect of size on ΔCoVaR of Eurozone banks is under commensurate, it nonetheless indicates that increasing total assets contribute positively to their systemic riskiness. The effect of bank leverage on ΔCoVaR is, however, slightly more ambiguous. Empirical results for the entire sample period suggest that an increase in Eurozone bank leverage is accompanied by a decrease in ΔCoVaR, although the time plot of both variables implies that considerable increases in leverage are more likely interpreted as aftereffects of severe financial distress.

From a macroprudential regulatory perspective, key implications of the empirical analysis for the sample of Eurozone banks in the 2000-2012 period using the ΔCoVaR framework can therefore be summarized as: 1) VaR is a poor measure of relative systemic riskiness of individual banks in the cross-section but provides important insight into potential intertemporal tail spillover effects from individual banks to the banking system, 2) increasing total assets have a positive effect on systemic risk of banks, 3) increasing bank leverage does not result in increased systemic risk but is more likely the result of strong systemic events, and 4) beta of banks' stocks does not provide a material link to their systemic riskiness.

Given the current state of affairs there is still room for improvement of empirical analyses of systemic risk. A major challenge in this regard relates to data availability issues, particularly for the Eurozone case, which tends to restrict both the temporal and cross-sectional scope of analysis. Richer data series for Eurozone banks that span longer time periods would enable a more detailed assessment of idiosyncratic systemic risk factors. Still, theoretical and empirical advancements in the field of systemic risk measurement in recent years have contributed significantly to the ongoing debate regarding macroprudential regulation. At the very least, these novel systemic risk measurement methods have made the implementation of a comprehensive, macroprudential regulatory regime a viable objective in the foreseeable future.

POVZETEK

UVOD

Problematika finančne stabilnosti in sistemskega tveganja je po izbruhu svetovne finančne krize zopet postala pomemben del agende raziskovalcev in regulatorjev. Kriza je namreč razkrila kopico pomanjkljivosti v globalnem finančnem regulatornem sistemu, predvsem njegovo inherentno procikličnost in neustreznost mikrobonitetnega nadzora. Glavni cilj pokriznega reformnega programa je torej vzpostavitev bolj učinkovitega regulatornega mehanizma s poudarkom na makrobonitetnem pristopu (glej Borio, 2003, in De Nicolò, Favara & Ratnovski, 2012). Prav makrobonitetni nadzor predstavlja ključni člen v novem regulatornem pristopu, ki naj bi regulatorjem omogočal pravočasno zaznavanje povišanega sistemskega tveganja in ukrepanje na *ex-ante* osnovi.

Obseg strokovne literature na temo sistemskega tveganja je v pokriznem obdobju doživel razcvet. Pomemben segment pokrizne literature predstavljajo novi empirični in teoretični pristopi k merjenju sistemskega tveganja. Ključni prispevki na tem področju so: 1) metoda delta CoVaR (ΔCoVaR) (Adrian & Brunnermeier, 2011), ki temelji na metodologiji tvegane vrednosti (*ang. Value-at-Risk* ali VaR), 2) metoda sistemske pričakovane izgube (*ang. systemic excpected shortfall* ali SES) (Acharya, Pedersen, Philippon & Richardson, 2010), 3) indeks sistemskega tveganja ali SRISK (Brownlees & Engle, 2012), ter 4) metoda stresne zavarovalne premije (*ang. distressed insurance premium* ali DIP) (Huang, Zhou & Zhu, 2009).

Večina empiričnih analiz prispevanja posameznih finančnih institucij sistemskemu tveganju, ki uporabljajo zgoraj navedene metode, se ukvarja z ameriškim finančnim sistemom. Navkljub dejstvu, da so imele nekatere evropske države precejšnje težave s sistemskimi neravnovesji, je obseg kvantitativnih analiz sistemskega tveganja v evropskih državah omejen. Acharya in Steffen (2013) tako analizirata sistemsko tveganje bank v EU z uporabo SES metode, medtem ko Engle, Jondeau in Rockinger (2012) analizirajo širši evropski finančni sistem z metodo SRISK.

Glede na obseg in intenziteto sistemskih dogodkov v bančnih sektorjih nekaterih držav v Evroobmočju, ostaja tovrstna analiza sistemskega tveganja relevantna. V magistrskem delu sem si torej zastavil dva cilja. Prvič, predstaviti pokrizni premik od mikro- k makrobonitetnemu regulatornemu pristopu in analizirati njune ključne značilnosti. Drugič, z uporabo ΔCoVaR metode empirično analizirati prispevanje bank v Evroobmočju sistemskemu tveganju ter vpliv sistemskih faktorjev tveganja na ΔCoVaR s testiranjem sledečih hipotez:

Hipoteza 1: Banke evroobmočja z večjo bilančno vsoto imajo večji ΔCoVaR

Hipoteza 2: Banke evroobmočja, ki operirajo z večjim vzvodom, imajo večji ΔCoVaR
Hipoteza 3: Banke evroobmočja z večjo beto imajo večji ΔCoVaR

Magistrsko delo je sestavljeno iz treh delov. V prvem delu se ukvarjam s konceptom finančne nestabilnosti. Po kratkem pregledu ključnih teoretičnih prispevkov analiziram pomanjkljivosti predkriznega regulatornega pristopa, predvsem njegovo procikličnost in težave mikrobonitentega nadzora. V drugem delu povzamem različne definicije sistemskega tveganja in predstavim metodologije za modeliranje in merjenje sistemskega tveganja. V tretjem delu analiziram prispevanje bank v Evroobmočju sistemskemu tveganju z uporabo metode ΔCoVaR. V zaključku kratko povzamem ključne ugotovitve.

1 FINANČNA NESTABILNOST

Prva teoretična dognanja o fenomenu finančne nestabilnosti segajo v začetek modernega kapitalizma. Pionir na tem področju je bil Bagehot (1873), ki je vzroke likvidnostnih panik in begov na banke pripisal tako endogenim kot eksogenim dejavnikom, kot primeren način za preprečevanje finančnih kriz pa je predlagal uporabo instituta posojilodajalca v skrajni sili. Po veliki depresiji je Fisher (1933) razvil teorijo finančnih kriz, ki temelji na dvojni negativni spirali razdolževanja in deflacije. Po tej teoriji je sprožilec ekonomskih depresij nevzdržno visoka zadolženost ekonomskih subjektov. Proces razdolževanja ima zaradi padca povpraševanja posledično precejšen negativen vpliv na cene, oba vpliva pa skupaj tvorita pozitivno povratno zanko, ki depresijo poglablja.

Minsky (1982) je na podlagi Fisherjevega prispevka razvil hipotezo finančne nestabilnosti, ki temelji na padajoči vzdržnosti kreditnega financiranja v kapitalističnih sistemih. Po Minskyju (1982) so kreditni cikli posledica spreminjajoče se kapitalske strukture podjetij, ki v ugodnih makroekonomskih razmerah povečujejo zadolženost, banke pa z rahljanjem standardov posojanja zadolževanje dodatno vzpodbujajo. V zaključni fazi cikla postane kapitalska struktura podjetij podobna piramidni shemi, saj lahko obveznosti do bank financirajo samo še z dodatnim zadolževanjem, kar sčasoma privede do prilagoditve v obliki razdolževanja in deflacije.

Teorija finančnega pospeševanja se ukvarja z amplifikacijskimi učinki bančne kreditne aktivnosti na gospodarske cikle. Bernanke in Gertler (1989) analizirata amplifikacijski učinek kreditiranja tako, da model splošnega ravnovesja nadgradita s trenji v obliki stroškov preverjanja kakovosti dolžnikov. Kashyap et al. (1993) analizirajo pomembnost bančnega posojanja pri transmisiji monetarne politike, medtem ko Kiyotaki in Moore (1997) amplifikacijski učinek modelirata z uporabo kreditnih omejitev.

Cecchetti et al. (2009) pri tem opozarjajo, da večina makroekonomskih modelov ne vsebuje endogenih virov finančne nestabilnosti, tako da so primerni zgolj za analizo odzivov na eksogene šoke. Prav modeliranje endogenih gonilcev finančne nestabilnosti je po mnenju avtorjev eden od večjih izzivov moderne makroekonomske teorije.

Po daljšem obdobju relativno nizke volatilnosti v mednarodnem finančnem okolju, ki so ga v ZDA poimenovali Velika moderacija (glej Bernanke, 2004), so se razmere po izbruhu svetovne finančne krize močno zaostrile. Kriza je tako razblinila mit o robustnosti finančnih sektorjev najrazvitejših držav. Ta domneva je deloma temeljila na predpostavki, da so banke z uporabo novih metod za upravljanje s tveganji uspele omejiti tveganja na ravni celotnega finančnega sistema (za primer glej Greenspan, 2004). Regulatorji pri tem večinoma niso bili pozorni na negativne posledice teh sprememb, predvsem izrazito povečanje finančnega vzvoda bank in razcvet trga kompleksnih kreditnih derivatov.

Kot ugotavljata Nijskens in Wagner (2011), je uporaba kreditnih derivatov v predkriznem obdobju posameznim bankam sicer omogočila bolj učinkovito upravljanje s kreditnim tveganjem, vendar se je sočasno tveganje na sistemski ravni močno povečalo. Slednje je v precejšnji meri posledica mikrobonitetnega regulatornega pristopa, pri katerem se regulatorji ukvarjajo predvsem s stabilnostjo posameznih institucij, in ne celotnega finančnega sistema.

1.2 Procikličnost bančne kapitalske regulative

Procikličnost finančnih sistemov navadno označuje proces prekomernega prevzemanja tveganj v obdobju rasti, ki poveča negativne pritiske na gospodarstvo v obdobju recesije. Procikličnost je posledica ekosgenih dejavnikov, npr. makroekonomskih trendov, in endogenih dejavnikov, s katerimi se med drugim ukvarjata hipoteza institucionalnega spomina (glej Berger & Udell, 2003) in teorija finančnega pospeševanja. Dodaten endogen vir finančne procikličnosti so mednarodni bančni kapitalski standardi oz. Baselski standardi.

Na problem procikličnosti kapitalskih standardov, ki temeljijo na principu tehtanja tveganj, opozarjata Blum in Hellwig (1995). Po njunem mnenju lahko rigidna aplikacija kapitalskih standardov banke v obdobju recesije prisili v zmanjševanje kreditne aktivnosti, kar recesijo dodatno poglablja. Navkljub tem pomislekom je princip tehtanja tveganj, ki je bil uveden z Basel I standardom leta 1988, ostal osnova tudi posodobljenega Basel II standarda iz leta 2004. V Basel II standardu je bila metodologija ocenjevanja kreditnega tveganja ter tržnih in operativnih tveganj v bankah (glej tabelo 1) sicer občutno nadgrajena, vendar je problem procikličnosti ostal pereč.

Kashyap in Stein (2004) kot problematično izpostavljata predvsem uporabo enega intervala zaupanja pri ocenjevanju verjetnosti nastopa izredno neugodnih dogodkov, saj lahko podcenitev te verjetnosti občutno poveča tveganost bančne aktive in povzroči zmanjšanje kreditne aktivnosti. Togost Basel II standarda in posledično procikličnost izpostavljajo tudi Altman, Brady, Resti and Sironi (2005), saj se zaradi negativne koreliranosti verjetnosti neplačila in stopenj poplačila obveznosti kapitalske zahteve bank v obdobju recesije povečajo, v obdobju ekspanzije pa zmanjšajo, tako da kreditna aktivnost bank zaradi doseganja kapitalskih zahtev neposredno vpliva na gospodarsko cikličnost.

Kot odgovor na pomanjkljivosti kapitalskih standardov, ki so se pokazale med svetovno finančno krizo, je Basel Committee on Banking Supervision (2010a) leta 2010 izdal Basel III standarde, ki prinašajo novosti predvsem na področju upravljanja z likvidnostjo in pri strukturi kapitalskih zahtev. Poleg višjega količnika jedrnega kapitala, Basel III uvaja dva dodatna kapitalska blažilnika, in sicer varovalni kapitalni blažilnik in proticiklični kapitalski blažilnik. Vloga prvega je zagotavljanje primerne kapitaliziranosti bank, medtem ko je slednji namenjen prilagajanju kapitalske strukture bank sistemskemu tveganju. Basel III standard sicer ne vsebuje metodološkega okvirja za merjenje sistemskega tveganja.

1.2 Mikro- in makrobonitetne regulatorne politike

Četudi je koncept makrobonitetnega nadzora v uporabi že od 70-ih let prejšnjega stoletja (glej Borio, 2003), makrobonitnetni pristop še vedno nima celovitega metodološkega okvirja. Arnold et al. (2012) to pomanjkljivost pripisujejo predvsem omejenemu naboru teoretične literature na temo makrobonitetnega nadzora. Konsenz glede jasne delitve mikrobonitetnih in makrobonitenih pristojnosti pa se kljub temu počasi oblikuje. Ključno razliko med obema pristopoma po Boriu (2003) predstavljajo cilji, ki so pri mikrobonitetnem nadzoru osredotočeni predvsem na omejevanje izgub posameznih institucij in potrošnikov, medtem ko se makrobonitetni nadzor ukvarja z omejevanjem izgub na ravni sistema oz. gospodarstva.

Po mnenju Gortona (2009) so bili mikrobonitetni ukrepi med svetovno gospodarsko krizo neučinkoviti zaradi specifičnega razvoja krize, predvsem dejstva, da so klasični begi na banke igrali majhno vlogo. Dosti pomembnejšo vlogo pri poglabljanju in širitvi krize so imeli begi bank na druge banke ter izredno zaostrene likvidnostne razmere na medbančnem trgu, kar opisuje Brunnermeier (2009).

Med ustrezne makrobonitetne ukrepe Bank of England (2009) uvršča predvsem dinamične kapitalske zahteve. Te se lahko aplicirajo bodisi na ravni celotnega finančnega sistema, v kolikor odražajo sistemske faktorje tveganja, ali pa na ravni posamezne institucije, v kolikor so predmet specifičnega tveganja. Podobno funkcijo ima tudi sistem obveznih dinamičnih rezerv, ki je bil leta 2000 vpeljan v Španiji (glej Saurina, 2009), ki pa kljub vsemu ni uspel odpraviti sistemskih neravnovesij v španskem bančnem sistemu, zaradi katerih je moral evropski sklad EFSF v letu 2012 dokapitalizirati španske banke.

2 SISTEMSKO TVEGANJE

2.1 Definicija sistemskega tveganja

Kaufman in Scott (2003) definirata sistemsko tveganje kot verjetnost nastopa negativnega dogodka, ki vpliva na vse člene sistema, medtem ko je sistemsko tveganje v bančništvu posledica visoke stopnje koreliranosti donosnosti bančnih naložb in množičnih bančnih bankrotov. Po Boriu (2003) sistemsko tveganje označuje proces širitve eksogenih ali endogenih šokov v finančnem sistemu zaradi povezav med bankami in prekomernega odziva na negativne informacije.

De Bandt in Hartmann (2000) sistemsko tveganje definirata kot verjetnost pojava močnih sistemskih dogodkov, ki nimajo zgolj vpliva na posamezen trg ali institucijo, pač pa se s procesom okužbe (ang. *contagion*) razširijo na veliko število finančnih institucij in imajo precejšen negativen vpliv na delovanje finančnega sistema in celotnega gospodarstva (koncept sistemskih dogodkov je ponazorjen v tabeli 2).

Po mnenju Kaufmana (1994) so postale banke po Veliki depresiji dosti bolj regulirane prav zaradi večje verjetnosti širjenja okuženosti v bančnem sektorju. De Bandt in Hartmann (2000) kanale za širjenje finančne okuženosti delita na neposredne povezave zaradi skupnih izpostavljenosti in informacijske učinke zaradi asimetrične informiranosti (mogoči kanali širjenja finančne okuženosti v bančnem sistemu so prikazani v tabeli 4).

2.2 Merjenje sistemskega tveganja

2.2.1 Modeli begov na banke in finančne okuženosti

Večina modernih modelov begov na banke temelji na modelu več ravnotežij Diamonda in Dybviga (1983), ki koncept nelikvidnih sredstev in vlogo bančnega sistema modelirata z uporabo tehnoloških ovir, zaradi katerih je donosnost dolgoročnih investicij večja od donosnosti kratkoročnih investicij. Bančni depoziti v modelu so podobni zavarovanju, saj agentom omogočajo uravnavanje lastne potrošnje v času. Begi na banke v tem modelu so naključni dogodki, do katerih pride zaradi sprememb v pričakovanjih agentov.

Gorton (1988) testira domnevo o naključnosti begov na banke z uporabo zgodovinskih podatkov za ameriški finančni sistem. Rezultati njegove empirične analize kažejo, da je gospodarska cikličnost igrala pomembno vlogo pri ameriških bančnih panikah do vključno Velike depresije. Modela Allena in Galea (1998 in 2000) prav tako vključujeta vpliv gospodarskih ciklov, saj so begi na banke simulirani kot posledica poslabšanja gospodarskih razmer. Pomembna implikacija njunega prvega modela je dejstvo, da lahko vrednost naložb v obdobju bančne panike pade pod fundamentalno vrednost, medtem ko z drugim modelom pokažeta, da so močno povezani bančni sistemi, v katerih so vse banke povezane z vsemi ostalimi, stabilnejši od slabo povezanih sistemov.

Rochet in Tirole (1996) kot možen kanal za širjenje finančne okuženosti analizirata trg medbančnih posojil. Njune ugotovitve kažejo, da imajo ob prisotnosti prevelikih bank in močne povezanosti med bankami že relativno majhni likvidnostni šoki precejšen negativen vpliv na stabilnost bančnega sektorja. Bančne krize v modelu, ki ga razvijejo Freixas et al. (2000), pa so posledica pomanjkljivega nadzora nad bankami v obdobjih presežne razpoložljivosti posojil.

Kodres in Pritsker (2002) analizirata vpliv zunanjih informacijskih šokov in makroekonomskih sprememb na finančno stabilnost z uporabo koncepta nepodučenih in podučenih vlagateljev. Dokler je delež podučenih vlagateljev v določeni državi majhen, se zunanji šoki zaradi prekomernega odziva nepodučenih vlagateljev v to državo ne samo prelijejo, pač pa tudi ojačajo.

Cifuentes et al. (2005) analizirajo vpliv volatilnosti cen naložb na širitev finančne okuženosti. Podobno kot Allen in Gale (2000) tudi oni ugotavljajo, da so bolj povezani bančni sistemi stabilnejši, vendar ima volatilnost cen naložb nelinearen vpliv na prodajo naložb v obdobju krize, zaradi česar imajo močnejši likvidnostni šoki izredno negativen vpliv, saj pospešujejo negativno spiralo prodaje naložb in padanja cen.

Diamond in Rajan (2005) analizirata pojav bančnih panik in finančne okuženosti z uporabo koncepta skupnega bazena likvidnosti ter kombiniranimi bilančnimi šoki, ki vključujejo negativne učinke na strani naložb in obveznosti bank. Za razliko od ostalih modelov, je širitev okuženosti v modelu Diamonda in Rajana (2005) posledica izpostavljenosti skupnemu bazenu likvidnosti in ne neposrednih povezav med posameznimi bankami.

Brunnermeier in Pedersen (2009) analizirata fenomen likvidnostnih spiral kot posledico asimetrične informiranosti bank, ki zaradi negativnih cenovnih šokov povečajo marže za financiranje špekulativnega trgovanja, kar ima negativen vpliv na likvidnost naložb. Acharya et al. (2009) modelirajo likvidnost v bančnem sistemu kot posledico *ex-ante* strateškega pozicioniranja bank. Likvidnost in cena naložb likvidiranih bank je odvisna od strukture bančnih bilanc ter razmerja med bančnimi in nebančnimi investitorji v modelu.

2.2.2 Modeli temelječi na teoriji omrežij

Večina modelov finančne okuženosti, ki uporabljajo teorijo omrežij, temelji na algoritmu navideznega bankrota, ki sta ga razvila Eisenberg in Noe (2001). V mreži z n številom finančnih institucij, ki so med seboj povezane, algoritem preveri, ali lahko vsaka posamezna institucija poravna svoje obveznosti do ostalih, ob predpostavki da so ostale obveznosti v sistemu poravnane. Po večkratnem pregledu je mogoče institucije razvrstiti glede na njihovo robustnost, torej na institucije, ki same niso zmožne poravnati lastnih obveznosti in institucije, ki postanejo nezmožne poravnati obveznosti zaradi širitve finančne okuženosti. Elsinger et al. (2006) s tem pristopom analizirajo Avstrijski bančni sistem in ugotavljajo, da je za avstrijske banke večja verjetnost pojava finančne okuženosti kratkoročno kot pa dolgoročno ter da je pogoj za širitev okuženosti relativno veliko število začetnih bankrotov bank.

Nier et al. (2008) oblikujejo naključen model omrežja, v katerem so banke različnih velikosti, finančna okuženost pa se širi podobno kot pri algoritmu navideznega bankrota. Rezultati simulacij modela kažejo, da je vpliv povečevanja števila povezav med bankami v mreži na stabilnost sistema odvisen od kapitalske ustreznosti bank. V kolikor je agregatna kapitalska ustreznost bank nizka, potem povezave med bankami omogočajo hitrejše širjenje bančne okuženosti. V nasprotnem primeru, ko je agregatna kapitalska ustreznost bank visoka, pa povezave med bankami izboljšajo robustnost sistema zaradi vpliva diverzifikacije, podobno kot v modelu Allena in Galea (2000).

2.2.3 Modeli prispevanja k sistemskemu tveganju

Metoda ΔCoVaR (Adrian & Brunnermeier, 2011) je mera prispevanja posamezne institucije sistemskemu tveganju, ki temelji na konceptu tvegane vrednosti (analitična definicija VaR je podana v enačbi 1). ΔCoVaR je torej mera soodvisnosti posamezne finančne institucije in finančnega sistema, saj kaže spremembo pogojnega VaR finančnega sistema, ko se VaR finančne institucije spremeni glede na njeno normalno stanje. Analitična definicija ΔCoVaR je podana v enačbi 4.

Adrian in Brunnermeier (2011) analizirata ΔCoVaR na vzorcu ameriških finančnih institucij z uporabo metode kvantilnih regresij. Robustnost rezultatov pa preverita z uporabo diagonalnega bivariatnega (DVECH) modela splošne avtoregresivne pogojne heteroskedastičnosti (GARCH). Ustreznost slednje metode potrjuje empirična analiza Benoita el al. (2013), saj avtorji ugotavljajo, da je GARCH metodologija z dinamičnimi sekundarnimi momenti bolj ustrezna za ocenjevanje ΔCoVaR kot pa kvantilne regresije.

Metoda pričakovane sistemske izgube (SES), ki so jo razvili Acharya et al. (2010) temelji na metodologiji pričakovane izgube (ES). Po definiciji Arznerja et al. (1999) (analitična definicija je podana v enačbi 5) je ES metodologija bolj robustna od VaR, saj meri pričakovano izgubo, v primeru da je VaR presežen ter ustreza kriterijem koherentnih mer tveganja. Acharya et al. (2010) definirajo marginalno pričakovano izgubo kot občutljivost ES posamezne institucije na spremembo relativne pomembnosti oz. velikosti te institucije v finančnem sistemu. Brownlees in Engle (2012) metodo MES dodatno nadgradita ter razvijeta indeks sistemskega tveganja (SRISK), ki vključuje ocene MES, velikosti in finančnega vzvoda posamezne institucije. Avtorja pridobita ocene MES posameznih institucij z uporabo modela GARCH z dinamičnimi pogojnimi korelacijami (DCC). Huang et al. (2009) razvijejo metodo stresne zavarovalne premije (DIP), ki za ocenjevanje prispevanja posamezne institucije sistemskemu tveganju uporablja verjetnost neplačila (PD) ter podatke o CDS razmikih.

2.2.4 Alternativni modeli

Med pomembnejše alternativne modele merjenja sistemskega tveganja se uvršča pristop Hartmanna et al. (2004), ki temelji na metodologiji multivariatnih ekstremnih vrednosti. Mednarodne finančne tokove avtorji modelirajo z modelom CAPM ter analizirajo pojav bega h kakovosti, ki ga označuje ekstremno sočasno povišanje cen državnih obveznic, medtem ko je finančna okuženost posledica ekstremnih padcev cen delnic.

Lehar (2005) predlaga uporabo indeksa sistemskega tveganja, ki temelji na metodologiji analize pogojnih obveznosti (CCA), medtem ko Gray in Jobst (2013) za merjenje sistemskega tveganja predlagata uporabo kombiniranega pristopa, ki vključuje metodologiji ES in CCA. Basel Committee on Banking Supervision (2011) je v sklopu sprememb mednarodne bančne regulative oblikoval predlog za ocenjevanje sistemskega tveganja najpomembnejših svetovnih bank, ki temelji na pristopu indikatorjev (metodologija je povzeta v tabeli 5).

3 PRISPEVANJE BANK EVROOBMOČJA K SISTEMSKEMU TVEGANJU

3.1 ΔCoVar bank v evroobmočju

Prispevanje bank v evroobmočju sistemskemu tveganju analiziram z uporabo metode CoVaR (Adrian & Brunnermeier, 2011) za obdobje od 5. januarja 2000 to 31. decembra 2012 (skupaj 3330 podatkovnih točk). Pri tem celotno obdobje razdelim na dve podobdobji, ki predstavljata predkrizno obdobje od 27. decembra 2002 do 31. decembra 2007 ter krizno obdobje od 2. januarja 2008 do 31. decembra 2012 (obe obdobji sestavlja 1286 podatkovnih točk).

Za medčasovo ocenjevanje VaR in ΔCoVaR posameznih bank uporabim modele iz družine ARCH (glej Brownlees & Engle, 2012; Benoit et al., 2013). In sicer pridobim medčasovne ocene VaR z porabo univariatnega modela GARCH(1,1), CoVaR pa ocenim z bivariatnim modelom GARCH DCC(1,1), saj je slednji model glede na specifikacijo primeren način za ocenjevanje dinamičnih korelacijskih struktur (glej Engle, 2002) ob prisotnosti heteroskedastičnosti v časovnih vrstah (glej sliki 1 in 2).

3.1.1 Podatki

Za empirično analizo ΔCoVaR bank evroobmočja uporabim dnevne cene delnic 46 bank iz podatkovne baze Thomson Reuters Datastream, na podlagi katerih izračunam dnevne logaritemske donose. Banke v vzorcu so izbrane glede na dostopnost in celovitost časovnih vrst cen delnic v obdobju od 5. januarja 2000 to 31. decembra 2012. Poleg tega so izbrane zgolj tiste banke, katerih delnice so dovolj likvidne (banke, pri katerih je več kot 20 % vseh dnevnih donosov delnic enakih nič, niso vključene v vzorec). Kot približek za sistemsko spremenljivko uporabim dnevne podatke o donosnosti indeksa Euro Stoxx Banks (simbol SX7E), ki je tehtano povprečje kapitalizacij visoko likvidnih delnic velikih bank v evroobmočju.

3.1.2 Model

3.1.2.1 Časovno odvisni model VaR

Eksplicitna definicija VaR je podana v enačbi 8. Za ocenjevanje VaR uporabim ekonometrični pristop, ki ga predlaga Tsay (2010). Osnovni model dnevnih donosov je podan v enačbi 9. Aritmetično sredino modeliram z uporabo enostavnega avtoregresijskega modela s tremi časovnimi zamiki AR(3) v enačbi 10, ki omogoča izločitev avtokoreliranosti iz časovnih vrst donosov. Specifikacija reziduala avtoregresije je podana v enačbi 11, pri čemer rezidual modeliram kot GARCH(1,1) proces v enačbi 12. Proces za pogojno varianco je podan v enačbi 13, cenilka medčasovne pogojne variance pa je podana v enačbi 14. Povprečja medčasovnih ocen VaR za posamezne banke pri 99 % intervalu zaupanja so podana v dodatku 4, tabeli 1.

3.1.2.2 Časovno odvisni model ΔCoVaR

Po Benoit et al. (2013) in Adrian in Brunnermeier (2011) je mogoče ΔCoVaR, v primeru ko so pogojne porazdelitve dnevnih donosov simetrične, ponazoriti v obliki zaprte rešitve. Ob predpostavki, da so pogojne porazdelitve dnevnih donosov posameznih bank v vzorcu in finančnega sistema bivariatne normalne (enačba 15), je pogojna standardna normalna porazdelitev definirana z enačbo 16 (glej Alexander, 2008). S standardiziranjem parametrov v enačbi 3 dobim obliko zapisa CoVaR v enačbi 17, ki se poenostavi v zapis v enačbi 20, zaradi predpostavke, da so pogojne porazdelitve normalne.

Časovno odvisno volatilnost in pogojne korelacije v enačbi 20 ocenim z uporabo modela GARCH DCC(1,1), ki ga je razvil Engle (2002). Model je sestavljen iz dveh specifikacij pogojne variančno-kovariančne matrike. Prva specifikacije je podana v enačbi 22, v kateri je pogojna korelacijska matrika definirana kot rezultat delitve pogojne variančno-kovariančne matrike z uporabo diagonalne normalizacijske matrike. Rezultat v enačbi 27 dokazuje, da je matrika $\mathbf{R_t}$ zares pogojna korelacijska matrika. Druga specifikacija pogojne variančno-kovariančne matrike je podana v enačbi 28, časovno odvisna cenilka pogojne korelacije pa je podana v enačbi 29.

3.1.3 Rezultati

Podobno kot v prvotnem članku Adriana in Brunnermeierja (2011) presečni rezultati medčasovnih ocen VaR in ΔCoVaR za vzorec bank v evroobmočju kažejo, da med obema merama ni konkretne povezave (glej sliko 3). Ta rezultat kaže, da je VaR kot samostojna mera sistemskega tveganja bank lahko zavajajoča, saj relativne vrednosti VaR posameznih bank ne odražajo njihove relativne sistemske tveganosti. Največji VaR v vzorcu imajo namreč irske in grške banke, medtem ko imajo španske, francoske in italijanske banke največji ΔCoVaR.

Medčasovna povprečja ocen VaR in ΔCoVaR za vse banke v vzorcu so podana v sliki 4. Za razliko od presečnih podatkov, medčasovne ocene kažejo na precejšnjo usklajenost VaR in ΔCoVaR ocen bank v vzorcu. Slednji rezultat, torej močna medčasovna odvisnost in nizka presečna odvisnost VaR in ΔCoVaR, je v skladu z izsledki ocen ameriških bank v članku Adriana in Brunnermeierja (2011). V sliki 5 je predstavljeno medčasovno povprečje ocen pogojne korelacije za vse banke v vzorcu. Glede na rezultat se je povprečna korelacija med bankami in finančnim sistemom počasi povečevala v obdobju pred krizo ter bila močno pozitivna v obdobju krize.

Rangiranje bank v vzorcu glede na sistemsko tveganje, ocenjeno z ΔCoVaR je podano v dodatku 6, v tabelah 1-3. Rangiranje sistemsko najbolj tveganjih bank po posameznih obdobjih je relativno konsistentno, pri čemer na vrhu prevladujejo predvsem velike banke v evroobmočju. Za vse banke v vzorcu je opazno splošno povečanje tako VaR kot ΔCoVaR v obdobju krize glede na predkrizno obdobje. ΔCoVaR se je v kriznem obdobju najbolj povečal pri Intesi Sanpaolo (IT) in Banci Santander (ES), in sicer za 3,6 o.t., sledijo Pohjola Pankki (FI), Unicredit (IT), in BBVA (ES) s povečanjem za 3.5 o.t. ter Erste Group Bank (AT) s povečanjem za 3.4 o.t (glej tabelo 1 v dodatku 4).

Banke, pri katerih je prišlo v kriznem obdobju do največjih sprememb VaR pa so načeloma banke iz držav članic evroobmočja, ki so doživele izredno hude bančne krize. VaR Allied Irish Bank (IR) se je tako povečal za 11,5 o.t., VaR Bank of Ireland (IR) za 11,3 o.t., VaR Eurobank Ergasias (GR) za 7,9 o.t., VaR Alpha Bank (GR) za 7,2 o.t. in VaR Bank of Piraeus (GR) za 7,1 o.t.

Medčasovne ocene VaR, ΔCoVaR in dnevnih donosov za tri najvišje rangirane banke v kriznem obdobju so podane v sliki 6. Pri vseh treh bankah je medčasovna usklajenost VaR in ΔCoVaR precejšnja, kar kaže na močno soodvisnost ekstremnih donosov posameznih bank in finančnega sistema. To potrjujejo tudi načeloma visoke medčasovne ocene pogojnih koeficientov korelacije (glej sliko 7), ki so se v obdobju krize gibale na intervalu od 0,7 do 0,9. Na drugi strani pa so medčasovne ocene pogojnih koeficientov korelacije bank z visokim VaR in srednjevisokim ΔCoVaR (glej sliko 8) gibale na intervalu med 0,2 in 0,7, po izbruhu evropske dolžniške krize pa so se zmanjšale. Slednje kaže, da je prišlo po izbruhu evropske dolžniške krize do odklona med ekstremnimi donosi bank v najbolj prizadetih državah evroobmočja in finančnega sistema.

3.2 Analiza dejavnikov sistemskega tveganja

V empirični literaturi so kot najpomembnejši dejavniki sistemskega tveganja finančnih institucij izpostavljeni predvsem finančni vzvod, velikost, (glej Brownlees & Engle, 2012, in Acharya et al., 2010) ter beta in VaR (glej Adrian & Brunnermeier, 2011). Empirično analiziram tri hipoteze, v analizo pa vključim tudi VaR zaradi pomembne medčasovne vloge:

Hipoteza 1: Banke evroobmočja z večjo bilančno vsoto imajo večji ΔCoVaR
Hipoteza 2: Banke evroobmočja, ki operirajo z večjim vzvodom, imajo večji ΔCoVaR
Hipoteza 3: Banke evroobmočja z večjo beto imajo večji ΔCoVaR

3.2.1 Spremenljivke

V empirični analizi uporabim četrtletne in letne bilančne podatke iz podatkovne baze Bloomberg za 44 bank v vzorcu ter četrtletne povprečne medčasovne ocene VaR in ΔCoVaR. Bilančni podatki iz Bloomberg baze niso dostopni za banki Bank of Pireus in General Bank of Greece, medtem ko so podatki za francoske, irske in nizozemsko banko dostopni samo na letni frekvenci. Panelni vzorec pokriva obdobje od 1. četrtletja 2000 do 4. četrtletja 2012 in vsebuje 1551 podatkovnih točk. Četrtletne ocene bete za posamezne banke v vzorcu ocenim s CAPM specifikacijo v enačbi 30 (glej Brigham & Daves, 2004, str. 88). Finančni vzvod posameznih bank v vzorcu pa ocenim z uporabo metode kvazi tržne vrednosti naložb, ki jo predlagajo Acharya et al. (2010) in je izračunana po formuli v enačbi 31.

3.2.2 Model

Po Greeneu (2012) je ustrezna specifikacija modela panelnih podatkov odvisna od predpostavke o korelacijski strukturi izpuščenih vplivov in neodvisnih spremenljivk. Ustrezen model izberem tako, da ocenim model s fiksnimi vplivi (FE) z uporabo LSDV metode in model z naključnimi vplivi (RE) z uporabo GLS metode ter opravim Hausmanov specifikacijski test. Specifikacija modela s fiksnimi vplivi je podana v enačbi

32, specifikacija modela z naključnimi vplivi pa v enačbi 33. Oba modela vsebujeta vplive, ki so specifični za posamezne banke ter časovne vplive.

Po Wooldridgeu (2010) Hausmanov test omogoča testiranje hipoteze o koreliranosti med izpuščenimi vplivi in neodvisnimi spremenljivkami. FE model temelji na predpostavki, da korelacijska struktura obstaja, medtem ko RE test temelji na predpostavki, da so neodvisne spremenljivke neodvisne od izpuščenih vplivov in porazdeljene naključno. Rezultati Hausmanovega testa za oba modela (glej tabelo 1 v dodatku 8) kažejo, da pri 99 % intervalu zaupanja ne morem sprejeti hipoteze, da je razlika med učinkovito cenilko in njeno razliko glede na neučinkovito cenilko različna od nič. Posledično je za panelni vzorec bolj primeren FE model.

3.2.3 Rezultati

Rezultati obeh panelnih modelov so podobni, vrednost R^2 je za FE model nekoliko višja (glej tabelo 1 v dodatku 8). Pri modelu RE je ocena regresijskega koeficienta za beto statistično značilna pri 95 % intervalu zaupanja, medtem ko pri FE modelu ni statistično značilna. Ocene regresijskih koeficientov za ostale tri spremenljivke so v obeh modelih statistično značilne pri 99 % intervalu zaupanja, ocena regresijske konstante pa pri obeh modelih ni značilna.

Rezultati panelne analize kažejo, da hipoteze 1 ni mogoče zavrniti, saj je regresijski koeficient za spremenljivko velikost (*SIZE*) močno statistično značilen in pozitiven. Koeficient je manjši od 1, kar kaže na to, da medčasovno povečanje bilančne vsote banke v vzorcu za 1 mrd EUR poveča ΔCoVaR banke za 22 b.t. Na drugi strani je na podlagi rezultatov panelne analize hipoteza 2 zavrnjena, saj je regresijski koeficient za spremenljivko finančni vzvod (*LEV*) statistično značilen in negativen. Možna razlaga takega rezultata je dejstvo, da se finančni vzvod bank v vzorcu načeloma poveča po povečanju ΔCoVaR (glej sliko 6 v dodatku 9), torej so večje spremembe vzvoda bank posledica sistemskih dogodkov in ne obratno.

Hipoteze 3 na podlagi rezultatov panelne analize ni mogoče definitivno zavrniti ali sprejeti, saj je pri FE modelu regresijski koeficient za spremenljivko beta (*BETA*) statistično neznačilen in ima precejšnjo standardno napako. Čeprav presečni podatki kažejo na določen linearni odnos med beto in ΔCoVaR (glej sliko 1 v dodatku 9), pa medčasovna dinamika obeh spremenljivk ne kaže konkretnejše povezave (glej sliko 2 v dodatku 9). Slednje vpliva predvsem na rezultat FE modela, ki upošteva zgolj variabilnost znotraj posamezne skupine oz. posamezne banke v vzorcu. Posledično je regresijski koeficient v RE modelu statistično značilen pri 95 % intervalu zaupanja, saj se lahko RE model interpretira tudi kot tehtano povprečje cenilk med skupinami in znotraj skupin (glej Greene, 2012). Navkljub metodološki podobnosti mer beta in ΔCoVaR, obe sta namreč meri soodvisnosti delniških donosov posameznih institucij in finančnega sistema, za vzorec bank v evroobmočju beta nima razlagalne vrednosti. Ocenjeni regresijski koeficient za spremenljivko VaR (*VaR*) je statistično značilen pri 99 % intervalu zaupanja, pozitiven in manjši od 1, kar kaže na to, da ima povečanje VaR posamezne banke v vzorcu manjši, pozitiven vpliv na povečanje ΔCoVaR.

ZAKLJUČEK

Izredno turbulentno obdobje v mednarodnem finančnem okolju, ki se je začelo z izbruhom svetovne finančne krize v letih 2007/08 je pomembno vplivalo na paradigmatsko spremembo finančnega regulatornega sistema. Poleg implementacije bolj koherentnih, makrobonitetnih oblik nadzora je pokrizno obdobje zaznamoval tudi precejšen napredek v metodoloških rešitvah za ocenjevanje sistemske tveganosti finančnih institucij. Med pomembnejše nove metode tako spadajo MES, ΔCoVaR, SRISK in DIP.

V magistrskem delu sem analiziral sistemsko tveganosti 46 bank v evroobmočju v obdobju od 2000 do 2012, ki vključuje svetovno finančno krizo in začetek evropske dolžniške krize. Na podlagi medčasovnih ocen VaR in ΔCoVaR posameznih bank sem oblikoval lestvice sistemske tveganosti za posamezna opazovalna obdobja, ki kažejo, da so predvsem večje evropske banke razmeroma konstantno visoko rangirane. Z analizo dejavnikov sistemskega tveganja pa sem prišel do spoznanja, da medčasovno na sistemsko tveganje bank v evroobmočju, merjeno s ΔCoVaR, pozitivno vplivata VaR in bilančna vsota, medtem ko ima finančni vzvod negativen vpliv, beta pa značilnega vpliva na ΔCoVaR bank v evroobmočju nima.

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APPENDIXES

TABLE OF APPENDIXES

APPENDIX 1: LIST OF ABBREVIATIONS

Table 1: *List of abbreviations*

AR	Autoregression
ARCH	Autoregressive conditional heteroscedasticity
CAPM	Capital asset pricing model
CCA	Contingent claims analysis
CDS	Credit default swap
CI	Confidence interval
CLO	Collateralized debt obligation
CoES	Conditional expected shortfall
CoVaR	Conditional Value-at-Risk
ΔCoVaR	Delta conditional Value-at-Risk
DIP	Distressed insurance premium
EAD	Exposure at default
EBA	European Banking Authority
ECB	European Central Bank
EFSF	European Financial Stability Fund
EL	Expected loss
ES	Expected shortfall
ESRB	European Systemic Risk Board
EWMA	Exponentially weighted moving average
FE	Fixed effects
FSB	Financial Stability Board
FSOC	Financial Stability Oversight Counsel
GARCH	General autoregressive conditional heteroscedasticity
GARCH DCC	General autoregressive conditional heteroscedasticity with dynamic conditional correlations
GARCH DVECH	General autoregressive conditional heteroscedasticity with a diagonal vech structure
GDP	Gross domestic product
GLS	Generalized least squares
G-SIB	Global systemically important bank
IMF	International Monetary Fund
IRB	Internal rating based approach
LCR	Liquidity coverage ratio
LGD	Loss given default
LSDV	Least squares dummy variable
LTRO	Long-term refinancing operation

Table 1 continued

M	Maturity
MES	Marginal expected shortfall
NSFR	Net stable funding ratio
OTC	Over-the-counter
PCA	Principal component analysis
PD	Probability of default
PIT	Point-in-time
RE	Random effects
RWA	Risk weighted assets
SES	Systemic expected shortfall
SIV	Systemic risk index based on assets
SRISK	Systemic risk index
TBTF	Too-big-to-fail
TTC	Through-the-cycle
UL	Unexpected loss
VaR	Value-at-Risk
VAR	Vector autoregression

APPENDIX 2: Examples of macroprudential instruments

Table 1: *Examples of macroprudential instruments*

1) Risk management methodologies	Examples
By banks	Risk measures calibrated through the cycle or to the cycle through
By supervisors	Cyclical conditionality in supervisory ratings of firms, measures of systemic vulnerability (e.g. commonality of exposures and risk profiles, intensity of inter-firm linkages) as basis for calibration of prudential tools, Communication of official assessments of systemic vulnerability and outcomes of macro stress tests
2) Financial reporting	
Accounting standards	Use of less procyclical accounting standards, dynamic provisions
Prudential filters	Adjust accounting figures as a basis for calibration of prudential tools, Prudential provisions as add-on to capital, smoothing via moving averages of such measures, time-varying target for provisions or for maximum provision rate
Disclosures	Disclosures of various types of risk (e.g. credit, liquidity) and of uncertainty about risk estimates and valuations in financial reports or disclosures
3) Regulatory capital	
Pillar 1	Systemic capital surcharge, reduced sensitivity of regulatory capital requirements to current point in the cycle and with respect to movements in measured risk, cycle-dependent multiplier to the point-in-time capital figure, increased regulatory capital requirements for particular exposure types (higher risk weights than on the basis of Basel II, for macroprudential reasons)
Pillar 2	Link of supervisory review to state of the cycle
4) Funding liquidity standards	Cyclically-dependent funding liquidity requirements, concentration limits, FX lending restrictions, FX reserve requirements, currency mismatch limits, open FX position limits
5) Collateral arrangements	Time-varying Loan-to-value (LTV) ratios, conservative maximum loan-to-value ratios and valuation methodologies for collateral, limit extension of credit based on increases in asset values, through-the-cycle margining

Table 1 continued

6) Risk concentration limits	Quantitative limits to growth of individual types of exposures, (time-varying) interest rate surcharges for particular types of loans
7) Compensation schemes	Guidelines linking performance-related pay to ex ante longer-horizon measures of risk, back-loading of pay-offs, supervisory review process for enforcement
8) Profit distribution restrictions	Limit dividend payments in good times to help build up capital buffers in bad times
9) Insurance mechanisms	Contingent capital infusions, pre-funded systemic risk insurance schemes financed by levy related to bank asset growth beyond certain allowance, pre-funded deposit insurance with premia sensitive to macro (systemic risk) in addition to micro (institution specific) parameters
10) Managing failure and resolution	Exit management policy conditional on systemic strength, trigger points for supervisory intervention stricter in booms than in periods of systemic distress

Source: G. Galati & R. Moessner, Macroprudential Policy – A Literature Overview, 2011, p. 10.

APPENDIX 3: Descriptive statistics

Table 1: *Descriptive statistics for banks in the sample*

			Descriptive statistics*				
	Bank	Country	Min	Max	Mean	Std dev	Corr
1	Erste Group Bank	AT	-0.2001	0.1703	0.0002	0.0274	0.6299
2	Dexia	BE	-0.3517	0.3001	-0.0016	0.0353	0.5394
3	KBC Group	BE	-0.2866	0.4048	-0.0002	0.0332	0.6692
4	Bank of Cyprus	CY	-0.1452	0.2007	-0.0011	0.0273	0.2842
5	Hellenic Bank	CY	-0.1892	0.1613	-0.0011	0.0237	0.2618
6	Commerzbank	DE	-0.2825	0.1946	-0.0009	0.0302	0.7096
7	Deutschebank	DE	-0.1807	0.2231	-0.0002	0.0259	0.8038
8	IKB Deutsche Industriebank	DE	-0.2727	0.4927	-0.0011	0.0327	0.2167
9	Banco Popular Espanol	ES	-0.1315	0.1880	-0.0005	0.0205	0.7143
10	Banco Santander	ES	-0.1272	0.2088	-0.0001	0.0230	0.8765
11	Bankinter	ES	-0.1239	0.1354	-0.0003	0.0222	0.6508
12	BBVA	ES	-0.1367	0.1991	-0.0002	0.0225	0.8901
13	Pohjola Pankki	FI	-0.1812	0.1964	0.0003	0.0210	0.5308
14	BNP Paribas	FR	-0.1893	0.1898	0.0000	0.0258	0.8780
15	Crédit Agricole Alpes Provence	FR	-0.4179	0.1795	-0.0002	0.0149	0.1270
16	Crédit Agricole Ile de France	FR	-0.1956	0.1906	0.0001	0.0153	0.1608
17	CIC	FR	-0.0874	0.1049	0.0000	0.0141	0.2906
18	Caisse Régionale de Crédit Agricole d'Ile-et-Vilaine	FR	-0.0930	0.1033	-0.0001	0.0152	0.1682
19	Credit Agricole Nord de France	FR	-0.1205	0.0953	-0.0002	0.0147	0.2094
20	Natixis	FR	-0.1922	0.3279	-0.0002	0.0282	0.6430
21	Société Général	FR	-0.1771	0.2143	-0.0002	0.0287	0.8584
22	Alpha Bank	GR	-0.2159	0.2624	-0.0008	0.0356	0.3718
23	Attica Bank	GR	-0.5064	0.3525	-0.0010	0.0378	0.2537
24	Bank of Greece	GR	-0.1545	0.1816	-0.0005	0.0213	0.2869
25	Bank of Piraeus	GR	-0.2559	0.2803	-0.0010	0.0348	0.3619
26	Eurobank Ergasias	GR	-0.2263	0.2584	-0.0011	0.0359	0.3494
27	General Bank of Greece	GR	-0.2231	0.2607	-0.0024	0.0358	0.2825
28	National Bank of Greece	GR	-0.2331	0.2557	-0.0009	0.0332	0.4437
29	Allied Irish Banks	IR	-0.8824	0.3610	-0.0016	0.0466	0.3963
30	Bank of Ireland	IR	-0.7931	0.3927	-0.0011	0.0458	0.4359
31	Banca Carige	IT	-0.1165	0.1507	-0.0002	0.0183	0.5276
32	Banca Monte Dei Paschi	IT	-0.1553	0.1620	-0.0007	0.0233	0.6700
33	Banca Popolare di Milano	IT	-0.2829	0.2015	-0.0005	0.0260	0.6305

Table 1 continued

	Bank	Country	Min	Max	Mean	Std dev	Corr
34	Banca Popolare Emilia Romagna	IT	-0.1126	0.1448	-0.0003	0.0183	0.5094
35	Banca Popolare Etruria Lazio	IT	-0.1090	0.1258	-0.0008	0.0183	0.4250
36	Banco di Desio e della Brianza	IT	-0.1207	0.1122	-0.0001	0.0187	0.3123
37	Banco di Sardegna	IT	-0.0932	0.1551	-0.0003	0.0172	0.3155
38	Banco Popolare	IT	-0.1787	0.1735	-0.0006	0.0251	0.6421
39	Credito Bergamasco	IT	-0.1229	0.1125	0.0000	0.0163	0.2456
40	Credito Emiliano	IT	-0.1597	0.1704	-0.0001	0.0242	0.6088
41	Intesa Sanpaolo	IT	-0.1846	0.1796	-0.0003	0.0269	0.7921
42	Mediobanca	IT	-0.1101	0.1533	-0.0002	0.0199	0.6608
43	Unicredit	IT	-0.1895	0.1901	-0.0006	0.0270	0.8181
44	Van Lanschot	NL	-0.0965	0.1088	-0.0003	0.0149	0.2024
45	Banco BPI	PT	-0.1165	0.2302	-0.0004	0.0203	0.5049
46	Banco Espirito Santo	PT	-0.1322	0.1530	-0.0005	0.0187	0.5523
	EUROSTOXX Banks		-0.1083	0.1776	-0.0003	0.0200	1

*Note: values are calculated for daily log returns, sample from 5 Jan 2000 to 31 Dec 2012, 3330 observations. Corr is the uncoditional correlation coefficient between individual bank returns and the returns of the EUROSTOXX Banks Index.

APPENDIX 4: Estimates of VaR and ΔCoVaR for Eurozone banks

Table 1: *Estimates of VaR with GARCH (1,1) and ΔCoVaR with GARCH DCC (1,1) at 99% CI**

			Dec 2002 - Dec 2007		Jan 2008 - Dec 2012		Jan 2000 - Dec 2012	
	Bank	Country	VaR	Δ CoVaR	VaR	Δ CoVaR	VaR	Δ CoVaR
1	Erste Group Bank	AT	3.7817	0.9920	8.0930	4.3516	5.5190	2.3406
2	Dexia	BE	3.3565	1.5972	10.356	3.4719	6.4235	2.3469
3	KBC Group	BE	3.1654	1.4594	10.097	4.3512	6.2030	2.7302
4	Bank of Cyprus	CY	3.8879	0.4914	7.9112	2.0330	5.5838	1.1066
5	Hellenic Bank	CY	4.2513	0.5006	6.0107	1.9394	5.1464	1.0604
6	Commerzbank	DE	4.4329	1.5586	8.2022	4.3415	6.1107	2.8485
7	Deutschebank	DE	3.4183	1.8458	6.8378	4.7565	5.2797	3.2667
8	IKB Deutsche Industriebank	DE	3.7050	0.8696	10.204	1.0827	6.8455	0.9604
9	Banco Popular Espanol	ES	2.3890	1.4635	6.1485	4.7372	4.2935	2.8233
10	Banco Santander	ES	3.0169	1.9496	6.0945	5.5107	4.8720	3.6045
11	Bankinter	ES	3.2237	1.4955	6.1301	4.3132	4.7644	2.7331
12	BBVA	ES	2.9971	1.9760	6.0619	5.4304	4.7539	3.6472
13	Pohjola Pankki	FI	3.4235	0.5734	6.1141	4.0995	4.5100	1.9337
14	BNP Paribas	FR	3.3749	2.0283	7.2372	5.2418	5.2821	3.5594
15	Crédit Agricole Alpes Provence	FR	1.4504	0.0525	3.7235	1.1942	2.8195	0.5371
16	Crédit Agricole Ile de France	FR	2.7621	0.4368	3.2958	1.4272	3.2780	0.6616
17	CIC	FR	2.9129	0.1937	3.7346	2.3141	3.1536	1.1288
18	Caisse Régionale de Crédit Agricole d'Ile-et-Vilaine	FR	2.4587	0.0420	4.2593	1.4038	3.3521	0.6453
19	Credit Agricole Nord de France	FR	2.3668	0.2182	3.8925	1.9119	3.2131	0.8086
20	Natixis	FR	3.6245	1.0587	8.8878	4.2773	5.5732	2.5117
21	Société Général	FR	3.5068	2.0041	8.2207	5.2430	5.9761	3.4991
22	Alpha Bank	GR	4.0404	0.9169	11.216	2.5952	6.9382	1.6336
23	Attica Bank	GR	6.3814	0.5951	11.139	1.8356	8.1793	1.1020
24	Bank of Greece	GR	3.1546	0.4511	5.1940	2.1866	4.4417	1.1825
25	Bank of Piraeus	GR	3.8986	0.9674	10.954	2.6120	6.7078	1.6706
26	Eurobank Ergasias	GR	3.6827	0.8463	11.578	2.6833	6.7384	1.6186
27	General Bank of Greece	GR	4.9168	0.6884	10.838	1.7278	7.3104	1.2151
28	National Bank of Greece	GR	4.1493	0.9623	10.400	3.0184	6.7275	1.8563
29	Allied Irish Banks	IR	3.2219	1.2542	14.686	2.5025	8.3147	1.8255
30	Bank of Ireland	IR	3.2452	1.1497	14.495	3.0367	8.0549	1.9006

Table 1 continued

	Bank	Country	Dec 2002 - Dec 2007 VaR	Δ CoVaR	Jan 2008 - Dec 2012 VaR	Δ CoVaR	Jan 2000 - Dec 2012 VaR	Δ CoVaR
31	Banca Carige	IT	2.6040	0.7005	5.7103	3.7768	3.6686	1.8986
32	Banca Monte Dei Paschi	IT	3.3593	1.4120	6.4517	4.2933	4.9376	2.7205
33	Banca Popolare di Milano	IT	3.7456	1.3075	7.2688	4.2471	5.6596	2.5942
34	Banca Popolare Emilia Romagna	IT	1.7353	0.3785	6.0290	3.6729	3.8376	1.6915
35	Banca Popolare Etruria Lazio	IT	3.0712	0.7446	5.1220	2.9944	3.9027	1.6935
36	Banco di Desio e della Brianza	IT	3.9885	0.5511	4.1639	2.3854	4.2219	1.2896
37	Banco di Sardegna	IT	2.5106	0.5976	4.3295	2.0927	3.6601	1.3059
38	Banco Popolare	IT	3.2032	1.3079	7.6088	4.2804	5.1939	2.5577
39	Credito Bergamasco	IT	2.9149	0.4562	4.4951	1.6981	3.5575	0.9700
40	Credito Emiliano	IT	3.6820	1.2657	6.3475	4.0108	5.3544	2.4803
41	Intesa Sanpaolo	IT	3.5093	1.5356	7.2024	5.1668	5.5625	3.1351
42	Mediobanca	IT	3.0516	1.4158	5.3034	4.3701	4.3287	2.7438
43	Unicredit	IT	2.8977	1.6535	7.9812	5.1558	5.3400	3.2707
44	Van Lanschot	NL	3.0071	0.5102	3.6307	1.2878	3.3350	0.8293
45	Banco BPI	PT	2.8183	0.6201	5.9326	3.5912	4.4076	1.9316
46	Banco Espirito Santo	PT	1.5378	0.8433	6.0894	3.7887	3.5913	2.1478

*Note: values are averages of estimated time series for conditional variances and conditional correlations; the 2002-07 interval and the 2008-12 interval are of equal length (1286 observations each). Δ CoVaR and VaR are given in %.

APPENDIX 5: VaR and ΔCoVaR of Eurozone banks for both subperiods

Figure 1: *VaR and ΔCoVaR (99% CI), 2002-2007 (in %)*

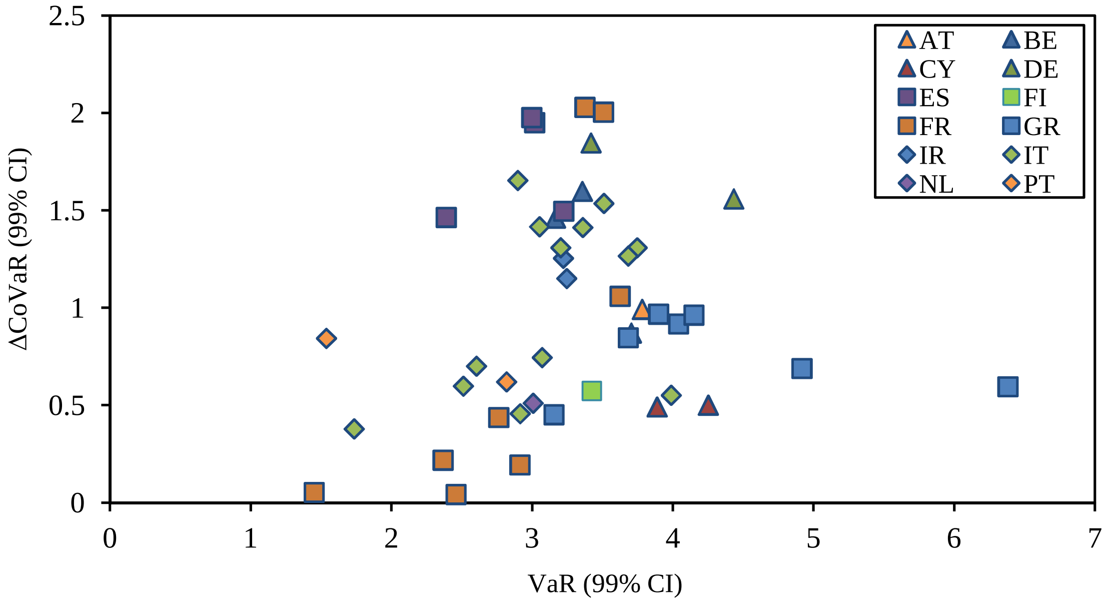
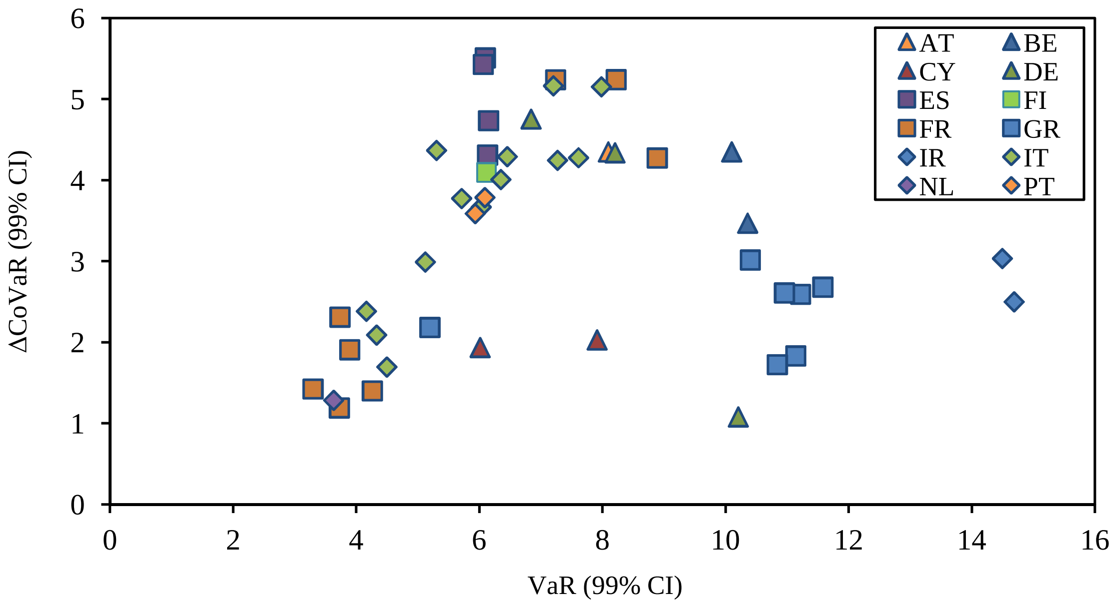


Figure 2: *VaR and ΔCoVaR (99% CI), 2008-2012 (in %)*



APPENDIX 6: Systemic risk rankings of Eurozone banks

Table 1: *Pre-crisis period (2002-2007)*

	Bank	Country	ΔCoVaR
1	BNP Paribas	FR	2.0283
2	Société Général	FR	2.0041
3	BBVA	ES	1.9760
4	Banco Santander	ES	1.9496
5	Deutschebank	DE	1.8458
6	Unicredit	IT	1.6535
7	Dexia	BE	1.5972
8	Commerzbank	DE	1.5586
9	Intesa Sanpaolo	IT	1.5356
10	Bankinter	ES	1.4955

Table 2: *Crisis period (2008-2012)*

	Bank	Country	ΔCoVaR
1	Banco Santander	ES	5.5107
2	BBVA	ES	5.4304
3	Société Général	FR	5.2430
4	BNP Paribas	FR	5.2418
5	Intesa Sanpaolo	IT	5.1668
6	Unicredit	IT	5.1558
7	Deutschebank	DE	4.7565
8	Banco Popular Espanol	ES	4.7372
9	Mediobanca	IT	4.3701
10	Erste Group Bank	AT	4.3516

Table 3: *Entire sample period (2000-2012)*

	Bank	Country	ΔCoVaR
1	BBVA	ES	3.6472
2	Banco Santander	ES	3.6045
3	BNP Paribas	FR	3.5594
4	Société Général	FR	3.4991
5	Unicredit	IT	3.2707
6	Deutschebank	DE	3.2667
7	Intesa Sanpaolo	IT	3.1351
8	Commerzbank	DE	2.8485
9	Banco Popular Espanol	ES	2.8233
10	Mediobanca	IT	2.7438

APPENDIX 7: Descriptive statistics for panel data

Table 1: *Descriptive statistics for panel data*

	ΔCoVaR	VaR	Beta	Size	Leverage
min	-0.7164	0.4465	-0.3895	1	2.01
max	2.1076	38.0181	10.1583	2289	717.56
average	0.5992	5.1546	2.0026	191	23.02
std.dev	0.4265	3.3072	1.6821	342	32.53
Total number of observations					1551
Total number of groups					44
Average number of observations per group					35.25

Note: ΔCoVaR and VaR are given in % and calculated at 99% CI, size is given in bn EUR.

APPENDIX 8: Results of panel data models

Table 1: *Results of panel data models*

	1Q 2000-4Q 2012		1Q 2002-4Q 2007		1Q 2008-4Q 2012	
	FE (LSDV)	RE (GLS)	FE (LSDV)	RE (GLS)	FE (LSDV)	RE (GLS)
Dependent variable	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
VaR	0.3644***	0.3487***	0.47***	0.3608***	0.2988***	0.1924***
	[0.0108]	[0.011]	[0.0175]	[0.0198]	[0.0161]	[0.0172]
	(33.69)	(31.62)	(26.82)	(18.24)	(18.52)	(0.0198)
Beta	-0.0908	0.2634**	-0.517***	0.1787**	-0.5692***	1.2348***
	[0.1098]	[0.1012]	[0.0923]	[0.0907]	[0.2031]	[0.1753]
	(-0.83)	(2.6)	(-5.6)	(1.97)	(-2.8)	(7.04)
Size	0.0222***	0.0159***	0.0024	0.0131***	0.0039	0.0095***
	[0.0018]	[0.0012]	[0.0028]	[0.0016]	[0.0076]	[0.0014]
	(12.15)	(13.2)	(0.88)	(8.35)	(0.51)	(6.94)
Leverage	-0.0107***	-0.0108***	-0.0083	-0.0129***	-0.01***	-0.0119***
	[0.001]	[0.0011]	[0.0036]	[0.0031]	[0.0012]	[0.0013]
	(-10.29)	(-10.07)	(-2.3)	(-4.23)	(-8.18)	(-8.88)
Constant	0.3066*	0.1677*	-0.1752	-0.0585	2.5676***	1.2534***
	[0.1734]	[0.0904]	[0.1696]	[0.0865]	[0.3676]	[0.1523]
	(1.77)	(1.85)	(-1.03)	(-0.68)	(6.98)	(8.23)
R^2	0.6361	0.4411	0.7004	0.4223	0.6428	0.3523
Hausman test	32.89 {0.0000}		244.09 {0.0000}		239.60 {0.0000}	

Note: Both models include time effects. Standard errors are given in squared brackets, t-values are given in round brackets. * indicates significance at 10% CI, ** at 5% CI and *** at 1% CI. Hasuman test H0: difference between fixed and random effects is not systematic, test statistic is distributed Chi2 with 4 degrees of freedom, p value is given in curly brackets.

APPENDIX 9: Systemic risk factors

Figure 1: *Average beta and ΔCoVaR (in %) by bank*

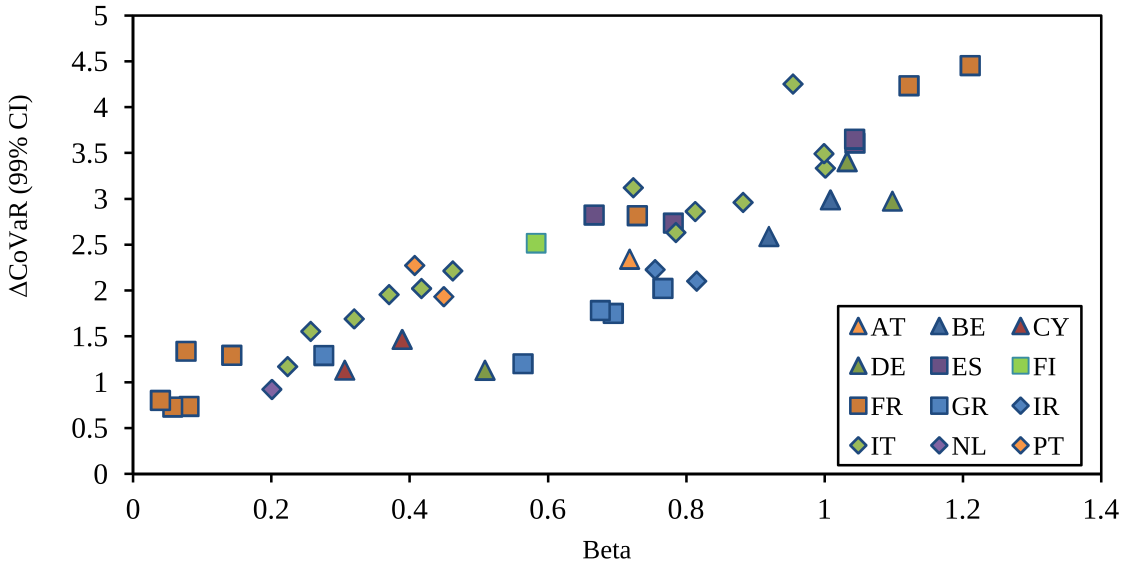


Figure 2: *Intertemporal average beta and ΔCoVaR (in %)*

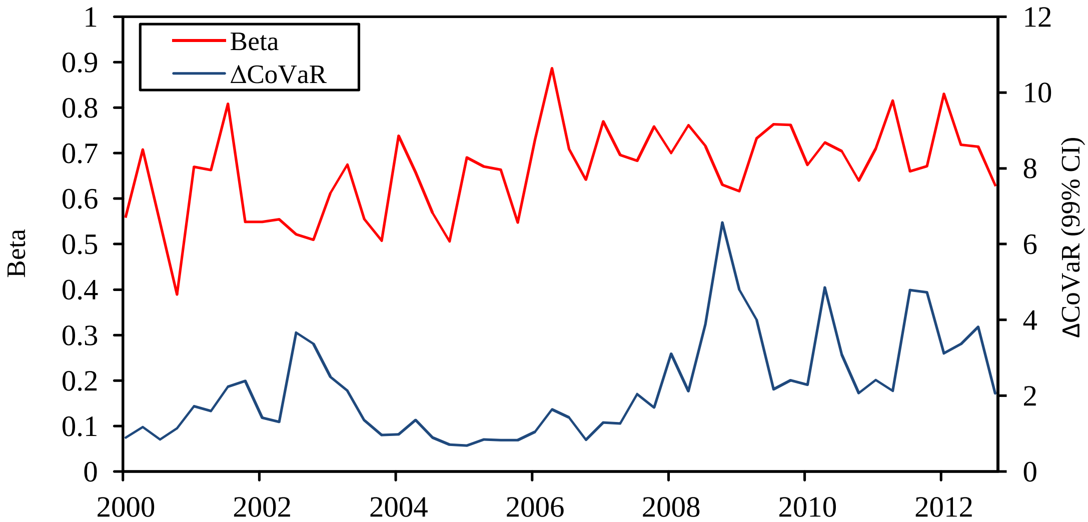


Figure 3: *Average size in bn EUR and ΔCoVaR (in %) by bank*

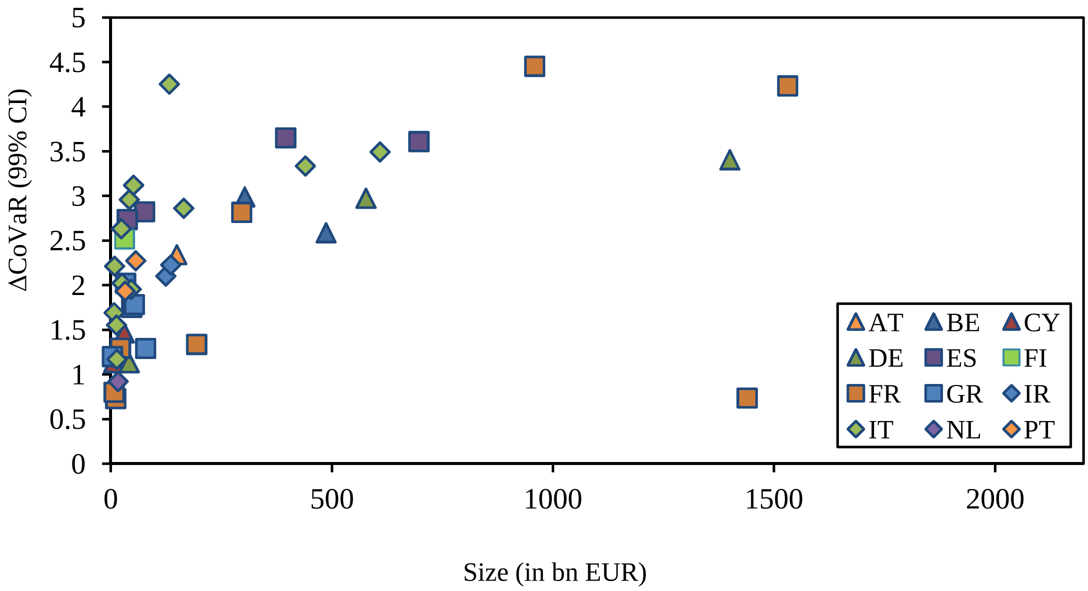


Figure 4: *Intertemporal average size in bn EUR and ΔCoVaR (in %)*

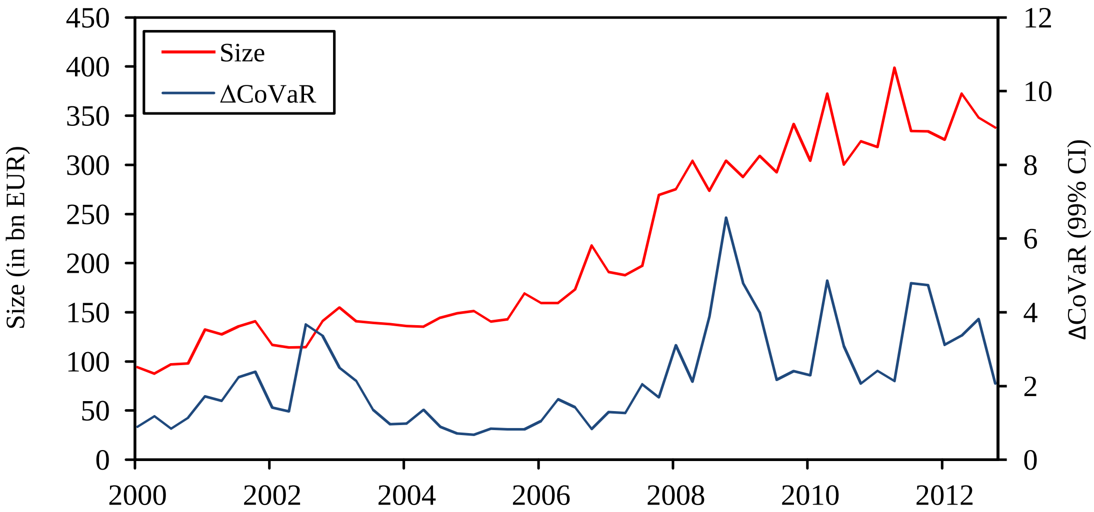


Figure 5: *Average leverage and ΔCoVaR (in %) by bank*

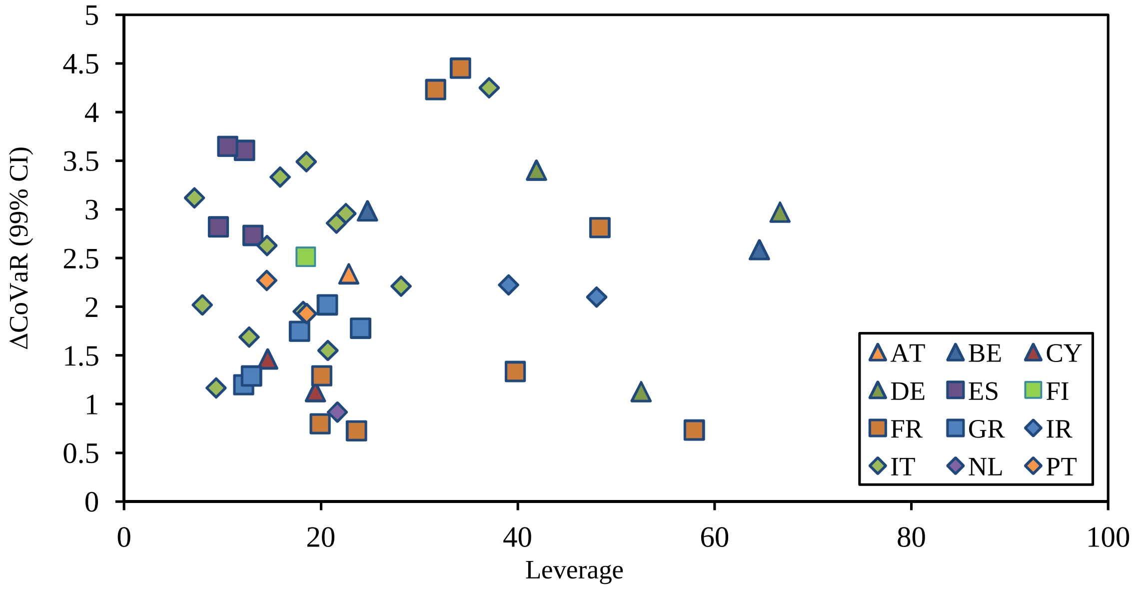


Figure 6: *Intertemporal average leverage and ΔCoVaR (in %)*