BANK RISK, INTERCONNECTEDNESS AND BANK BUSINESS MODELS

Valerie De Bruyckere

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Supervisor: Prof. dr. Rudi Vander Vennet

Co-Supervisor: Prof. dr. Lieven Baele

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by Valerie De Bruyckere

DOCTORAL JURY

Prof. dr. Marc De Clercq

(Ghent University, Dean)

Prof. dr. Patrick Van Kenhove

(Ghent University, Academic Secretary)

Prof. dr. Rudi Vander Vennet

(Ghent University, Supervisor)

Prof. dr. Lieven Baele

(Tilburg University, Co-Supervisor)

Prof. dr. Koen Schoors

(Ghent University)

Prof. Dr. Hans Degryse

(KULeuven and Tilburg University)

Prof. Dr. Hans Dewachter

(KULeuven and National Bank of Belgium)

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Nederlandstalige samenvatting

Het is niemand ontgaan dat de recente financiële crisis een grote impact heeft gehad op ons dagelijks leven. Sinds het uitbreken van de financiële crisis in augustus 2007, kwamen niet alleen tal van banken in de problemen, maar ook de overheden van een aantal Europese landen. Tenslotte is de financiële crisis uitgemond in een wereldwijde recessie. Om te vermijden dat problemen in de banksector overslaan op de reële economie, hebben we nood aan een stabiele banksector. Elk van deze vier hoodstukken in dit doctoraat belicht een aspect van het risicogedrag van banken. Een betere en accuratere kennis van het risicogedrag van banken moet bedragen tot een betere financiële stabiliteit van ons economisch systeem.

In een eerste hoofdstuk ga ik na of marktdiscipline echt werkt in het beïnvloeden van de strategische bedrijfsvoering van banken. In een tweede hoofdstuk ga ik na welke risicofactoren een effect hebben op aandelenkoersen van banken, en hoe deze variëren over de tijd heen. In een derde hoofdstuk ga ik empirisch na of er sprake was van besmetting tussen banken en landen tijdens de recente soevereine schuldcrisis in Europa, en wat de bepalende factoren zijn. In een laatste hoofdstuk stel ik een methodologie voor die beleidsmakers kunnen hanteren bij het uitvoeren van een stress test van de banksector.

<u>Hoofdstuk 1: Kan marktdiscipline de strategische bedrijfsvoering van banken beïnvloeden?</u>

In het eerste hoofdstuk van mijn doctoraat ga ik empirisch na of marktdiscipline via aandelenkoersen van banken in staat is hun gedrag te beïnvloeden. Marktdiscipline bij financiële instellingen betekent dat managers hun beleid of strategie aanpassen aan signalen die ze ontvangen vanuit de markt waarin ze effecten uitgeven. Dit kunnen bijvoorbeeld deposito's zijn, maar ook obligaties of aandelen. Deze paper gaat na of er marktdiscipline is bij banken op basis van de aandelenkoersen van financiële instellingen. Marktdiscipline maakt deel uit van het huidige regulerende kader van banken, nl. het Basel II akkoord en ook het recent overeengekomen Basel III akkoord dat de nieuwste reglementering op het bankwezen vastlegt. Op basis hiervan zou men verwachten dat marktdiscipline effectief is en bijdraagt tot de stabiliteit van het banksysteem. Toch bestaat er weinig empirisch onderzoek dat deze hypothese staaft. Om een antwoord te bieden op de vraag of marktdiscipline echt bijdraagt in de supervisie van banken, volg ik de theoretische literatuur waarbij marktdiscipline opgesplits wordt in twee componenten, nl. markttoezicht en marktinvloed. Markttoezicht betekent dat marktparticipanten wijzigingen en onderlinge verschillen in de conditie van banken correct kunnen inschatten, en die informatie opnemen in de effecten die de bank uitgeeft. Marktinvloed daarentegen betekent dat marktparticipanten via koersveranderingen in staat zijn om de acties van het bank management te beïnvloeden. Om de hypothese te staven dat marktdiscipline werkt, moet ik het empirisch bewijs leveren voor de beide componenten. Daarom probeer ik op basis van innovatieve econometrische technieken om signalen uit de aandelenkoersen van banken te identificeren. In een volgende stap ga ik na of er, als reactie op deze signalen, wijzigingen zijn in een aantal strategische ratios die het business model van de bank bepalen. Hierbij kijk ik naar de kapitaalratio van banken, het percentage deposito's in de totale schuld van de bank, hoeveel dividenden er uitgekeerd worden, etc. Ik kom tot de conclusie dat banken wel degelijk hun gedrag aanpassen indien ze signalen ontvangen uit de aandelenmarkt. Zo vind ik bijvoorbeeld dat een risicosignaal ertoe leidt dat banken hun kapitaalratio optrekken en meer liquide activa aanhouden. Bij een marktsignaal van onderwaardering reageren banken door relatief minder kosten te maken en minder dividenden uit te keren.

Hoofdstuk 2: Op zoek naar de relevante risicofactoren van bank aandelenkoersen

In dit hoofdstuk ligt de nadruk op aandelenkoersen van financiële instellingen en ga ik na in welke mate deze informatie bevatten over hun risicoprofiel. In de empirische bankliteratuur gebeurt dit doorgaans door het schatten van een één-factor CAPM (capital asset pricing model), waarbij aandelenkoersen in een regressie gerelateerd worden aan een marketindex. De geschatte beta (marktbeta) geeft aan in welke mate het aandeel gevoelig is voor marktschommelingen. Dit model is echter al meermaals uitgebreid en aangepast, doordat additionele risicofactoren worden opgenomen. Hierbij denk ik aan renterisico, kredietrisico, risico voor schommelingen in huizenprijzen (denk maar aan de subprime mortgage crisis in de VS), maar recentelijk ook liquiditeitsrisico. Sinds het uitbreken van de financiële crisis werd immers duidelijk dat evoluties op de interbankenmarkt zeer grote gevolgen kunnen hebben voor banken met een business model dat te veel gebruik maakt van korte termijnfinanciering (vb. Dexia bank in België, of Northern Rock in het Verenigd Koninkrijk). Om na te gaan of aandelenkoersen van banken informatie bevatten over hun markt-, krediet-, rente-, huizenprijs- en liquiditeitsrisico ga ik uit van de hypothese van "modelonzekerheid". In de academische literatuur is er namelijk geen consensus over welke factoren thuishoren in een dergelijk model, noch over de impact van de toegevoegde risicofactoren. Daarom maak ik gebruik van een econometrische techniek, "Bayesian Model Averaging", die toelaat om niet één, maar verschillende modellen te schatten. Deze modellen verschillen in de factoren die ze bevatten. Concreet betekent dit dat op basis van een set van x factoren, 2^x verschillende combinaties gemaakt kunnen worden. Al deze modellen bevatten een deel van de informatie. Daarom wordt in de finale schattingen de informatie uit al deze modellen simultaan opgenomen, waarbij de informatie uit elk model gewogen wordt met de kans dat elk van deze modellen het juiste model is. Deze econometrische techniek verschaft een uniek inzicht in het belang van deze risicofactoren. Over een tijdsperiode van 1986 tot eind 2010 vind ik dat de marktfactor met een zekerheid van 100% moet worden opgenomen in het model. Bovendien vinden we dat het marktrisico zeker niet de enige risicofactor is voor banken, maar dat ook additionele factoren belangrijk zijn, zoals bijvoorbeeld schommelingen in huizenprijzen, die ook met een zekerheid van 100% moeten opgenomen worden. Ook de high-minus-low Fama French factor blijkt zeer belangrijk.

Uit een analyse met tijdsvariatie blijkt opnieuw dat bovenstaande risicofactoren doorheen genomen zeer belangrijk zijn. Daarnaast blijkt ook sommige factoren regelmatig aan belang winnen, en daarna opnieuw verdwijnen. Voorbeelden daarvan zijn de marktvolatiliteit, de term spread en de small-minus-big Fama French factor. Deze conclusies blijken relatief robuust te zijn voor groepen banken met verschillende karakteristieken.

Tenslotte toont dit hoofdstuk aan wat de implicaties zijn voor toekomstig onderzoek in het vakgebied, met name voor (i) het uitvoeren van event studies, (ii) het meten van bank "opaqueness" of ondoorzichtigheid van het risicoprofiel van banken, en (iii) het meten van systematisch bank risico.

Hoofdstuk 3: De relatie tussen bankrisico en soeverein risico tijdens de Europese schuldencrisis

In het derde hoofdstuk ga ik na in welke mate bankspecifiek risico interageert soeverein risico. Daarmee sluit dit werk nauw aan bij de recente actualiteit van de schuldencrisis in Europa. Meer specifiek analyseer ik of er sprake is van besmetting of "spillovers" in de kredietwaardigheid van banken naar landen, en andersom. De kredietwaardigheid van banken en landen wordt gemeten op basis van tijdreeksen van Credit Default Swap (CDS) spreads. Dit zijn verzekeringscontracten die financiële instellingen onder elkaar afsluiten om zich in te dekken tegen falingsrisico. Hoe hoger de CDS spread, hoe groter het kredietrisico en hoe groter de kans op falen. Nadat ik met behulp van empirische testen bewijs lever voor de hypothese van besmetting van kredietwaardigheid tussen banken en landen, ga ik na welke determinanten bepalend zijn voor de kans op besmetting. Hier wordt een onderscheid gemaakt tussen bank- en landspecifieke variabelen. Wat bankspecifieke variabelen betreft, tonen we aan dat banken met een hogere kapitaalratio en banken die zich in grote mate financieren op langere termijn beter bestand zijn tegen besmetting van andere landen. Bovendien nemen we de recent vrijgegeven informatie door de European Banking Authority over de blootstelling van banken aan de verschillende Europese landen mee in de analyse. Op basis hiervan weten we (sinds juli 2010) voor hoeveel deze banken blootgesteld zijn aan Europese overheidsobligaties. Deze cijfers tonen aan dat (i) banken meer blootgesteld zijn aan besmetting van landen naarmate ze een groter deel van hun soevereine obligatieportefeuille belegd hebben in deze landen, (ii) dat banken die een groter deel van hun portefeuille belegd hebben in een bepaald land kwetsbaarder zijn voor schokken in het kredietrisico van dat land. Wat landspecifieke variabelen betreft is de schuldraad van het land de belangrijkste determinant. Besmetting of "spillover" doet zich vaker voordoet tussen landen en banken indien deze landen kampen met een grotere overheidsschuld.

Hoofdstuk 4: Methodologie voor een stress test van de Europese banksector op basis van publiek beschikbare data

In het laatste hoofdstuk van mijn doctoraat ontwikkel ik een nieuwe methodologie voor een stress test van de banksector op basis van publiek beschikbare data. Het opzet van een stress test is om te kijken of banken bestand zijn tegen bepaalde schokken. Deze schokken worden gedefinieerd als bepaalde hypothetische scenarios die zich kunnen voordoen, bijvoorbeeld een substantiële krimp in de economische activiteit, of een verslechtering van de kredietwaardigheid van een aantal (vb Zuid-Europese) landen. Om een stabiel financieel systeem te waarborgen, moeten alle banken overeind blijven indien zich dergelijke scenarios voordoen. Beleidsmakers voeren deze stress testen doorgaans uit op basis van de balansgegevens van banken. Dit hoofdstuk toont aan dat een gelijkaardige stress test ook mogelijk is op basis van de aandelenkoersen van de banken. De methodologie gaat ervan uit dat een bank niet alleen onderhevig is aan schokken in de macroeconomische omgeving, maar ook aan mogelijke schokken bij alle andere banken. De mogelijke risicofactoren worden ingedeeld in blokken: een macroeconomisch blok (met daarin o.a. inflatie, economische groei, maar ook kredietrisico, marktvolatiliteit), een soverein blok (dat het landenrisico in de verschillende Europese landen meet), een financieel blok (voor sector specifieke financiële schokken), een blok met Europese huizenprijzen en een bank blok (dat alle andere banken in het financieel systeem bevat).

Ten eerste geeft dit hoofdzicht extra inzicht in hoe het belang van de verschillende risicofactoren varieert over de tijd heen. Ten tweede construeer ik een netwerk van de banksector in Europa. Dit geeft aan wat de belangrijkste relaties zijn tussen de banken. Ten derde toon ik aan hoe dit model gebruikt kan worden voor het opzetten van een stress test. Het model is in staat om in 81% van de gevallen een correcte voorspelling te doen van de toekomstige evolutie van de aandelenkoersen van banken, over een horizon van 3 kwartalen. De mogelijke toepassing van het model wordt verder geïllustreerd aan de hand van drie concrete stress test scenarios, nl. (1) een verslechtering van het Euopese sovereine crisis, (2) een stijging in het kredietrisico en een zwakkere economische economische omgeving en (3) een toename in de spanningen op de Europese geldmarkt.

Tenslotte laat het model toe om maatstaven te berekenen die inzicht verschaffen in de centraliteit van het financiële netwerk. Deze maatstaven tonen aan dat de centraliteit van het netwerk hoger is indien de groei in industriële productie lager is, wanneer het kredietrisico in de economie hoger is, wanneer de de aandelenkoersen lager staan en wanneer de geldmarkt krapper is.

Contents

CHAPTER 1

Introduction

Introduction

In this introductory chapter, we first discuss the general context of this dissertation in order to position it in the economics literature. The three main topics (bank risk, interconnectedness and business models) are discussed, as well as the different data sources and the methodologies that are used in this dissertation. The second section looks in more detail into the specific research questions that we tackle, and the frameworks that are used. We then also offer a glimpse of our results and their implications.

1 Orientation and Motivation

Everybody agrees that the recent financial crisis had a considerable impact on the daily lives of many people. Since the outbreak of the financial crisis in August 2007, numerous banks got into trouble, but also the governments of several European countries. Ultimately, the financial crisis led to a global recession. To avoid problems in the banking sector to spill over to the real economy, we need a stable banking sector. Each of the four chapters in this dissertation highlights an aspect of risk-taking behavior of banks. A better and more accurate knowledge of the risk-taking behavior of banks must contribute to a more stable financial system, and ultimately a higher welfare.

This dissertation deals with different aspects of financial stability. The three main topics of this dissertation (bank risk, interconnectedness, and bank business models) are present in all chapters of this dissertation.

First, the topic of **bank risk** is multi-faceted, and each chapter considers a different aspect of bank risk. In the first chapter, bank risk is measured as total risk, and is related to a wide range of business model characteristics. The second chapter offers a decomposition of total risk is in exposure to common risk factors and idiosyncratic risk. The common risk factors considered in this chapter are market risk, interest rate risk, credit risk, liquidity risk, currency risk, real estate risk, economic sentiment and the Fama-French factors. The focus of the third chapter is on bank credit risk, as bank credit risk is here measured with bank CDS spreads. This chapter considers the relationship between bank risk and sovereign risk, and investigates whether there is contagion between bank and sovereign risk. In the final chapter, bank risk is again decomposed in exposure to common factors, but this time, all other banks in the system are also considered as potential risk factors. Hence, banks are potentially exposed to common risk factors, but also to all other banks in the system.

The second topic, **intereconnectedness**, has gained in importance since the outbreak of the recent financial crisis. A major shock stemming from the banking system was the demise of Lehman Brothers in September 2008, which provoked a substantial increase of CDS spreads for banks and also for certain countries, typically smaller countries with large banks or countries where banks had to be rescued. This lead to the view that bank risk can not be seen in isolation, i.e. banks are interconnected. This topic of interconnectedness is addressed in the third and fourth chapter of this dissertation. In the third chapter, the focus is on the connections between banks and sovereigns during the recent sovereign debt crisis, whereas in the fourth chapter the focus is on the connections of banks with other banks in the financial system.

The third topic, the **bank business model**, connects the first, second and third chapter. The chapter investigating market discipline starts from a model that relates bank risk (and valuation) to different business model charachteristics. The business model characteristics proxy for (i) overall bank strategy (capital adequacy, asset quality, management quality, earnings and liquid assets), (ii) the bank's funding structure, (iii) asset mix, and (iv) revenue diversity. In the second chapter, we take a broader perspective, and compare the factor exposures of different subgroups of banks, defined along specific criteria. We differentiate between four types of financial intermediaries: depository institutions, insurance companies, security and commodity brokers, and other non-depository institutions. In addition, we differentiate between various 'types' by constructing portfolios of bank holding companies (BHCs) according to size, sound versus distressed BHCs and BHCs with a stable retail focus versus diversified and fast-growing banks. The topic of bank business models is also related to interconnectedness, i.e. the degree of contagion between banks and sovereigns. Therefore, the chapter investigating contagion between banks and sovereigns considers several measures of the bank business model, i.e. indicators of their retail orientation, funding structure, diversification and, especially, the banks' capital adequacy.

To address the research questions in this dissertation, we make use of two **types of data**: market prices on the one hand, and balance sheet and income statement information on the other. Market prices are used in all chapters of this dissertation. Chapter one, two and three make use of bank stock prices, whereas the third chapter uses (bank and sovereign) CDS spreads. This information is merged with balance sheet and income statement information in the first three chapters. Balance sheet and income statement information is usually available at a lower frequency (quarterly) than market prices (daily), but offers interesting information on the business model of the bank. Finally, depending on the research question, this information is merged with data from other sources. Examples of this are data on earnings per share forecasts of bank holding companies (first chapter), country specific data (such as debt-to-GDP, government revenues to GDP and the size of the bank sector in each country) (third chapter) and data on the sovereign exposures of the banks (third chapter).

This dissertation makes use of both standard and non-standard **methodologies** in the field of empirical banking. First, standard pandel data techniques are used to combine both the time dimension and the cross sectional dimension of the data. Extensions of this technique, i.e. stochastic frontier analysis and multiplicative heteroscedasticity regression are used in the first chapter. Second, Bayesian Model Averaging is used as a technique in the second and fourth chapter. The use of Bayesian Model Averaging is new and innovative in the field of empirical banking. This technique is used in the context of model uncertainty, where the researcher wants to extract the relevant regressors, out of a larger set of regressors.

2 Research Questions, results and contributions

The **second chapter** of this dissertation investigates empirically whether the stock market is an effective channel of market discipline. It is generally assumed that bank managers are disciplined by internal governance mechanisms and by their supervisors. Whether or not banks are also disciplined by financial markets is less clear. Yet, the Basel capital adequacy rules, one of the cornerstones of modern bank regulation, mention market discipline as a separate third pillar (next to capital ratios and supervisory interventions). In this chapter we revisit this issue by focusing on the stock market as a potential source of market discipline on banks. The crucial question is: Can the stock market assess bank risk *and* influence bank behavior? This chapter presents evidence that bank managers adjust key strategic variables following a risk and/or valuation signal from the stock market. This is interpret as evidence of stock market influencing.

Market discipline can be decomposed in two components: market monitoring and market influencing. Market monitoring is defined as the ability of securityholders to accurately assess the condition of the firm, and market influencing as subsequent managerial actions in response to these assessments. While there is considerable evidence of market monitoring, research examining the market influencing channel is more scarce and generally inconclusive.

The main contribution of this chapter is the design of a new test for direct market influencing. Our procedure starts by identifying stock market-based risk and (negative) valuation signals at the individual bank level. Consequently, we test to what extent bank managers adjust key strategic variables following a (combination of a) risk and negative valuation signal. Using a partial adjustment model, we test both for a change in the long-term target value of the strategic variable, as well as in the speed of adjustment towards that long-term target value.

The main result of this chapter is that we find substantial evidence in favor of the direct market influencing hypothesis. We show that banks that receive a risk signal react by increasing their long-term target capital buffer and their desired level of retail funding, and by decreasing their liquidity risk and reliance on potentially volatile sources of non-interest income. Banks that receive a negative valuation signal react by increasing their target profit level, primarily by lowering the cost-to-income ratio. This suggests that managers trying to improve the market assessment of their bank's value attempt this mainly by improving cost efficiency. Apart from adjusting their long-term target ratios, we also find banks to more quickly bridge the gap between the current and target rate following a market signal. These adjustments are in line with expectations and with the objectives of supervisors.

The **third chapter** of this dissertation examines the driving factors of equity returns of U.S. financial institutions and connects to an expanding literature that measures banking risk as the exposure of bank (sector) stock returns to some set of predefined risk factors. The challenge is to discover which risk factors are relevant for which types of financial institutions at a specific point in time. In this chapter, we attempt to answer this question within a Bayesian framework that explicitly takes into account the uncertainty about the relevant set of factors ("model uncertainty"). We apply our methodology to US Bank Holding Companies over the period $1986 - 2010$.

Based on a broad literature survey, it is fair to state that there is little consensus on the risk factors, apart from the market factor, that drive bank stock returns. The chapter presents an overview of 24 papers that relate bank stock returns to various combinations of no less than 17 different risk factors. The uncertainty about which risk factors to include in a bank factor model is labeled "model uncertainty". In this chapter, we explicitly take model uncertainty into account by using Bayesian Model Averaging techniques to estimate bank factor models. To the best of our knowledge, we are the first to apply Bayesian Model Averaging in the banking literature. The main advantage of BMA is accounting for model uncertainty. Suppose that the literature offers a list of k potential explanatory risk factors. In the set of linear factor models, 2^k different model combinations can be made, where each model consists of (a subset of) the explanatory variables. Using Bayesian Model Averaging techniques, we are able to account for this considerable model uncertainty.

First, we relate the stock returns of US Bank Holding Companies to innovations in the different risk factors. The results reveal that the market and real estate factor, as well as the high-minus-low book-to-market Fama-French factor, are the most important risk factors. Other factors, maybe with the exception of the 3-month T-Bill rate, do not seem to be reliably related to the returns on the broad bank index. Moreover, our results indicate that there is no correct or dominant model. The most likely model has a model probability of less than 25%, suggesting that accounting for model uncertainty is important.

Next, we investigate whether or not bank factor models vary over time. In fact, some risk factors may be 'dormant' for a long time, and hence undetectable in short (tranquil) samples, to suddenly appear in times of market stress. The analysis reveals that factors such as the implied volatility index and term and default spread frequently switch between being economically and statistically relevant or not. Hence, specific periods (typically those characterized by increased financial market stress) may be associated with different bank risk exposures. To investigate whether or not different types of financial intermediaries are exposed to different risk factors, our benchmark results are compared to those of four types of financial intermediaries: depository institutions, insurance companies, security and commodity brokers, and other non-depository institutions . In addition, we differentiate between various 'types' by constructing portfolios of bank holding companies (BHCs) according to size, sound versus distressed BHCs and BHCs with a stable retail focus versus diversified and fast-growing banks. The general conclusion from this analysis is that while the relevant set of exposures does vary substantially over time, it is relatively stable across bank types.

Finally, we discuss some implications of our findings for empirical banking research based on stock returns. Computing abnormal returns in event studies requires the specification of a benchmark model. Residual-based measures of uncertainty (idiosyncratic volatility) or transparency (R-squared) require an accurate identification of risk factors and a correct specification of the factor model. Accurate measures of banks' exposures to stock market movements (e.g. to compute capital charges for systematic risk) also hinge on the correct specification of a factor model.

The **fourth chapter** of this dissertation investigates the presence of contagion between bank risk and sovereign risk in Europe over the period 2006-2011. Contagion is defined as excess correlation, i.e. correlation between banks and sovereigns over and above what is explained by common factors, using CDS spreads at the bank and at the sovereign level. Moreover, we investigate the determinants of contagion by analyzing bank-specific as well as country-specific variables and their interaction.

Due to the absence of a common European policy framework for handling the banking crisis as well as missing bank resolution mechanisms, several European governments were forced to respond at the national level by rescuing troubled banks headquartered in their countries during the financial crisis. Various measures have been taken, ranging from equity injections in troubled banks to the setting-up of bad banks Invariably, these rescue operations have increased national debt burdens and caused a deterioration of public finances. One consequence of the risk transfer from the private sector to sovereign treasuries has been an increased interdependence of banks and states, causing negative feedback loops between their financial conditions. With the rise of the sovereign debt crisis in Europe, the link between bank- and country risk has intensified further, especially for the countries that were quickly identified as vulnerable, namely Greece, Ireland, Italy, Portugal and Spain.

Considering this increased interaction between sovereign and bank credit risk, the objective of this chapter is twofold. First, we analyze whether we find empirical evidence of contagion. We investigate the time-varying intensity of the risk spillovers using excess correlations as our preferred contagion metric. Second, we attempt to explain the contagion effect by investigating the relationship between excess bank/sovereign correlations and both bank and country characteristics. While there have been several papers investigating the determinants of either bank risk or sovereign risk in isolation, there is less evidence on the potential mutual contagion effects. By analyzing a number of relevant variables and the interplay between bank and country characteristics, we are able to identify critical interactions that are related to bank/country contagion. This allows us to tackle a series of relevant policy questions concerning the banking system as well as the financial condition of sovereigns.

The main findings of this chapter can be summarized as follows. We document significant empirical evidence of contagion between bank and sovereign credit risk during the European sovereign debt crisis. In 2009, when the sovereign debt crisis emerged, we find significant spillovers for 86% of the banks in our sample. Second, given the home bias in banks' government exposures, i.e. their typically larger exposure towards the home sovereign, we provide empirical evidence confirming the expectation that contagion between banks and their home country is stronger. Third, we find that the degree of contagion is significantly linked to bank capital adequacy, and this effect is economically very significant. Furthermore, the higher a bank's reliance on short-term funding sources, the higher the intensity of spillovers between banks and sovereigns. Finally, we confirm that higher sovereign debt holdings are associated with a stronger bank-sovereign contagion.

The **fifth chapter** of this dissertation presents a methodology to stress test the European banking sector using publicly available stock market data. The use of stress tests as a supervisory tool have gained in importance since the recent financial crisis and frames into the context of macroprudential supervision. The goal of macroprudential supervision is to focus on the financial system as a whole. This implies identifying, assessing and prioritizing system-wide risks, and formulating recommendations on how to mitigate them. This chapter aims to contribute to this by developing a stress test tool for the European financial sector. The proposed technique takes into account the network structure of the European financial sector. Banks are not only exposed to shocks from common risk factors (macroeconomic risk factors, sovereign risk, financial risk and housing price risk), but also to shocks from all other banks in the system. To do so, this chapter relies on Bayesian Model Averaging (BMA) of Locally Weighted Regression models.

Bayesian Model Averaging techniques allow to identify a set of relevant risk factors out of a larger set of potentially important regressors. The idea departs from "model uncertainty", meaning that a researcher is a priori uncertain about which (constellation of) risk factors affects a particular financial institution. To address this issue of "model uncertainty", this chapter uses Bayesian Model Averaging techniques. In the logic of Bayesian Model Averaging, the model space includes all model combinations which can be made out of a given set of regressors. More specifically, if there is a list of k potential explanatory variables, 2^k different model combinations can be made, where each model is defined through the inclusion or exclusion of (a subset of) the explanatory variables. Locally Weighted Regression models allow to condition the estimate of bank risk exposure on a certain state vector. This can for instance be the market index being on its 5th percentile, in line with previously proposed measures of bank tail risk, but it can also be conditioned on a recession (measured by a specific value for industrial production), or any other common factor in the model. To the best of my knowledge, this is the first paper which introduces and implements a Bayesian Locally Weighted Regression model. This approach is especially usefull from a financial stability (or stress testing) perspective, since the supervisor is particularly interested in bank risk exposures during times of financial market stress, during a recession, during times of money market stress, ... Moreover, I show that this particular feature of the model improves its perfornance as a stress test tool.

The usefullness of this model is illustrated with different applications. First, this model provides insight into the time varying importance of risk factors for financial institutions, using the posterior inclusion probabilities. Second, ability of this model to correctly project future evolutions bank equity prices is assessed by analysing the percentage of correctly estimated directions of change in bank equity prices. The model correctly projects 77% of bank equity price changes over an horizon ranging from one quarter to four quarters ahead. Moreover, I show that the performance of my model increases to 81% due to the local feature of the BMA set-up, further indicating the usefullness of this model as a stress test tool. Third, I illustrate how this model can be used for stress testing under three hypothetical stress test scenarios, on three stress test dates (the two CEBS/EBA stress test release dates, 1st of July 2010 and 1st of July 2011, as well as the 1st of January 2012). Finally, I compute key indicators of network centrality (degree, closeness and betweenness), and I assess the structure of the network over different realizations of state vectors (such as industrial production, stress in the money market and economy wide credit risk).

CHAPTER 2

Do Stock Markets Discipline US Bank Holding Companies: Just Monitoring, or also Influencing?

Do Stock Markets Discipline US Bank Holding Companies: Just Monitoring, or also Influencing?*

Lieven Baele† Valerie De Bruyckere‡ Olivier De Jonghe§ Rudi Vander Vennet¶

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†CentER, Netspar, Tilburg University, Warandelaan 2, Tilburg, The Netherlands.
‡Ghent University, W. Wilsonplein 5D, 9000 Ghent, Belgium.
§CentER, European Banking Center, Tilburg University, Warandelaan 2, Tilburg, The Netherlands.
¶Ghent University, W. Wilsonplein 5D, 9000 Ghent, Belgium.

Abstract

This paper presents evidence that bank managers adjust key strategic variables following a risk and/or valuation signal from the stock market. Banks receive a risk signal when they exhibit substantially higher volatility compared to the best performing bank(s) with similar characteristics, and a valuation signal when they are undervalued relative to the average bank with similar characteristics. We document, using a partial adjustment model, that bank managers adjust the long-term target value of key strategic variables and the speed of adjustment towards those targets following a risk and/or negative valuation signal. We interpret this as evidence of stock market influencing. We show that our results are unlikely to be driven by indirect influencing by regulators, subordinated debtholders, or wholesale depositors. Finally, we show that the likelihood that banks receive a risk and/or valuation signal increases with opaqueness, managerial discretion and specialization.

Keywords: monitoring, influencing, stochastic frontier, partial adjustment, multiplicative heteroscedasticity regression, opaqueness, earnings forecast dispersion, bank risk

JEL: G21, G28, L25

1 Introduction

It is generally assumed that bank managers are disciplined by internal governance mechanisms and by their supervisors. Whether or not banks are also disciplined by financial markets is less clear. Yet, the Basel capital adequacy rules, one of the cornerstones of modern bank regulation, mention market discipline as a separate third pillar (next to capital ratios and supervisory interventions). Relatedly, stress testing exercises have expanded the disclosure requirements of banks, with the explicit objective to foster market discipline. In this paper we revisit this issue by focusing on the stock market as a potential source of market discipline on banks. The crucial question is: Can the stock market assess bank risk *and* influence bank behavior?

Bliss and Flannery (2002) distinguish two components of market discipline: market monitoring and market influencing. They define market monitoring as the ability of securityholders to accurately assess the condition of the firm, and influencing as subsequent managerial actions in response to these assessments. While there is considerable evidence of market monitoring (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990) and Morgan and Stiroh (2001)), research examining the market influencing channel is more scarce and generally inconclusive. Bliss and Flannery (2002) fail to find evidence that bank stockholders or bondholders effectively influence bank indicators controlled by bank managers, such as the leverage position of the BHC, factors affecting bank asset risk, changes in the number of employees and the amount of uninsured liabilities. Gendreau and Humphrey (1980) find that banks are penalized for higher leverage by a higher cost of debt and equity, but find no evidence that these relative cost changes induce bank managers to alter their leverage position relative to other banks. Ashcraft (2008) shows that the proportion of subordinated debt in total regulatory capital affects the probability of failure and future distress, suggesting that bank debtholders are able to significantly influence the behavior of distressed banks. Schaeck, Cihak, Maechler, and Stolz (2012) find evidence for debtholder discipline in a sample of small and medium-sized commercial banks in the US over the period 1990-2007: Bank managers are more likely to be removed if the bank is financially weak and this effect is stronger for banks subject to discipline exerted by large debtholders. The authors find no conclusive evidence of discipline exerted by shareholders or depositors, nor that forced turnovers consistently improve bank performance (even at windows of three years after the turnover). Hence, current empirical research predominantly supports the view that market discipline is, at best, a relatively weak disciplining device.

The main contribution of this paper is the design of a new test for direct market influencing. Our procedure starts by identifying stock market-based risk and (negative) valuation signals at the individual bank level. Consequently, we test to what extent bank managers adjust key strategic variables following a (combination of a) risk and negative valuation signal. Using a partial adjustment model, we test both for a change in the long-term target value of the strategic variable, as well as in the speed of adjustment towards that long-term target value. This partial adjustment model has been used quite often to model various firm characteristics, for example by Flannery and Rangan (2006) and Flannery and Rangan (2008) for leverage, Lintner (1956) for dividend payout ratios and Fama and French (2000), Raymar (1991) and Sarkar and Zapatero (2003) for earnings.

An important innovation is the way we define the risk and valuation signals. We model our risk measure, total equity return volatility (TV, measured over one quarter of daily data), along a stochastic frontier. The stochastic frontier describes the level of risk that the best performing banks with similar characteristics can attain. We call a bank inefficient from a risk perspective when it is situated above the risk frontier, i.e. when it has more risk than its best performing peers. A bank will receive a risk signal at time t if its inefficiency score at that time is situated in the 10 percent worst inefficiency scores and is hence substantially above the risk frontier. We use a similar approach for our valuation measure, the market-to-book (MTB) ratio, only here we allow banks to be either under- or overvalued relative to the average bank with similar characteristics. We say that a bank receives a negative valuation signal when its quarterly valuation score belongs to the 10 percent largest undervaluations. Looking at large signals relative to the best performing peer is crucial. As market prices are forward looking, they reflect information on firms' fundamentals, but also on expected corrective actions. If investors expect a corrective action, the resulting signal will be smaller (Bond, Goldstein, and Prescott (2010)). Using the most extreme signals makes it less likely that we look at events where investors have strong expectations on corrective behavior.

The main result of this paper is that we find substantial evidence in favor of the direct market influencing hypothesis. We show that banks that receive a risk signal react by increasing their long-term target capital buffer and their desired level of retail funding, and by decreasing their liquidity risk and reliance on potentially volatile sources of non-interest income. Banks that receive a negative valuation signal react by increasing their target profit level, primarily by lowering the cost-to-income ratio. This suggests that managers trying to improve the market assessment of their bank's value attempt this mainly by improving cost efficiency. Apart from adjusting their long-term target ratios, we also find banks to more quickly bridge the gap between the current and target rate following a market signal. These adjustments are in line with expectations and with the objectives of supervisors.[1]

Furthermore, we investigate whether or not our findings can be interpreted as evidence of direct influencing rather than indirect influencing. As mentioned in Flannery (2001) and Federal Reserve System (1999), market influencing has two components. Direct market influence means that a certain stakeholder can assess the riskiness of bank holding companies (market monitoring) and induce bank managers to change their risk behavior (market influencing) in their interest. Indirect market discipline means that the change in bank behavior is enforced by other stakeholders (e.g. supervisors) than the stakeholder exerting the monitoring effort (see also Curry, Fissel, and Hanweck (2008)). First, we argue that the number of Prompt Corrective Actions (PCAs) is so small that our signals are unlikely to be proxies for regulatory interventions. Second, our results do not appear to be driven by influencing from subordinated debtholders, as we find that our influencing results are most pronounced for those banks that do not have subordinated debt. Third, we test whether or not our results are potentially driven by influencing exercised by wholesale deposit holders. We do observe that the share of retail funding in total funding is larger for banks receiving a risk signal. This is mainly due to increasing the core deposits, as we do not find evidence that it is more likely for a bank to lose wholesale funding following a risk signal. Finally, we investigate in more detail which characteristics make it more likely that a bank will receive a risk or valuation signal. We consider the variance of the signal to be the scope for pressure from stock market investors. Therefore, in an extension of our setup, we allow the variance of the residuals to vary through time and change with bank characteristics. We find that stock market investors punish discretionary accounting behavior and that the degree of bank opacity has a positive effect on the variance of the residuals (and hence the likelihood of observing market signals).

Many studies already addressed the issue of bank monitoring, i.e. the first step in a test for market discipline, by relating bank risk and/or return to bank-specific characteristics (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990), Stiroh (2004), Stiroh (2006b), Hirtle and Stiroh (2007) or (Calomiris and Nissim (2007)). Our focus and contribution lies in testing for market influencing. Nevertheless, to allow comparison with existing studies and to be transparent with respect to the other steps of

[1] The key identification problem here is that stock returns reflect news about (expected) fundamentals. Changes in fundamentals will themselves independently influence future behavior of the bank. For example, a current undervaluation signal may be an indication that investors worry about future cash flows and profitability (negative relation between signal and outcome), whereas influencing implies that managers take actions to improve profitability after a negative valuation signal (positive relation between signal and outcome). Hence, the identified support for the influencing hypothesis is a lower bound of the overall corrective behavior. Moreover, we only use extreme signals which correspond with situations where stock market investors have low expectations of subsequent corrective behavior.

the analysis, we briefly describe the results of the baseline equation of monitoring in an appendix. While not the main contribution of this paper, we believe we still add to this literature by considering a more comprehensive range of bank characteristics.

The remainder of this paper is structured as follows. Section 2 introduces a new setup to assess the different components of market discipline, i.e. market monitoring and influencing, in a unified framework. The first part discusses the stochastic frontier model for Total Volatility and the linear regression model for the Market-to-Book ratio. Next, we show how to extract risk and valuation signals from both models. The final section presents the partial adjustment model that we use to empirically test for market influencing. Section 3 contains the main empirical findings for the influencing hypothesis. In Section 4, we show that the results are evidence of direct influencing following stock market signals, rather than indirect influencing via regulators or wholesale financiers. In Section 5 we analyze which banks are more likely to get signals. A final section concludes.

2 A New Setup to Test Market Discipline

2.1 Monitoring by Equityholders

Bliss and Flannery (2002) define market monitoring as the ability of securityholders to accurately assess the condition of the firm. Previous papers have tested the market monitoring hypothesis by relating bank risk and valuation to bank-specific characteristics in a linear regression framework (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990), Stiroh (2004), Stiroh (2006b), Hirtle and Stiroh (2007), Calomiris and Nissim (2007)):

$$Y_{i,t} = \beta_0 + \beta X_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

Equation (1) relates bank-specific stock market-based risk and valuation measures $Y_{i,t}$ to various lagged[2] bank-specific characteristics $X_{i,t}$. We relate the dependent variable to four sets of bank characteristics, proxying for respectively: (i) the bank's funding structure, (ii) asset mix, (iii) revenue diversity and (iv) overall bank strategy. Our vector $X_{i,t}$ of bank-specific characteristics, which appears in Equation (1), is

[2] We use one-quarter lagged values rather than contemporaneous values to alleviate potential endogeneity problems and to account for the lag with which accounting information is disclosed. A detailed appendix discusses the construction of these indicators with a reference to the FRY9C codes of the constituent items.

hence given by:

$$X_{i,t} = [Bank\ Strategy,\ Funding\ Structure,\ Asset\ Mix,\ Revenue\ Streams]_{i,t} \qquad (2)$$

Following Calomiris and Nissim (2007), we use the market-to-book value of equity as a measure of the long-run value of the bank. The market-to-book value of equity (MTB) is measured as the end of quarter market value divided by tangible common equity. As a measure of risk, we use the quarterly total volatility (TV) measured over a quarterly moving window of excess stock returns for bank i. Instead of using a linear regression for risk, we model total volatility along a stochastic frontier. This allows us distinguishing between banks that are on the frontier (given the characteristics associated with their business model) and risk inefficient banks. The best performing bank, relative to its peers with similar characteristics, has minimal risk, and will be situated close or on the frontier.[3] We call banks risk inefficient if they are situated (much) above the frontier, i.e. have much more risk compared to their best performing peers.

Summary statistics on the dependent and independent variables are reported in Table 1. Our sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters in the period 1991-2007.[4] The total sample consists of 17,264 observations on 899 bank holding companies. We exclude illiquid stocks as well as control for important mergers and acquisitions[5].

< Insert Table 1 around here >

Finding significant relationships between these bank characteristics and the risk and valuation measure would be evidence of the first step in market discipline, market monitoring. If so, we can conclude that equityholders track the different risks associated with the balance sheet and income statement characteristics.

[3] More specifically, contrary to the linear model, we assume that the part of $TV_{i,t}$ not explained by bank characteristics can be further decomposed in a pure noise component, $\nu_{i,t} \sim iid\ N(0, \sigma_v^2)$ and in one-sided departures (risk inefficiencies), $u_{i,t}$, from the stochastic frontier. The stochastic frontier is determined by the equation $\hat{\beta}_0 + \hat{\beta} X_{i,t-1}$.

[4] All data are collected from the publicly available FR Y-9C reports. Consequently, we link the FR Y-9C reports to banks' stock prices (obtained from CRSP) using the match provided on the Federal Reserve Bank of New York website http://www.ny.frb.org/research/banking_research/datasets.html

[5] As a liquidity threshold, we impose that the bank stock's traded volume should be non-zero in at least 80 percent of trading days during the quarter. We control for mergers and acquisitions and create a new bank identity whenever a bank's total assets increase more than 10% on a quarterly basis and there is a change in activity mix. The change in activity mix is identified as follows. We measure activities along three dimensions (funding structure, loan portfolio composition and revenue mix). For each of these dimensions, we create a measure of focus/diversification. If there is a large change in focus in one of these measures, i.e. a change larger than one standard deviation, within three years after a large jump in total assets (10% growth on a quarterly basis), we label this as a change in activity composition following the expansion.

Many studies already addressed the issue of bank monitoring by relating bank risk and/or return to bank-specific characteristics. Our focus and contribution lies in testing for market influencing. Nevertheless, to allow comparison with existing studies and to be transparent with respect to the other steps of the analysis, we briefly describe the results of the baseline equation in an online appendix.

2.2 Extracting Stock Market Signals

Market influencing refers to managerial actions in response to the risk and valuation assessments made in the market monitoring stage (Bliss and Flannery (2002)). Hence, for the purpose of our study, the crucial output from this first stage regression described in the previous section are risk and valuation signals. We say a bank receives an undervaluation signal when its residual (calculated using equation (1)) belongs to the bottom decile. Equityholders are said to give a risk signal if the inefficiency score is situated in the highest decile, where risk inefficiency is measured as the difference between the bank's total volatility and the stochastic frontier (representing similar banks with the lowest risk). By only looking at the most extreme deciles, we reduce the likelihood that investors incorporate the expected response in their assessment. Put differently, if investors expect a corrective action (as in Bond, Goldstein, and Prescott (2010)), the resulting residual/inefficiency score will be smaller. This actually works against establishing a link between signals and outcome variables, as we only exploit the information in signals where stock market investors have low expectations of subsequent corrective behavior. We form deciles over the full sample, rather than at each point in time, as the intensity of market discipline may vary over time.

Graph 1 provides information on the level and dynamics of the risk inefficiency scores (Panel A) and MTB residuals (Panel B). Each subplot presents the average inefficiency score (the deviation from the stochastic frontier or the fitted regression line) of three portfolios in "event time". Each quarter, we sort BHCs into deciles according to the level of the market signal[6]. The most extreme decile (highest risk or lowest value) is represented by the thick line. We also report the least extreme decile as well as the two middle deciles (combined in one line). The portfolio formation quarter is denoted as time period 1. We then compute the average inefficiency score for each portfolio in each of the subsequent 10 quarters, holding the portfolio composition constant (except for BHCs that exit the sample). We repeat these two steps of sorting and averaging for every quarter in the sample period (1993-2007). This process generates 60 sets of event-time

[6]The figure is inspired by Lemmon, Roberts, and Zender (2008), who investigate the persistence of firm capital ratios. This methodology is ideally suited for investigating the cross-sectional dispersion and time evolution of bank characteristics over longer periods.

averages, one for each quarter in our sample. We then compute the average risk inefficiency score and undervaluation residual of each portfolio across the 60 sets within each event quarter. The dashed lines surrounding the portfolio averages represent 90% confidence intervals. They are computed as the average standard error across the 60 sets of averages (Lemmon, Roberts, and Zender (2008)).

< Insert Figure 1 around here >

At portfolio formation time (event time 1), there are large and significant differences between the three groups. The differences between the extreme signal and the average signal remain significant for about 5 to 6 quarters. The risk inefficiency score of the highest decile portfolio improves substantially in the first four quarters after which portfolios are created, but is still significantly higher than the mean. The persistence in the market-to-book signal is even slightly higher than the stickiness of the TV signal. Differences between the best and worst group are evenmore persistent. The graphs show that there is substantial between and within variation in the signals, which will allow us to identify whether or not banks respond to temporary signals. The graph also highlights that extreme market signals are sticky in the medium run but are not persistent or long-lived.

2.3 Influencing by Equityholders

The influencing channel of market discipline implies that bankers should take off-setting actions to align their performance with the interest of monitors, which are stock market investors in the context of this paper. We investigate the market influencing hypothesis by testing whether or not bank managers make strategic reallocations following a negative risk and/or valuation signal. We are particularly interested in the effect of market signals on the capital ratio and the profitability of the bank (here measured as ROE), since an increase in bank capital reduces risk and higher profits boost bank value. However, strategic reallocations may take different forms. Therefore, we focus on an set of eight strategic bank characteristic which are next to the capital ratio and profitability (ROE), also asset quality (non-performing loans ratio), cost inefficiency (cost-to-income ratio), liquidity (the ratio of liquid assets to total assets), the ratio of non-interest income to total income, the share of retail deposits in total deposit funding and the dividend pay-out ratio. The six additional strategic bank variables can be interpreted as the underlying drivers of profits and capital levels. We believe that these ratios reflect the main strategic decision variables directly under the control of bank management.

To account for a gradual and potentially incomplete adjustment in the different strategic variables, we estimate a partial adjustment model.[7] The general specification for a partial adjustment model is:

$$\Delta y_{i,t} = \gamma(y^* - y_{i,t-\tau}) + \varepsilon_{i,t} \tag{3}$$

where y represents a strategic bank characteristic, y^* is the target level of y and γ the speed of convergence to this target level. To formally test for market influencing, we investigate whether or not (i) the implied target level is different for banks that receive a market signal and (ii) banks receiving a market signal converge faster to the target. Therefore, Equation (3) is modified such that the adjustment speed and target level can vary by bank and over time:

$$\Delta y_{i,t} = \left(\gamma_0 + \gamma_0^* D^y_{i,t-\tau} + \gamma_1 D^{TV}_{i,t-\tau} + \gamma_2 D^{MTB}_{i,t-\tau} + \gamma_3 D^{TV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}\right) \times \left(y^*_{i,t} - y_{i,t-\tau}\right) + \varepsilon_{i,t}$$

with

$$y^*_{i,t} = f(D^y_{i,t-\tau},\ D^{TV}_{i,t-\tau},\ D^{MTB}_{i,t-\tau},\ X_{i,t-\tau}) \tag{4}$$

where $D^{TV}_{i,t-\tau}$ is a dummy variable equal to one if bank i receives a risk signal at time period $t-\tau$. Similarly, $D^{MTB}_{i,t-\tau}$ is a dummy variable equal to one if bank i receives a valuation signal at time period $t-\tau$. The interaction term ($D^{TV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}$) captures the additional effect of banks receiving both signals simultaneously. Since bank strategies are sticky in the short term and restructuring typically occurs as a series of incremental adjustments, we measure reallocations over a two year period and define $\tau = 8$ quarters to estimate Equation (4).[8] In addition, we allow for a different target level and a different speed of adjustment for banks that are situated in the worst decile of the cross-sectional distribution of the strategic bank characteristic ($D^y_{i,t-\tau}$ is a dummy variable equal to one if the strategic bank characteristic for bank i at time $t-\tau$ is weak and zero otherwise). Finally, we allow the target level y^* to be a function of the other strategic bank characteristics $X_{i,t-\tau}$ (i.e. the eight strategic bank characteristics excluding the dependent variable). We estimate a reduced form of Equation (4), for each of the eight strategic bank variables:

[7] The partial adjustment model has been used quite often to model various firm characteristics, for example by Flannery and Rangan (2006) for firm leverage (Flannery and Rangan (2008) for bank leverage), Lintner (1956) for dividend payout ratios and Fama and French (2000), Raymar (1991) and Sarkar and Zapatero (2003) for earnings.

[8] A concern is that the worst performers, which are more likely to fail or be acquired, would bias the results. Therefore, we discard all observations up to eight quarters before the last quarter the BHC appears in the sample. Hence, this implies that the last potential signal for each BHC occurs 16 quarters before the BHC disappears from the sample (as we look at a change in strategic bank variables over a period of eight quarters following a risk or valuation signal).

$$\Delta y_{i,t} = \begin{array}{c} c_0 + c_1 D^{y}_{i,t-\tau} + c_2 D^{TV}_{i,t-\tau} + c_3 D^{MTB}_{i,t-\tau} + +c_4 D^{TV}_{i,t-\tau} D^{MTB}_{i,t-\tau} + X_{i,t-\tau}\beta \\ +c_5 y_{i,t-\tau} + c_6 D^{y}_{i,t-\tau} y_{i,t-\tau} + c_7 D^{TV}_{i,t-\tau} y_{i,t-\tau} + c_8 D^{MTB}_{i,t-\tau} y_{i,t-\tau} + c_9 D^{TV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau} y_{i,t-\tau} + \varepsilon_{i,t} \end{array} \quad (5)$$

Pooling all terms that contain $y_{i,t-\tau}$ (and bringing this combination in front) yields:

$$\Delta y_{i,t} = \begin{array}{c} -\left(c_5 + c_6 D^{y}_{i,t-\tau} + c_7 D^{TV}_{i,t-\tau} + c_8 D^{MTB}_{i,t-\tau} + c_9 D^{TV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}\right) \\ \times \left[\frac{c_0 + c_1 D^{y}_{i,t-\tau} + c_2 D^{TV}_{i,t-\tau} + c_3 D^{MTB}_{i,t-\tau} + +c_4 D^{TV}_{i,t-\tau} D^{MTB}_{i,t-\tau} + X_{i,t-\tau}\beta}{-(c_5 + c_6 D^{y}_{i,t-\tau} + c_7 D^{TV}_{i,t-\tau} + c_8 D^{MTB}_{i,t-\tau} + c_9 D^{TV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau})} - y_{i,t-\tau}\right] + \varepsilon_{i,t} \end{array} \quad (6)$$

Hence, the term before the square brackets corresponds with the first term in Equation (4), whereas the first term in square brackets corresponds with the expression of the conditional target, y^*in Equation (4). Rather than reporting the estimated coefficients of the reduced-form partial adjustment model[9], which we estimate for each of the eight strategic bank variables under consideration, we summarize the relevant information in two statistics that we think are easy to interpret: the long-run target level and adjustment speed. Calculating the target levels and speed of adjustment for the eight indicators using the coefficients of Equation (6) results in eight 2 by 2 matrices in Table 2:

	$D^{MTB}_{i,t-\tau} = 0$	$D^{MTB}_{i,t-\tau} = 1$
$D^{TV}_{i,t-\tau} = 0$	$-\frac{c_0}{c_5}$	$-\frac{c_0+c_2}{c_5+c_8}$
$D^{TV}_{i,t-\tau} = 1$	$-\frac{c_0+c_3}{c_5+c_7}$	$-\frac{c_0+c_2+c_3+c_4}{c_5+c_7+c_8+c_9}$

and

	$D^{MTB}_{i,t-\tau} = 0$	$D^{MTB}_{i,t-\tau} = 1$
$D^{TV}_{i,t-\tau} = 0$	$-c_5$	$-(c_5 + c_8)$
$D^{TV}_{i,t-\tau} = 1$	$-(c_5 + c_7)$	$-(c_5 + c_7 + c_8 + c_9)$

The left[10] hand side table contains information on the target level of the bank characteristic. The upper left cell is the target level for each of the strategy variables implied by the influencing equation in the absence of market signals. The upper right cell contains the target level when there is only a valuation signal and the lower left cell shows the target level in case of only a risk signal. The lower right cell contains the target level when both market signals occur simultaneously. In each case we report the p-value to assess the statistical significance[11] of the differences with the benchmark case of no signals, i.e. the upper left cell. In the right hand side panel, the corresponding findings for the speed of adjustment are presented. Hence, from this table we can infer whether or not the target level and speed of adjustment are different for banks receiving either a risk signal, a valuation signal or both.

[9]Results are available upon request.

[10]We evaluate the expression of the targets at the sample mean of the variables in the X-vector. As we standardize all variables in the X-vector , this simply implies that they drop from the equation. Furthermore, in the paper we report results when the dummy variable $D^{y}_{i,t-\tau} = 1$. Results for $D^{y}_{i,t-\tau} = 0$ are similar and available upon request.

[11]We cluster the standard errors at the bank level in the estimation of Equation (4).

3 Empirical Evidence of Market Influencing from a New Test Setup

Table 2 contains the main results of this paper and are generally supportive for the hypothesis of stock market influencing in US banking. Starting with the capital ratio and bank profitability (here measured as ROE), we expect to find that bank capital increases after a risk signal and that a negative valuation signal induces bank management to improve profitability. The target capital ratio in the no-signal case is 11.4%, which is in line with the summary statistics reported in Table 1. Banks that receive a risk signal (TV inefficiency in the highest decile) have a significantly higher target capital ratio (12.6%). This indicates that bank management reacts to a perceived increase in the riskiness of their bank by increasing the capital buffer, as expected. Banks that receive a valuation signal from the stock market react by adjusting the target capital ratio downwards (to 10.6%). This is in line with the results of Table A.1 (in appendix) which indicate that higher capitalized banks have lower risk and lower market-to-book ratios. These findings support the hypothesis that banks adjust their capital adequacy target as a reaction to pressure from the stock market. On the profit side, we observe that the target ROE ratio remains unaltered (at 3.4%) when the bank receives a risk signal from the stock market. However, in case the bank gets a valuation signal, bank management reacts by significantly increasing the target profit level (to 4.1%). Note that ROE is expressed at the quarterly frequency. On an annual basis, this implies an increase in target ROE from 13.6% to 16.4%. Hence, bank management responds to market pressure by signaling a strategic refocusing aimed at increasing ROE, although the speed of adjustment does not change significantly, presumably indicating that increased profits take time to materialize. However, we observe a reduction in target profitability if banks get both a risk and valuation signal. While this may at first sight be surprising, it may be caused by a shift to their core business and a search for retail funding. Acharya and Mora (2012) document that the banking system in its role as a stabilizing liquidity insurer acts as an active seeker of deposits via managing bank deposit rates. This is reflected in the significant increase in the share of retail deposits following a joint signal (possibly at the expense of lower interest margins and hence lower profits).

< Insert Table 2 around here >

The other strategic bank variables can be interpreted as the underlying drivers of profits and capital levels. The following picture emerges. When banks are confronted with a risk signal, they not only adjust their target capital level upwards, but also reduce their liquidity risk by increasing the target liquid assets ratio from 2.3% to 5.6%. The target level for the reliance on non-interest income is lowered substantially, although not significantly, but the speed of adjustment towards the target increases from 14% to 26%. Banks in the highest risk inefficiency decile tend to increase their target proportion of non-performing loans, which may be surprising at first. However, credit risk in the loan portfolio is only one dimension of total bank risk, which we measure as total stock market volatility. The increased non-performing loans ratio may be the outcome of increased transparency (i.e. management having to report more accurately), rather than an actual change in credit risk.

We showed before that in case of a valuation signal, banks respond by increasing their target ROE level. Table 2 shows that at the same time, bank managers substantially and significantly reduce the target cost-to-income ratio (from 61.3% in the base case to 55.3%). This indicates that bank managers try to improve profits primarily by focusing on the cost efficiency of their organization. Since management has a large degree of discretion in altering the bank's cost structure[12], this may be interpreted as a credible signal by the stock market. When both signals occur simultaneously, the most pronounced impact, both economically and statistically, can be observed for the implied target levels of the retail funding ratio (from 65.5% to 81.5%).

The findings for the speed of adjustment towards the implied target levels exhibit a similar pattern, although the degree of significance is usually lower. Nevertheless, whenever the adjustment speed is statistically different from the benchmark no-signal case, the evidence points in the direction of a faster adjustment towards the target. Hence, banks respond by either changing a strategic bank characteristics or by reacting more swiftly to deviations from the optimal level. Based on these results, we conclude that bank management does react to stock market-based risk and valuation signals. Market signals influence banks to adjust the target levels of capital, profits and the main drivers of these two strategic indicators in the requested direction. Our results help in explaining a pattern documented by Calomiris and Nissim (2007). They show

[12] In unreported regressions, we investigate whether decisions in human capital management take place in response to market signals. As a dependent variable, we constructed a binary variable, equal to one if a drop in full-time equivalent employees takes place over a two year horizon, and equal to 0 in all other cases. The effect of market signals is investigated with a probit regression. The control variables in this set-up are the eight quarter lag in the number of employees, in addition to the strategic bank characteristics that are also included in the specification of the target (Equation (4)). To investigate the potential reaction to market signals, both the risk signal, the valuation signal and the interaction of both are included. The constant in the probit regression indicates that the average probability for a layoff is 22%. The most important determinant of the probability of lay-offs, both in economic and statistical terms, is past profitability. In addition, the likelihood of layoffs is 11% higher for banks that simultaneously get a risk and valuation signal.

that BHCs that have lower than predicted market-to-book ratios (compared to an estimated model) tend to experience large, statistically significant, predictable increases in market values in subsequent quarters. They also investigate whether the predictable changes in stock prices reflect priced risk factors and find that they do not. Our results lend support for the view that future increases in market value in response to a large undervaluation signal are caused by corrective actions taken by managers.

Moreover, the identified support for the influencing hypothesis is a lower bound of the overall corrective behavior. The key identification problem here is that stock returns reflect news about (expected) fundamentals. Expected changes in fundamentals will lead to a spurious relationship between current signals and future values of bank strategic variables in the opposite direction of the influencing hypothesis. For example, a current valuation signal may be an indication that investors worry about future cash flows and profitability, whereas influencing implies that managers take actions to improve profitability after a negative valuation signal. In general, we find evidence for corrective behavior as risk signals lead to more prudent behavior and undervaluation leads to improved performance. If it would be a reflection of fundamentals, it would go in the other direction (as for example the increase in non-performing loans following a risk signal). As the two effects are difficult to disentangle empirically, we prefer emphasizing the finding of influencing, rather than focusing on the magnitude of the impact of influencing.

4 Direct or Indirect Influencing?

Some caution is necessary in the interpretation of our evidence of market discipline. As mentioned in Flannery (2001) and Federal Reserve System (1999), market influencing has two components. Direct market influence means that a certain stakeholder can assess the riskiness of bank holding companies (market monitoring) and induce bank managers to change their risk behavior (market influencing) in their interest. Indirect market discipline means that the change in bank behavior is enforced by other stakeholders (e.g. supervisors) than the stakeholder exerting the monitoring effort (see also Curry, Fissel, and Hanweck (2008)). In our case, indirect market discipline would then only be partly based on stock market information. For example, managerial decisions could be taken in response to supervisory intervention, which could itself be triggered by stock market signals. Disentangling direct from indirect influence is probably the most daunting task in the market discipline literature and probably requires a setup of a (controlled or natural) experiment or full access to all actions (formal/informal) taken by the supervisor. In the absence thereof, we cannot completely rule out that our findings of market discipline are evidence of indirect influencing. Nevertheless, we believe that we can exclude several potential channels of indirect influence.

4.1 Regulatory Interventions

We are not able to compare the timeliness and accuracy of regulatory bank assessments against market evaluations, as in Berger, Davies, and Flannery (2000) or Evanoff and Wall (2002). However, as a first attempt to mitigate the impact of indirect discipline exerted by supervisors, we check whether or not there were regulatory interventions by the Federal Reserve or FDIC (as listed on their respective websites). One of the best known supervisory interventions is Prompt Corrective Action (PCA) enacted by the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991. FDICIA established capital ratio zones that mandate PCA but also allow for discretionary intervention by regulators. This would allow us to distinguish between direct influence (the amount of influencing when no PCA takes place) and indirect influence (the strength of the market signal over and above the supervisory intervention). We find, however, that there were very few enforcements or interventions[13], hence our signals are unlikely to be proxies for these regulatory interventions. Next to discretionary intervention by regulators, FDICIA also defines thresholds on three capital ratios which may trigger automatic PCA if banks are undercapitalized. We find also these to be rare events[14]. Moreover, given that we allow the target and adjustment speed to be different for significantly undercapitalized banks, we believe that this is not driving our results.

[13]The FDIC provides on its website a list of all enforcement decisions and orders against FDIC-insured institutions. Similar information on PCAs with respect to Bank Holding Companies is provided by the Federal Reserve on their website. Hence, we are able to withdraw information on all past PCAs, either for the BHC or for the underlying commercial banks. Overall, we find 72 records in the FDIC database, of which 67 are PCA proscriptions, 5 PCA dismissal of Officers or Directors and 9 PCA Submission of Capital Plans. However, only 38 of the 72 PCAs take place during the sample period in this paper (1991-2007). These 38 PCAs take place in 20 distinct financial institutions. 14 of these institutions are not a member of a bank holding company. Only three banks are member of a one-bank holding company. With respect to the financial insitutions under supervision by the Federal Reserve, we find 27 PCAs in the period 1991-2007. However, only 6 of them (in 5 distinct institutions) took place during our sample period.

[14]In our sample, we observe 91 bank-quarter observatios in which a BHC is categorized as undercapitalized. 41 of these breaches occur in 1991 and 1992. As of 1993, we observe on average less than one bank per quarter that is forced to take a prompt corrective action.

4.2 Subordinated Debtholders

The majority of studies on market discipline look at subordinated debt[15] to infer evidence of monitoring and influencing. The reason is that subordinated debtholders have a concave claim on the value of the bank. Thus, the price of subordinated debt will be informative about the probability of left-tail outcomes, and subordinated debtholders[16] will have strong incentives to monitor and curb bank risk-taking. Using subordinated debt prices, most studies tend to find no response in bank behavior when the price of subordinated debt changes (Krishnan, Ritchken, and Thomson (2005)). This could be interpreted in two ways. On the one hand, it may indicate a failure to find evidence of market influencing, possibly because the choice of issuing subordinated debt is endogenous. Most likely, only safer banks, or banks with a conjectured support of a safety net, will issue subordinated debt. On the other hand, the mere presence of subordinated debt may be sufficient to discipline banks and make future signals (i.e. changes in price rather than the first issuance of subordinated debt) uninformative.

< Insert Table 3 around here >

Therefore, we examine the presence of influencing in the subsets of BHCs with and without outstanding subordinated debt. The results are reported in Table 3. Summary statistics on the bank characteristics in both subsamples are reported in Table 4. The general finding is that we obtain stronger evidence of market discipline in the subsample of BHCs *without* subordinated debt. We find in general less support for market influencing in the subgroup of banks issuing subordinated debt. For the latter, the target capital is not significantly different for banks which receive a risk or valuation signal. In the subgroup of banks that have subordinated debt, the target ROE increases from 14% to 16% after a valuation signal, whereas banks without subordinated debt increase this target from 13.2% to almost 17%. A higher target liquidity ratio is observed for banks receiving both signals simultaneously. In contrast to the subsample of banks without subordinated debt, there is no significant effect on the retail funding share and dividend pay-out ratio for

[15] For example, Ashcraft (2008), Flannery and Sorescu (1996), Goyal (2005), Sironi (2003), Balasubramnian and Cyree (2011), Evanoff and Wall (2002), and Blum (2002).

[16] Subordinated debt, which is typically used in studies of market discipline, is junior to insured debt and senior to equity. Subordinated debtholders give credit to shareholders for the portion of risk shifted past them to the senior claimant (insured depositors and hence the guarantor). Levonian (2001) documents that subordinated debt therefore has features of both sources of funding. Hence, he claims that (changes in) subordinated debt prices reveal two pieces of information about the bank: Info on market value of assets and asset volatility. Exactly the same information can be obtained from bank stock prices and for a larger sample of banks.

banks with subordinated debt (neither on the target or the adjustment speed). The lack of robust results in the sample of BHCs with subordinated debt is in line with the previous literature using subordinated debt prices that finds no or weak evidence of influencing (Bliss and Flannery (2002)). The influencing results for the subgroup of banks without subordinated debt are much stronger. As for the full sample, we find significantly different target levels for the bank capital ratio, the ROE ratio, liquidity, retail funding and the dividend pay-out ratio. Note that this sample, which is by definition omitted from most of the previous literature, is also much larger than the set of BHCs with outstanding subordinated debt. Since there can be no contemporaneous action or signal by debtholders, it is also more likely to support the direct influence hypothesis.

4.3 Wholesale Depositors

While we can to a significant extent exclude that our stock market based signals coincide with supervisory interventions or pressure from the subordinated debtholders, it may still be that the response following the risk signal is indirect if the pressure would be coming from wholesale depositors (Calomiris and Kahn (1991), Huang and Ratnovski (2011)). We observe that the share of retail funding in total funding is larger for banks receiving a joint valuation and risk signal (see Table 2). However, we do not find evidence that a BHC is more likely to observe a decrease in the amount of wholesale deposits in response to a risk signal. We interpret the latter as the absence of a run by uninsured wholesale financiers (in contrast to what happened to some banks in the recent crisis).

4.4 Risk versus Market-to-Book

We explore two dimensions of bank performance: risk and value. While bank risk is of interest to many stakeholders (especially debtholders, regulators and depositors), stock market investors also care about the long-term value of the bank. In particular, they care about the value of the bank relative to a peer group of banks (that is why we use MTB signals conditional on a large set of bank characteristics). As no other stakeholder is harmed by a low valuation, especially if there is no contemporaneous risk signal, a response to a MTB signal (upper right cell of the two-by-two matrices in Table 2) can be interpreted as influencing in favor of the stakeholder who is giving the signal (hence direct influencing). The results in Table 2 convincingly show that there are significant relationships between an undervaluation signal (MTB is substantially lower than its peers; i.e. residual is situated in the lowest decile) and future changes in strategic bank variables. This can be interpreted as evidence of direct influencing in response to a valuation signal by bank equityholders.

4.5 Stock prices versus subordinated debt yields

Apart from a new testing strategy, this paper differs from many other studies on market discipline because it infers evidence on market monitoring and influencing from stock prices (as in Curry, Fissel, and Hanweck (2008)), rather than from subordinated debt (e.g., Ashcraft (2008), Flannery and Sorescu (1996), Goyal (2005), Sironi (2003) or Krishnan, Ritchken, and Thomson (2005)). This is motivated by at least three reasons. First, while bank risk is of interest to many stakeholders (especially debtholders, regulators and depositors), stock market investors also care about the long-term value of the bank. A response to a valuation signal can be interpreted as direct influencing in favor of the stakeholder who is giving the signal, as no other stakeholder is harmed by a low valuation (especially if there is no contemporaneous risk signal). Second, subordinated debtholders have a concave claim on the value of the bank. Equityholders, on the other hand, have a convex claim on banks' assets, which may cause risk-shifting incentives (Jensen and Meckling (1976)). However, this need not be beneficial to stockholders if the charter value is eroded. Park and Peristiani (2007) show that there is a distinct convex nonlinear relationship between the market-to-book ratio and bank risk. Based on their empirical tests, they conclude that for publicly held US BHCs, the interests of bank stockholders are aligned with those of regulators and debtholders (except for a small subset of extremely risky ones). Stockholders penalize riskier strategies to preserve charter value. Only when the option value becomes large enough to compensate for the loss of charter value, stockholders elect instead to reward risk-taking to further increase the put option value, but this only happens for a very small portion of their sample. Third, in comparison with subordinated debt, stock prices are available for a larger sample of banks. In addition, according to Kwan (2002), stock market data have an advantage over bond market data in terms of higher quality. Stock market data are more likely to timely incorporate information than bond prices, because stocks are traded more frequently, are easier to short, and because they are followed by more professional analysts than bonds. Hence, we extend the test of market disciplining to the sample of BHCs that do not have outstanding subordinated debt. This allows us to examine whether the lack of empirical support for market discipline is due to the sample under consideration, the risk signal (subordinated debt prices versus stock prices) or both.

Tying this evidence together, we conclude that banks respond to risk and value signals by equityholders. Moreover, it is unlikely that other stakeholders give contemporaneous signals, which reinforces the case in favor of direct influencing. Moreover, we find that banks shift to less risky activities in response to a total volatility signal, even though equityholders have a convex payoff function and may like risk. Moreover, this claim is even more convincing in the case where there is both a risk and valuation signal. In these situations, equityholders strongly indicate that the bank is taking risks for which they are not compensated and banks react accordingly.

5 Which banks are more likely to get signals?

We now investigate in more detail which characteristics make it more likely that a bank will receive a risk or valuation signal. Recall that these signals are based on the extreme inefficiency scores (risk signal) or residuals (valuation signal). All else equal, banks for which the variance of the inefficiency scores or residuals is larger, will have a higher chance of receiving a risk or valuation signal. Therefore, we investigate which bank characteristics drive the variance of the total risk inefficiencies or market-to-book residuals. For the total volatility setup, we add scale heterogeneity to the stochastic frontier model. For the market-to-book ratio, we use a regression model with multiplicative heteroscedasticity as in Harvey (1976).[17] We make the variance a function of time-varying bank-specific characteristics $Z_{i,t}$, such that $\sigma^2_{u_{i,t}} = \exp(\delta_0 + \delta Z_{i,t})$. We use the exponential function to guarantee that the variance is positive. A positive and significant δ implies that bank characteristics $Z_{i,t}$ increases the variance. A larger variance makes a larger risk inefficiency score or MTB residual, which may lead to influencing, more likely. Therefore, we consider this dispersion or variance to be the scope for pressure or signals coming from stock market investors conditional on their assessment of banks' risk and value profiles. We hypothesize and test whether or not this pressure by stock market investors is related to (1) complexity, (2) managerial discretion, and (3) opaqueness. We motivate each of these variables individually and discuss the estimation results in parallel.

5.1 Complexity: Funding, asset and revenue composition[18]

In complex, diversified firms such as large BHCs, determining the financial condition of a conglomerate might be harder compared to assessing the financial strength of a specialized firm. Diversification of activities might,

[17] Recently, Cerqueiro, Degryse, and Ongena (2011) use a similar model to analyze the dispersion in interest rates on loans issued to small and medium-sized enterprises.

[18] Although the stochastic frontier model with scale heterogeneity or the multiplicative heteroscedastic regression model is modelled in one step, the results are discussed in two steps.

however, also yield more risk-efficient banks if the shocks to the different types of activities are imperfectly correlated (Laeven and Levine (2007)). Hence, one view is that equityholders use less discretion as they expect shocks to different activities to cancel out. The other is that more diversified banks may be harder to monitor as they leave more scope for managerial discretion. We include Hirschman Herfindahl indices (HHI) of specialization in each of the core activities of banks: a HHI for diversification in funding (deposit diversification), a HHI for loan diversification, a HHI for revenue diversity in general (the mix between interest and non-interest income) and a HHI capturing diversity of four non-interest income components. A higher value of the HHI indicates that a bank has a more focused orientation[19]. Lower values point to more diversification. As the two effects of complexity work in opposite directions, we include earnings volatility to control for the risk reduction generated by portfolio diversification. If the portfolio risk-reduction view holds, we should find that more stable profits (potentially caused by combining imperfectly correlated activities) lead to a lower variance. In addition, BHCs may alter their scope either by restructuring their activities or by expanding their size. We include loan growth to control for banks' overall expansion strategies. A high growth rate might indicate that banks expanded via mergers and acquisitions or attracted a new pool (of probably more risky) borrowers[20].

< Insert Table 5 around here >

The estimation results can be found in Table 5. The variance of total risk inefficiency is positively related to specialization. This indicates that, from a monitoring perspective, the portfolio effects of diversification more than compensate the cost of increased complexity that diversification may entail. Note that this effect is not only statistically, but also economically significant. A one standard deviation increase in income specialization increases the dispersion of total risk with 18.3%.

[19] The general formula of the Hirschman Herfindahl index is $HHI_{i,t} = \sum_{j=1}^{J} \left(\frac{X_{i,j,t}}{\sum_{j=1}^{J} X_{i,j,t}} \right)^2$ and is the sum of the squared activity shares (i is a bank indicator, t is time and j=1,...,J refers to the activities over which one measures specialization/diversification). We compute four different HHI-measures: a HHI for diversification in funding (J=3, Noninterest Bearing Deposits, Interest Bearing Core Deposits and Wholesale funding), a HHI for loan diversification (J=5, C&I Loans, Real Estate Loans, Agriculture Loans, Consumer Loans, Other Loans), a HHI for revenue diversity in general (J=2, interest and non-interest income) and a HHI capturing diversity of the four non-interest income components (J=4, Fiduciary Activities, Service Charges on Deposits Accounts, Trading Revenue, Other Non Interest Income).

[20] For example by an expansion into subprime loans (see e.g. Knaup and Wagner (2012)) or by increasing the share of difficult-to-value Level III assets. Unfortunately, these conjectures cannot be tested in our sample as (i) the build up of subprime loans only happened in the latter sample years and (ii) reporting the amount of "Level 3 fair value measurements of loans and leases" (item bhckf245) only became compulsory in the last year of our sample (more precisely as of 2007-03-31).

A higher loan growth rate leads to a larger variance in the valuation of BHCs but at the same time to a lower variance in the risk inefficiency scores. Hence, an expansionary strategy makes it more difficult to assess the true value, but makes banks safer (which is in line with the diversification results if the expansion mitigates portfolio risk). More stable earnings, reflected by a lower ROE volatility, lead to a lower dispersion in total risk inefficiency scores as well as in the residual variance of the market-to-book ratio. For instance, a one standard deviation increase in ROE volatility leads to an increase in the variance of (risk) inefficiency of 24%. This suggests that the preference equityholders have for stable revenue streams dominates the potential negative effects that earnings smoothing and managerial discretion may have on their ability to assess the situation of the bank. However, volatility of profits is only a crude proxy of managerial discretion and earnings smoothing. As emphasized in Hirtle (2007), disclosure plays an important role in market discipline since market participants need to have meaningful and accurate information on which to base their judgments of risk and performance.

5.2 Managerial Discretion and Earnings Forecast Dispersion

We measure disclosure in a qualitative sense and focus on the extent to which bank managers have discretion in reporting certain accounting items, with a potential impact on the bank's perceived value and risk profile. We hypothesize that the variance of the inefficiency term will be larger for banks with more discretion in earnings reporting.

To empirically investigate this hypothesis, we test whether or not bank-specific volatility, $\sigma^2_{u_{i,t}}$, of either the MTB residual or the risk inefficiency term, is increasing in measures of managerial discretion. Managers can both over- and underprovision for expected loan losses and either postpone or prepone the realization of securities gains and losses. As in Beatty, Ke, and Petroni (2002) and Cornett, McNutt, and Tehranian (2009), we measure discretionary loan loss provisions by regressing[21] loan loss provisions on total assets, non-performing loans, loan loss allowances and the different loan classes. The discretionary component of loan loss provisioning is the absolute value of the error term of this regression. Similarly, the discretionary component of realized security gains and losses is the absolute value of the error term of the regression of realized security gains and losses on total assets and unrealized security gains and losses. If managers use more discretion in loan loss provisioning and realizing trading gains, the residuals of these models will be larger. Both point to discretion in earnings management which may obscure true performance. While

[21] Results from these regressions are available upon request.

unexpected loan loss provisions and security gains and losses may make bank performance more difficult to assess, it is often used to smooth earnings over time (Laeven and Majnoni (2003)).

Secondly, we relate the volatility of the TV inefficiency term and the MTB residual to opaqueness, measured by the dispersion in analysts' earnings per share (EPS) forecasts. This measure is widely used in the accounting literature to measure firm transparency (see e.g. Lang, Lins, and Maffett (2012)), as well as in the banking literature by Flannery, Kwan, and Nimalendran (2004) who compare the opaqueness of US bank holding companies with similar-sized non-banking firms. We obtain the earnings forecast data from the Institutional Brokers Estimate System (IBES). We calculate the dispersion measure on a quarterly basis as the cross-sectional dispersion in the most recent forecast of all analysts that made their prediction within the last year. We include only the analysts' last forecasts and require this forecast to be made in the 4 quarters prior to the end of the quarter to avoid that stale forecasts would bias our dispersion measure. To avoid the documented downward bias in forecasted EPS induced by the way IBES adjusts for stock splits, we closely follow the adjustment method described in Diether, Malloy, and Scherbina (2002) and Glushkov and Robinson (2006). Finally, we only include the quarterly dispersion measure if at least two separate analyst forecasts are available. After applying the different filters, we end up with a dataset consisting of 495 banks[22] and 8271 bank-quarter observations. The average number of analyst forecasts per bank per quarter is a satisfying 9.04.

The estimation results are presented in Table 5. We not only include the managerial discretion and earnings forecast disagreement measures, but also loan growth, ROE volatility and the different complexity indicators. It is comforting that the results for those variables are very similar in the reduced sample compared to the full sample. With respect to management discretion, we find that stock market investors exert more pressure in their assessment of risk for banks exhibiting a high discretionary behavior in the realization of securities gains/losses. A one standard deviation increase in this discretion measure leads to a 14% increase in the dispersion of total risk inefficiencies. Discretionary behavior in loan loss provisioning matters less for risk. However, the main goal of active discretion in loan loss provisioning is earnings smoothing, which is considered favorably (i.e. stable profit streams lead to a lower variance of the MTB

[22] We lose a significant number of bank-quarter observations when matching the existing dataset with IBES data. Both datasets are merged as follows. The main identifier in IBES is the IBES ticker, whereas the main identifier in CRSP is the permno of the bank. Hence, in order to merge the information of both files, the best approach is to use common secondary identifiers to construct a linking table that relates the permno of the bank to the IBES ticker. We follow the procedure proposed by WRDS (Moussawi (2006)), which assigns a score to each match, according to the quality of the link.

residuals and the TV inefficiencies). In fact, the leeway managers permit themselves in dealing with problem loans leads to more pressure by bank equityholders in their assessment of bank value. Dispersion in IBES analyst forecasts unambiguously increases the variance of both signals. This not only suggests that banks differ substantially in their degrees of opaqueness, but also that stock market investors take these differences into account. The dispersion in total risk inefficiencies increases by 17% (12.4% for MTB residuals) in response to a one standard deviation increase in analyst forecasts dispersion.

6 Conclusion

The financial crisis of 2007-09 has illustrated that the choice of business models and (lack of) transparency in banking may have profound consequences for the risk profile of the banks. Even within certain bank business models, we noticed a large discrepancy of banks' vulnerability to adverse shocks. The question we address is whether or not information about BHC risk and valuation can be extracted from stock market information and whether or not market signals are sufficiently strong to force banks to alter their risk and performance profile. These are the two faces of market discipline: monitoring and influencing. If the stock market is able to monitor bank risk, this information is useful for supervisors and they should include market-based risk indicators in their information set. If the stock market is able to influence bank risk behavior, this can be complementary to supervisory actions and reinforce them. In this paper, we develop an empirical setup to examine the ability of stock market investors to monitor and influence bank risk and performance in a sample of US BHCs over the period 1991-2007.

We investigate the influencing hypothesis by analyzing if and to what extent bank managers react to risk and valuation signals from the stock market over a medium to long-run horizon. The hypothesis is that banks exhibiting a relatively high degree of risk inefficiency will respond by taking remedial action in order to adjust their risk profile. Similarly, banks that are judged to underperform relative to their peers are expected to alter their cost and revenue structure to improve bank value. In contrast to most of the extant literature, we do find evidence of stock market influencing in US banking. Banks that receive a risk signal react by increasing their capital buffer and lowering their liquidity risk. These actions are in line with predictions and with the objective of supervisors. Banks receiving a negative valuation signal react by increasing their target profit level, primarily by lowering the cost-to-income ratio, indicating that most of the performance improvement is intended to come from the cost efficiency side. Hence, these corrective actions taken by managers in response to a large undervaluation signal may lead to future increases in market value, which may explain the finding by Calomiris and Nissim (2007) that BHCs that have lower than predicted market-to-book ratios (compared to an estimated model) tend to experience large, statistically significant, predictable increases in market values in subsequent quarters. Finding evidence of influencing in this setup is indicative for a type of market discipline that Bliss and Flannery (2002) label "more benign and commonplace" compared to, e.g., a distressed takeover, outright defaults or executive turnovers.

Next to investigating the response to risk and valuation signals, we also analyze which banks are more likely to get signals. We find that stock market investors punish discretionary behavior, especially in the case of security gains and losses. More unpredictable banks exhibit larger deviations in terms of risk and valuation. We also find strong evidence that the degree of opaqueness is positively related to the variance of the risk inefficiencies and valuation residuals. Regulation should be designed to lower the degree of discretion that bank managers can exercise. A reduction in the opacity of banks can be achieved by fostering information disclosure, e.g. through a timely and accurate publication of relevant on and off balance sheet risk exposures. Providing better information may allow banks to avoid large random stock market penalties in terms of risk or valuation.

To rule out that our results are driven by indirect influencing, we also investigate the contribution of other potential monitors, such as subordinated debtholders, wholesale depositors and supervisors. We find that regulatory enforcement actions are unlikely to explain our results, that influencing is most pronounced in banks without subordinated debt and that wholesale depositors are not reacting to our risk signals. Nevertheless, as in most other studies addressing this issue, there is a need for caution since other sources of discipline, such as unobserved actions taken by the supervisory authorities, may affect bank behavior.

References

Acharya, V. V., and N. Mora, 2012, "Are Banks Passive Liquidity Backstops? Deposit Rates and Flows during the 2007-2009 Crisis," *National Bureau of Economic Research Working Paper Series*, No. 17838.

Ashcraft, A. B., 2008, "Does the market discipline banks? New evidence from regulatory capital mix," *Journal of Financial Intermediation*, 17(4), 543–561.

Balasubramnian, B., and K. B. Cyree, 2011, "Market discipline of banks: Why are yield spreads on bank-issued subordinated notes and debentures not sensitive to bank risks?," *Journal of Banking and Finance*, 35(1), 21–35.

Beatty, A., B. Ke, and K. Petroni, 2002, "Earnings management to avoid earnings declines across publicly and privately held banks," *The Accounting Review*, 77(3), 547–570.

Berger, A. N., S. M. Davies, and M. J. Flannery, 2000, "Comparing Market and Supervisory Assessments of Bank Performance: Who Knows What When?," *Journal of Money, Credit and Banking*, 32(3), 641–667.

Bliss, R., and M. Flannery, 2002, "Market discipline and the governance of U.S. bank holding companies: monitoring versus influencing," *European Finance Review*, 6(3), 361–395.

Blum, J. M., 2002, "Subordinated debt, market discipline, and banks' risk taking," *Journal of Banking and Finance*, 26(7), 1427–1441.

Bond, P., I. Goldstein, and E. S. Prescott, 2010, "Market-Based Corrective Actions," *Review of Financial Studies*, 23(2), 781–820.

Calomiris, C., and D. Nissim, 2007, "Activity-based valuation of bank holding companies," *NBER Working Paper*, No. 12918.

Calomiris, C. W., and C. M. Kahn, 1991, "The Role of Demandable Debt in Structuring Optimal Banking Arrangements," *The American Economic Review*, 81(3), 497–513.

Cerqueiro, G., H. Degryse, and S. Ongena, 2011, "Rules versus discretion in loan rate setting," *Journal of Financial Intermediation*, 20(4), 503–529.

Cornett, M., J. McNutt, and H. Tehranian, 2009, "Corporate governance and earnings management at large U.S. bank holding companies," *Journal of Corporate Finance*, 15(4), 412–430.

Curry, T. J., G. S. Fissel, and G. A. Hanweck, 2008, "Equity market information, bank holding company risk, and market discipline," *Journal of Banking and Finance*, 32(5), 807–819.

De Jonghe, O., 2010, "Back to the basics in banking? A Micro-Analysis of Banking System Stability," *Journal of Financial Intermediation*, 19(3), 387–417.

Demirguc-Kunt, A., and H. Huizinga, 2010, "Bank activity and funding strategies: The impact on risk and returns," *Journal of Financial Economics*, 98(3), 626–650.

Diether, K. B., C. J. Malloy, and A. Scherbina, 2002, "Differences of opinion and the cross section of stock returns," *Journal of Finance*, 57(5), 2113–2141.

Evanoff, D. D., and L. D. Wall, 2002, "Measures of the riskiness of banking organizations: Subordinated debt yields, risk-based capital, and examination ratings," *Journal of Banking and Finance*, 26(5), 989–1009.

Fama, E. F., and K. R. French, 2000, "Forecasting Profitability and Earnings," *The Journal of Business*, 73(2), 161–175, ArticleType: research-article / Full publication date: April 2000 / Copyright ÃĆÂľ 2000 The University of Chicago Press.

Federal Reserve System, ., 1999, "Using subordinated debt as an instrument of market discipline, Report of a study group on subordinated notes and debentures," *Board of Governors Staff Study Nr. 172*.

Flannery, M., 2001, "The faces of market disciplie," *Journal of Financial Services Research*, 20(2-3), 107–119.

Flannery, M., S. Kwan, and M. Nimalendran, 2004, "Market evidence on the opaqueness of banking firm's assets," *Journal of Financial Economics*, 71(3), 419–460.

Flannery, M., and S. Sorescu, 1996, "Evidence of bank market discipline in subordinated debenture yields: 1983-1991," *The Journal of Finance*, 51(4), 1347–1377.

Flannery, M. J., and K. P. Rangan, 2006, "Partial adjustment toward target capital structures," *Journal of Financial Economics*, 79(3), 469–506.

Flannery, M. J., and K. P. Rangan, 2008, "What Caused the Bank Capital Build-up of the 1990s?," *Review of Finance*, 12(2), 391–429.

Gatev, E., T. Schuermann, and P. E. Strahan, 2009, "Managing bank liquidity risk: How deposit-loan synergies vary with market conditions," *Review of Financial Studies*, 22(3), 995–1020.

Gendreau, B., and D. Humphrey, 1980, "Feedback effects in the market regulation of bank leverage: time-series and cross-section analysis," *The Review of Economics and Statistics*, 62(2), 277–280.

Glushkov, D., and D. Robinson, 2006, "Note on IBES Unadjusted Data," *WRDS Documentation on IBES*.

Goyal, V. K., 2005, "Market discipline of bank risk: Evidence from subordinated debt contracts," *Journal of Financial Intermediation*, 14(3), 318–350.

Harvey, A., 1976, "Estimating regression models with multiplicative heteroscedasticity," *Econometrica*, 44(3), 461–466.

Hirtle, B., 2007, "Public disclosure, risk and performance at bank holding companies," *Federal Reserve Bank of New York Staff Report Nr. 293*.

Hirtle, B., and K. Stiroh, 2007, "The return to retail and the performance of U.S. banks," *Journal of Banking and finance*, 31(4), 1101–1133.

Huang, R., and L. Ratnovski, 2011, "The dark side of bank wholesale funding," *Journal of Financial Intermediation*, 20(2), 248–263.

Hughes, J. P., L. J. Mester, and C.-G. Moon, 2001, "Are scale economies in banking elusive or illusive?: Evidence obtained by incorporating capital structure and risk-taking into models of bank production," *Journal of Banking and Finance*, 25(12), 2169–2208.

Jensen, M. C., and W. H. Meckling, 1976, "Theory of the firm: Managerial behavior, agency costs and ownership structure," *Journal of Financial Economics*, 3(4), 305–360.

Knaup, M., and W. Wagner, 2012, "A Market-Based Measure of Credit Portfolio Quality and Banks' Performance During the Subprime Crisis," *Management Science*, 58(8), 1423–1437.

Krishnan, C. N. V., P. H. Ritchken, and J. B. Thomson, 2005, "Monitoring and Controlling Bank Risk: Does Risky Debt Help?," *The Journal of Finance*, 60(1), 343–378.

Kwan, S., 2002, "Bank security prices and market discipline," *FRBSF Economic Letter Nr. 37*.

Laeven, L., and R. Levine, 2007, "Is there a diversification discount in financial conglomerates?," *Journal of Financial Economics*, 85(2), 331–367.

Laeven, L., and G. Majnoni, 2003, "Loan loss provisioning and economic slowdowns: too much, too late?," *Journal of Financial Intermediation*, 12(2), 178–197.

Lang, M., K. V. Lins, and M. Maffett, 2012, "Transparency, Liquidity, and Valuation: International Evidence on When Transparency Matters Most," *Journal of Accounting Research*, 50(3), 729–774.

Lemmon, M. L., M. R. Roberts, and J. F. Zender, 2008, "Back to the beginning: Persistence and the cross-section of corporate capital structure," *Journal of Finance*, 63(4), 1575–1608.

Lintner, J., 1956, "Distribution of Incomes of Corporations Among Dividends, Retained Earnings, and Taxes," *The American Economic Review*, 46(2), 97–113.

Mester, L., 1997, "Measuring efficiency at U.S. banks: Accounting for heterogeneity is important," *European Journal of Operational Research*, 98(2), 230–242.

Morgan, D., and K. Stiroh, 2001, "Market disciplie of banks: the asset test," *Journal of Financial Services Research*, 20(2), 195–208.

Moussawi, R., 2006, "Linking CRSP and IBES data," *WRDS Documentation on IBES*.

Park, S., and S. Peristiani, 2007, "Are bank shareholders enemies of regulators or a potential source of market discipline?," *Journal of Banking and Finance*, 31(8), 2493–2515.

Raymar, S., 1991, "A Model of Capital Structure when Earnings are Mean-Reverting," *The Journal of Financial and Quantitative Analysis*, 26(3), 327–344.

Sarkar, S., and F. Zapatero, 2003, "The Trade-off Model with Mean Reverting Earnings: Theory and Empirical Tests," *The Economic Journal*, 113(490), 834–860.

Saunders, A., E. Strock, and N. G. Travlos, 1990, "Ownership structure, deregulation, and bank risk taking," *Journal of Finance*, 45(2), 643–654.

Schaeck, K., M. Cihak, A. Maechler, and S. Stolz, 2012, "Who Disciplines Bank Managers?," *Review of Finance*, 16(1), 197–243.

Sironi, A., 2003, "Testing for market discipline in the European banking industry: Evidence from subordinated debt issues," *Journal of Money, Credit and Banking*, 35(3), 443–472.

Stiroh, K., 2004, “Diversification in banking: Is noninterest income the answer?,” *Journal of Money, Credit and Banking*, 36(5), 853–882.

——— , 2006, “A portfolio view of banking with interest and noninterest activities,” *Journal of Money, Credit and Banking*, 38(5), 1351–1361.

——— , 2006b, “New evidence on the determinants of bank risk,” *Journal of Financial Services Research*, 30(3), 237–263.

Table 1: Summary Statistics of Variables Used in the Analysis of Bank Monitoring

Variable	Mean	Std. Dev.	Min.	Max.	N
PANEL A					
Valuation and risk metric based on banks' share price					
Total volatility	0.3159	0.1423	0.1125	0.8938	17264
Market-to-Book Value of Equity	2.3758	1.1545	0.5196	7.2331	17216
PANEL B					
Bank Strategy Variables					
ln(Total Assets)	15.0901	1.5793	12.194	19.7077	17264
Tier 1 Risk-Based Capital Ratio	11.7388	3.1518	6.2556	27.72	17264
Non-Performing Loans Ratio	0.0114	0.013	0	0.0853	17264
Cost to Income	0.6384	0.12	0.3732	1.188	17264
Return on Equity	0.0324	0.0179	-0.0836	0.0686	17264
Liquid Assets	0.0455	0.0909	-0.1711	0.3711	17264
Funding Structure					
Non-Interest-Bearing Deposits Share	0.1326	0.0704	0.0158	0.391	17264
Interest-Bearing Core Deposits Share	0.6687	0.1123	0.2867	0.8827	17264
Wholesale Funding Share	0.197	0.1052	0.0277	0.5896	17264
Deposits to Total Assets	0.7609	0.1056	0.3603	0.9238	17264
Asset Mix					
Real Estate Loan Share	0.6316	0.1876	0.0653	0.9797	17264
Commercial and Industrial Loan Share	0.1935	0.1185	0.0034	0.6332	17264
Agricultural Loan Share	0.01	0.0208	0	0.1295	17264
Consumer Loan Share	0.1175	0.0999	0.001	0.5009	17264
Other Loan Share	0.0415	0.0592	0	0.3464	17264
Loans to Total Assets	0.6432	0.1209	0.2144	0.8709	17264
Revenue Streams					
Interest Income Share	0.7373	0.1382	0.2487	0.9613	17264
Non-Interest Income Share	0.2627	0.1382	0.0387	0.7513	17264
Fiduciary Activities Income Share	0.0379	0.06	0	0.3835	17264
Service Charges on Deposit Accounts Share	0.0747	0.0369	0.0003	0.1806	17264
Trading Revenue Share	0.006	0.0186	-0.0078	0.1117	17264
Other Non-Interest Income Share	0.1405	0.1139	0.0075	0.6652	17264
Deposit-Loan Synergies					
Deposit Loan Synergies	0.039	0.0306	0.0006	0.2723	17264
Unused Loan Commitments Share	0.1765	0.0957	0.0203	0.536	17264
Transaction Deposits Share	0.2214	0.1084	0.0298	0.5079	17264

This table contains summary statistics on the variables used in the analysis of bank monitoring and consists of two parts. In panel A, we provide information on the equity market-based risk and value measures (the dependent variables). For the calculation of total volatility, we take the standard deviation of the daily bank stock returns within a quarter. We then annualize total volatility by multiplying with the squared root of 252. We also compute a market-based valuation metric, which is the market value to the book value of tangible common equity. Both variables are measured over the period 1991-2007 on a quarterly basis. Panel B of this table contains information on the independent variables. Bank size is measured as the natural logarithm of total assets expressed in US dollar thousands and deflated to 2007:Q4 values. All other variables are measured as ratios. For detailed information on the exact computation of the ratios, we refer to the Appendix. Income statement data are reported on a calendar year-to-date basis in the FRY9C reports and are therefore converted to quarter-to-quarter changes before computing ratios. The variables are measured over the period 1991-2007 on a quarterly basis. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters. Furthermore, we exclude banks of which the stock has zero trading volume for at least twenty percent of the observations. The final sample consists of 17264 observations on 899 bank holding companies. All variables are winsorized at the 1 percent level.

Table 2: Evidence of market Influencing: The impact of market signals on the Target ratio and Adjustment Speed

		Target Ratio		Adjustment Speed	
		MTB=0	MTB=1	MTB=0	MTB=1
Tier 1 Risk-Based Capital Ratio	TV=0	11.385	**10.628**	0.296	**0.406**
			0.027		**0.056**
	TV=1	**12.582**	11.554	0.307	**0.573**
		0.004	0.729	0.843	**0.000**
Non-Performing Loans Ratio	TV=0	0.708	0.647	0.560	0.588
			0.263		0.338
	TV=1	**0.913**	0.855	0.648	**0.768**
		0.001	0.128	0.188	**0.018**
Cost to Income Ratio	TV=0	0.613	**0.553**	0.335	0.332
			0.001		0.958
	TV=1	**0.659**	**0.668**	0.325	0.464
		0.005	**0.033**	0.844	0.255
Return on Equity	TV=0	0.034	**0.041**	0.524	0.539
			0.000		0.840
	TV=1	0.032	**0.030**	0.622	0.597
		0.132	**0.046**	0.111	0.448
Liquidity Ratio	TV=0	0.023	0.037	0.227	0.293
			0.158		0.134
	TV=1	**0.056**	0.051	0.233	0.230
		0.005	0.175	0.913	0.973
Non-Interest Income Share	TV=0	0.324	0.392	0.142	0.109
			0.296		0.416
	TV=1	0.302	0.329	**0.258**	**0.434**
		0.331	0.867	**0.033**	**0.009**
Retail Deposit Share	TV=0	0.655	**0.617**	0.187	0.177
			0.093		0.808
	TV=1	0.688	**0.815**	0.171	0.248
		0.137	**0.014**	0.696	0.422
Dividend Payout Ratio	TV=0	0.392	**0.349**	0.572	**0.702**
			0.002		**0.075**
	TV=1	0.377	0.334	0.594	0.658
		0.510	0.130	0.728	0.532

This table contains results on the market influencing tests. We use a partial adjustment model to test whether or not reallocations in strategic bank characteristics occur in response to a risk (TV) and/or valuation (MTB) signal. We focus on the effect on eight strategic bank characteristics: the capital ratio, asset quality (non-performing-loans ratio), cost efficiency (cost-to-income ratio), profitability (ROE), liquidity ratio (the ratio of liquid assets to total assets), the ratio of non-interest income to total income, the share of retail deposits in total deposit funding and the dividend pay-out ratio. For each characteristic, we estimate the following equation:

$$\Delta y_{i,t} = \left(\gamma_0 + \gamma_0^* D^{y}_{i,t-\tau} + \gamma_1 D^{TV}_{i,t-\tau} + \gamma_2 D^{MTB}_{i,t-\tau} + \gamma_3 D^{TV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}\right) \times \left(y^*_{i,t} - y_{i,t-\tau}\right) + \varepsilon_{i,t}$$

with

$$y^*_{i,t} = \alpha_0 + \alpha_0^* D^{y}_{i,t-\tau} + \alpha_1 D^{TV}_{i,t-\tau} + \alpha_2 D^{MTB}_{i,t-\tau} + \alpha_3 D^{TV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau} + X_{i,t-\tau}\beta$$

For sake of space and clarity, we only report the target level (left panel) and the speed of adjustment (right panel) for the eight indicators. We report the target and adjustment speed in four distinct cases where (1) the bank neither gets a a risk nor valuation signal (dummy TV= dummy MTB=0, the upper left cell), (2) the bank gets only a risk signal (dummy TV=1, dummy MTB=0, the lower left cell), (3) the bank gets only a valuation signal (dummy TV=0, dummy MTB=1, the upper right cell) and (4) the bank gets both a risk and a valuation signal (dummy TV= dummy MTB=1, the lower right cell). This results in sixteen 2 by 2 matrices. In each case, we report the p-value in parentheses to assess the statistical significance of the differences with the benchmark case of no signal, i.e. the upper left cell. Significant differences (w.r.t. to the benchmark case) at the 10 per cent level are highlighted in bold.

Table 3: Target Ratio and Adjustment Speed: Sample split based on Subordinated Debt

		Target Ratio				Adjustment Speed			
		No Sub. Debt		Sub. Debt		No. Sub. Debt		Sub Debt	
		MTB=0	MTB=1	MTB=0	MTB=1	MTB=0	MTB=1	MTB=0	MTB=1
Tier 1 Risk-Based Capital Ratio	TV=0	12.242	11.850	9.832	9.462	0.336	**0.535**	0.445	0.424
			0.167		0.474		**0.008**		0.845
	TV=1	**13.005**	12.380	10.775	10.356	0.310	**0.659**	0.286	0.493
		0.066	0.738	0.460	0.610	0.675	**0.000**	0.224	0.827
Non-Performing Loans Ratio	TV=0	0.670	0.540	0.744	0.726	0.497	0.523	0.583	0.608
			0.109		0.820		0.619		0.494
	TV=1	**0.896**	**0.907**	0.913	0.702	**0.694**	**0.751**	0.433	**0.694**
		0.001	**0.093**	0.291	0.782	**0.000**	**0.063**	0.322	**0.100**
Cost to Income Ratio	TV=0	0.625	**0.532**	0.610	0.583	0.311	0.282	0.413	0.479
			0.001		0.167		0.710		0.302
	TV=1	**0.670**	0.644	0.596	**0.689**	0.373	**0.514**	**0.239**	0.420
		0.010	0.552	0.833	**0.063**	0.323	**0.095**	**0.060**	0.975
Return on Equity	TV=0	0.033	**0.042**	0.035	**0.040**	0.426	0.416	0.659	0.687
			0.000		**0.004**		0.924		0.691
	TV=1	0.031	0.029	0.036	0.033	**0.608**	**0.651**	0.701	0.459
		0.167	0.170	0.757	0.628	**0.062**	**0.022**	0.532	0.401
Liquidity	TV=0	0.022	0.034	0.011	0.022	0.245	**0.363**	0.241	0.266
			0.139		0.588		**0.005**		0.661
	TV=1	**0.051**	0.011	0.042	**0.073**	0.213	0.119	0.336	**0.577**
		0.034	0.817	0.193	**0.003**	0.619	0.236	0.316	**0.085**
Non-Interest Income Share	TV=0	0.261	0.255	0.331	0.414	0.209	0.237	0.140	0.108
			0.850		0.178		0.715		0.571
	TV=1	0.252	0.272	0.384	0.399	0.348	**0.461**	0.218	0.412
		0.667	0.708	0.314	0.131	0.133	**0.040**	0.302	0.196
Retail Deposit Share	TV=0	0.666	0.588	0.655	0.624	0.195	**0.113**	0.161	0.261
			0.117		0.199		**0.086**		0.137
	TV=1	0.698	**0.788**	0.642	0.785	0.191	**0.409**	0.131	0.228
		0.183	**0.012**	0.803	0.115	0.937	**0.042**	0.472	0.504
Dividend Payout Ratio	TV=0	0.392	**0.338**	0.386	0.343	0.507	0.655	0.688	0.785
			0.008		0.018		0.211		0.254
	TV=1	0.371	**0.329**	0.346	0.338	0.586	**0.803**	0.696	0.485
		0.432	**0.093**	0.322	0.503	0.318	**0.083**	0.926	0.167

This table provides information on whether the evidence for market influencing is different in the subsample of banks without subordinated debt holders, versus banks with subordinated debt holders. We assess whether reallocations in strategic bank characteristics occur in response to a risk (TV) and/or valuation (MTB) signal, by means of a partial adjustment model. We focus on the effect on eight strategic bank characteristics: the capital ratio, asset quality (non-performing-loans ratio), management quality (cost-to-income ratio), earnings (ROE), liquidity ratio (the ratio of liquid assets to total assets), the ratio of non-interest income to total income, the share of retail deposits in total deposit funding and the dividend pay-out ratio. For each characteristic, we estimate equation (3). For sake of space and clarity, we only report the target level (left panel) and the speed of adjustment (right panel) for the eight indicators. We report the target and adjustment speed in four distinct cases where (1) the bank neither gets a risk nor valuation signal (dummy TV=dummy MTB=0, the upper left cell), (2) the bank gets only a risk signal (dummy TV=1, dummy MTB=0, the lower left cell), (3) the bank gets only a valuation signal (dummy TV=0, dummy MTB=1, the upper right cell) and (4) the bank gets both a risk and a valuation signal (dummy TV=dummy MTB=1, the lower right cell). We report the results for both the subsample without subordinated debt and with subordinated debt. In each case, we report the p-value in parentheses to assess the statistical significance of the differences with the benchmark case of no signal, i.e. the upper left cell. Significant differences (w.r.t. to the benchmark case) at the 10 per cent level are highlighted in bold.

Table 4: Summary statistics of a sample split of banks with and without Subordinated Debt

	Subordinated Debt		
	NO	YES	p-value
Number of Observations	4363	1821	
ln(Total Assets)	14.363	16.684	0.000
Tier 1 Risk-Based Capital Ratio	12.886	9.810	0.000
Non-Performing Loans Ratio	0.884	1.042	0.000
Cost to Income	0.624	0.629	0.135
Return on Equity	0.033	0.038	0.000
Liquid Assets	0.088	0.104	0.000
Non-Interest Income Share	0.218	0.348	0.000
Retail Deposit Share	0.679	0.628	0.000
Dividend Payout ratio	0.342	0.362	0.000
Subordinated debt/Total Capital	0.000	0.213	0.000
Risk Signal	0.150	0.077	0.000
Valuation Signal	0.097	0.120	0.010
Joint Signal	0.007	0.008	0.891

This table provides summary statistics on bank size, the eight strategic bank characteristics, the amount of subordinated debt in total capital and the frequency of risk signals, valuation signals or joint signals. We compare the means of the variables in the subsamples of banks with subordinated debt (the first column) and bank without subordinated debt (the second column). The third column contains the p-value of the difference-in-mean test for these variables.

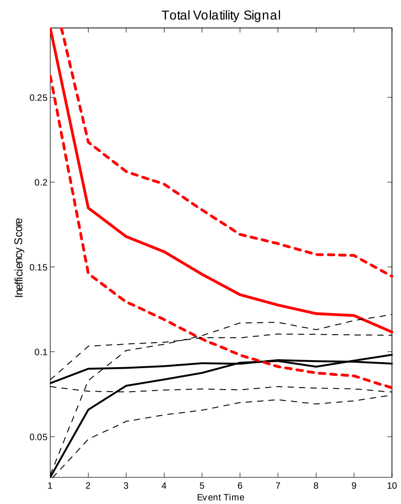
Table 5: Which banks are more likely to get signals: complexity and opacity

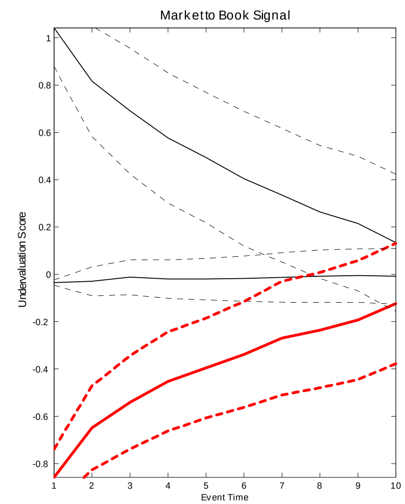
VARIABLES	Mean *Std. Deviation*	(1) Full Sample Total Volatility SFA scale	(2) Reduced Sample Total Volatility SFA scale	(3) Full Sample Market-to-Book (Equity) Cond. Het. regression scale	(4) Reduced Sample Market-to-Book (Equity) Cond. Het. regression scale
Volatility of ROE	0.0081	0.242***	0.148***	0.224***	0.220***
	0.0096	(0.0135)	(0.0258)	(0.0445)	(0.0647)
Loan Growth	0.1304	-0.0602***	-0.0412**	0.129***	0.166***
	0.1528	(0.0132)	(0.0209)	(0.0430)	(0.0619)
Funding Specialization	0.5352	0.0763***	0.0142	-0.100	-0.120
	0.0922	(0.0151)	(0.0251)	(0.0613)	(0.0817)
Loan Portfolio Specialization	0.5234	0.0736***	0.0949***	-0.0305	-0.0335
	0.1605	(0.0167)	(0.0270)	(0.0777)	(0.101)
Income Specialization	0.652	0.183***	0.0911***	-0.346***	-0.250***
	0.0976	(0.0158)	(0.0273)	(0.0665)	(0.0884)
Specialization in non-traditional, non-interest	0.4901	0.134***	0.152***	0.347***	0.412***
income generating activities	*0.1389*	(0.0156)	(0.0241)	(0.0633)	(0.0794)
Dispersion in IBES analyst forecasts	0.0704		0.172***		0.124***
	0.1232		(0.0202)		(0.0381)
Discretion in loan loss provisioning	0.0132		0.0284		0.129***
	0.0246		(0.0188)		(0.0429)
Discretion in realizing security gains and losses	0.0374		0.141***		0.0655
	0.0645		(0.0230)		(0.0435)
Constant		-4.002***	-4.584***	-1.408***	-1.378***
		(0.0198)	(0.0318)	(0.0715)	(0.0863)
Observations		17264	8271	17216	8249

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this table we provide the estimation results for the scale heterogeneity in the stochastic frontier model and the conditional heteroscedastic regression model, where the volatility of the inefficiency term is related to two sets of variables. In the Full Sample, the bank-specific volatility of the inefficiency term is related to the complexity or specialization of the banking firm. We use Hirschmann-Herfindahl indices of specialization or diversification regarding funding, activity mix as well as revenue sources. The higher the value of the index, the more the bank is specialized in that area. We also include the past loan growth and the volatility of the ROE as independent variables. In the Reduced Sample, we introduce the dispersion in IBES analyst forecast as a measure of bank opaqueness and proxies for various aspects of (discretion in) (earnings) management, such as discretion in loan loss provisioning and the realization of securities gains and losses and earnings volatility. In the first column, we report for each variable the mean (first line) and its standard deviation (second line, in italics).

Figure 1: Dynamic Behavior of the Risk and Valuation Signals





This graph consists of two subplots, one for the total volatility signal and one for the market-to-book signal. Each subplot presents the average inefficiency score or extent of misvaluation of three portfolios in event time. Each quarter, we sort BHCs into deciles according to the size of the signal. The portfolio formation quarter is denoted time period 1. We then compute the average signal size for each portfolio in each of the subsequent 10 quarters, holding the portfolio composition constant (except for BHCs that exit the sample). We repeat these two steps of sorting and averaging for every quarter in the sample period (1993-2007). This process generates 60 sets of event-time averages, one for each quarter in our sample. We then compute the average signal size of each portfolio across the 60 sets within each event quarter. The most extreme decile (highest risk or lowest value) is indicated by the thicker red line. The least extreme decile as well as the two middle deciles (combined in one portfolio) are indicated in black. The dashed lines surrounding the portfolio averages represent 90 per cent confidence bounds. They are computed as the average standard error across the 60 sets of averages (Lemmon et al., 2008).

A Online Appendix - Monitoring Bank Risk and Equityholder Value

An essential first step in our test for market influencing is to establish a relationship between bank-specific risk and performance measures and various (lagged) bank-specific characteristics, this within either a stochastic frontier (risk) or linear regression (valuation) framework. The extensive literature on market monitoring, which shows that securityholders indeed distinguish between banks with different risk profiles, provides good guidance on which proxies to include (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990), Stiroh (2004), Stiroh (2006b), Hirtle and Stiroh (2007)). To allow comparison with existing studies and to be transparent with respect to the other steps of the analysis, we briefly describe in this appendix the results of the baseline equation. While not the main contribution of this paper, we believe we still add to this literature by considering a more comprehensive range of bank characteristics which affect a bank's business model. To assess how potential differences in the banks' composition of assets, liabilities and operational characteristics are reflected in bank risk and value, we relate TV and MTB to four sets of bank characteristics, proxying for: (i) overall bank strategy, (ii) the bank's funding structure (Calomiris and Nissim (2007), Demirguc-Kunt and Huizinga (2010), Hirtle and Stiroh (2007)), (iii) asset mix (as e.g., Calomiris and Nissim (2007), Morgan and Stiroh (2001)), and (iv) revenue diversity (as e.g., Stiroh (2006), Stiroh (2006b), De Jonghe (2010)), as well as variables proxying for deposit-loan liquidity synergies (Gatev, Schuermann, and Strahan (2009)). Our vector $X_{i,t}$ of bank-specific characteristics, which appears in Equation (1) in the paper, is hence given by:

$$X_{i,t} = [Bank\ Strategy,\ Funding\ Structure,\ Asset\ Mix,\ Revenue\ Streams]_{i,t} \tag{A.1}$$

Summary statistics are reported in Table 1 of the paper. All data are collected from the publicly available FR Y-9C reports. The definition and construction of each variable is described in Appendix B. Consequently, we link the FR Y-9C reports to banks' stock prices using the match provided on the Federal Reserve Bank of New York website[23]. Controlling for a large set of bank characteristics is important for our tests of market influencing. Both the magnitude and the accuracy of the risk and valuation signals, and hence the accuracy of our test of market influencing, will depend to a great extent on the quality and level of the bank-specific characteristics included in either the stochastic frontier (TV) or linear regression (MTB) model.

Our sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters in the period 1991-2007. The total sample consists of 17,264 observations on 899 bank

[23] http://www.ny.frb.org/research/banking_research/datasets.html

holding companies. Our sample period covers two full business cycles as well as a number of stressed periods. The impact of these events and the business cycle is captured by time fixed effects. We now motivate the bank-specific variables and their effect on risk and value group by group. The discussion is based on the estimation results reported in the first two columns of Table A.1, which correspond with a model without conditional variance. In columns 3 and 4, we report the results of a model with conditional variance (as used in Section 5 of the paper). We only refer to the latter results in the few cases where they differ from the former.

< Insert Table A.1 around here >

To facilitate the economic interpretation of the coefficients, we standardize all independent variables. Bank fixed effects are included in all estimations.

Bank Strategy Variables The bank-specific proxies for overall bank strategy capture strategic choices made by bank managers that may affect a bank's risk and valuation profile. We include the regulatory Tier 1 capital ratio[24] and the liquid-to-total-assets ratio to incorporate the possibility that better capitalized and more liquid institutions may be less vulnerable to shocks. Asset quality is measured by the ratio of loans past due 90 days or more and non-accrual loans to total loans. We also include the cost-to-income ratio as a measure of cost efficiency. This ratio measures the overheads or costs of running the bank as a percentage of total operating income before provisions. Finally, we include (the log of) bank size[25] as larger banks may diversify their risk more and may enjoy economies of scale (Hughes, Mester, and Moon (2001)), and bank profitability (ROE) to control for a risk-return trade-off. The first part of Table A.1 indicates that stock market participants accurately identify and assess the effect of the different bank strategy variables on total volatility and the market-to-book value. Larger banks are more have less total risk and a higher market-to-book ratio. More cost efficient banks, with less credit risk (higher asset quality) that are more

[24] The capital measure used in this paper is the Tier 1 risk-based capital ratio. However, as mentioned in Ashcraft (2008), the relevant capital measure for regulators is equity capital plus subordinated debt, as this is the cushion regulators consider before the claims of depositors are affected. Comparison of both capital measures indicates that the correlation is very high. Estimating the frontier set-up with the regulatory capital measure yields similar results. They are available upon request.

[25] Bank size is, to a large extent, the outcome of strategic choices made by banks and is hence highly correlated with the other control variables, and, more importantly, with the measures that capture the various business models we consider. Therefore, we orthogonalize size with respect to all other variables. The natural logarithm of total assets is regressed on all independent variables. The idea is to decompose bank size in an organic growth component and a historical size component, the residual.

profitable will have lower risk and higher valuations. A larger regulatory capital ratio makes banks safer but harms their long-term value.

Funding Structure We decompose total deposits in three types: Interest-bearing core deposits, non-interest-bearing deposits and wholesale funding. The first is the share of deposits held by retail depositors, which are protected by the deposit insurance scheme. Wholesale funding providers are generally more sensitive to changes in the credit risk profile of the institutions to which they provide these funds. As such, they are expected to track the institution's financial condition more closely and withdraw money more swiftly when they detect a deterioration in the bank's risk profile. With respect to the funding composition, we find that a larger share of interest-bearing core deposits increases total risk (vis-à-vis the omitted share of demand deposits), but has no effect on the MTB ratio. However, the impact on total risk is different in column 3. The latter findings are in line with Hirtle and Stiroh (2007), who conclude that retail banking may be a relatively stable activity. In line with expectations, we find that banks with a larger fraction of wholesale funding are considered as more risky.

Asset Mix We find that banks which mainly focus on their core activity (a large loans-to-asset ratio) exhibit lower market-to-book values (but are also less risky). Next to including the loan-to-asset ratio, we classify loans according to borrower types. The loan portfolio composition[26] may have an impact on stock market participants' perceptions of banks' risk exposures. We categorize loans as commercial and industrial (C&I) loans, real-estate loans, consumer loans, agricultural loans and a catch-all share that includes all other loans. We leave the real estate loan share out of the equation to avoid perfect collinearity. Table 1 in the paper shows that banks' loan portfolio composition varies substantially in the sample. The average bank's loan portfolio consists of 63% real estate loans, 19% C&I loans and 12% consumer loans. Banks with a higher proportion of consumer loans face lower total volatility. The commercial and industrial loan share has a small positive impact on total risk. Hence, we confirm the evidence by Morgan and Stiroh (2001) who found that bond spreads are increasing in commercial and industrial lending.

[26] The FRY9C reports do not allow to distinguish directly between high and low quality loans within each category (e.g.: focus on subprime versus prime loans within real estate loans). Note, however, that such differences should show up in the non-performing loans ratio. Moreover, to the extent that this is a deliberate, time-invariant choice, it will be captured by the bank fixed effects. In unreported regressions, we included charge-off rates by loan type. This does not affect our findings on monitoring and the identification of the risk and valuation signals.

Revenue Streams The activities of deposit-taking and lending predominantly generate interest margin. However, some banks also generate a substantial amount of non-interest income (Stiroh (2006)). Therefore, we also include variables capturing the importance of income generated by fiduciary activities and trading-related income. All other activities that generate non-interest income are captured in the other non-interest income share. Previous studies have documented that non-interest income is in general more risky than interest income (e.g. Stiroh (2006b) and Demirguc-Kunt and Huizinga (2010)). Our breakdown of non-interest income in four subcomponents yields additional insights. First, relative to the omitted interest income share, trading revenues and other non-interest income[27] subcomponents lead to higher total volatility. Second, banks with a larger fraction of their income generated by service charges on deposit accounts experience lower stock market volatility. However, this coefficient is no longer significant in column 3.

Finally, we include three indicators to measure the potential diversification effects of liquidity risk on the asset and liability side of the balance sheet. Gatev, Schuermann, and Strahan (2009) find scope for **deposit-loan synergies**. Banks exposed to loan-liquidity risk without high levels of transaction deposits have higher risk. Bank risk is expected to rise with unused commitments (reflecting asset-side liquidity risk exposure) and the use of transaction deposits (reflecting liability-side liquidity risk exposure). The synergy effect is measured by the interaction term between the ratio of unused loan commitments and transaction deposits. All three effects are confirmed in our sample. Both unused loan commitments and transaction deposits increase total bank risk, but the combination of both provides a statistically and economically significant hedge against liquidity risk and reduces the risk of the bank.

Overall, we can conclude that stock market investors accurately identify the different risks associated with the balance sheet and income statement characteristics and use this in their assessment of the banks' valuation and risk profile. Although this evidence does not yet establish that market discipline can effectively control banking firms, it soundly rejects the hypothesis that investors cannot rationally differentiate among the risks undertaken by the major U.S. banking firms. This is evidence of the first step in market discipline, market monitoring, which is a necessary but not a sufficient condition to support the market influencing hypothesis.

Robustness and remarks As a robustness check, we also include state fixed effects for at least two

[27] Other non-interest income are predominantly fees and commissions from investment banking and underwriting, (re)insurance underwriting and venture capital revenue.

reasons. First, unobserved heterogeneity at the state level, such as state-specific regulation or the composition of the local economy may affect banks' riskiness as well as their business mix. Second, Mester (1997) has documented that controlling for heterogeneity in stochastic frontier analysis is important to obtain accurate estimates of inefficiency. Rather than estimating the frontier at the state or region level, which would yield imprecise estimates as the number of observations is small for many states, we allow the intercept of the stochastic frontier to be different across states. Significance and magnitude of the coefficients are quite similar in both specificiations. In the few differences, we never obtain conflicting results in terms of sign. It is worth stressing that the (rank)correlation between the inefficiency scores with and without state fixed effects is almost perfect. In sum, including state fixed effects does not alter the results.

In the multiplicative heteroscedastic regression setup (the setup for MTB), we cluster the standard errors at the bank level (which yields the most conservative standard errors). Unfortunately, clustering techniques have not yet been implemented in the standard stochastic frontier models. Moreover, it is even more complicated in our extended approach in which we also model the variance of the inefficiency score. Fortunately, as clustering does not affect the coefficients or inefficiency score/residual, but only the standard errors of the coefficients; our setup to test for the presence and strength of influencing (which is our main contribution) is unaffected by the choice of clustering.

Finally, the signals obtained from estimating a model with and without scale heterogeneity (i.e. modelling the variance as a function of bank characteristics) are very similar. The correlation between the inefficiency scores in column 1 and 3 is 95%, whereas the correlation between the residuals of equation 2 and 4 is even higher 98%. Recall that we defined signals as belonging to the highest decile. 84% of the TV signals based on column 3 would also be classified as signals in column 1. An additional 14% of signals based on column 3, belongs to the 9th decile (rather than the 10th decile) if signals were based on column 1. The correspondence is even higher with respect to market-to-book-signals. 90% of the MTB signals based on column 4 belong to the extreme decile based on column2. An additional 9.6% belongs to the 9th decile of residuals based on column 2.

Table A.1: Total Volatility and Market-to-Book: evidence of monitoring

	Total Volatility SFA	Market-to-Book OLS	Total Volatility SFA (with scale)	Market-to-Book Cond. Het. regression
	Bank Strategy Variables			
Bank Size	-0.00724**	0.183*	-0.00215	0.231**
	(0.00355)	(0.110)	(0.00323)	(0.0932)
Tier 1 Risk-Based Capital Ratio	-0.00927***	-0.277***	-0.0103***	-0.273***
	(0.00197)	(0.0471)	(0.00190)	(0.0423)
Non-Performing Loans Ratio	0.0152***	-0.0862***	0.00978***	-0.0948***
	(0.000710)	(0.0299)	(0.00126)	(0.0253)
Cost to Income	0.00435**	-0.128**	0.00443**	-0.148***
	(0.00213)	(0.0592)	(0.00199)	(0.0520)
Return on Equity	-0.00724***	0.0868***	-0.00661***	0.124***
	(0.00105)	(0.0221)	(0.00131)	(0.0227)
Liquid Assets	0.00586***	0.00473	0.00345**	0.0204
	(0.00122)	(0.0362)	(0.00167)	(0.0304)
	Funding Structure			
Interest-Bearing Core Deposits Share	0.00526**	-0.0407	-0.00627*	-0.0202
	(0.00268)	(0.0748)	(0.00367)	(0.0646)
Wholesale Funding Share	0.00687**	-0.0819	-0.00522	-0.0655
	(0.00290)	(0.0780)	(0.00369)	(0.0662)
Deposits to Total Assets	0.00335	-0.0666	-0.000937	-0.126**
	(0.00225)	(0.0668)	(0.00231)	(0.0574)
	Asset Mix			
Commercial and Industrial Loan Share	0.0102***	-0.0308	0.0157***	0.0111
	(0.00246)	(0.0512)	(0.00234)	(0.0427)
Agricultural Loan Share	0.00115	-0.0404	0.00231	-0.0483
	(0.00102)	(0.0382)	(0.00207)	(0.0367)
Consumer Loan Share	-0.0163***	0.00345	-0.0107***	0.0363
	(0.00200)	(0.0644)	(0.00232)	(0.0526)
Other Loan Share	-0.000713	0.139**	0.00541**	0.118*
	(0.00228)	(0.0651)	(0.00230)	(0.0669)
Loans to Total Assets	-0.00358**	-0.120***	-0.00618***	-0.120***
	(0.00154)	(0.0455)	(0.00190)	(0.0387)
	Revenue Streams			
Fiduciary Activities Income Share	-0.00322	0.199	0.00615**	0.286**
	(0.00285)	(0.161)	(0.00276)	(0.122)
Service Charges on Deposit Accounts Share	-0.00558***	0.0423	-0.00147	0.0306
	(0.00197)	(0.0590)	(0.00214)	(0.0476)
Trading Revenue Share	0.00416***	0.0707**	0.00424***	0.0803**
	(0.00105)	(0.0350)	(0.00154)	(0.0316)
Other Non-Interest Income Share	0.00562***	0.167***	0.00951***	0.170***
	(0.00183)	(0.0561)	(0.00197)	(0.0505)
	Deposit-Loan Synergies			
Deposit Loan Synergies	-0.00775**	-0.108*	-0.00999***	-0.0925
	(0.00356)	(0.0617)	(0.00308)	(0.0599)
Unused Loan Commitments Share	0.00607*	0.112	0.00410	0.0959
	(0.00326)	(0.0710)	(0.00298)	(0.0645)
Transaction Deposits Share	0.00916***	0.0300	0.00636**	0.0438
	(0.00253)	(0.0553)	(0.00266)	(0.0472)
Observations	17264	17216	17264	17216
Bank Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents estimation results for equation (1) in the paper. Columns 1 and 2 contain the results of the stochastic frontier model (total volatility) and the conditional heteroscedastic regression model (market-to-book value of equity). Column 3 contains the results of the stochastic frontier model (total volatility) where the variance of the inefficiency term is a function of bank-specific characteristics (hence, we allow for scale heterogeneity). Column 4 contains the results of the conditional heteroscedastic regression model, in which the volatility of the error terms is a function of bank characteristics. We estimate a 'cost' function for total risk. That is, the inefficiency score measures excess risk above the frontier, which is determined by the banks with minimum risk given a set of bank characteristics. In particular, stochastic frontier analysis allows decomposing the error term in random noise and a measure of risk inefficiency. As firms (banks) can be both over- or undervalued with respect to their fundamentals, we employ a standard OLS regression model (with both positive and negative residuals) rather than a stochastic frontier model which only allows for one-sided deviations from the frontier. The variables are measured over the period 1991-2007 at a quarterly basis. Bank balance sheets are observed and measured as stock values at a quarterly basis. Data from the income statement is reported on a cumulative basis over the accounting year and are therefore first transformed to quarterly increments. The independent variables are lagged one quarter. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters. Furthermore, we exclude banks of which the stock has zero trading volume for more than 20 percent of the observations. The total sample consists of 17.264 observations on 899 bank holding companies. Time and bank fixed effects are included in each column (but not reported). In the second column, the standard errors are robust and clustered at the bank level.

CHAPTER 3

Model Uncertainty and Systematic Risk in US Banking

Model Uncertainty and Systematic Risk in US Banking*

Lieven Baele† Valerie De Bruyckere‡ Olivier De Jonghe § Rudi Vander Vennet¶

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†CentER, Netspar, Tilburg University, Warandelaan 2, Tilburg, The Netherlands. Lieven.Baele@tilburguniversity.edu

‡Corresponding author: Ghent University, W. Wilsonplein 5D, Ghent, Belgium. Valerie.Debruyckere@ugent.be.

§CentER, European Banking Center, Tilburg University, Warandelaan 2, Tilburg, The Netherlands. O.dejonghe@tilburguniversity.edu

¶Ghent University, W. Wilsonplein 5D, Ghent, Belgium. Rudi.Vandervennet@ugent.be

Abstract

This paper uses Bayesian model averaging (BMA) techniques to examine the driving factors of equity returns of U.S. financial institutions. The main advantage of BMA is accounting for model uncertainty. For the period 1986-2010, we find that the most likely model explaining banking sector returns has a probability of 25% only. We also show that the optimal model changes considerably over time and across types of BHCs. The market, high-minus-low (HML) Fama-French factor, and real estate factor are part of most specifications. Finally, we highlight some implications for banking studies using measures of idiosyncratic volatility, abnormal returns or market betas.

Keywords: bayesian model average, bank risk, systematic risk, bank stock returns, bank supervision, financial stability

JEL: G01, G20, G21, G28, L25

1 Introduction

The nature of their business exposes banks to various types of risk. Not only may these risks fluctuate over time as economic conditions change, also the exposure of banks to these risks may vary over time. Since bank instability may spill over to the real economy, banks are subject to prudential regulation and oversight by dedicated supervisors. However, extensive regulation and supervision were unable to prevent the 2007-9 banking and economic crisis. As a result, there is renewed interest in the identification of relevant risk factors affecting banks and their evolution over time. One potential set of indicators relies on market prices, such as bank stock market returns. These indicators can be obtained by relating bank stock returns to various risk factors, such as market, interest rate, and other relevant risks. The challenge is to discover which risk factors are relevant for which types of financial institutions at a specific point in time. In this paper, we attempt to answer this question within a Bayesian framework that explicitly takes into account the uncertainty about the relevant set of factors ("model uncertainty"). We apply our methodology to US Bank Holding Companies over the period $1986 - 2010$.

Our paper contributes to an expanding literature that measures banking risk as the exposure of bank (sector) stock returns to some set of predefined risk factors. However, based on a broad literature survey, it is fair to state that there is little consensus on the risk factors, apart from the market factor, that drive bank stock returns. This is clear from Table 1 which gives an overview of the different (combinations of) risk factors that have been used in the literature so far. The 24 papers we refer to have related bank stock returns to various combinations of no less than 17 different risk factors. The uncertainty about which risk factors to include in a bank factor model is labeled "model uncertainty". When estimating only one model, the researcher imposes the chosen model on the data and the only uncertainty that is considered is parameter uncertainty, where one typically interprets the coefficients of significant variables. In this paper, we explicitly take model uncertainty into account by using Bayesian Model Averaging techniques to estimate bank factor models. Bayesian Model Averaging (BMA) was first developed by Leamer (1973), and has since been used in several disciplines, ranging from statistics (Raftery, Madigan, and Hoeting (1997) and Hoeting, Madigan, Raftery, and Volinsky (1999)), over a large literature on cross-country growth regressions (Fernandez, Ley, and Steel (2001b), Brock and Durlauf (2001) and Sala-I-Martin, Doppelhofer, and Miller (2004) among others) to finance (Cremers (2002), Avramov (2002) and Wright (2008)). To the best of our knowledge, we are the first to apply Bayesian Model Averaging in the banking literature.

Suppose that the literature offers a list of k potential explanatory risk factors. In the set of linear factor models, 2^k different model combinations can be made, where each model consists of (a subset of) the explanatory variables. Using Bayesian Model Averaging techniques, we are able to account for this considerable model uncertainty. BMA compares all models simultaneously, as opposed to conditioning on a single individual model. Each individual model is attributed a posterior probability and the posterior parameter estimate is obtained as the weighted average of the parameters over the different models, where the posterior model probabilities are used as weights. Because this approach considers all models simultaneously, we obtain useful insight into the importance of each regressor. For each risk factor, we can compute its posterior inclusion probability, i.e. how likely it is that a particular risk variable is part of the model, making it a useful tool to evaluate the relevance of the different risk factors.

In the first part of the analysis, we compare the results of BMA versus OLS in explaining the impact of various risk factors on the returns of a banking index. More specifically, we relate weekly excess returns of an equally-weighted portfolio of the 50 largest (in terms of total assets) US Bank Holding Companies to innovations in the different risk factors. We cover most of the candidate risk factors that have been previously used in the literature, but we also introduce some risk factors that have received attention only in recent times, such as the volatility implied by option prices on the S&P500 and the TED spread, an indicator of financial sector credit risk. Details on the theoretical motivation for including those factors and on their construction can be found in Section 2.2. Full sample $(1986-2010)$ results reveal that the market and real estate factor, as well as the high-minus-low book-to-market Fama-French factor, are the most important risk factors, with posterior inclusion probabilities close to a 100 percent. Other factors, maybe with the exception of the 3-month T-Bill rate, do not seem to be reliably related to the returns on the broad bank index. We show that our BMA approach that takes into account model uncertainty leads to different conclusions than one that does not (OLS). Moreover, our results indicate that there is no correct or dominant model. The most likely model has a posterior model probability of less than 25%, suggesting that accounting for model uncertainty is important.

In the second part of the analysis we investigate whether or not bank factor models vary over time or differ according to the type of financial institution we consider. Differences across studies with respect to the most relevant risk factors may not only be due to a failure to account for model uncertainty, but may also be the consequence of looking at different periods. In fact, some factors may be 'dormant' for a long time, and hence undetectable in short (tranquil) samples, to suddenly appear in times of market stress. In a first step, we estimate the BMA model with the same set of risk factors on a pre- and post 2007 sample. In a more general analysis, we conduct rolling-window BMA regressions, basically re-estimating the BMA model each quarter using two years of weekly data. We find that factors such as the implied volatility index and term and default spread frequently switch between being economically and statistically relevant or not. Hence, specific periods (typically those characterized by increased financial market stress) may be associated with different bank risk exposures, which may have implications for, e.g., the supervision of bank risk or cost of capital considerations.

Another reason why different studies may report a different set of risk factors is that they focus on different types of financial institutions. To investigate whether or not different types of financial intermediaries are exposed to different risk factors, we compare the results of our baseline portfolio of the 50 largest Bank Holding Companies with those (both static and time-varying) of four types of financial intermediaries: depository institutions, insurance companies, security and commodity brokers, and other non-depository institutions (see Acharya, Pedersen, Philippon, and Richardson (2012) for a similar classification). In addition, within the sample of Bank Holding Companies (BHCs), we differentiate between various 'types' by constructing portfolios of BHCs according to size (largest 15 versus smallest 50), sound versus distressed BHCs and BHCs with a stable retail focus versus diversified and fast-growing banks. Details on the construction of these portfolios are mentioned in Section 2.1. The general conclusion from this analysis is that while the relevant set of exposures does vary substantially over time, it is relatively stable across bank types.

Finally, we discuss some implications of our findings for empirical banking research based on stock returns. In fact, return-generating models of bank stocks are not only a useful (supervisory) tool to uncover risk exposures, but also serve as an input in various setups in empirical banking research. Computing abnormal returns in event studies requires the specification of a benchmark model. Residual-based measures of uncertainty (idiosyncratic volatility) or transparency (R-squared) require an accurate identification of risk factors and a correct specification of the factor model. Accurate measures of banks' exposures to stock market movements (e.g. to compute capital charges for systematic risk) also hinge on the correct specification of a factor model. In Section 5, we discuss the implications of our findings for these setups.

The paper is organized as follows. Section 2 describes in detail the data used in this paper. Section

3 presents the BMA framework we use to analyze the importance of the risk factors. Section 4 in which empirical results are presented consists of two subsections. In the first subsection, we document the results in a static time-invariant framework (section 4.1). In subsection 4.2, we allow for time variation in the model specifications as well as the significance and magnitude of the factor exposures. We discuss the implications of our findings for different strands of empirical banking research (event studies, market risk, idiosyncratic volatility) in Section 5. Section 6 concludes.

2 Data

Since this paper is essentially empirical, we start with a detailed description of the data used in this paper. Subsection 2.1 explains how the overall bank index and the cross-sectional portfolios sorted on bank characteristics are constructed. Subsection 2.2 motivates our choice of the set of risk factors and discusses their construction.

2.1 Portfolio construction

Our main analysis is conducted on a portfolio of the 50 largest (based on total assets) US Bank Holding Companies (BHCs, henceforth) over the period 1986 – 2010. The set of BHCs is rebalanced quarterly to reflect the actual, time-varying ranking. The portfolio return is an equally weighted average of the underlying weekly returns and measured in excess of the 3-Month Treasury Bill rate. In addition to this portfolio of large US BHCs, we also examine in Section *4.1.2* portfolios of other types of financial intermediaries as well as portfolios of BHCs with a specific business model.

We differentiate between the following types of financial intermediaries: (1) Depository institutions, (2) Insurance companies, (3) Security and Commodity Brokers and (4) Other non-depository institutions. This distinction is based on Acharya, Pedersen, Philippon, and Richardson (2012)[1] and implemented by using (CRSP) stock returns of the 100 largest financial companies (in terms of market capitalization) with SIC codes 60, 61, 62, 63, 64 and 67.

[1] Acharya, Pedersen, Philippon, and Richardson (2012) also include real estate companies (SIC code 65). We decided to drop companies with SIC code 65 from the sample, because we include a real estate factor as a regressor (see below) based on the returns of the stock of these companies.

Secondly, we construct different portfolios of BHCs with different business models. We construct portfolios according to size (large versus small), sound versus distressed banks, and BHCs with a steady retail versus an expansionary, wholesale focus. To define the universe of publicly traded BHCs and relate the stock price information to accounting data, we use the link provided by the New York Fed[2]. We construct two portfolios based on a size criterium: the **largest** 15 BHCs and the **smallest** 50 BHCs, based on total assets (and quarterly rankings). In contrast to small BHCs, the largest 15 banks operate nationwide, are more interconnected through interbank payments or correlated exposures and may benefit from implicit too-big-to-fail guarantees. **Sound** versus **distressed** banks are determined based on two characteristics: profitability and leverage. A bank is considered to be sound (in a given quarter) if it belongs to the highest quartile in terms of both return on assets and the equity-to-total-assets ratio. Sound banks are hence profitable and protect this source of franchise value by means of prudent capitalization. A bank is categorized as distressed in a given quarter if it is combining low profits and high leverage (lowest quartile of ROA and equity to assets). We purposely identify sound and distressed BHCs using two dimensions to distinguish them from (successful) gambling (poorly capitalized with high profits) or bad luck (low profits while strongly capitalized). Finally, we construct a portfolio of BHCs with a **retail focus** and one of **expanding, diversified BHCs**. De Jonghe (2010) and Fahlenbrach, Prilmeier, and Stulz (2012) show which bank characteristics make banks more subject to extreme systematic risk. Large and expanding banks with low leverage, a reliance on wholesale funding and focused on non-interest income generating activities experienced the largest stock price drops in the 1998 and $2007-08$ crises (Fahlenbrach, Prilmeier, and Stulz (2012)) and have higher tail betas (De Jonghe (2010)). To construct these two portfolios, we take the following steps. First, we compute, by quarter, the quartiles of each of the following five dimensions[3]: size, asset growth, leverage, wholesale funding and share of interest income; and allocate a score of 1 to 4 to the corresponding quartile. Subsequently, we sum the quartile-based scores and obtain an index between 5 and 20. Diversified banks are those with a score of at least 17, implying that they should score high in almost all dimensions, while retail

[2] This link is only available until the of 2007, but is manually extended until the end of 2010. Similar to the procedure described by the NY Fed, we use information of the SNL financial database containing all publicly traded bank holding companies in a quarterly file format.

[3] The idea is to differentiate between retail banks and wholesale oriented and revenue-diversified banks (Large and Complex Banking groups, LCBGs, or Systemically Important Financial Institutions, SIFIs) as well as how aggressively they pursue their strategy. Hence, next to the retail-wholesale dimension, we also control for asset growth and size.

banks are those with a score of eight or less.

Summary statistics of the returns on the various portfolios are reported in panel A of Table 2, while Table 3 provides more detailed information on the (variables used in the) construction of the portfolios. The average annualized return on the benchmark portfolio (largest 50 BHCs) is 14.1%. Brokerage companies and diversified BHCs earned a higher annualized return over the period $1986 - 2010$. While most portfolios yield an annualized return of almost 10% or higher, the distressed BHC portfolio's return is almost zero. Larger BHCs, sound or diversified BHCs yield a higher annualized return vis-à-vis small, distressed or retail-oriented BHCs. Depository institutions, insurance companies and other types of FIs yield similar annualized returns, around 12% on an annual basis. The correlation between the returns for broker-dealers and the other portfolios (around 50%) is lower than all other pairwise correlations (around 70%). In general, the correlations between contrasting portfolios of BHCs (large versus small, sound versus distressed, and retail versus diversified) are also slightly lower than the average pairwise correlation indicating that we are indeed identifying types of BHCs with different strategies. In addition, the returns on the brokers-dealer portfolio also differ from most other portfolios by exhibiting a much larger positive skewness and higher kurtosis.

More evidence on the heterogeneity between the identified BHC types is reported in Table 4. For each constructed portfolio of BHCs, we report the average value of a set of bank characteristics as well as the p-value of a difference in means test for the opposite portfolios. The largest 15 versus smallest 50 BHCs portfolios are determined only based on total assets, which is reflected in the large difference in the logarithm of their total assets. However, large and small banks also differ substantially in their level of capitalization, reliance on deposit funding and loan granting, and consequently also in the source of income (mainly interest income for small banks). Sound, high franchise value banks are contrasted with distressed banks based on their level of capitalization and profits. Distressed banks hold 50% less Tier 1 capital compared to sound banks and are loss-making over the sample period. In addition, the BHCs in these two portfolios differ markedly in the amount of loan loss provisions as well as their cost effectiveness. Poor credit risk management and inefficient cost management lead to undercapitalization and poor profitability. Retail banks are differentiated from diversified, wholesale-oriented banks in many dimensions. By construction, the retail banks are smaller, better capitalized, experience stable (near zero) growth, and focus more on retail deposits and interest income generating activities as compared to diversified, financial conglomerates. Nevertheless, they are equally profitable and cost efficient and provision similarly for potential credit risk.

We relate excess returns (of each of the aforementioned portfolios) to innovations in a total of twelve risk factors, which are classified in eight groups. In the next section, we briefly explain, for each risk factor, how it is constructed and why we expect it to be a potential source/contributor to bank risk.

2.2 Bank Risk Factors

2.2.1 Market risk

We include returns on a broad equity market portfolio (**Market**) as a first factor, as in all previous studies explaining (bank) stock returns. This exposure, or 'market beta', measures how sensitive (individual) bank stock returns are to aggregate market movements, and hence to changes in general economic and financial market conditions. As a proxy for the market portfolio, we use the Non-Financial Market Index from Datastream (code TOTLIUS). We use a market index excluding the financial sector to avoid spurious results when explaining the returns on an index of US BHCs.

2.2.2 The Fama French factors

Since the seminal work of Fama and French (1996), a large literature has emerged showing that stock returns are not only related to market returns, but also to returns on a size and a value factor[4]. More often than not, however, the financial sector is excluded from asset pricing tests. Nevertheless, Schuermann and Stiroh (2006) show for a sample of US BHCs that the Fama-French factors are, next to the market, the dominant factors explaining bank stock returns. Viale, Kolari, and Fraser (2009) in contrast show that a model that includes a bank sector specific size and value factor, next to a market factor, is outperformed by a model that includes the market and term spread. We follow these papers and common practice in the finance literature, and include both the size and value factor in our set of potential risk drivers. We use the size (**SMB**) and value (**HML**) factors made available by Kenneth French on his website. Both the size and value factor earn a positive risk premium, implying that risk increases with exposures to both factors. Liew and Vassalou (2000) argue that persistently high Book-to-Market stocks face a higher risk of distress and that they are more likely to survive when the economic outlook is good rather than bad. Similarly, small capitalization stocks are more likely to do well during periods of economic growth, and more likely to be the

[4]The size factor is calculated as the difference in return between small and large stocks (SMB); the value factor is the difference in return between stocks characterized by high and low (HML) book-to-market value.

first to disappear during periods of economic slowdown. The vulnerability of high Book-to-Market and small capitalization stocks to changes in the economic cycle leads to a positive link between the performance of the HML and SMB strategies and future economic growth. They show that both factors contain information about future economic growth not captured by the market factor. Vassalou and Xing (2004) argue that both the HML and SMB contain some default-related information, but that this is not the main source of priced information embedded in both factors. Chen and Zhang (1998) show that firms with high book-to-market equity have persistently low earnings, higher financial leverage and are more likely to cut dividends than their counterparts with low book-to-market ratios. Campbell and Vuolteenaho (2004) show that value and small stocks are relatively more exposed to shocks in cash-flow expectations than large and growth shocks. Zhang (2005) relates the higher riskiness of value relative to growth stocks, and hence their higher returns, to asymmetries in capital adjustment costs and time-varying prices of risk, which make assets-in-place much riskier than growth options in bad times, while growth options are riskier than assets-in-place in good times, and to a lesser extent. In sum, both the size and value factor seem to contain information about the future state of the economy not captured by the market factor alone, and are hence also candidate risk factors for bank stock returns.

2.2.3 Interest rate risk

In theory, one would expect BHCs to be more exposed to interest rate movements than non-financial companies. A financial intermediary is, through its activity of maturity transformation, exposed to interest rate risk caused by differences in the duration of its assets and liabilities. Since Flannery and James (1984a), most studies also include at least one interest rate factor, in addition to a proxy for market risk. As a short-term interest rate risk factor, we include the three-month Treasury bill rate (**TB3**). As the duration of bank liabilities is usually shorter than the duration of banks' assets, we expect rate increases to negatively affect bank stock returns. Not finding a significant exposure does not necessarily mean that banks are not exposed to interest rate risk, but that they may have succesfully hedged their exposure, e.g. by means of interest-rate derivatives. Table 1 shows that most studies include the short-term interest rate, often combined with either the term spread or a long-term interest rate. Hence, as a second interest rate risk factor, we include the term spread (**TS**), calculated as the difference between the yield on a 10-year government bond and the three-month Treasury bill rate[5]. Depending on the duration mismatch between assets and liabilities, the exposure to changes in the term spread may either be negative or positive. In models with both the short rate and the term spread, the short rate captures the effect of a parallel shift in the term structure, while the term spread tests for the effect of a change in the slope of the term structure of interest rates. Notice that while both the short rate and term spread may also convey information about the (future) state of economy, inflation and monetary policy (see e.g. Ang, Piazzesi, and Wei (2006)), we expect that the business cycle information in both variables is already captured by the market factor.

2.2.4 Default Risk

Banks are exposed to corporate default risk, directly through loan exposures as well as indirectly via their securities portfolio or investment vehicles (e.g. corporate securities, ABS, SPVs...). As a measure of economy-wide corporate default risk, we include the yield difference between Moody's BAA and AAA-rated corporate bonds (**DS**). Because a rise in the default spread increases the probability of losses in the bank's loan portfolio, we expect a negative relationship between bank stock returns and innovations in the default spread.

Banks are also exposed to potential defaults of other banks, either directly through the interbank market or indirectly through potential contagion effects and correlated exposures. As an indicator of credit risk in the financial system, we include the Treasury-EuroDollar spread (**TED** spread), defined as the difference between the three-month LIBOR and the three-month Treasury bill rate (IMF (2009) and Garleanu and Pedersen (2011)). Because a widening of the spread is an indication of increased distress risk in the financial sector, we expect bank stocks to react negatively to shocks in the TED spread[6].

2.2.5 Liquidity risk

Banks provide liquidity to the economy (by financing illiquid assets with liquid claims) but this also poses a risk. As a measure of liquidity tightness in the market of bank deposits, we use the spread between the three month deposit rate (three month unregulated time deposit) and the three month Treasury Bill rate (**DepS**) (see e.g. Dewenter and Hess (1998)). The second liquidity measure is the difference between the Federal

[5] We do not include the long-term interest rate to avoid perfect multicollinearity as we already include the short rate and term spread, defined as the difference between the long and the short rate.

[6] The three-month LIBOR-OIS (overnight index swap) spread would be an alternative to the TED spread (Giesecke and Kim (2011)) but is unfortunately not available over the entire period 1986-2010.

Funds Overnight rate and the three month LIBOR rate (**MMS**, i.e. money market spread) and measures tightness in the money market (see e.g. Taylor and Williams (2009)). While both measures are unlikely to have an effect on bank stock prices in tranquil times, we expect their importance to increase substantially when stress in the financial system increases. However, the sign is unpredictable. On the one hand, banks can provide liquidity as deposit inflows that are seeking a safe haven provide banks with a natural hedge to fund drawn credit lines and other commitments (Gatev and Strahan (2006)). On the other hand, the banking system in its role as a stabilizing liquidity insurer acts as an active seeker of deposits via managing bank deposit rates (Acharya and Mora (2012)). Since MMS is related to funding conditions in the more volatile money market, we expect it to be a more important risk factor in times of financial market stress.

2.2.6 Real Estate risk

Real estate price drops and subsequent losses on (subprime) mortgage loans are often indicated as one of the culprits of the financial crisis of 2007-2009. Decreasing real estate prices may hence affect the value of banks negatively directly through their effect on the value of outstanding mortgages[7], or indirectly through the resulting drop in the value of mortgage-backed securities. While there exist several proxies for price movements in the US real estate market (such as the Case-Shiller index), none of them is available at a daily or weekly frequency. Inspired by the work of Adrian and Brunnermeier (2009), we construct a value-weighted real estate index (**RE**) of all publicly traded real estate companies (with (header) SIC (major group) code 65[8]) from CRSP.

2.2.7 Market Sentiment indicator

While most of the previous state variables already capture market sentiment in one or another way, we additionally include the VXO implied volatility index[9]. Our main motivation is that the **VXO** is a forward-

[7] The largest share of loans in banks' overall loan portfolio are residential and commercial real estate loans, even for large BHCs.

[8] SIC code 65 consists of the following subgroups: 6510 (real estate operators (no developers) & lessors), 6512 (operators of nonresidential buildings), 6513 (operators of apartment buildings), 6519 (lessors of real property), 6531 (real estate agents & managers (for others)), 6532 (real estate dealers (for their own account)), 6552 (land subdividers & developers (no cemeteries)).

[9] This is a weighted index of American implied volatilities calculated from eight near-the-money, near-to-expiry, S&P 100 call and put options with a 1 month maturity. We use the VXO rather than the better known S&P500-based VIX index because the former is already available from 1986 on (compared to 1990 for the VIX index). Notice that the VIX and VXO index

looking risk measure that has predictive power for returns at relative short horizons (up to 3 months), while most of the other state variables have predictive power (if any) beyond that horizon (see e.g. Londono (2011)). We expect bank stock returns to have a negative exposure to VXO innovations.

2.2.8 Currency risk

Some large banks may have exchange rate exposure, e.g. through foreign lending or derivative exposures. As a measure of currency risk (**FX**), we use the Nominal Major Currencies Index, available from the Federal Reserve Board's H 15 filings. An increase in the index is associated with an appreciation of the USD with respect to a trade-weighed basked of (main) currencies. Such appreciation of the USD will affect banks either negatively or positively, depending on whether they are long or short the foreign currency (see e.g. Chamberlain, Howe, and Popper (1997)). Of course, bank risk may also be indirectly affected by FX fluctuations to the extent that the impact of these fluctuations on the real economy leads to increased riskiness of the existing loan portfolio and lower demand for new loans. The expected sign is ambiguous, depending on how all the individual effects aggregate.

2.2.9 Summary

To summarize, we relate excess returns to a total of twelve risk factors, which are classified in eight groups. Note, however, that part of the information in the other risk factors will be captured by the market factor, to the extent that they convey information relevant to the valuation of the market portfolio. Hence, exposures to the other risk factors will capture the exposure of banks over and above the exposure to the market. Moreover, according to the efficient market hypothesis, we only expect a relationship between bank stock returns and *unanticipated* changes in risk factors. To ensure that we capture unexpected movements in the risk factors, we take the residuals from an $AR(n)$ model for each risk variable, where n is determined by the Schwarz Bayesian Information Criterion. Panel B of Table 2 reports summary statistics for the different factor shocks (and reports both the name and abbreviation used throughout the paper), as well as the expected signs of the factor exposures. Two features of the data seem noteworthy. First of all, the volatility of the bank sector index returns is a factor two higher than that of the aggregate market or the Fama-French

overlap perfectly until 22 September 2003, as until that date also the VIX was based on SP&P100 option prices. In the post 2003 period, both indices remain highly correlated.

factors. Second, returns on the real estate index are highly volatile, even more than those on the market and similar to the brokers-dealers' return volatility.

3 Methodology

3.1 Estimation: Prior distribution and the likelihood function

This section outlines Bayesian Model Averaging in the normal linear regression model[10], similar as in Cremers (2002), Sala-I-Martin, Doppelhofer, and Miller (2004), Wright (2008) and Magnus, Powell, and Prufer (2010). We start from the linear regression framework (as in Magnus, Powell, and Prufer (2010)):

$$y = x\beta + \varepsilon = x_1\beta_1 + x_2\beta_2 + \varepsilon, \qquad \varepsilon \backsim N(0,\sigma^2) \tag{1}$$

where y is the $(n \times 1)$ vector of bank index returns, and ε is the vector of random disturbances. x_1 denotes the $(n \times k_1)$ matrix of variables for which there is no model uncertainty. In our setup, $k_1 = 1$ such that x_1 is vector of ones (the constant term) to emphasize that the constant is included in each model. x_2 is an $(n \times k_2)$ matrix of at most k_2 independent variables theorized to be predictors of bank stock returns. β_1 and β_2 are the unknown parameter vectors. We assume that the disturbances $(\varepsilon_1, ..., \varepsilon_n)$ are independently and identically distributed. Model uncertainty implies that the researcher does not know ex ante the exact composition of the matrix of independent variables x_2 (out of a known and defined set of potential variables). Since model averaging takes place over k_2 regressors, there exist $K = 2^{k_2}$ different model combinations (in the linear case). Let $M^{(k)}$ denote model k under consideration, then

$$y = x_1\beta_1 + x_2^{(k)}\beta_2^{(k)} + \varepsilon \tag{2}$$

with $x_2^{(k)}$ a subset of matrix x_2 with dimension $(n \times k_2^{(k)})$. For model k, $\beta_2^{(k)}$ is the corresponding subvector of interest.

Bayesian model averaging implies that one has to chose prior distributions for the model parameters and the model probability. In specifying priors for BMA, the following general rule applies (Koop (2003)): "When comparing different models, it is acceptable to use non-informative priors over parameters which are common

[10] We stick to a general description of Bayesian Model Averaging in which we explain the main ingredients. For more technical details, we would like to refer the reader to Magnus, Powell, and Prufer (2010)).

to all models. However, informative, proper priors should be used over all other parameters". As mentioned in Kass and Raftery (1995), flat priors are specified only up to an undefined multiplicative constant and so the posterior model probabilities contain an undefined constant. Hence, a non-informative (improper) prior for σ^2 and β_1, respectively Equation (3)[11] and Equation (4), can be used since these parameters are common to all models. The prior for β_2, Equation (5) is informative and centered around zero.

$$p(\sigma^2|M^{(k)}) \propto \sigma^{-2} \tag{3}$$

$$p(\beta_1|\sigma^2, M^{(k)}) \propto 1 \tag{4}$$

$$p(\beta_2^{(k)}|\beta_1, \sigma^2, M^{(k)}) \propto N(0, \sigma^2 V_0^{(k)}) \tag{5}$$

These priors have been used by Fernandez, Ley, and Steel (2001a) and many others in the BMA literature. We specify the prior variance $V_0^{(k)}$ using Zellner's (1986) g-prior. Following Fernandez, Ley, and Steel (2001a) among others, we set $g = inv(\max(n, k_2^2))$ and assume

$$V_0^{(k)} = g^{-1}(x_2^{(k)} M_1 x_2^{(k)})^{-1} \tag{6}$$

where $M_1 = I_n - x_1(x_1^{'}x_1)^{-1}x_1^{'}$. Intuitively, when the data is more informative (the sample size n is larger or the number of explanatory variables k_2 is larger) a weaker prior for β_2 can be used. A larger dataset or a large list of explanatory variables causes g to be smaller, and hence $V_0^{(k)}$ to be larger. This means that the prior is weaker, and hence the model will give more weight to the data, relative to the prior. The value $g = 0$ corresponds to a perfectly non-informative prior.

Similar to the priors for the model parameters, we assign a prior for the model probability for each of the 2^{k_2} possible combinations of regressors. As is common practice in the model averaging literature, we

[11] This stems from $p(\log(\sigma^2)|M_k) \propto 1$. The log transformation is applied to define the probability over both positive and negative values. Since the logarithmic function is a monotone transformation, it holds that $f_Y(y) = f_X(x)\left|\frac{dx}{dy}\right|$, where $y = \exp(x)$, $x = \log(y)$ and $f_X(x) \propto 1$. The second term in the equation can be expressed as $1/y$ or $1/\sigma^2$. Hence, we obtain that $p(\sigma^2|M_k) \propto \sigma^{-2}$.

will assign equal[12] prior probability to all models under consideration. Hence, the prior model probability of model $M^{(k)}$ is expressed as

$$p(M^{(k)}) = \frac{1}{K} \tag{7}$$

The advantage of using the above priors is that the posterior density can be obtained analytically and no posterior simulation is required for the calculation of the posterior and the standard deviation. Under the normal linear regression framework, the likelihood function, assuming model $M^{(k)}$ is the most likely model, is given by

$$p(y|\beta_1, \beta_2^{(k)}, \sigma^2, M^{(k)}) \propto (\sigma^2)^{-n/2} \exp(-\frac{(y - \beta_1 x_1 - x_2\beta_2^{(k)})'(y - \beta_1 x_1 - x_2\beta_2^{(k)})}{2\sigma^2}) \tag{8}$$

By combining the likelihood function and the above priors, given the data y and model M_k, one obtains the joint posterior density (for more info, see e.g.: Koop (2003), O'Hagan (1994), Magnus, Powell, and Prufer (2010)), which takes the form of a normal-gamma distribution.

3.2 Inference: posterior estimates, posterior variance and posterior inclusion probabilities

The above findings can be used to carry out posterior inference conditional on a specific model. However, our goal is to combine information from multiple models. Given the data y and a prior model probability for model $M^{(k)}$ (Equation (7)), the posterior model probability[13] -i.e. the probability that model $M^{(k)}$ is the most likely model, after seeing the data and updating the prior belief- can be expressed as

$$p(M^{(k)}|y) = \frac{p(M^{(k)})p(y|M^{(k)})}{\sum_j p(M^{(j)})p(y|M^{(j)})} = \lambda^{(k)} \tag{9}$$

[12] In an online appendix, we describe an alternative setup, i.e. using the collinearity adjusted dilution prior of George (2010). We document the robustness of our results compared with this model prior.

[13] In a traditional setup, researchers may use the Akaike's information criterion (Akaike (1974)), the Schwarz's criterion (a Bayesian information criterion, Schwarz (1978)) or the Fisher's information criteria (Wei (1992)), among others (Bossaerts and Hillion (1999)) to select a single, most likely model. Because researchers may 'search' for the best specification among a set of alternatives, data snooping and overfitting are genuine concerns, in particular when there are many plausible risk factors that are potentially correlated. Our approach, on the other hand, does not seach for a unique model, but averages over all possible linear models giving a higher weight to more likely models.

where $p(y|M_k)$ is the marginal likelihood. Since all model probabilities sum to one, we must also have that

$$\sum_{k=1}^{K} \lambda^{(k)} = 1$$

To obtain posterior estimates of the slope parameters β_{2i} with $i = 1, ..., k_2$, Bayesian Model Averaging combines the information from all models. The posterior parameter estimate is obtained as the weighted average of the parameter estimates over the different models, where the weights are determined by the posterior model probability $\lambda^{(k)}$.

$$E(\beta_{2i}|y) = \sum_{k=1}^{K} \lambda^{(k)} \cdot E(\beta_{2i}^{(k)}|y, M^{(k)}) \tag{10}$$

where $E(\beta_{2i}^{(k)}|y, M^{(k)})$ is the estimate for the slope parameter β_{2i} given model $M^{(k)}$. Hence, the posterior mean is a weighted average of the estimated slope coefficients.

Following Leamer (1978), the posterior variance is defined as

$$V(\beta_{2i}|y) = \sum_{k=1}^{K} \lambda^{(k)} \cdot V(\beta_{2i}^{(k)}|M^{(k)}) + \sum_{k=1}^{K} \lambda^{(k)} \cdot \left[E(\beta_{2i}^{(k)}|y, M^{(k)}) - E(\beta_{2i}|y)\right]^2 \tag{11}$$

As one can see from equation 11, the posterior variance of β_{2i} consists of two terms: the first is the weighted sum of the variances across all models, whereas the second terms depends on the difference between the posterior mean (equation 10) and the model specific estimates $E(\beta_{2i}^{(k)}|y, M^{(k)})$. Hence, if the parameter estimate is very dispersed across models, this implies larger model uncertainty which is translated into larger parameter uncertainty.

The posterior model probability gives insight into which model is most likely. However, a model is defined through the inclusion or exclusion of a set of explanatory variables. Hence, it would be more interesting to have a metric that expresses how likely it is a certain regressor should be included in the "true" model. This is what is captured by the "posterior inclusion probability". This can be interpreted as the probability that the corresponding explanatory variable should be included in the model. Using this metric, (static) Bayesian Model Averaging gives insight into the probability that a factor should be included in a model explaining bank stock returns. Following Leamer (1978) and Doppelhofer and Weeks (2009), it is calculated as the sum of the posterior model probabilities of the models that include variable x_{2i} with $i = 1, ..., k_2$. Formally, the posterior inclusion probability of variable x_{2i} is given by

$$p(x_{2i}|y) = \sum_{k=1}^{K} \lambda^{(k)} \cdot I(x_{2i} \in x_2^{(k)}|y, M^{(k)}) \tag{12}$$

where I is an indicator equal to one if the variable x_{2i} is present in model $M^{(k)}$ and zero otherwise. Since a model is defined through the inclusion or exclusion of a set of variables, the importance of a variable (captured by its posterior inclusion probability) and its significance (captured by its estimated standard error) are related objects. Masanjala and Papageorgiou (2008) state that a posterior inclusion probability of 0.50 corresponds approximately to an absolute t statistic of 1. This idea is similar to the relationship between the adjusted R^2 and the t statistic in frequentist economics. If one variable is deleted from a model, it will always decrease the R^2, but it will only decrease the adjusted R^2 if the t statistic is below 1 in absolute value (Magnus, Powell, and Prufer (2010)).

4 Empirical Results

4.1 Bayesian Model Averaging: Full Sample Results

4.1.1 The sample of the 50 largest BHCs

Table 5 summarizes the full-sample estimation results for the Bayesian Model Averaging approach using the 12 bank risk factors discussed in Section 2.2 and the benchmark index of the 50 largest BHCs. In the top panel, we report for each risk factor (12 columns) the OLS factor exposure and t-statistic, the BMA factor exposure and t-statistic as well as the Posterior Inclusion Probability of that factor. We see that the market, HML, and real estate factor have a Posterior Inclusion Probability (PIP)[14] of 100 percent, strongly indicating that these three factors should be included in a model for bank stock returns. The low uncertainty

[14] In addition to the posterior mean and the posterior inclusion probability of the coefficient, we also compute the sign certainty statistic, as used in Sala-I-Martin, Doppelhofer, and Miller (2004) and Doppelhofer and Weeks (2009). This is a measure of the posterior confidence in the sign of the coefficient, and it is calculated as the posterior probability that the coeffcient is on the same side of zero as its mean conditional on inclusion. We find that the sign certainty statistic is very much in line with the posterior inclusion probability of the risk factors. When the posterior inclusion probability of a variable is high (such as for the market factor, the HML and the real estate factor), the sign certainty statistic is also high, meaning that we can be quite confident about the direction of the impact of a change in the risk factor on bank stock returns.

about the inclusion of these three factors is reflected in the small differences between the OLS and BMA factor exposures. In line with previous literature, we find the estimated market beta to be around 1 over the full sample period. The HML exposure is highly statistically significant and has a positive sign, as expected given its positive (negative) association with future economic growth (distress risk). Given that booming and subsequently rapidly decreasing housing prices were one of the key causes of the financial crisis that started in 2007, our finding of a positive and significant association of our real estate factor with bank stock returns is unsurprising[15]. All other factors, with the exception maybe of the short rate (TB), have PIPs and factor exposures close to zero. That PIPs are either relatively close to a 100 or 0 percent signals the ability of the model to distinguish between important and redundant factors.

BMA also provides information on how likely a given model is, represented by the posterior model probability. In the lower panel of Table 5, we report information on the ten model specifications that get the highest model probability. We report information on the likelihood of the model, which factors are included in the model as well as its adjusted R-squared. The combined information in the upper panel and lower panel is indicative of why relying solely on OLS and/or including all factors at the same time may yield misguided conclusions. First, the 12 factor model is not among the top 10 models. The richest top 10 model contains at most 5 factors. Not surprisingly, the market, HML, and real estate factor are part of all these models (thus leading to a PIP of 100%). Second, a model consisting of only these three factors is the most likely. Nevertheless, it has a posterior model probability of 'only' 23.83 per cent. One other specification (which also includes the T-bill rate) is almost as likely and has a PMP of 23.5%. None of the other models has a posterior model probability exceeding 7.5%. Alternative models include other factors (2 of the top-10 models include the default spread or money market spread; the TED spread, the deposit spread, the effective exchange rate, and the VXO each appear once), but have much lower PMPs (7.3 percent for the $3rd$ most likely model to only 1.8 percent for the $10th$ most likely model). Third, based on the full specification and OLS results, we would conclude that the 3 month T-bill, interbank distress (MMS) and market sentiment (VXO) are also significantly related to bank stock returns. However, they only appear sporadically in the

[15]Because our real estate factor is based on a market-weighted index of listed real estate companies that invest both in residential and commercial real estate, this factor may not only reflect movements in housing prices, but also broader changes in the economic environment. However, when we orthogonalize this factor with respect to contemporaneous innovations in the market and Fama-French factors, its PIP remains close to a 100 percent, and the factor exposure is positive and significant.

top 10 models. For example, there is a large difference between the OLS and BMA factor exposure for the three month Treasury Bill (-2.37^{***} versus -0.69). From an OLS regression of returns on our benchmark index on all 12 risk factors, the econometrician would conclude that this factor is an important explanatory variable for bank stock returns. The much lower BMA exposure suggests, however, that this model has a very low Posterior Model Probability (PMP) and that it is not an important component of much more likely models. Fourth, while PIPs are in general much better in discriminating between good and bad models (see e.g. Ciccone and Jarocinski (2010)), it is still worth noting that the differences in adjusted R^2 between a specification with just the market, HML, and real estate factor and more elaborate models is rather small, casting serious doubt on the usefulness of these additional factors in explaining bank stock returns[16].

4.1.2 Heterogeneity across types of Financial Institutions and BHCs

The findings for our benchmark portfolio of the 50 largest BHCs are largely replicated for samples of Depository, Insurance, Broker-Dealer, and other non-depository financial institutions. These result are reported in Columns 2 to 5 of Table 6 (the first column reproduces the results of the baseline portfolio). The market and real estate factor are part of the preferred model for all types of financial institutions, whereas the HML factor is significant for all except insurance corporations. All exposures to these factors have the expected positive sign, are highly statistically significant, but the estimated coefficients vary in magnitude across the different portfolios. The other factors have PIPs close to zero with very few exceptions. The VXO factor has a PIP of 51 percent for depository and of 72 percent for other non-depository financial institutions, and

[16] Multicollinearity between the regressors could prevent us from finding the correct significant relationships, as it tends to blow up standard errors. To test the robustness of our results to multicollinearity, we replace the TED, money market, and deposit spread – all measures of some aspect of liquidity stress – with their first principal component. Additionally, we orthogonalize the VIX and the real estate indicator to innovations in the market and Fama-French portfolio returns. Our BMA results remain qualitatively the same. The change in posterior inclusion probability between the results in Table 5 and the results with this new set of regressors is 2% at most (for the three month Treasury Bill rate). Second, we test the robustness of our results with respect to a different model prior. One could argue that the uninformative model prior, giving equal prior probability to all models, puts too much weight on redundant models with correlated regressors, and too few weight on good but unique models. To address this critique, we use the collinearity adjusted dilution prior (George (2010)) to downweight models with highly collinear regressors. Again, our conclusions remain unchanged. The highest difference in posterior inclusion probability between the two different model priors is 3% (for the VIX). Results of these additional tests are available upon request.

the expected negative sign. The term spread factor is part of the preferred model for other non-depository institutions, while its PIP is only marginally below 50 percent for broker-dealers. We observe similar PIP's of about 40 percent for the Treasury Bill factor for depository institutions and broker-dealers, both with the expected negative sign.

For the various BHC portfolios (Columns 6-11 of Table 6), the preferred models include the SMB Fama-French factor next to the market, HML, and real estate factor. Again, other factors have PIPs close to zero with very few exceptions. The volatility index VXO has PIPs of 85 and 90 percent for the portfolios of smallest 50 and retail BHCs, respectively, while the difference between the Federal Funds Overnight Interest Rate and the 3-month Treasury Bill rate seems significantly related to the portfolio returns of the smallest 50 BHCs.

In sum, our full-sample BMA results suggest that the market, Fama-French, and real estate factors are the most relevant factors for bank stock returns, and that most other factors, maybe with the exception of the volatility index VXO, are largely unimportant. While the limited support for many of the additional risk factors confirms previous evidence of e.g. Schuermann and Stiroh (2006), the lack of finding significant exposures over the full sample may just reflect structural instability in the parameters. For instance, factors mimicking stress in the interbank or deposit market may only become important during business cycle downturns or financial crises. The focus on liquidity risk, for instance, intensified since the collapse of the UK-based bank Northern Rock, which failed mainly because it was too heavily reliant on wholesale funding, and hence, could not refund itself in case of a dry-up in the interbank market. Therefore, we introduce time variation in the model selection and factor exposures in the next subsection.

4.2 Modelling Time Variation in Model Uncertainty

To show the importance of allowing for time variation, we proceed in two steps. In a first step, we show in Table 7 the composition of the top-10 models before and after the start of the financial crisis in 2007 for our benchmark portfolio of the largest 50 BHCs[17]. We notice a number of interesting differences between the full and subsample results. First, the optimal number of factors seems to be somewhat larger in the pre-2007 period, suggesting that the lack of accommodating for structural breaks may indeed be one of the reasons for the lack of significant factor exposures. The VXO volatility index, the T-Bill rate as well as the difference

[17]The sample period is split in two: January 1986 - July 2007 and August 2007 - December 2010.

between the three month deposit rate and the three month Treasury Bill rate (DepS) are part of most, if not all, top-10 models pre-2007. Hence, in the pre-2007 period, banks did not have significant exposure to credit risk, but were exposed to market sentiment (VXO) as well as interest rate risk. Most of these factors disappear after 2007, but are replaced by the default spread factor, which is part of all of the top-10 models in the post-2007 period. As the banking crisis started to spill over to the real economy, default risk started to increase, further depressing bank stock returns. Second, while before August 2007 the top-3 models have a joint probability of nearly 60 percent (23.5% for the top model), this drops to less than 22 percent in the post-2007 period (8.06% for top model). Somehow it seems that the uncertainty induced by the financial crises also leads to higher model uncertainty. Relying on a single model during a crisis to assess and monitor bank risk is clearly insufficient. Third, the adjusted R^2 of the top-10 models is much higher in the post-2007 period (83% versus 51%), which is consistent with the notion that common factors (and hence correlations between banks) become more important in times of high volatility.

In a second step, we investigate the time-varying factor inclusion and exposures in more detail. We estimate our BMA model over quarterly rolling windows of two years using weekly data[18]. Panel A of Table 8 shows for each 'bank type-risk factor' pair the percentage of observations with a PIP larger than 50 percent. Panel B of the same Table 8 shows for each 'bank type-risk factor' pair the corresponding marginal R^2. The latter is calculated as the average (over time) difference in R^2 between a model that does and one that does not include a particular risk factor, conditional on that risk factor having at that point in time a PIP larger than 50 percent[19] In panel C, we report the average factor exposure for a given portfolio, conditional on that risk factor having at that point in time a PIP larger than 50 percent. Figure 1 gives a graphical representation of when which factors are important and for which types of banks.

On average across all portfolios, the market factor has in 92% of times a PIP larger than 50 percent, with an interquartile range (difference between value of 75^{th} and 25^{th} percentile) of 14%. The smallest percentage is observed for the portfolio of 50 smallest BHCs (66%). Panel A of Figure 1 shows that small banks were mainly disconnected from the market over the 2000-2008 period, after which the connection was restored

[18] The first estimate is obtained for the last quarter of 1987.

[19] The marginal R^2 is calculated as follows: for each risk factor and in each estimation window, we take the difference between the model weighted R^2 (where the weights are given by the posterior model probabilities), and the model weighted R^2 of all models, excluding the specific risk factor. In the latter case, the posterior model probabilities are rescaled to ensure that the posterior model probabilities sum up to one.

again. For large banks (both 50 or 15 largest BHCs), we find, on the other hand, that the market factor loses significance from the second half of 2009 onwards (which corresponds with an estimation window of 2007Q2-2009Q2). In the last six quarters of our sample period, the HML factor, which captures distress and credit risk, becomes more important than the market factor for the (larger and) largest BHCs.

Panel A of Table 8 confirms the result from the full-sample analysis that the Fama-French and real estate factors are the most important bank risk factors other than the market. The HML factor is on average 'on' in 58.3% of observations, with a tight interquartile range of 27%. In contrast to the full sample results (see Table 6), where the SMB factor was found to be an unimportant factor for the returns on depository, broker-dealer, and insurance corporations, the rolling-window estimates reveal that the SMB factor enters the optimal model in on average 53.5% of observations, though with a rather broad interquartile range (44%). Not including the HML and SMB factors in times their PIP is larger than 50 percent would lead to a substantial (absolute) loss in R^2 of 7.9% and 6.3%, respectively. Despite having a PIP of 100% in the full-sample analysis, our time-varying analysis reveals that the real estate factor has a PIP larger than 50% in on average 25% of observations, with an interquartile range of 19%. Wrongly excluding the real estate factor would lead to a moderate loss in R^2 of 2.2% on average. Figure 1 shows that nearly all cross-sectional BHC portfolios disconnect from the HML factor in the 2004-2007 period, to reconnect again during the global financial crisis. The HML is 'on' most of the other times, except for the Broker-Dealer and other non-depository financial institutions, which seem rather unexposed to the HML factor. The SMB risk factor seems to mainly affect the cross-sectional portfolios of BHC's, and to a lesser extent the Insurance, Broker-Dealer, and other non-depository financial institutions. The largest BHCs and broker-deal and other non-depository institutions are, however, most frequently exposed to real estate shocks. The marginal increase in R^2 from including the real estate factor is largest for the portfolio of 50 smallest BHCs (5%).

The other factors exhibit a considerably smaller proportion of observations with a PIP larger than 50%. The implied volatility index (VXO) is 'on' in on average 13.8% of cases. The VXO seems most relevant during the LTCM-Russian crisis and to some lesser extent during the global financial crisis. We observe the largest proportions for the distressed BHCs (18.7%) and 50 largest banks (17.6%). The marginal increase in R^2 is comparable to that of the real estate factor, about 2.2%, with a narrow interquartile range. The term spread factor is part of the preferred model in 11.9% of cases, and increases the R^2 with on average 3.1% (interquartile range of 1%). The highest frequencies of 'on' states are observed for the Broker-Dealer

(20.9%) and other non-depository financial institutions (22%). The largest 15 banks are more exposed to term spread shocks than the smallest 50 banks (12.1% versus 4.4%). Similarly, non-retail banks have a more frequent exposure than retail banks (12.1% versus 4.4%).

To further investigate whether other factors than the market are significantly related to bank stock returns, Figure 2 plots at each point in time the number of factors with a PIP larger than 50 percent, (left axis) and the average difference in R^2 between the 'optimal' and a simple market model (dotted line with scale on the right axis). The optimal number of factors seems to vary mostly between 1 and 6 (in some exceptional cases 0 or 7), and seems to be highest on average in the aftermath of the Russian/LTCM crisis and subsequent burst of the technology bubble, and since the start of the financial crisis (third quarter of 2007). The lowest number of relevant factors is observed during the relatively tranquil 2004-2006 period. The increase in adjusted R^2 from including risk factors other than the market ranges from slightly negative[20] to more than 10%. For our benchmark index (Panel A of Figure 2), the marginal R^2 peaks to values close to 10% in the mid-nineties, directly after the Russian/LTCM crisis, and during the global financial crisis. The increase in R^2 is not purely the result of increased explanatory power of existing factors, as the increase in R^2 seems also associated with an increase in the optimal number of factors. We obtain similar results for the cross-sectional portfolio analysis. For each of the four types of FIs, the time-varying optimal number of factors with a PIP exceeding 50%, ranges between 1 and 6, with incremental gains in the adjusted R-squared (with respect to a single factor model) of up to 10%. For the various portfolios of BHCs, we find similar results with respect to the number of factors (with a maximum of seven relevant factors around the turn of the millennium for small BHCs, diversified BHCs and sound BHCs). The gains in R-squared can be even more substantial, with maximal gains of 20% (for distressed BHCs) and 15% for the smallest BHCs and diversified BHCs. The main conclusion drawn from Figure 2 is that factors other than the market are important. Moreover, how many factors are important and their impact on explanatory power varies over time (especially in times of market stress) and across types of BHCs and FIs.

[20] Because we look at adjusted R^2s, this difference can indeed be negative.

5 Implications for empirical bank research using stock returns

Models of bank stock returns are used as inputs in various types of empirical banking research, e.g., event studies, the decomposition of total bank risk in relevant components, proxies for bank opacity, and various related types of analysis. We document that the optimal combination of relevant risk factors may vary over time and may differ according to the type of financial institution under investigation. This implies that due diligence is required in the specification of the bank factor model and that each empirical setup has to be tailored to the specific research question.

Many empirical banking studies examine the impact of an exogenous event on banks' valuation. These events could be bank-specific, such as mergers and acquisitions (Kane (2000) and Hankir, Rauch, and Umber (2011)), or sector-wide; e.g. banking or financial crises or regulatory changes (Johnson and Sarkar (1996) and Mamun, Hassan, and Maroney (2005)). To conduct such an event study, it is crucial to obtain an accurate measure of the (cumulative) abnormal return in response to the announced event. Our study yields three suggestions for the computation of cumulative abnormal returns. First, it is important to control for other risk factors in addition to returns on a broad market portfolio. For example, for the set of the 50 largest banks, the optimal number of factors varies over time between one and six. The explained variation in bank stock return can be increased by as much as 10%. Not controlling for other factors may yield a misspecified factor model leading to incorrect abnormal returns. A simple exercise gives an indication of the potential magnitude. For the portfolio of 50 largest BHCs, we compute for each quarter (event window) the cumulative abnormal return, using the previous 8 quarters as the estimation window, based on our model as well as a single factor model. The average difference over the 91 events (quarters) is small (-0.4%)[21]. However, the bias can be quite substantial during specific quarters and especially during NBER-dated recessions. In recessions, the average deviation in quarterly CARs is -4.9%. Second, the BMA implied model specification varies over time. Hence, in an ideal setup, the specification of the factor model changes for events that take place at different points in time (for example, M&As). Third, imposing the same model for various types of BHCs in a given time period may yield biased (cumulative) abnormal returns, since different types of BHCs sometimes imply different models. For example, in 2000, a model with a single factor (the market)

[21] This difference in abnormal returns between our model and a single factor model is conceptually the same as the difference in one-quarter ahead forecast errors between these two models.

is sufficient for retail BHCs, but would underestimate the R-squared of the richest model by almost 14% for diversified BHCs. Hence, abnormal returns (or other performance indicators such as alpha), based on a single factor model, could lead to an incorrect comparison between diversified banks and retail banks at the turn of the millennium.

The flip side of the above comment is that idiosyncratic volatility is overestimated whenever R-squared is underestimated. Using BMA, we document that this measurement is heterogeneous in two dimensions. Model uncertainty (both in terms of number of factors and the goodness of fit) varies over time, but more importantly, also in the cross-section. Many studies try to explain the cross-section of banks' idiosyncratic volatility. For example, Stiroh (2006b) and Baele, De Jonghe, and Vander Vennet (2007) document that banks with more non-interest income have lower idiosyncratic risk up to a turning point (at which they become overexposed to non-traditional banking activities). In both studies, a similar return-generating model is used for the entire set of banks. However, we document that the model specifications (and increased goodness of fit) for retail and diversified BHCs can be substantially different from each other over certain episodes, which may affect the results of the aforementioned studies.

There is a large literature that studies the link between opacity and R-squared (see e.g. Jin and Myers (2006) and Hutton, Marcus, and Tehranian (2009)). Firms with more opaque financial reports have stock returns that are more synchronous with market-wide factors and hence have a higher R-squared. In addition, there is theoretical and empirical evidence that opaque firms (with higher R-squared) are more prone to stock price crashes. Our results in Table 8 indicate that opacity is substantially larger in the post-2007 period compared with the pre-2007 period. When the R-squared is based on a single factor model, substantial mismeasurement can occur. For the benchmark portfolio of the 50 largest BHCs the underestimation of the R-squared ranges between 0% and 10%. More important, however, is that ignoring model heterogeneity for different banking types can lead to imprecise (but not necessarily incorrect) conclusions. For example, the difference in R-squared between distressed and sound banks is underestimated (based on a single factor, market model) by 5 to 10 percent over the period 1999-2002. Based on an extended and more appropriate model, the difference in opacity and crash risk between distressed and sound banks would be estimated more precisely. Similarly, in the 4 years prior to the 2007 crisis, the crash risk of broker dealers was underestimated when measured with a single factor model.

Finally, omitting important risk factors may lead to biased estimates of market betas. Accurate estimation of the market beta is important for several reasons. First, the estimate of a bank's systematic risk directly affects the bank's cost of capital[22]. A second reason is that the estimate of systematic risk may affect the bank's (regulatory) provisions for market risk. Finally, systematic risk is used as a measure of risk in several studies (see e.g., Stiroh (2006) and Saunders, Strock, and Travlos (1990)). In these papers, the estimate of market risk exposure (obtained in a first step) is used in a second step as a dependent variable, and related to the riskiness of non-interest related sources of income, or the bank's ownership structure. Hence, it is important that systematic risk is properly measured in the first step.

Figure 3 shows the divergence in market beta estimated in a benchmark one-factor model versus our posterior estimates of market risk exposure in the BMA analysis. During the period between 2000 and 2006, we find a steady increase in the market beta from 0.5 to 0.9, a finding that has also been documented by Bhattacharyya and Purnanandam (2012), who report an increase in market beta from 0.4 in 2000 to 1 in 2006. During this period, both market beta estimates are very similar, suggesting a minor role for the other risk factors. However, during the most recent financial crisis, we find that the market beta obtained from a benchmark one-factor model increases, whereas the BMA market beta decreases; a clearly opposite pattern (see Figure 3). This suggests that the other risk factors gain in importance, as discussed in Section 4.2. In the recent crisis, the HML Fama-French factor, an indicator of distress, becomes more important. A similar pattern emerges during the period of the millennium change, where the market beta estimated in a one-factor model is overestimated with respect to our BMA estimate, although to a lesser extent.

The figure shows that both measures are not always equal and that the largest differences arise during periods of market stress, such as the period around the millennium change, and most strikingly during the recent financial crisis. In a single factor model, the market beta "absorbs" information contained in the (missing) risk factors and tends to increase[23]. Yet, as is reflected by the substantially higher R-squared of the multifactor model and the many significant factor exposures, information is lost in this "absorption"

[22]This paper does not provide evidence on the pricing of the risk factors. To do so, one would need to set up cross sectional asset pricing tests such as in Fama and French (1992), or in Viale, Kolari, and Fraser (2009) in the empirical banking literature. However, such an analysis is beyond the scope of this paper.

[23]To show this, we also run our time-varying BMA analysis on the twelve factors, in which each of the factors (except the market factor) is orthogonalized with respect to the market. Even in this setup, some of the other factors are significant and the fit of the regression is improved, indicating that these factors contain additional information.

process. We believe that studies trying to understand bank risk should not just relate bank-specific variables to the market beta, but to exposures of the full set of risk factors that are found to be relevant at a particular point in time.

6 Conclusion

Banks are exposed to various risks by the nature of their business. Through interconnectedness and contagion, individual bank defaults may affect financial system stability and ultimately spill over to the real economy. Therefore, prudential regulation in the banking industry tries to limit banks' risk taking incentives. However, regulation did not prevent the $2007-9$ crisis. Therefore, it remains important for supervisors to adequately track bank risk over time. The identification of relevant bank risks and their measurement remains an important challenge. Therefore we investigate the question: Which risk factors are relevant to which type of financial institution at which point in time?

This paper contributes to the literature that measures banking risk as the exposures of bank stock returns to a set of pre-defined risk factors. We start by arguing that there is no consensus on what the correct set of risk factors is. The 24 previous papers that we identify relate bank stock returns in various combinations to no less than 17 different risk factors. All models include a market and (combinations of different) interest rate factor(s).

Factor exposures are typically estimated using ordinary least squares (OLS) with a fixed set of risk factors. There is, however, considerable uncertainty about what the appropriate set of risk factors is. Missing important factors may lead to underperforming models at best and wrong conclusions at worst. We apply an empirical technique, Bayesian Model Averaging (BMA), which explicitly takes into account this 'model uncertainty'. BMA compares all models (potential combinations of the different risk factors) simultaneously, instead of focusing on just one specification, and attaches a posterior probability to each model. Individual factors will only be considered important (have a high posterior inclusion probability) to the extent that the models in which they appear have a high posterior model probability.

We apply BMA to a benchmark portfolio of Bank Holding Companies, as well as to returns on portfolios of other types of financial institutions (insurance companies and broker-dealers) and of Bank Holding Companies with different characteristics (large/small, retail/diversified, and sound/distressed BHCs). Our set of 12 candidate risk factors includes most of the risk factors used in previous papers, as well as some that recently emerged, such as the implied volatility on S&P500 options (as a measure of sentiment) and the TED spread (as a measure of financial sector credit risk).

Full sample (1986−2010) results reveal that the market, real estate, and the high-minus-low (HML) Fama-French factor are the most important drivers of bank stock returns, with posterior inclusion probabilities close to 100 percent. The importance and positive and significant sign of the HML factor exposure is consistent with the findings of Liew and Vassalou (2000) that the HML factor is positively (negatively) associated with news about the future state of the economy (distress risk) that is not captured by the market portfolio. Given that booming and subsequently rapidly decreasing housing prices were one of the key causes of the financial crisis that started in 2007, our finding of a positive and significant association of our real estate factor with bank stock returns is a relevant finding for bank supervisors. What is more surprising is that other factors, and in particular interest rate factors, do not seem to be reliably related to bank stock returns. This may suggest that changes in the risk factors were largely anticipated by market participants or that financial institutions are expected to hedge their associated exposures. Overall, we find limited evidence that the relevant set of risk factors varies significantly across different types of financial institutions / BHCs. Our time-varying analysis shows that our failure to find significant exposures to risk factors other than the market, HML and real estate factor in the full sample is at least to some extent caused by structural instability in the estimated parameters. Other factors, such as the implied volatility, term spread, and SMB factor, which remained undetected in the full sample estimations, frequently switch between the 'on' and 'off' state. The optimal number of factors varies between 1 (just the market) and 7, and tends to increase with market uncertainty. The increase in (adjusted) R-squared from including risk factors other than the market amounts at times to more than 20 percent (10 percent for our benchmark model). Hence, relevant bank risk exposures vary over time, which may have implications for bank management (e.g., the cost of capital), investors (e.g., expected returns from investing in bank stock) and supervisors (e.g., time-varying exposures of financial institutions to unexpected economic or financial market shocks).

A final section explores the implications of our findings for empirical banking research based on stock returns and for bank supervisors. Using a simple simulation exercise, we show that abnormal returns typically used in event studies are meaningfully affected by a (suboptimal) choice of risk factors, especially in bad times. Failing to include relevant risk factors also biases residual-based measures of uncertainty (idiosyncratic volatility), measures of opaqueness (R-squared), and, as we show, also indicators of systematic risk (betas).

This paper has focused on the set of linear factor models only. Future research could explore non-linear models as well. Theoretical work by Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), and Santos and Veronesi (2004) shows that firm betas may change with the state of the economy and firm characteristics. Baele, Bekaert, and Inghelbrecht (2010) show that the exposures of stock and bond returns to a set of fundamental factors varies with measures of market sentiment and liquidity. As a first exploration, we perform a full sample BMA estimation for our benchmark portfolio on our 12 risk factors, and those same risk factors interacted with the implied volatility index. We find the number of linear factors with a PIP larger than 50 percent to increase (apart from the market, HML, and real estate, also the T-bill rate, term and default spread). The exposure to the real estate and HML increases with the implied volatility index, while the exposure to the term and default spread decreases. We leave a full exploration of such nonlinear models for further research.

References

Acharya, V., L. H. Pedersen, T. Philippon, and M. Richardson, 2012, "Measuring Systemic Risk," *CEPR Discussion Papers 8824*.

Acharya, V. V., and N. Mora, 2012, "Are Banks Passive Liquidity Backstops? Deposit Rates and Flows during the 2007-2009 Crisis," *National Bureau of Economic Research Working Paper Series*, No. 17838.

Adrian, T., and M. Brunnermeier, 2009, "CoVar," *Federal Reserve Bank of New York Staff Report Nr 348*.

Akaike, H., 1974, "New Look at Statistical-Model Identification," *Ieee Transactions on Automatic Control*, Ac19(6), 716–723.

Ang, A., M. Piazzesi, and M. Wei, 2006, "What does the Yield Curve Tell us about GDP Growth?," *Journal of Econometrics*, 131, 359–403.

Avramov, D., 2002, "Stock return predictability and model uncertainty," *Journal of Financial Economics*, 64(3), 423–458.

Baele, L., G. Bekaert, and K. Inghelbrecht, 2010, "The Determinants of Stock and Bond Return Comovements," *Review of Financial Studies*, 23(6), 2374–2428.

Baele, L., O. De Jonghe, and R. Vander Vennet, 2007, "Does the stock market value bank diversification?," *Journal of Banking and Finance*, 31(7), 1999–2023.

Berk, J. B., R. C. Green, and V. Naik, 1999, "Optimal Investment, Growth Options, and Security Returns," *The Journal of Finance*, 54(5), 1553–1607.

Bhattacharyya, S., and A. Purnanandam, 2012, "Risk-Taking by Banks: What Did we Know and When Did We Know it?," *AFA 2012 Meetings Paper*.

Bossaerts, P., and P. Hillion, 1999, "Implementing statistical criteria to select return forecasting models: What do we learn?," *Review of Financial Studies*, 12(2), 405–428.

Brock, W. A., and S. N. Durlauf, 2001, "Growth empirics and reality," *World Bank Economic Review*, 15(2), 229–272.

Campbell, J. Y., and T. Vuolteenaho, 2004, "Bad beta, good beta," *American Economic Review*, 94(5), 1249–1275.

Chamberlain, S., J. S. Howe, and H. Popper, 1997, "The exchange rate exposure of US and Japanese banking institutions," *Journal of Banking and Finance*, 21(6), 871–892.

Chaudhry, M. K., R. Christie-David, T. W. Koch, and A. K. Reichert, 2000, "The risk of foreign currency contingent claims at US commercial banks," *Journal of Banking and Finance*, 24(9), 1399–1417.

Chen, N.-f., and F. Zhang, 1998, "Risk and Return of Value Stocks," *The Journal of Business*, 71(4), 501–535.

Choi, J. J., and E. Elyasiani, 1997, "Derivative exposure and the interest rate and exchange rate risks of US banks," *Journal of Financial Services Research*, 12(2-3), 267–286.

Choi, J. J., E. Elyasiani, and K. J. Kopecky, 1992, "The Sensitivity of Bank Stock Returns to Market, Interest and Exchange-Rate Risks," *Journal of Banking and Finance*, 16(5), 983–1004.

Ciccone, A., and M. Jarocinski, 2010, "Determinants of Economic Growth: Will Data Tell?," *American Economic Journal-Macroeconomics*, 2(4), 222–246.

Cremers, M., 2002, "Stock Return Predictability: A Bayesian Model Selection Perspective," *Review of Financial Studies*, 15(4), 1223–1249.

De Jonghe, O., 2010, "Back to the basics in banking? A Micro-Analysis of Banking System Stability," *Journal of Financial Intermediation*, 19(3), 387–417.

Demsetz, R., and P. Strahan, 1997, "Diversification, Size and Risk at Bank Holding Companies," *Journal of Money, Credit and Banking*, 29(3), 300–313.

Dewenter, K. L., and A. C. Hess, 1998, "An international comparison of banks' equity returns," *Journal of Money, Credit and Banking*, 30(3), 472–492.

Doppelhofer, G., and M. Weeks, 2009, "Jointness of Growth Determinants," *Journal of Applied Econometrics*, 24(2), 209–244.

Elyasiani, E., and I. Mansur, 1998, "Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: A GARCH-M model," *Journal of Banking and Finance*, 22(5), 535–563.

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz, 2012, "This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis," *The Journal of Finance*, 67(6), 2139–2185.

Fama, E. F., and K. R. French, 1992, "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47(1992), 427–465.

Fama, E. F., and K. R. French, 1996, "Multifactor explanations of asset pricing anomalies," *Journal of Finance*, 51(1), 55–84.

Fernandez, C., E. Ley, and M. F. J. Steel, 2001a, "Benchmark priors for Bayesian model averaging," *Journal of Econometrics*, 100(2), 381–427.

——— , 2001b, "Model uncertainty in cross-country growth regressions," *Journal of Applied Econometrics*, 16(5), 563–576.

Flannery, M. J., A. S. Hameed, and R. H. Harjes, 1997, "Asset pricing, time-varying risk premia and interest rate risk," *Journal of Banking and Finance*, 21(3), 315–335.

Flannery, M. J., and C. M. James, 1984a, "The Effect of Interest-Rate Changes on the Common-Stock Returns of Financial Institutions," *Journal of Finance*, 39(4), 1141–1153.

——— , 1984b, "Market Evidence on the Effective Maturity of Bank Assets and Liabilities," *Journal of Money, Credit and Banking*, 16(4), 435–445.

Garleanu, N., and L. H. Pedersen, 2011, "Margin-based Asset Pricing and Deviations from the Law of One Price," *Review of Financial Studies*, 24(5).

Gatev, E., and P. E. Strahan, 2006, "Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market," *The Journal of Finance*, 61(2), 867–892.

George, E. I., 2010, "Dilution priors: Compensating for model space redundancy," *IMS Collections, Borrowing Strength: Theory Powering Applications; A Festschrift for Lawrence D. Brown*, 6, 158–165.

Giesecke, K., and B. Kim, 2011, "Systemic Risk: What Defaults are Telling Us," *Management Science*, 57(8), 1387–1405.

Gomes, J., L. Kogan, and L. Zhang, 2003, "Equilibrium Cross Section of Returns," *Journal of Political Economy*, 111(4), 693–732.

Hankir, Y., C. Rauch, and M. P. Umber, 2011, "Bank Mergers and Acquisitions: A market power story?," *Journal of Banking and Finance*, 35(9), 2341–2354.

He, L. T., F. C. N. Myer, and J. R. Webb, 1996, "The sensitivity of bank stock returns to real estate," *Journal of Real Estate Finance and Economics*, 12(2), 203–220.

Hess, A. C., and K. Laisathit, 1997, "A market-based risk classification of financial institutions," *Journal of Financial Services Research*, 12(2-3), 133–158.

Hirtle, B. J., 1997, "Derivatives, portfolio composition, and bank holding company interest rate risk exposure," *Journal of Financial Services Research*, 12(2-3), 243–266.

Hoeting, J. A., D. Madigan, A. E. Raftery, and C. T. Volinsky, 1999, "Bayesian model averaging: A tutorial," *Statistical Science*, 14(4), 382–401.

Hutton, A. P., A. J. Marcus, and H. Tehranian, 2009, "Opaque financial reports, R-2, and crash risk," *Journal of Financial Economics*, 94(1), 67–86.

IMF, 2009, "Responding to the Financial Crisis and Measuring Systemic Risks," *Global Financial Stability Report*, April 2009.

Jin, L., and S. C. Myers, 2006, "R-2 around the world: New theory and new tests," *Journal of Financial Economics*, 79(2), 257–292.

Johnson, S. A., and S. K. Sarkar, 1996, "The valuation effects of the 1977 Community Reinvestment Act and its enforcement," *Journal of Banking and Finance*, 20(5), 783–803.

Kane, E. J., 2000, "Incentives for banking megamergers: What motives might regulators infer from event-study evidence?," *Journal of Money, Credit and Banking*, 32(3), 671–701.

Kane, E. J., and H. Unal, 1988, "Change in Market Assessments of Deposit-Institution Riskiness," *Journal of Financial Services Research*, 1(3), 207–229.

Kass, R. E., and A. E. Raftery, 1995, "Bayes Factors," *Journal of the American Statistical Association*, 90(430), 773–795.

Koop, G., 2003, "Bayesian Econometrics," *Wiley*.

Lajeri, F., and J. Dermine, 1999, "Unexpected inflation and bank stock returns: The case of France 1977-1991," *Journal of Banking and Finance*, 23(6), 939–953.

Leamer, E. E., 1973, "Multicollinearity - Bayesian Interpretation," *Review of Economics and Statistics*, 55(3), 371–380.

——— , 1978, "Specification Searches: Ad Hoc Infererence with Nonexperimental Data," *Wiley*, New York.

Liew, J., and M. Vassalou, 2000, "Can book-to-market, size and momentum be risk factors that predict economic growth?," *Journal of Financial Economics*, 57(2), 221–245.

Lloyd, W. P., and R. A. Shick, 1977, "Test of Stones 2-Index Model of Returns," *Journal of Financial and Quantitative Analysis*, 12(3), 363–376.

Londono, J. M., 2011, "The variance risk premium around the world," *International Finance Discussion Papers*, 2011-1035.

Lynge, M. J., and J. K. Zumwalt, 1980, "An Empirical-Study of the Interest-Rate Sensitivity of Commercial Bank Returns - a Multi-Index Approach," *Journal of Financial and Quantitative Analysis*, 15(3), 731–742.

Magnus, J., O. Powell, and P. Prufer, 2010, "A comparison of two model averaging techniques with an application to growth empirics," *Journal of Econometrics*, 154(2), 139–153.

Mamun, A., M. K. Hassan, and N. Maroney, 2005, "The Wealth and Risk Effects of the Gramm-Leach-Bliley Act (GLBA) on the US Banking Industry," *Journal of Business Finance and Accounting*, 32(1-2), 351–388.

Masanjala, W. H., and C. Papageorgiou, 2008, "Rough and lonely road to prosperity: A reexamination of the sources of growth in Africa using Bayesian model averaging," *Journal of Applied Econometrics*, 23(5), 671–682.

O'Hagan, A., 1994, "Bayesian Inference," *Kendall's Advanced Theory of Statistics*, 2B(Edward Arnold, London).

Raftery, A., D. Madigan, and J. A. Hoeting, 1997, "Bayesian Model Averaging for linear regression models," *Journal of the American Statistical Association*, 92, 179–191.

Sala-I-Martin, X., G. Doppelhofer, and R. I. Miller, 2004, "Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach," *American Economic Review*, 94(4), 813–835.

Santos, T., and P. Veronesi, 2004, "Conditional Betas," *NBER Working Paper*, 10413, 1–47.

Saunders, A., E. Strock, and N. G. Travlos, 1990, "Ownership Structure, Deregulation, and Bank Risk Taking," *Journal of Finance*, 45(2), 643–654.

Schuermann, T., and K. Stiroh, 2006, "Visible and hidden risk factors for banks," *Federal Reserve Bank of New York Staff Report Nr 252*.

Schwarz, G., 1978, "Estimating Dimension of a Model," *Annals of Statistics*, 6(2), 461–464.

Song, F. M., 1994, "A 2-Factor Arch Model for Deposit-Institution Stock Returns," *Journal of Money, Credit and Banking*, 26(2), 323–340.

Stiroh, K., 2006, "A portfolio view of banking with interest and noninterest activities," *Journal of Money, Credit and Banking*, 38(5), 1351–1361.

——— , 2006b, "New evidence on the determinants of bank risk," *Journal of Financial Services Research*, 30(3), 237–263.

Sweeney, R. J., and A. D. Warga, 1986, "The Pricing of Interest-Rate Risk - Evidence from the Stock-Market," *Journal of Finance*, 41(2), 393–410.

Tarhan, V., 1987, "Unanticipated Interest-Rates, Bank Stock Returns and the Nominal Contracting Hypothesis," *Journal of Banking and Finance*, 11(1), 99–115.

Taylor, J. B., and J. C. Williams, 2009, "A Black Swan in the Money Market," *American Economic Journal-Macroeconomics*, 1(1), 58–83.

Vassalou, M., and Y. H. Xing, 2004, "Default risk in equity returns," *Journal of Finance*, 59(2), 831–868.

Viale, A., J. Kolari, and D. Fraser, 2009, "Common risk factors in bank stocks," *Journal of Banking and finance*, 33(3), 464–472.

Wei, C. Z., 1992, "On Predictive Least-Squares Principles," *Annals of Statistics*, 20(1), 1–42.

Wright, J. H., 2008, "Bayesian Model Averaging and exchange rate forecasts," *Journal of Econometrics*, 146(2), 329–341.

Zhang, L., 2005, "The Value Premium," *The Journal of Finance*, 60(1), 67–103.

Table 1: Independent variables used in factor models for bank stock returns: a summary of 24 studies

This table presents an overview of the independent variables that have been included in models for bank stock returns. The independent variables are numbered from 1 to 17, indicating 1 (market risk), 2 (interest rate risk, short term), 3 (term spread risk), 4 (default risk), 5 (liquidity risk), 6 (market volatility), 7 (real estate risk), 8 (small-minus-big), 9 (high-minus-low), 10 (momentum), 11 (market dividend yield), 12 (inflation risk), 13 (interest rate risk long term), 14 (deposit demand), 15 (exchange rate risk), 16 (bank portfolio return) and 17 (money supply).

	Period	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Lloyd and Shick (1977)	1969-1972	X												X				
Lynge and Zumwalt (1980)	1969-1975	X	X											X				
Flannery and James (1984a)	1976-1981	X	X											X				
Flannery and James (1984b)	1976-1981	X	X											X				
Sweeney and Warga (1986)	1960-1979	X	X											X				
Tarhan (1987)	1979-1982	X	X															X
Kane and Unal (1988)	1975-1985	X												X				
Saunders, Strock, and Travlos (1990)	1978-1985	X	X											X				
Choi, Elyasiani, and Kopecky (1992)	1975-1987	X	X													X		
He, Myer, and Webb (1996)	1986-1991	X	X					X										
Song (1994)	1976-1987	X	X															
Demsetz and Strahan (1997)	1980-1993	X	X	X	X													
Hess and Laisathit (1997)	1981-1988	X		X	X	X								X	X			
Chamberlain, Howe, and Popper (1997)	1986-1993	X														X	X	
Hirtle (1997)	1986-1994	X												X				
Choi and Elyasiani (1997)	1975-1992	X	X													X		
Flannery, Hameed, and Harjes (1997)	1973-1990	X												X				
Dewenter and Hess (1998)	1984-1996	X		X	X	X												
Elyasiani and Mansur (1998)	1970-1992	X												X				
Lajeri and Dermine (1999)	1977-1991	X	X										X					
Chaudhry, Christie-David, Koch, and Reichert (2000)	1989-1993	X	X											X		X		
Stiroh (2006)	1997-2004	X	X	X	X													
Schuermann and Stiroh (2006)	1997-2005	X	X	X	X	X	X		X	X								
Viale, Kolari, and Fraser (2009)	1986-2003	X	X	X	X				X	X	X	X						

Table 2: Summary statistics of the dependent and independent variables

This table reports summary statistics of the returns on the different bank indices in Panel A. All series have a weekly frequency and span the period 1986-2010. We report the annualized mean and volatility as well as the skewness and kurtosis of the portfolio returns. Each portfolio return is constructed as an equally weighted return (with quarterly rebalancing of the portfolio if based on BHC characteristics). Below the summary statistics, we present a correlation table of the returns on the eleven portfolios. These eleven portfolios are the benchmark portfolios, four portfolios of different types of financial institutions as well as six portfolios of various 'types' of bank holding companies. The numbers correspond with: (1) Largest 50 BHCs, (2) Depositories, (3) Insurance, (4) Broker-Dealers, (5) Other: Non-depository Institutions, (6) Largest 15 BHCs, (7) Smallest 50 BHCs, (8) Sound BHCs, (9) Distressed BHCs, (10) Retail BHCs, (11) Diversified BHCs. In panel B we report the innovations in the different risk factors included in the analysis. Innovations are the residuals from a AR(n) model estimated on the different risk variables, where n is the optimal lag chosen by the Schwarz Bayesian Information Criterion. We also report the expected sign of the impact of a given risk factor on bank stock returns.

Panel A: Summary Statistics for Bank Portfolio Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Portfolio Returns - Summary Statistics											
Annualized Average Return	0.141	0.124	0.129	0.150	0.117	0.134	0.103	0.146	0.004	0.093	0.170
Annualized Volatility	0.274	0.264	0.220	0.390	0.289	0.308	0.113	0.148	0.242	0.129	0.232
Skewness	1.014	0.623	0.368	4.488	1.081	1.338	-0.636	0.237	1.356	-0.726	1.360
Kurtosis	17.005	11.163	16.244	84.176	16.251	22.774	13.107	10.213	30.517	14.536	22.179
Portfolio Returns - Correlation Table											
(2) Depositories	0.914										
(3) Insurance	0.727	0.725									
(4) Broker-Dealers	0.582	0.584	0.547								
(5) Other Non-depository Institutions	0.763	0.781	0.708	0.640							
(6) Largest 15	0.962	0.906	0.720	0.589	0.761						
(7) Smallest 50	0.568	0.559	0.497	0.363	0.493	0.555					
(8) Sound Banks	0.839	0.781	0.666	0.511	0.694	0.777	0.604				
(9) Distressed Banks	0.711	0.648	0.550	0.418	0.547	0.680	0.722	0.644			
(10) Retail Banks	0.649	0.625	0.546	0.421	0.561	0.614	0.780	0.748	0.687		
(11) Diversified Banks	0.925	0.851	0.725	0.573	0.740	0.896	0.612	0.835	0.787	0.692	

Panel B: Summary Statistics Risk Variables

	mean	**st. dev**	**min**	**max**	**expected sign**
Market	0.0010	0.0240	-0.1765	0.1185	+
Small minus Big (SMB)	0.0001	0.0133	-0.0935	0.0642	+
High minus Low (HML)	0.0007	0.0135	-0.0695	0.0983	+
3-month T-Bill (TB3)	0.0000	0.0013	-0.0163	0.0061	-
Term Spread (TS)	0.0000	0.0015	-0.0057	0.0089	"+/-"
Default Spread (DS)	0.0000	0.0005	-0.0036	0.0051	-
TED spread (TED)	0.0000	0.0014	-0.0083	0.0103	-
3-month unregulated time deposit - 3-month T-Bill (DepS)	0.0000	0.0013	-0.0088	0.0146	-
FF Overnight - 3 month LIBOR (MMS)	0.0000	0.0020	-0.0147	0.0167	-
Effective Exchange Rate (FX)	-0.0003	0.0099	-0.0375	0.0446	"+/-"
Market Volatility (VXO)	-0.0001	0.0362	-0.1889	0.6613	-
Real Estate returns (RE)	0.0028	0.0357	-0.2132	0.2404	+

Table 3: Data Description, Source codes and Construction of Portfolios

Portfolio Construction

Portfolio Name	*Description (for each portfolio, we allow for quarterly rebalancing)*
Depositories	2-digit SIC code=60 (as in Acharya, Pedersen, Philippon, and Richardson (2012))
Insurance	2-digit SIC code=63 and 64 (as in Acharya, Pedersen, Philippon, and Richardson (2012))
Broker-Dealers	4-digit SIC code=6211 (as in Acharya, Pedersen, Philippon, and Richardson (2012))
Other: Non-depository Institutions	2-digit SIC code=61, 62(except 6211), 67 (as in Acharya, Pedersen, Philippon, and Richardson (2012))
Largest 15	The 15 largest publicly traded BHCs (BHCs) measured by Total Assets
Smallest 50	The 50 smallest publicly traded BHCs measured by Total Assets
Sound Banks	The intersection of the 25% best capitalized and 25% most profitable (ROA) BHCs in a given quarter
Distressed Banks	The intersection of the 25% worst capitalized and 25% least profitable (ROA) BHCs in a given quarter
Retail Banks	We sort BHCs in quartiles according to five characteristics: Size (=ln(Total Assets), Growth in Total Assets, the leverage ratio (Total Assets/Total Equity), wholesale funding share and the share of non-interest income in total income. We attach a score of 1, 2, 3 or 4 for each quartile sort. If the sum of the scores is at most 8, we classify a BHC as a retail BHC, which is a small, well-capitalized, slow-growing BHC, that is relying on core funding and interest generating activities
Diversified Banks	We sort BHCs in quartiles according to five characteristics: Size (=ln(Total Assets), Growth in Total Assets, the leverage ratio (Total Assets/Total Equity), wholesale funding share and the share of non-interest income in total income. We attach a score of 1, 2, 3 or 4 for each quartile sort. If the sum of the scores is at least 17, we classify a BHC as a diversifeid BHC, which is a large, highly leveraged and expanding BHC, that is relying on wholesale funding and diversified into non-interest generating activities

Bank Characteristics

Variable Name	*Corresponding Codes*
Size (=ln(Total Assets))	ln(BHCK2170)
Growth in Total Assets	Δ(ln(BHCK2170))
Return on Assets	BHCK4340 / BHCK2170
Equity to Total Assets	BHCK3210/BHCK2170
Cost to Income ratio	BHCK4093 / (BHCK4074 + BHCK4079)
Non-Performing Loans over Total Loans	(BHCK5525 - BHCK3506 + BHCK5526 - BHCK3507 + BHCK1616) / BHCK2122
Deposits to Total Assets	(BHDM6631 + BHDM6636 + BHFN6631 + BHFN6636)/ BHCK2170
Core Deposits Share	$\frac{((BHCB3187 + BHOD3187) + (BHCB2389 + BHOD2389) + (BHCB6648 + BHOD6648) + BHFN6636)}{(Deposits + FedFundsPurchased)}$
Wholesale Funding Share	(BHCB2604 + BHOD2604) + FFpSs / (Deposits + FedFundsPurchased)
Loans To Total Assets	BHCK2122 / BHCK2170
C&I Loans Share	(BHCK1763 + BHCK1764) / BHCK2122
Interest Income Share	BHCK4074 / (BHCK4074 + BHCK4079)

Table 4: Definition and Summary Statistics of the Bank Holding Company portfolios

This table presents descriptive statistics on the characteristics of the constituents of the six portfolios we construct. We present information on the average value of a number of bank characteristics. For each portfolio, we first compute an equally weighted average bank characteristic per quarter for the constituent banks. Subsequently, we average over time. We also report p-values of differences in means test for contrasting portfolios: i.e., Small vs Large, Sound vs Distressed and Retail vs Diversified BHCs. The definition and construction of the characteristics and portfolios are described in Table 3.

	(1) Largest 15	(2) Smallest 50	P-value of H_0:mean(1)=mean(2)	(3) Sound Banks	(4) Distressed Banks	P-value of H_0:mean(3)=mean(4)	(5)Retail Banks	(6) Diversified Banks	P-value of H_0:mean(5)=mean(6)
Size (=ln(Total Assets))	18.524	12.795	0.000	14.352	14.432	0.039	13.142	16.346	0.000
Growth in Total Assets	0.019	0.023	0.020	0.023	0.022	0.399	-0.002	0.055	0.000
Return on Assets	0.009	0.007	0.000	0.016	-0.002	0.000	0.010	0.010	0.198
Equity to Total Assets	7.537	9.097	0.000	11.600	5.973	0.000	10.343	6.931	0.000
Cost to Income ratio	0.657	0.719	0.000	0.563	0.813	0.000	0.667	0.666	0.791
Non-Performing Loans	0.021	0.018	0.000	0.011	0.027	0.000	0.015	0.015	0.751
Deposits to Total Assets	0.606	0.824	0.000	0.766	0.763	0.412	0.824	0.666	0.000
Core Deposits Share	0.616	0.684	0.000	0.687	0.664	0.000	0.747	0.563	0.000
Wholesale Funding Share	0.242	0.163	0.000	0.174	0.213	0.000	0.111	0.299	0.000
LoansTo Total Assets	0.567	0.660	0.000	0.638	0.633	0.120	0.651	0.579	0.000
C&I Loans Share	0.263	0.197	0.000	0.190	0.194	0.211	0.168	0.234	0.000
Interest Income Share	0.543	0.809	0.000	0.745	0.759	0.000	0.849	0.605	0.000

Table 5: Baseline results: Portfolio of 50 largest BHCs, full sample period

This table summarizes estimation results for the static linear model estimated over the full sample (January 1986 to December 2010). Panel A reports results for our benchmark index of the 50 largest bank holding companies. Each column corresponds with a different risk factor. In the upper part of the table, we report 5 statistics, i.e. the OLS factor exposure and t-statisitc, the BMA factor exposure and corresponding t-statistic and the Posterior Inclusion Probability. The lower panel of this table provides the specification of the top 10 models, ranked in terms of posterior model probability. The inclusion of a variable is indicated with a X. The table also contains the number of factors (all explanatory variables except the constant), the posterior model probability (PMP) and the adjusted R-squared.

Full sample: OLS versus BMA

Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE
β-OLS	0.96	0.04	1.15	-2.37	-0.47	2.17	0.49	-0.91	-0.8	0.1	-0.05	0.2
t-stat OLS	19.22	0.73	20.06	-3.15	-0.88	1.61	0.45	-0.87	-2.07	1.50	-1.75	7.13
β-BMA	0.99	0.00	1.14	-0.69	0.00	0.32	0.12	0.01	-0.13	0.01	0.00	0.20
t-stat BMA	24.33	0.06	21.03	-0.84	-0.03	0.34	0.31	0.06	-0.43	0.22	-0.17	7.83
PIP	100%	3%	100%	47%	3%	13%	12%	5%	19%	7%	5%	100%

Top 10 models, full sample

Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE	# factors	PMP	Adj R^2
1	X		X									X	3	23.83%	61.67%
2	X		X	X								X	4	23.45%	61.86%
3	X		X	X					X			X	5	7.30%	61.97%
4	X		X				X					X	4	7.05%	61.78%
5	X		X						X			X	4	5.24%	61.77%
6	X		X			X						X	4	4.16%	61.75%
7	X		X	X		X						X	5	3.49%	61.93%
8	X		X	X						X		X	5	2.00%	61.90%
9	X		X					X				X	4	1.81%	61.70%
10	X		X	X							X	X	5	1.76%	61.89%

Table 6: Bayesian Model Averaging in the static linear model

This table summarizes estimation results for the static linear model estimated over the full sample (January 1986 to December 2010). The columns correspond with the eleven portfolios we use. These eleven portfolios are the benchmark series (column 1), four portfolios of different types of financial institutions (columns 2-5) as well as six portfolios of various 'types' of bank holding companies (columns 6-11). For each risk factor-portfolio pair, we report 5 statistics, i.e. the OLS factor exposure and t-statisitc, the BMA factor exposure and corresponding t-statistic and the Posterior Inclusion Probability.

		Largest 50	Depository	Insurance	Broker Dealers	Other	Largest 15	Smallest 50	Sound	Distressed	Retail	Diversified
Market	β_{OLS}	0.96	0.86	1.26	1	0.72	1.07	0.23	0.51	0.67	0.33	0.9
	t_{OLS}	19.22	17.16	14.89	18.52	17.18	18.75	8.43	18.52	12.41	11.49	21.02
	β_{BMA}	0.99	0.93	1.27	1.05	0.77	1.11	0.23	0.53	0.74	0.36	0.88
	t_{BMA}	24.33	16.18	19.05	22.78	15.56	22.27	7.38	22.69	12.14	9.58	24.43
	PIP	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
SMB	β_{OLS}	0.04	-0.06	0.1	0.03	-0.1	-0.21	0.23	0.39	0.51	0.36	0.33
	t_{OLS}	0.73	-0.98	1.05	0.42	-2.10	-3.18	7.40	12.24	8.24	11.07	6.71
	β_{BMA}	0.00	0	0	0	-0.02	-0.22	0.23	0.39	0.52	0.37	0.3
	t_{BMA}	0.06	-0.21	0.07	0.02	-0.45	-2.8	7.35	12.57	7.93	10.44	6.17
	PIP	3%	6%	3%	3%	21%	95%	100%	100%	100%	100%	100%
HML	β_{OLS}	1.15	0.93	0.14	0.51	0.61	1.19	0.35	0.61	1.03	0.52	0.97
	t_{OLS}	20.06	16.10	1.39	8.18	12.65	18.27	11.19	19.31	16.60	15.92	19.78
	β_{BMA}	1.14	0.95	0.01	0.51	0.64	1.19	0.35	0.62	1.05	0.53	0.95
	t_{BMA}	21.03	17.12	0.17	8.6	13.14	17.95	11.07	19.74	15.58	14.86	19.59
	PIP	100%	100%	5%	100%	100%	100%	100%	100%	100%	100%	100%
TB3	β_{OLS}	-2.37	-2.97	-2.51	-3.14	-1.42	-2.23	-0.17	-0.68	-1.1	-0.84	-2.18
	t_{OLS}	-3.15	-3.95	-1.98	-3.85	-2.25	-2.60	-0.41	-1.62	-1.34	-1.94	-3.34
	β_{BMA}	-0.69	-0.68	-0.04	-0.75	-0.03	-0.2	0	-0.06	0.01	-0.02	-0.52
	t_{BMA}	-0.84	-0.68	-0.14	-0.72	-0.14	-0.38	-0.06	-0.3	0.04	-0.15	-0.74
	PIP	47%	38%	4%	40%	5%	16%	3%	11%	3%	5%	42%
TS	β_{OLS}	-0.47	-1.26	-0.96	-1.97	-1.86	-0.62	-0.33	0.13	-1.05	-0.34	-0.89
	t_{OLS}	-0.88	-2.35	-1.06	-3.40	-4.13	-1.02	-1.14	0.43	-1.80	-1.11	-1.93
	β_{BMA}	0.00	-0.34	0	-0.77	-1.82	-0.01	-0.01	0.03	-0.24	-0.02	-0.06
	t_{BMA}	-0.03	-0.53	-0.02	-0.85	-4.14	-0.05	-0.15	0.25	-0.47	-0.2	-0.25
	PIP	3%	27%	3%	48%	99%	3%	5%	8%	22%	6%	9%
DS	β_{OLS}	2.17	-0.07	0.21	-0.03	-1.33	2.12	-0.8	0.22	-1.96	-0.18	-0.06
	t_{OLS}	1.61	-0.05	0.09	-0.02	-1.17	1.38	-1.10	0.29	-1.33	-0.24	-0.05
	β_{BMA}	0.32	0.01	0.01	0.01	-0.05	0.25	-0.04	0	-0.15	-0.01	0.01
	t_{BMA}	0.34	0.05	0.02	0.03	-0.16	0.28	-0.17	0.04	-0.22	-0.04	0.07
	PIP	13%	3%	3%	3%	5%	10%	5%	3%	7%	3%	3%
TED	β_{OLS}	0.49	-0.17	-2.42	-1.32	-2.92	0.73	0.51	-0.54	-0.53	-0.69	-0.16
	t_{OLS}	0.45	-0.15	-1.32	-1.13	-3.21	0.59	0.88	-0.90	-0.45	-1.12	-0.18
	β_{BMA}	0.12	-0.01	0.01	0	-0.17	0.11	0	0.04	-0.12	-0.22	0.01
	t_{BMA}	0.31	-0.03	0.04	0.02	-0.37	0.29	0	0.25	-0.32	-0.58	0.06
	PIP	12%	4%	3%	3%	16%	11%	4%	9%	12%	30%	4%
DepS	β_{OLS}	-0.91	-1.2	1.97	0.45	1.37	-1.1	-1.7	0.58	-0.5	-0.45	-0.55
	t_{OLS}	-0.87	-1.14	1.10	0.39	1.55	-0.92	-3.02	1.00	-0.44	-0.74	-0.61
	β_{BMA}	0.01	-0.05	0.04	0.01	0.02	0.01	-1.4	0.11	-0.12	-0.27	-0.01
	t_{BMA}	0.06	-0.17	0.14	0.05	0.06	0.07	-4.22	0.41	-0.31	-0.65	-0.07
	PIP	5%	6%	4%	3%	4%	4%	99%	18%	12%	35%	4%
MMS	β_{OLS}	-0.8	-0.89	-0.94	-1.03	-0.75	-0.87	0.14	-0.33	0.02	-0.21	-0.65
	t_{OLS}	-2.07	-2.30	-1.43	-2.45	-2.31	-1.97	0.69	-1.57	0.05	-0.97	-1.97
	β_{BMA}	-0.13	-0.05	-0.02	-0.07	-0.01	-0.13	0	-0.02	0.02	0	-0.03
	t_{BMA}	-0.43	-0.24	-0.12	-0.28	-0.12	-0.39	0.1	-0.23	0.15	0	-0.22
	PIP	19%	8%	4%	10%	4%	17%	3%	8%	5%	3%	7%
Exchange	β_{OLS}	0.1	0.06	0.27	0.07	0.09	0.09	-0.02	0.02	0.04	-0.01	0.12
	t_{OLS}	1.50	0.90	2.33	0.93	1.62	1.19	-0.48	0.57	0.49	-0.36	1.94
	β_{BMA}	0.01	0	0.04	0	0	0	0	0	0	0	0.01
	t_{BMA}	0.22	0.09	0.38	0.09	0.2	0.16	-0.1	0.06	0.04	-0.09	0.28
	PIP	7%	3%	16%	3%	6%	5%	3%	3%	3%	3%	10%
VXO	β_{OLS}	-0.05	-0.1	-0.09	-0.06	-0.08	-0.06	-0.05	-0.03	-0.05	-0.06	0
	t_{OLS}	-1.75	-3.58	-1.95	-2.14	-3.46	-1.98	-3.05	-1.68	-1.69	-3.59	0.06
	β_{BMA}	0.00	-0.04	-0.01	-0.01	-0.05	0	-0.04	0	-0.01	-0.04	0
	t_{BMA}	-0.17	-0.89	-0.29	-0.28	-1.35	-0.17	-1.89	-0.18	-0.3	-2.16	0.14
	PIP	5%	51%	10%	10%	72%	5%	85%	5%	11%	90%	4%
RE	β_{OLS}	0.2	0.17	0.18	0.22	0.13	0.22	0.06	0.09	0.09	0.05	0.13
	t_{OLS}	7.13	6.06	3.91	7.43	5.65	6.89	3.75	5.78	3.02	2.87	5.65
	β_{BMA}	0.20	0.16	0.22	0.23	0.12	0.22	0.05	0.09	0.08	0.03	0.13
	t_{BMA}	7.83	6.02	5.18	8	5.19	6.62	3.14	5.8	1.67	1.21	5.69
	PIP	100%	100%	100%	100%	100%	100%	97%	100%	81%	67%	100%

Table 7: The top 10 models, ranked in terms of posterior model probability.

This table provides the specification of the top 10 models, ranked in terms of posterior model probability, for two subperiods. In panel A, we estimate the model on the portfolio of 50 largest BHCs over the period 1986 until July 2007. In panel B, we report post August 2007 results for the same portfolio. The inclusion of a variable is indicated with X. The table also contains the number of explanatory variables (except the constant), the posterior model probability (PMP) and the adjusted R squared.

Panel A: Top 10 models, pre-2007

Model Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE	# factors	PMP	Adj R^2
1	X		X	X				X			X	X	6	23.54%	50.60%
2	X		X	X	X			X			X	X	7	18.25%	50.85%
3	X	X	X	X				X			X	X	7	15.77%	50.84%
4	X	X	X	X	X			X			X	X	8	4.91%	51.01%
5	X		X	X	X		X				X	X	7	4.44%	50.72%
6	X		X	X	X						X	X	6	3.43%	50.43%
7	X	X	X					X			X	X	6	2.42%	50.39%
8	X		X	X			X				X	X	6	2.17%	50.38%
9	X		X					X			X	X	5	2.00%	50.10%
10	X		X								X	X	4	1.76%	49.81%

Panel B: Top 10 models, post-2007

Model Nr.	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE	# factors	PMP	Adj R^2
1	X		X			X						X	4	8.06%	82.54%
2	X		X	X		X						X	5	6.77%	82.94%
3			X			X						X	3	6.63%	82.05%
4	X		X		X	X						X	5	5.56%	82.89%
5	X		X			X	X					X	5	5.12%	82.88%
6	X		X			X					X	X	5	4.53%	82.85%
7			X		X	X						X	4	3.06%	82.33%
8	X		X			X		X				X	5	2.95%	82.76%
9	X		X	X		X					X	X	6	2.08%	83.12%
10	X		X	X		X				X		X	6	2.03%	83.11%

Table 8: Time-Varying BMA Estimation Results

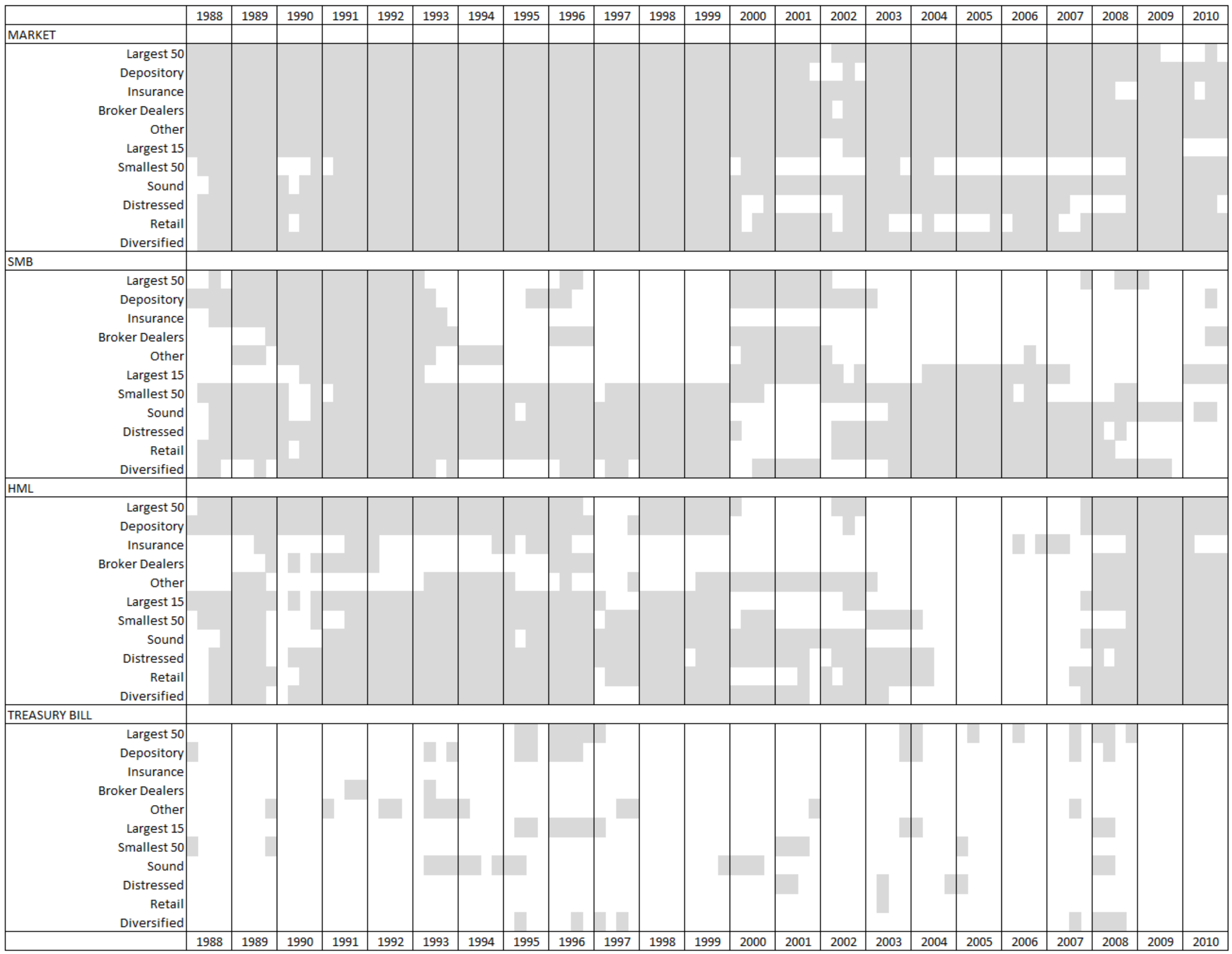
This table summarizes estimation results for the time-varying BMA analysis over the period 1986-2010, using quarterly rolling windows of two years of weekly data. The table consists of three equally designed panels. The columns correspond with a risk factor, whereas the rows correspond with a bank type. Panel A (top panel) shows for each bank type-risk factor pair the percentage of observations with a PIP larger than 50 percent. In panel B, we report a marginal R-squared. The latter is calculated as the average (over time) difference in (model weighted) R-squared between a model that does and one that does not include a particular risk factor, conditional on that risk factor having at that point in time a PIP larger than 50 percent. Finally, the lower panel C contains for each bank type-risk factor pair the average factor exposure, conditional on the pair having a PIP $>$ 50 percent. In each panel, we also report for each risk factor the average and the interquartile range of the results for the eleven portfolios.

	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE
					Panel A: Percentage of PIP's >50%							
Largest 50	0.93	0.36	0.65	0.16	0.19	0.10	0.11	0.07	0.09	0.02	0.18	0.26
Depository	0.96	0.43	0.64	0.12	0.11		0.07	0.05	0.08	0.03	0.15	0.08
Insurance	0.97	0.23	0.23		0.18		0.05	0.16	0.03	0.04	0.09	0.16
Broker Dealers	0.99	0.34	0.26	0.03	0.21		0.03	0.02	0.07	0.03	0.09	0.36
Other	1.00	0.33	0.45	0.13	0.22		0.03	0.02		0.04	0.12	0.45
Largest 15	0.93	0.43	0.63	0.12	0.12	0.02	0.05	0.07	0.14	0.01	0.15	0.35
Smallest 50	0.66	0.74	0.63	0.05	0.04	0.02	0.03	0.10	0.11	0.04	0.09	0.26
Sound	0.98	0.78	0.70	0.15	0.07	0.08	0.05	0.02	0.09	0.09	0.16	0.21
Distressed	0.85	0.79	0.77	0.05	0.01	0.01	0.08	0.04	0.04	0.02	0.19	0.20
Retail	0.85	0.78	0.74	0.01	0.04	0.07	0.14	0.04	0.08	0.08	0.13	0.15
Diversified	1.00	0.68	0.73	0.09	0.12	0.02	0.07	0.03	0.07	0.03	0.16	0.25
mean	0.92	0.54	0.58	0.09	0.12	0.05	0.07	0.06	0.08	0.04	0.14	0.25
IQR	0.14	0.44	0.27	0.09	0.14	0.05	0.04	0.04	0.03	0.02	0.08	0.19
					Panel B: Contribution to R-squared							
Largest 50	0.11	0.06	0.09	0.02	0.03	0.01	0.03	0.03	0.02	0.01	0.02	0.01
Depository	0.10	0.07	0.09	0.02	0.04		0.02	0.03	0.01	0.01	0.02	0.02
Insurance	0.10	0.03	0.05		0.01		0.02	0.03	0.01	0.02	0.02	0.03
Broker Dealers	0.12	0.03	0.02	0.02	0.03		0.01	0.02	0.01	0.03	0.02	0.01
Other	0.09	0.06	0.05	0.02	0.03		0.01	0.02		0.01	0.01	0.02
Largest 15	0.09	0.06	0.08	0.03	0.05	0.01	0.03	0.03	0.02	0.01	0.02	0.03
Smallest 50	0.09	0.08	0.09	0.05	0.02	0.02	0.07	0.02	0.03	0.04	0.03	0.05
Sound	0.11	0.08	0.09	0.04	0.03	0.02	0.03	0.01	0.02	0.02	0.02	0.02
Distressed	0.12	0.09	0.13	0.03	0.03	0.01	0.01	0.01	0.03	0.02	0.05	0.03
Retail	0.09	0.10	0.10	0.00	0.03	0.02	0.03	0.01	0.03	0.04	0.02	0.01
Diversified	0.11	0.04	0.09	0.02	0.04	0.01	0.03	0.04	0.02	0.01	0.02	0.01
mean	0.10	0.06	0.08	0.02	0.03	0.01	0.03	0.02	0.02	0.02	0.02	0.02
IQR	0.02	0.05	0.04	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01
					Panel C: Beta							
Largest 50	0.91	0.33	1.10	-1.74	-2.53	7.99	18.52	-26.48	2.52	0.34	-0.22	0.31
Depository	0.99	0.42	1.11	-1.06	-4.13	NaN	29.33	-31.59	0.64	-0.18	-0.36	0.21
Insurance	1.40	0.90	0.41	NaN	-2.37	NaN	1.07	-1.72	-3.21	0.49	-0.32	0.49
Broker Dealers	1.09	0.38	0.77	-2.96	-4.16	16.33	22.91	-50.92	-3.02	-0.35	-0.42	0.29
Other	0.82	0.21	0.70	-3.11	-3.15	3.00	-13.24	-10.56	NaN	0.26	0.02	0.21
Largest 15	1.02	-0.15	1.26	-1.57	-4.56	8.38	25.74	-20.68	-0.05	0.31	-0.22	0.33
Smallest 50	0.38	0.39	0.46	-2.48	-1.40	-0.83	4.48	-3.77	-0.63	-0.25	-0.11	0.18
Sound	0.50	0.47	0.54	-0.38	-1.86	3.64	4.23	3.21	1.00	0.08	-0.12	0.16
Distressed	0.73	0.74	1.00	-2.92	-1.77	4.75	-3.12	-2.52	1.95	-0.27	-0.22	0.21
Retail	0.39	0.47	0.52	0.97	-1.33	-1.51	1.68	-2.95	0.46	-0.07	-0.07	0.15
Diversified	0.85	0.47	0.92	-2.78	-2.76	6.39	12.12	-22.19	1.49	0.05	-0.01	0.24
mean	0.83	0.42	0.80	-1.80	-2.73	5.35	9.43	-15.47	0.11	0.04	-0.19	0.25
IQR	0.52	0.14	0.58	2.04	2.36	7.10	21.84	23.96	2.83	0.56	0.24	0.13

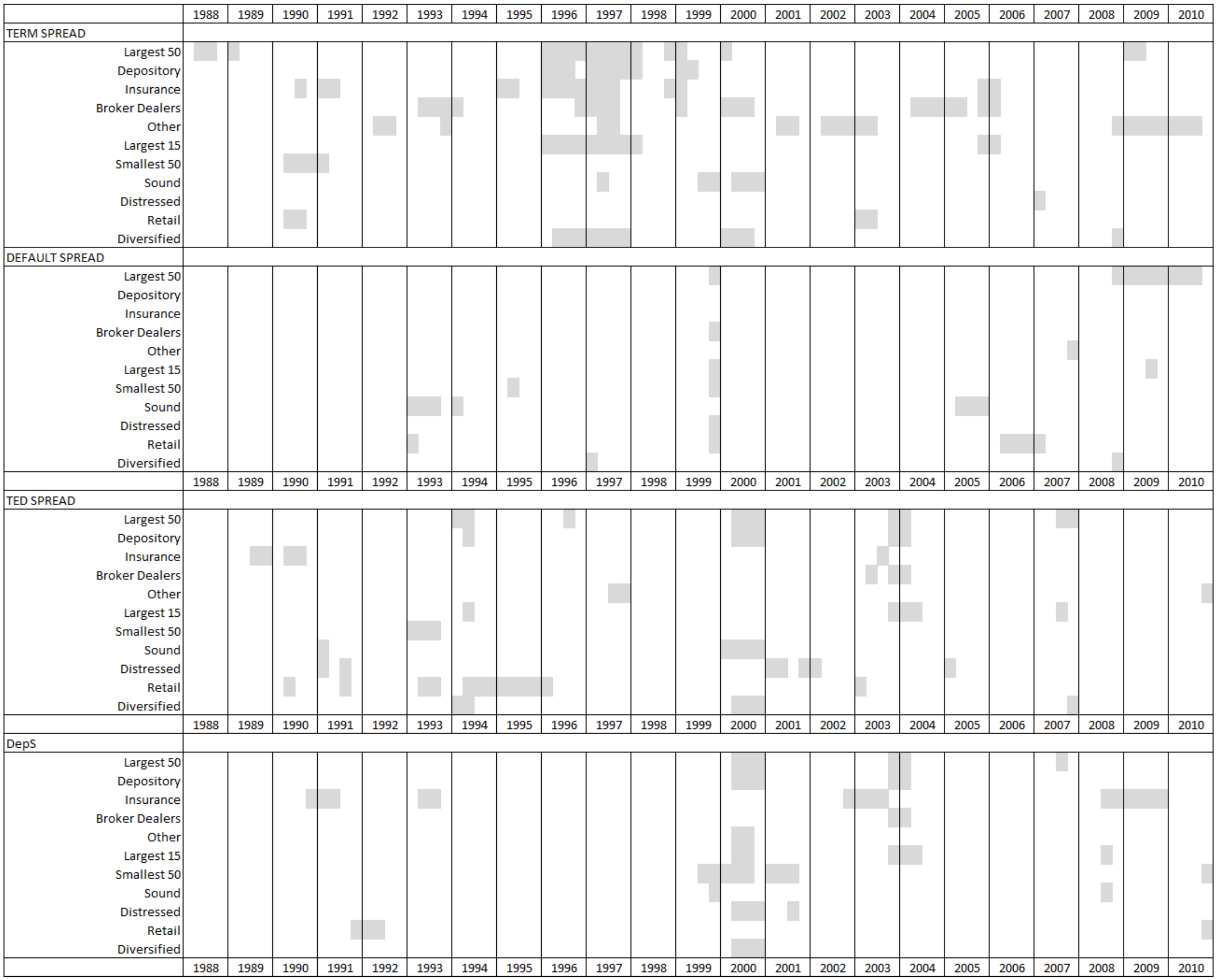
Figure 1: Relevance of Risk Factors for different Bank Types over time

This Figure shows for each quarter whether or not a particular bank type - risk factor pair has a PIP larger than 50 percent (grey) or not (white). It thus contains a geographical representation of when which factors are important and for which types of banks.

Panel A: Market, SMB, HML, TB3



Panel B: Term Spread, Default Spread, TED spread, Deposit Spread



Panel C: Money Market Spread, FX, VXO, Real Estate

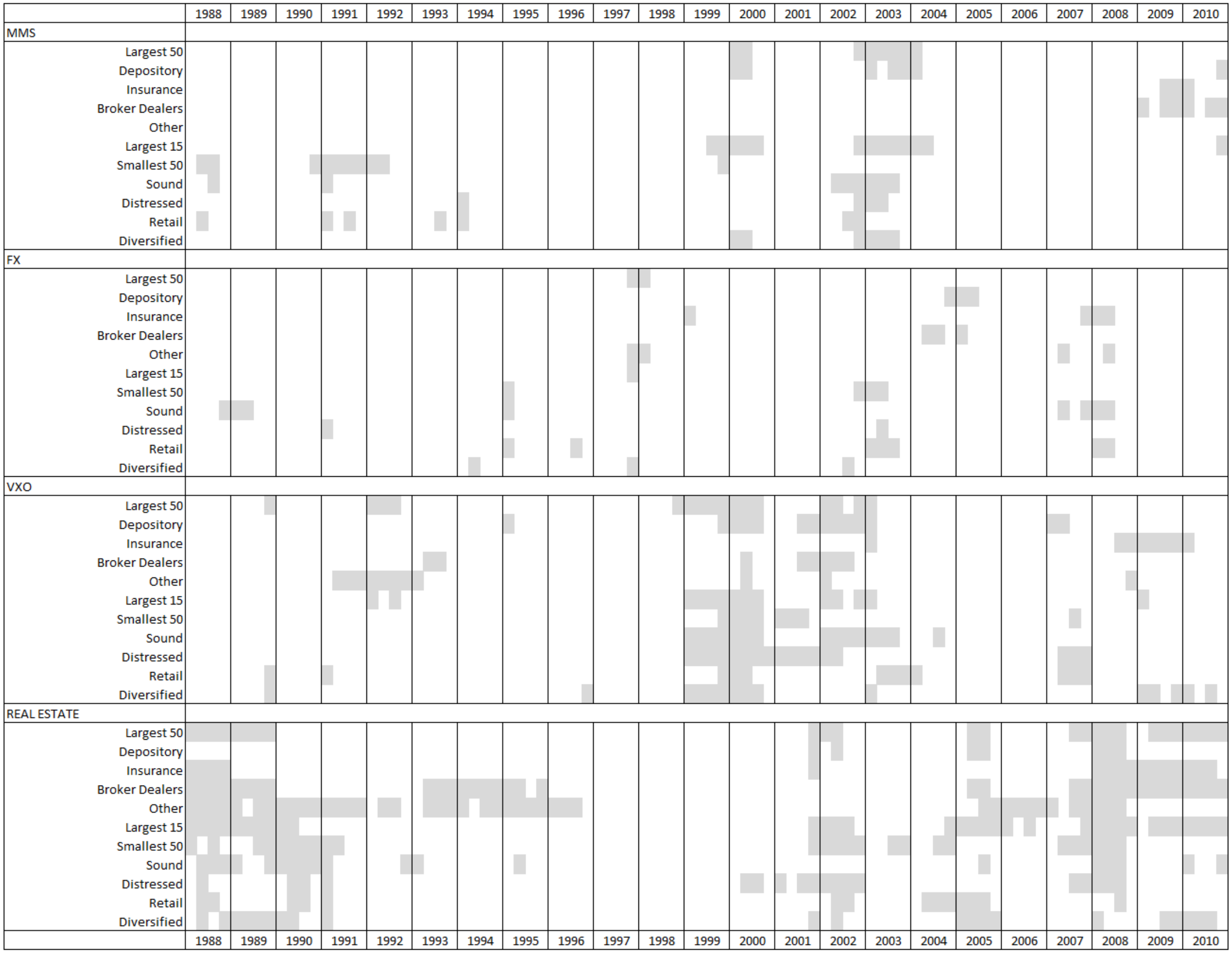
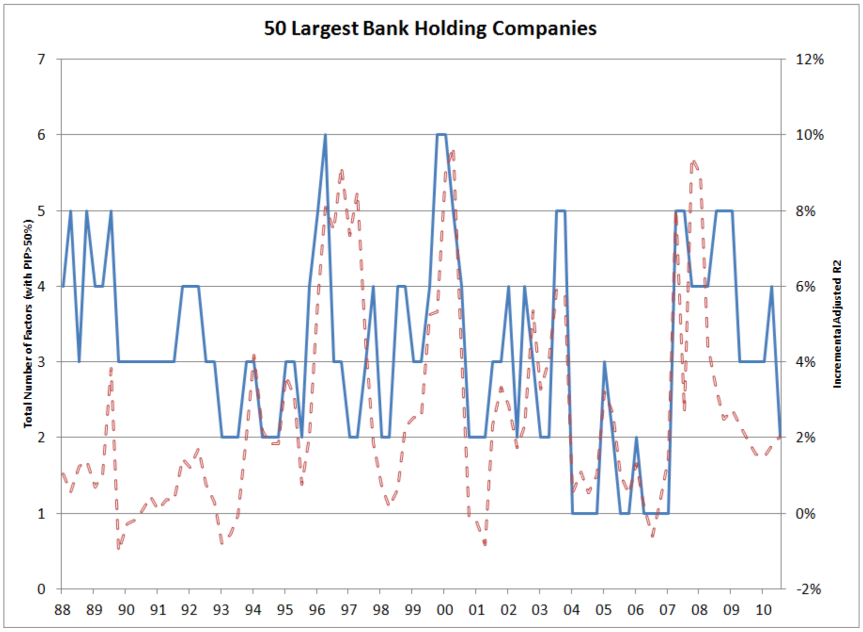


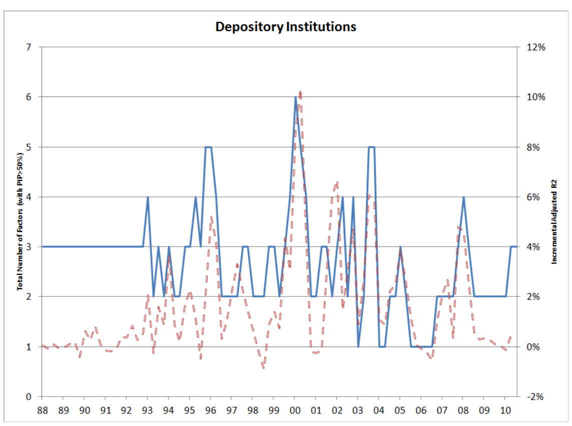
Figure 2: Number of Factors and Marginal R2: Cross-sectional and Time variation

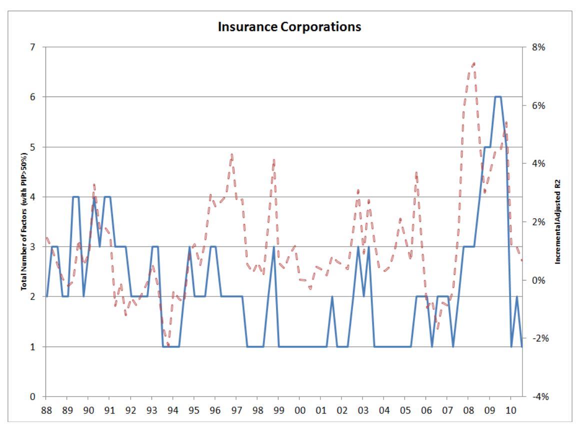
This Figure plots at each point in time the optimal number of factors (left axis) as well as the contribution of other factors than the market to the total (adjusted) R-squared (dotted line, scale on the right axis). Panel A reports results for our benchmark portfolio of the 50 largest BHCs, Panel B for the 4 cross-sectional portfolios of different types of financial institutions, and Panel C for different types of BHCs.

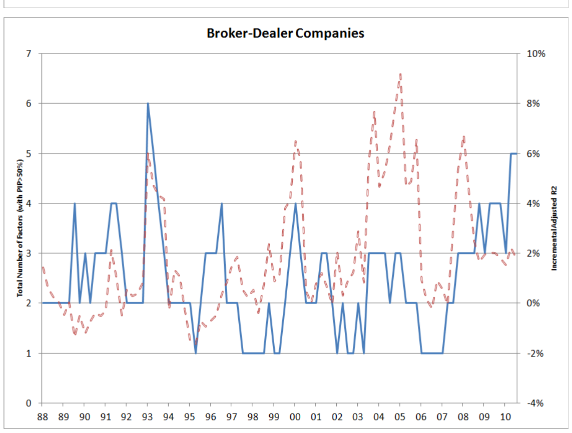
Panel A: 50 Largest BHCs

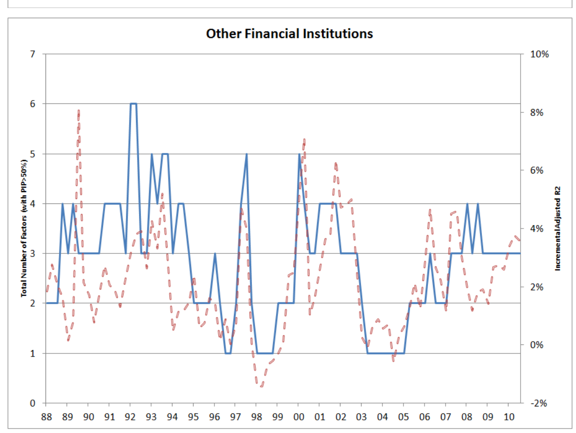


Panel B: Cross-section of Financial Institutions









Panel C: Cross-section of BHCs

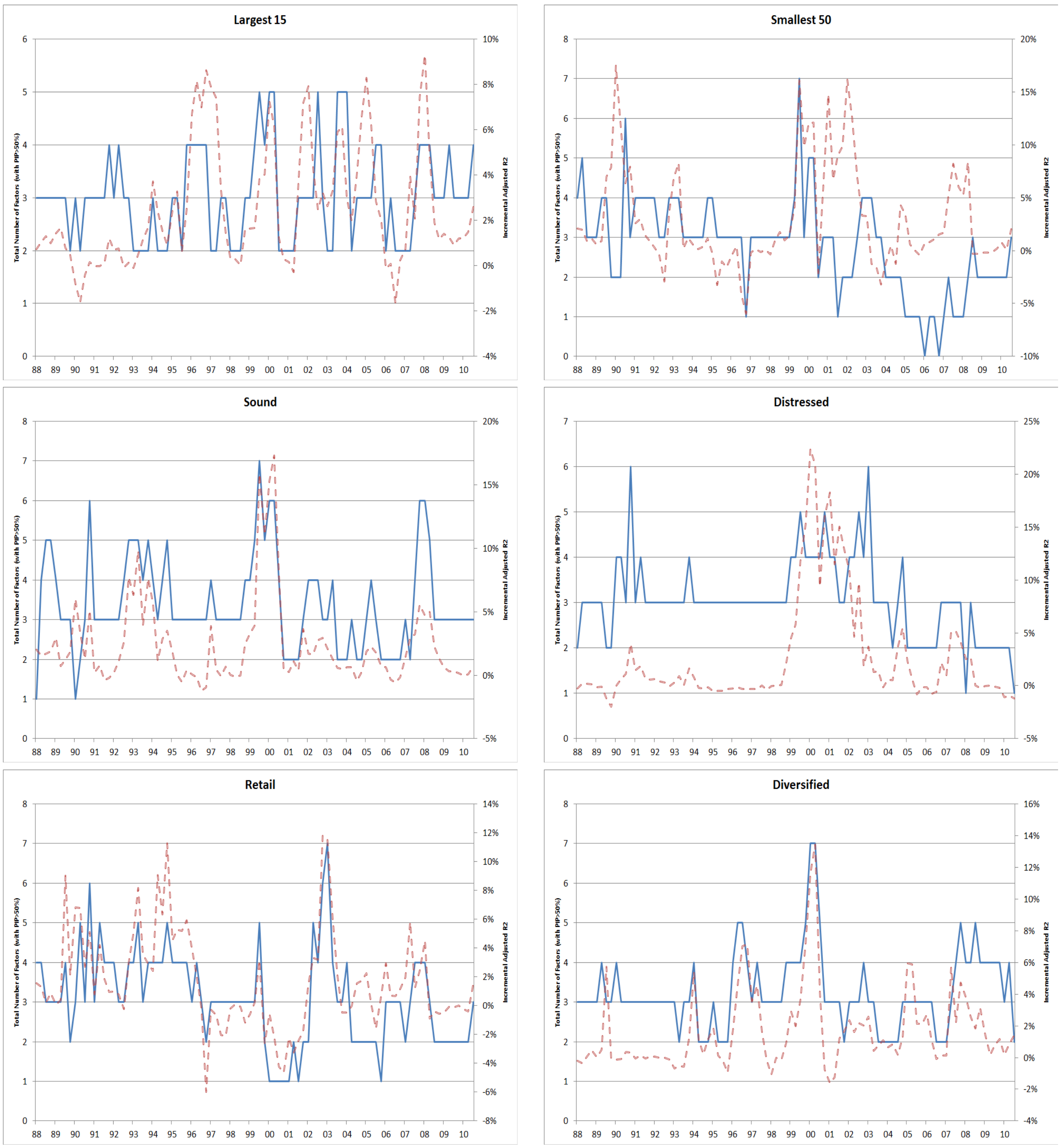
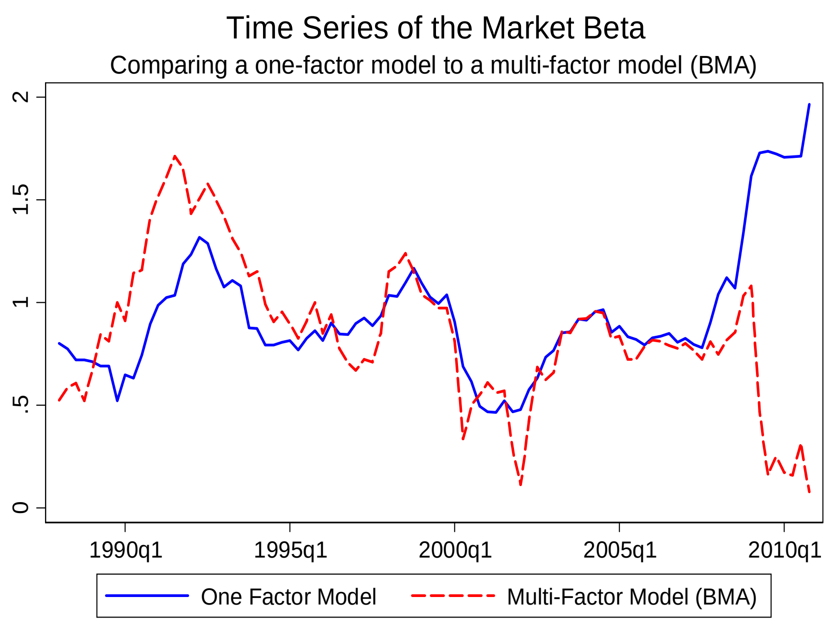


Figure 3: Estimates of the market beta in the benchmark one-factor model and in the BMA analysis

This Figure plots the market exposure obtained via two different approaches. The solid line depicts the time-varying market beta from a single factor model. The dashed line depicts the exposure to market risk estimated in the BMA analysis with eleven additional factors. The beta reported for a given quarter is obtained by using weekly stock returns of the preceding two years.



Online appendix to accompany the paper:

Model Uncertainty and Systematic Risk in US Banking

Lieven Baele[*] Valerie De Bruyckere[†] Olivier De Jonghe [‡]

Rudi Vander Vennet[§]

Abstract

This online appendix provides additional results using different model priors.

[*]CentER, Netspar, Tilburg University, Warandelaan 2, Tilburg, The Netherlands. lieven.baele@tilburguniversity.edu

[†]Corresponding author: Ghent University, W. Wilsonplein 5D, Ghent, Belgium. valerie.debruyckere@ugent.be.

[‡]CentER, European Banking Center, Tilburg University, Warandelaan 2, Tilburg, The Netherlands. o.dejonghe@tilburguniversity.edu

[§]Ghent University, W. Wilsonplein 5D, Ghent, Belgium. rudi.vandervennet@ugent.be

1 Correlated Regressors

One issue of potential concern is that the independent variables included in the analysis are correlated. This multicollinearity issue is best addressed by investigating the cross correlation matrix, displayed in Table 1.

<Insert Table 1 here>

From this matrix we can see that the market factor has a correlation of −69% with VXO and 65% with real estate. Moreover, the 3 Month Treasury Bill rate has a correlation of −47% with the TERM spread. The correlation between the liquidity related variables is also rather high. The correlation of the TED spread with DepS and MMS is 87% and −39% respectively, and the correlation of DepS with MMS is −28%. Hence, it seems that at least for some variables, the interdependencies between them might be an issue. We address the issue of collinearity in three ways.

Principal Components Analysis and Orthogonalization A first solution to deal with the correlation between the regressors is to use principal components analysis (PCA) to extract the first principal component of a set of related variables. Arguably, the TED spread, DepS (capturing funding need in the deposit market) and MMS (capturing funding need in the money market) are closely related variables, capturing some aspect of liquidity risk. We run a PCA on these three variables and retain only the first principal component. The first principal component explains almost 70% of the variation in the variables and has a coefficient of −0.66 on the TED spread, −0.64 on DepS and 0.40 on MMS. Moreover, the market factor has a strong correlation with the implied volatility index (−69%) and the Real Estate factor (65%). Therefore, we orthogonalize both variables with respect to the market factor, and use the residuals instead. The resulting correlations of these adjusted regressors with the other regressors is reported in the lower part of Table 1.

Table 2 reproduces the OSL and BMA results of the baseline regression reported in the paper. In addition, in the middle panel, we display the OLS and BMA results on the set of modified regressors. Our conclusions regarding the importance of each of the variables remains the same. The posterior inclusion probability of the first principal component of liquidity is 15%. Moreover, the results remain unchanged for the VIX and the real estate factor. For the other variables, the order of magnitude of the estimated regression coefficients and the posterior inclusions probabilities is similar.

<Insert Table 2 here>

Collinearity Adjusted Dilution Prior (George (2010)) First, we modify our model priors, such that models with correlated regressors get a lower prior model probability. We check the robustness of our results with respect to the dilution prior of George (2010). The model prior in equation 7 (in the paper) implicitly assumes that the probability that one regressor appears in the model is independent of the inclusion of others, whereas regressors are typically correlated. George (2010) argues that the assumption of prior independent inclusion of regressors is too strict. The model prior that gives equal prior probability to all models does not take into account similarity of models. This implies that these model priors assign too much probability to neighborhoods of redundant models. As a result, good but unique models will receive too little weight, whereas bad but similar models receive too much weight. George (2010) accounts for this by introducing a dilution prior. This type of prior assigns lower prior probability to models with correlated regressors. Hence, modifying the model priors is an ex ante way of correcting for the correlation between regressors. More specifically, the prior probability of each model $M^{(k)}$, is downweighted using the collinearity in $x_2^{(k)}$(George (2010)). Define $R^{(k)}$ to be the correlation matrix of $x_2^{(k)}$. Note that $|R^{(k)}|$ is an overall measure of collinearity. For $|R^{(k)}| = 1$, the columns of $x_2^{(k)}$ are orthogonal. The lower $|R^{(k)}|$, the greater the redundancy in a model $M^{(k)}$. Therefore, one can use this measure to alter equation 7 (in the paper) as follows

$$p(M^{(k)}) = h(|R^{(k)}|) \cdot \frac{1}{K}$$

where h(.) is a monotone function satisfying $h(1) = 1$ and $h(0) = 0$. Here, h(.) is modelled as h(r) = r.

In the lower panel of Table 2, we replicate the resuls in the upper panel of Table 2 with the dilution prior of George (2010). We can see that our conclusion with respect to the importance of our regressors and the estimated coefficients remain the same.

References

George, E. I., 2010, "Dilution priors: Compensating for model space redundancy," *IMS Collections, Borrowing Strength: Theory Powering Applications âĂŞ A Festschrift for Lawrence D. Brown*, 6, 158–165.

Table 1: Cross correlations of the independent variables

This table shows the cross correlations between the independent variables. In the upper part of the table, we report the correlation matrix of the factors included in the baseline setup. In the lower part of the table, we report the correlation matrix after making two adjustments. The TED spread, DepS (capturing funding need in the deposit market) and MMS (capturing funding need in the money market) are closely related variables. All three variables are capturing some aspect of liquidity risk. Therefore, we run a principal components analysis on these three variables and retain only the first principal component. The first principal component explains almost 70 per cent of the variation in the variables and has a coefficient of 0.62 on the TED spread, 0.63 on DepS and -0.40 on MMS. Moreover, the market factor has a strong correlation with the implied volatility index (-0.69) and the Real Estate factor (0.65). Hence, we orthogonalize both variables with respect to the market factor, and use the residuals instead. The correlation coefficients of these three adjusted regressors with respect to the others is displayed in the lower part of the this table.

Correlation matrix

	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO
SMB	-0.01										
HML	-0.25	-0.20									
TB3	0.14	0.14	-0.08								
TS	-0.05	0.09	0.07	-0.47							
DS	-0.13	-0.13	0.01	-0.06	-0.06						
TED	-0.17	-0.07	0.04	-0.54	0.42	0.08					
DepS	-0.15	-0.07	0.06	-0.52	0.45	0.04	0.87				
MMS	0.00	-0.03	0.05	-0.06	-0.11	-0.07	-0.39	-0.28			
FX	-0.10	-0.02	-0.07	0.07	-0.01	0.12	0.02	0.01	0.00		
VXO	-0.69	-0.08	0.11	-0.33	0.12	0.17	0.19	0.16	-0.01	0.08	
RE	0.65	0.22	0.06	0.13	0.00	-0.14	-0.15	-0.14	0.01	-0.07	-0.51

Correlation matrix (after PCA and orthogonalisation)

	Market	SMB	HML	TB3	TS	DS	PC(LIQ)	FX	VXO $\perp$
PC(LIQ)	-0.14	-0.06	0.03	-0.46	0.42	0.07		0.01	
VXO $\perp$	-0.01	-0.13	-0.09	-0.32	0.12	0.12	0.08	0.02	
RE $\perp$	0.01	0.30	0.29	0.06	0.04	-0.08	-0.06	-0.01	-0.12

Table 2: Bayesian Model Averaging in the static linear model

This table summarizes estimation results for the static linear model estimated over the full sample (January 1986 to December 2010). In this robustness check, we report results using our benchmark index of the 50 largest bank holding companies. Each column corresponds with a different risk factor. In the upper part of the table, we reproduce the baseline results for comparison. We report 5 statistics, namely the OLS factor exposure and t-statisitc, the BMA factor exposure and corresponding t-statistic (column 1) and the OLS factor exposure and the Posterior Inclusion Probability.
In the middle part of the table, we report OLS and BMA results after making two adjustments to the set of risk factors. First, we construct PC(LIQ), which is the first principal component of the set of liquidity related variables (TED spread, DepS and MMS). Second, VXO, the implied volatility index, and the real estate factor are orthogonalized with respect to the returns on the market factor. All other factors are unchanged.
In the lower part of the Table, we provide additional results using a different model prior in Bayesian Model Averaging. The model prior that gives equal prior probability to all models does not take into account similarity of models. As a result, good but unique models will receive too little weight, whereas bad but similar models receive too much weight. Therefore, we now use the collinearity adjusted dilution prior of George (2010) such that models with correlated regressors get a lower prior model probability. Hence, modifying the model priors is an ex ante way of correcting for the correlation between regressors.

Base results

	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE
β-OLS	0.96	0.04	1.15	-2.37	-0.47	2.17	0.49	-0.91	-0.80	0.10	-0.05	0.20
t-stat OLS	19.22	0.73	20.06	-3.15	-0.88	1.61	0.45	-0.87	-2.07	1.50	-1.75	7.13
β-BMA	0.99	0.00	1.14	-0.69	0.00	0.32	0.12	0.01	-0.13	0.01	0.00	0.20
t-stat BMA	24.33	0.06	21.03	-0.84	-0.03	0.34	0.31	0.06	-0.43	0.22	-0.17	7.83
PIP	100%	3%	100%	47%	3%	13%	12%	5%	19%	7%	5%	100%

Results BMA after PCA and orthogonalisation

	Market	SMB	HML	TB3	TS	DS	PC(LIQ)	FX	VXO $\perp$	RE $\perp$
β-OLS	1.20	0.05	1.15	-1.78	-0.54	2.36	0.00	0.10	-0.04	0.20
t-stat OLS	40.43	0.79	19.99	-2.62	-1.02	1.74	1.10	1.39	-1.50	7.17
β-BMA	1.18	0.00	1.14	-0.65	0.00	0.34	0.00	0.01	0.00	0.20
t-stat BMA	40.14	0.06	21.02	-0.81	-0.02	0.34	0.36	0.21	-0.16	7.83
PIP	100%	3%	100%	45%	3%	14%	15%	7%	5%	100%

Results with collinearity adjusted dilution prior (George (2010))

	Market	SMB	HML	TB3	TS	DS	TED	DepS	MMS	FX	VXO	RE
β-BMA	0.99	0.00	1.14	-0.66	0.00	0.31	0.11	0.02	-0.13	0.01	0.00	0.20
t-stat BMA	24.66	0.05	21.05	-0.81	-0.02	0.33	0.31	0.10	-0.42	0.21	-0.11	7.83
PIP	100%	2%	100%	46%	3%	13%	11%	4%	19%	7%	3%	100%

CHAPTER 4

Bank/sovereign risk spillovers in the European debt crisis

Bank/sovereign risk spillovers in the European debt crisis

Valerie De Bruyckere [*] Maria Gerhardt Glenn Schepens Rudi Vander Vennet

Abstract

This paper investigates contagion between bank risk and sovereign risk in Europe over the period 2006-2011. We define contagion as excess correlation, i.e. correlation between banks and sovereigns over and above what is explained by common factors, using CDS spreads at the bank and at the sovereign level. Moreover, we investigate the determinants of contagion by analyzing bank-specific as well as country-specific variables and their interaction. We provide empirical evidence that various contagion channels are at work, including a strong home bias in bank bond portfolios, using the EBA's disclosure of sovereign exposures of banks. We find that banks with a weak capital and/or funding position are particularly vulnerable to risk spillovers. At the country level, the debt ratio is the most important driver of contagion.

Keywords: Contagion, bank risk, sovereign risk, bank business models, bank regulation, sovereign debt crisis

JEL Classifications: G01, G21, G28,H6

[*] Ghent University, Department of Financial Economics, Woodrow Wilsonplein 5D, Ghent, Belgium. Authors' e-mail addresses: valerie.debruyckere@ugent.be, maria.gerhardt@ugent.be, glenn.schepens@ugent.be and rudi.vandervennet@ugent.be. The authors gratefully acknowledge financial support from the National Bank of Belgium. Valerie De Bruyckere acknowledges support from the Fund for Scientific Research (Flanders) as an FWO aspirant. Glenn Schepens acknowledges support from the Fund for Scientific Research (Flanders) under FWO project G.0028.08N. Financial support from the Hercules Foundation is gratefully acknowledged.

"The most serious threat to financial stability in the European Union stems from the interplay between the vulnerabilities of public finances in certain EU member states and the banking system, with potential contagion effects across the Union and beyond".

Jean-Claude Trichet, 22th of June 2011, ESRB[1]

1. Introduction

Due to the absence of a common European policy framework for handling the banking crisis as well as missing bank resolution mechanisms, several European governments were forced to respond at the national level by rescuing troubled banks headquartered in their countries during the financial crisis. Various measures have been taken, ranging from equity injections in troubled banks to the setting-up of bad banks (Petrovic and Tutsch (2009)). Invariably, these rescue operations have increased national debt burdens and caused a deterioration of public finances. One consequence of the risk transfer from the private sector to sovereign treasuries has been an increased interdependence of banks and states, causing negative feedback loops between their financial conditions. With the rise of the sovereign debt crisis in Europe, the link between bank- and country risk has intensified further, especially for the countries that were quickly identified as vulnerable, namely Greece, Ireland, Italy, Portugal and Spain (the GIIPS countries). This increased interdependence is illustrated in the figures in appendix. The figures depict the country CDS spread and the average bank CDS spread for the countries in our sample. They illustrate that there is a lot of heterogeneity in both the level of the sovereign and bank CDS spreads and in the comovement between the sovereign and bank spreads. The link between the risk profile of banks and countries in which they are headquartered varies over time and is partly influenced by shocks in the economy or the banking system. A major shock stemming from the banking system was the demise of Lehman Brothers in September 2008, which provoked a substantial increase of CDS spreads for banks and also for certain countries, typically smaller countries with large banks or countries where banks had to be rescued. The sovereign debt crisis further intensified the link between bank- and country risk. The sovereign debt crisis is usually considered to have started at the end of 2009, when the newly elected Greek government announced that the country's budget deficit was much larger than previously reported. In the case of Greece, two bailout packages were put together under the surveillance of the "troika" (IMF, ECB, European Commission), one of them including a substantial write-off of Greek

[1] http://www.esrb.europa.eu/news/pr/2011/html/is110622.en.html

debt in the books of private investors. Later, further rescue packages were implemented for Portugal and Ireland, all under the supervision of the troika. A series of credit rating downgrades of the affected countries followed, causing bond and CDS spreads to widen considerably, as shown, e.g., in the Global Financial Stability Reports of the IMF.[2]

During the sovereign debt crisis, banks in Europe were and remain confronted with stress in their capital and liquidity positions. A substantial number of banks had to rebuild their capital buffers after the losses they innitially incurred in their securities (mainly asset-backed) and lending portfolios, especially those with real estate exposures. A general lack of trust hampered the access of banks to money market funding, which was eventually alleviated, at least temporarily, by non-conventional longer-term refinancing operations set up by the ECB. Further, the European Banking Authority (EBA) decided to conduct a sovereign stress testing exercise and required that banks execute detailed capital rebuilding plans before mid-2012. The disclosure of detailed information on banks' exposures to sovereign risk in the EBA (and former CEBS) stress testing exercises provided valuable information to market participants to gauge the risk profile of European banks. Overall, the consequence of the continued stress in the banking system and the vulnerability of certain European sovereigns is that the financial conditions of banks and sovereigns became increasingly intertwined.

Considering this increased interaction between sovereign and bank credit risk, the objective of this paper is twofold. First, we analyze whether we find empirical evidence of contagion. We investigate the time-varying intensity of the risk spillovers using excess correlations as our preferred contagion metric. Second, we attempt to explain the contagion effect by investigating the relationship between excess bank/sovereign correlations and both bank and country characteristics. While there have been several papers investigating the determinants of either bank risk or sovereign risk in isolation, there is less evidence on the potential mutual contagion effects. By analyzing a number of relevant variables and the interplay between bank and country characteristics, we are able to identify critical interactions that are related to bank/country contagion. This allows us to tackle a series of relevant policy questions concerning the banking system as well as the financial condition of sovereigns.

The main findings of this paper can be summarized as follows. We document significant empirical evidence of contagion between bank and sovereign credit risk during the European sovereign debt crisis. In 2009, when the sovereign debt crisis emerged, we find significant spillovers for 86% of the banks in our sample. Second, given the home bias in banks' government exposures, i.e. their typically larger expo-

[2] Throughout the paper we use the terms contagion and risk spillover interchangeably.

sure towards the home sovereign, we provide empirical evidence confirming the expectation that contagion between banks and their home country is stronger. Third, we find that the degree of contagion is significantly linked to bank capital adequacy, and this effect is economically very significant. Furthermore, the higher a bank's reliance on short-term funding sources, the higher the intensity of spillovers between banks and sovereigns. Making use of the EBA stress test disclosures, which include bank-specific information on banks' sovereign debt holdings, we confirm that higher sovereign debt holdings are associated with a stronger bank-sovereign contagion. This suggests that the disclosures made in the context of the EBA stress tests have increased the degree of transparency of bank risk exposures and that market participants use this information to assess the creditworthiness of banks.

The remainder of this paper is structured as follows. Section 2 reviews the literature on contagion and more specifically the European sovereign debt crisis. In Section 3 we describe the data and the methodology. Section 4 reports our empirical findings, including robustness checks. Section 5 summarizes the conclusions and policy implications.

2. Bank/Sovereign Contagion: Literature Overview

This paper is closely related to three strands of the existing literature. First, our paper is linked to work on the emergence of the European sovereign debt crisis and the transmission channels through which it propagates. Second, our empirical analysis is closely related to work on financial contagion. The third strand of relevant literature investigates the risk profile of bank business models.

Regarding the risk transmission channels, BIS (2011b) identifies four main channels through which sovereign risk can have an impact on financial institutions. First, there is an *asset holdings channel*, since the asset side of banks' balance sheets may directly be weakened through losses on holdings of sovereign debt. This channel is investigated by Angeloni and Wolff (2012), who study whether banks' sovereign exposure to GIIPS countries had an effect on their stock market values. They find that banks' market performance in the period July to October 2011 was impacted by Greek debt holdings, and in October to December 2011 by Italian and Irish sovereign exposures. Spanish exposure did not appear to have an impact on banks' stock market values. On the relationship between sovereign risk and bank risk, Kyle and Wirick (1990) test whether the August 1982 advent of the Latin American debt crisis affected the implicit value of commercial bank equities. They find indeed that the market value of banks with major Latin American loan exposure was significantly reduced.The second transmission channel is a *collateral channel.* Sovereign risk can potentially spread to banks when the value of collateral that banks hold in the form of sovereign debt is reduced. This relates to studies such as Kiyotaki and Moore (2005) and Kaminsky et al. (2003), who describe how negative shocks in one market can directly affect collateral values or cash flows associated with securities in other markets. Related to this, a *rating channel* may impact banks' funding conditions, since downgrades of sovereigns may influence the rating of domestic banks negatively. This may in turn affect banks' funding costs and possibly worsen their access to money market and deposit markets. Arezki et al. (2011), for example, focus on European sovereigns between 2007 and 2010 and show that sovereign rating downgrades cause a significant spillover, both across markets and countries. Finally, the *guarantee channel* is related to the too-big-to-fail status of some large banks. When the fiscal position of sovereigns is weakened, implicit and explicit government guarantees might lose value, making it harder for the financial sector to derive benefits from such guarantees.

In line with the guarantee channel, Brown and Dinc (2011) provide evidence that a country's ability to support its financial sector, as reflected in its public deficit, affects its treatment of distressed banks. Demirguc-Kunt and Huizinga (2011) find that in 2008 systemically large banks saw a reduction in their market valuation in countries running large fiscal deficits, as these banks became too big to save. When governments bail out banks, Ejsing and Lemke (2011) show that there can be a 'credit risk transfer'. Exploring the developments of CDS spreads for Euro area countries and banks from January 2008 to June 2009, they show that the bailouts during that period caused a credit risk shift from the banking to the sovereign sector, with banks' CDS spreads decreasing at the expense of increasing sovereign risk spreads. Alter and Schuler (2012) also focus on bank bailouts during the recent financial crisis in Europe. They use a vector error correction framework to analyze price discovery mechanism of CDS spreads prior to and after government rescue packages. Their main results state that before bank bailouts, increased bank default risk was transmitted to sovereign CDS, yet the impact the other way around was weak. They further find that after bank rescues, increased sovereign default risk does have an impact on banks' CDS spreads.

We contribute to the literature on risk transmission channels by analyzing different credit risk transmission channels. First, we use detailed sovereign bond holdings data - collected from the EBA stress test reports - to better identify the asset holdings channel. Further, we focus on the collateral channel by investigating the impact of bank funding structures. The guarantee channel is addressed by including data on bank size relative to the GDP of the country where it is headquartered.

Second, this study is closely related to existing work on financial contagion. The literature on contagion is very broad; excellent overviews can be found in Pericoli and Sbracia (2003), Dungey et al. (2005) and Pesaran and Pick (2007). We are particularly interested in default risk contagion at the bank and the sovereign level. As mentioned by Caporin et al. (2012), recent research on sovereign credit contagion especially focused on the relationship between sovereign risk and common global and financial factors (see, e.g., Kamin and von Kleist (1999), Eichengreen and Mody (2000), Mauro et al. (2002), Pan and Singleton (2008), Longstaff et al. (2011) and Ang and Longstaff (2011)). At the bank level, there exists a vast literature on systemic risk, which is closely related to contagion, since systemic risk usually refers to situations where multiple financial institutions fail as a result of a common shock or a contagion process (Allen et al. (2010)). For an excellent overview on this topic, we refer to Allen et al. (2009). Papers looking at contagion between the sovereign and the banking level, however, are rather scarce as this topic only recently gained importance during the European debt crisis (see Angeloni and Wolff (2012), Ejsing and Lemke (2011), Demirguc-Kunt and Huizinga (2011), Alter and Schuler (2012), Acharya et al. (2012), Alter and Beyer (2012), Gross and Kok (2012) and Bosma and Wedow (2012)). Acharya et al. (2012), for example, provide empirical evidence of a two-way feedback between financial and sovereign credit risk during the recent crisis. They find evidence for widening sovereign spreads and narrowing bank spreads shortly after a bailout, but significantly higher comovement in the long term. Finally, sovereign credit risk is found to be related to the crash risk of the euro. Hui and Chung (2011) investigate the relationship and find that the impact of sovereign credit risk on crash risk is mainly driven by individual euro-area countries with weaker fiscal positions.

We add to this part of the literature by documenting the evolution of risk spillovers between the sovereign and the banking sector during the recent financial crisis and by explaining differences in spillovers based on observable characteristics of banks and sovereigns.

Finally, this paper relates to an extensive literature on the impact of bank business models on their risk profile. Previous studies primarily focused on the impact of business model characteristics on idiosyncratic or systematic bank risk. Wheelock and Wilson (2000) focus on US banks between 1984 and 1994 and find that lower capitalized banks are at greater risk of failure, as are banks with low earnings. Stiroh (2004), Stiroh (2010) and Baele et al. (2007) investigate the link between non-interest income and risk-taking. Others focus on the impact of funding structure on bank risk. Calomiris and Kahn (1991) argue that institutional investors tend to be relatively sophisticated compared to depositors and hence are expected to provide more market discipline. The recent crisis also brought out the dark side of bank wholesale funding, as described by Huang and Ratnovski (2011). They show that in an environment with a costless but noisy public signal about bank quality, short-term wholesale financiers have lower incentives to monitor, and instead may withdraw based on negative public news, which could lead to severe funding problems for banks. Related to this, several recent studies have linked these business models to bank performance and riskiness during the recent financial crisis. Beltratti and Stulz (2012) and Demirguc-Kunt and Huizinga (2010) find that banks heavily relying on wholesale funding were perceived as being more risky by the market during the recent financial crisis. Altunbas et al. (2011) confirm these findings and also show that undercapitalization was a major driver of bank distress. Ayadi et al. (2011) screen 26 major European banks for their business models before and after the crisis and conclude that wholesale banks had the worst performance and were most likely to receive state support, whereas retail banks exhibit less risk with a more stable performance. We contribute to this part of the literature by investigating the impact of bank business models on their vulnerability to contagion risk, which became particularly important during the European sovereign debt crisis. Rather than focussing on idiosyncratic or systematic bank risk, we are interested in business models that can allow banks to minimize contagion exposure.

3. Data & Methodology

3.1. Measuring credit risk

To make inference on contagion between bank and sovereign credit risk, we make use of the spreads on credit default swaps. CDS contracts are bilateral swap agreements that represent a protection provided by the CDS seller to the buyer. The seller engages to compensate the buyer in case of the occurrence of a pre-defined credit event.[3] The buyer makes regular payments to the seller, the so-called CDS spread, and in return receives a compensation for his loss in case of a credit event. Given the setup of CDS agreements, their spreads capture the credit risk of the underlying asset. An important feature of CDS quotes is that CDS markets react instantly to changes in credit risk. Hence, the premia reflect market perceptions in real time, as opposed to rating agencies, for instance, which may take a broader view before changing ratings of entities. Alternative indicators of sovereign and bank credit risk are government and bank bond yields. As mentioned by Aizenman et al. (2011), CDS spreads have three main advantages compared to sovereign

[3]CDS are typically based on the standard industry terms for credit events, as defined by the International Swaps and Derivatives Association (ISDA). For further information, see http://www.isda.org.

bond spreads. First, CDS spreads provide timelier market-based pricing. Second, using CDS spreads avoids the difficulty in dealing with time to maturity as in the case of using interest rate spreads (of which the zero coupon bonds would be preferred). Third, bond spreads include inflation expectations and demand/supply for lending conditions as well as default risk. As we explicitly want to capture default risk, we focus on CDS spreads. Similar to previous studies on CDS spreads (e.g. Aizenman et al. (2011), Alter and Schuler (2012), Anderson (2011) and Barrios et al. (2009)), we use CDS spreads on 5-year senior debt contracts, since these are known to be the most actively traded and therefore most liquid ones. All CDS quotes are obtained from Bloomberg, CMA.[4] We obtain CDS spread series for 15 countries[5] and for more than 50 banks over the years 2006-2011. The number of banks in our sample increases over time due to data availability. The CDS spread series are transformed into arithmetic returns. We impose strict liquidity criteria to ensure that the CDS spread changes reflect meaningful information on bank and sovereign credit risk. More specifically, we only retain CDS spread changes during a certain quarter if at least 70% of observations are non-zero during the quarter.

Table 1 shows the summary statistics of the CDS spread changes for both sovereigns and banks. The volatility of sovereign credit risk was highest during 2008, for the banks covered in our sample volatility was highest during 2007 and 2008.

3.2. *Measuring contagion*

The concept of contagion is difficult to grasp and there exist several different methodological approaches to analyze contagion. The first important question is: How to identify contagion? Constancio (2012) lists four criteria that have been used in the literature to define contagion, namely: "(i) the transmission is in excess of what can be explained by economic fundamentals; (ii) the transmission is different from regular adjustments observed in tranquil times; (iii) the events constituting contagion are negative extremes; (iv) the transmission is sequential, for example in a causal sense." There is no agreement in the literature on a single

[4]Credit Market Analysis. CMA receives quotes for credit instruments from large investors active in over-the-counter markets. Different sources are aggregated and combined by CMA to calculate one average quote. We use daily end-of-day London prices. Mayordomo, Peña and Schwartz (2010) find that the CMA quotes lead the price discovery process in comparison to quotes provided by other databases (GFI, Fenics, Reuters EOD, Market or JP Morgan). Leland (2009) mentions that CDS spreads from Bloomberg are frequently revised weeks after, and often disagree substantially with Datastream CDS spreads.

[5]The 15 countries are Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, the UK, Norway and Switzerland.

definition, however the first criterion, which is mainly attributed to Bekaert et al. (2005), has been widely used, and this is also the one we focus on in our study.[6]

As discussed in the introduction, we are interested in potential contagion between sovereign and bank default risk. The risk transfer from the private to the public sector through bank rescue schemes during the recent financial crisis has increased bank and sovereign interdependence. Furthermore, the exposure of banks to governments through sovereign debt and the potential lower probability of future bailouts for banks due to deteriorating public finances are additional reasons to expect higher interconnectedness between banks and states. An intuitive starting point to measure this potential increase in interdependence could be looking at simple correlations between two default risk indicators. However, simple correlations during crisis periods could be misleading, as one would simply expect higher correlations during periods of higher volatility (see Boyer et al. (1999) and Forbes and Rigobon (2002)). Following Bekaert et al. (2005), we define contagion as excess correlation, which is correlation over and above what one would expect from economic fundamentals. By defining a factor model in the first stage of our analysis, we avoid problems with the bias correction for correlations that Forbes and Rigobon (2002) propose. Assuming that CDS spreads are adequate credit risk proxies and assuming that CDS spread changes follow a linear factor structure, increased correlation between bank and sovereign credit risk can be driven by three potential sources (also see Anderson (2011)): (i) an increase in exposure of CDS spread changes to common factors, (ii) increased correlation between the common factors, and (iii) an increase in the correlation between unexplained CDS spread changes, which is what we label as contagion. More specifically, the correlation between CDS spread changes of a bank b and a country c can be decomposed as follows:

$$\begin{aligned} E[\Delta CDS_{b,t}\Delta CDS^{'}_{c,t}] &= E[(\beta_b F' + \varepsilon_{b,t})(\beta_c F' + \varepsilon_{c,t})'] \\ &= \beta_b E[F'F]\beta_c' + E[\varepsilon_{b,t}\varepsilon_{c,t}'] \end{aligned}$$

The excess correlation between a bank b and a country c is then defined as

[6] The difficulty of identifying contagion is not only present in academic literature, but practitioners and bankers face the same challenge. In 2009, the Fitch Global Credit Derivatives Survey revealed that many banks were surprised by the sovereign-bank contagion that built up in the markets during the previous year. In particular, "market participants, when referring to contagion, highlight the speed at which credit spreads widened, particularly for financial institutions and sovereigns, the volatility of credit spreads, the unanticipated convergence in correlation values across asset classes and the heightened perception of counterparty risk which resulted in many institutions refusing to deal with other ones in the financial markets."

$$corr_{b,c,t} = E[\varepsilon_{b,t}, \varepsilon_{c,t}]$$

Hence, we investigate the presence of contagion between banks and countries by considering excess correlation, which is the correlation between bank and sovereign credit risk over and above what can be explained by fundamental factors. When the jump in correlation is fully driven by fundamental factors, we expect the excess correlations to be zero. However, when bank and sovereign CDS spreads are still correlated after controlling for fundamental factors, we see this as evidence of contagion between the bank and the country level.

In order to address these common risk factors, we condition CDS spreads on four state variables. To control for market-wide credit risk, we include the *iTraxx Europe* index[7], an index constructed as the equally weigthed average of the 125 most liquid CDS series in the European market. A higher iTraxx indicates a higher overall default risk in the economy, thus we expect a positive relationship between the iTraxx index and the bank and sovereign CDS spreads. To control for market-wide business climate changes in the European Union, we include Datastream's *total stock market index* for the EU[8]. A better overall business climate should reduce default probabilities and hence we expect a negative sign for the stock market index in our factor models. The third common factor is the *Vstoxx*[9] volatility index, capturing market expectations of volatility in the Eurozone (also see, e.g., Berndt et al. (2005), Tang and Yan (2010)). This index is generally perceived as a market sentiment or investor fear indicator. The higher the volatility, the higher the economic uncertainty. We thus expect a positive relation between credit spreads and market volatility. Finally, we control for market expectations about future conditions in the financial market, measured with the *Term Spread*. The term spread is calculated as the difference between the 10-year government bond yield for each country and the 1-year Euribor rate. We expect a negative relationship between the term spread and CDS spreads. All state variables are obtained from Datastream and transformed into arithmetic returns, except for the term spread, which we include in first differences.

[7]DS mnemonic "DIXE5EC". Both financial and non-financial firms are included. In order to be consistent with our bank and sovereign CDS data, we use the index that is based on 5-year maturity assets with end-of-day quotes.

[8]DS mnemonic "TOTMKEU". It mirrors all EU stock markets, not only the financial sector.

[9]DS mnemonic "VSTOXXI". The calculation of the VSTOXX is based on option prices for EURO STOXX 50, which incorporates stocks from 50 supersector leaders from 12 Eurozone countries. For more information, see: http://www.stoxx.com.

With the above selection of state variables, the regression specification of the factor model looks as follows:

$$\Delta CDS_{i,t} = c + \beta_1 \cdot Market_t + \beta_2 \cdot Itraxx_t + \beta_3 \cdot Vstoxx_t + \beta_4 \cdot Term_t + \varepsilon_{i,t} \quad (1)$$

where $\Delta CDS_{i,t}$ is the change in CDS spread for bank or country i, $Market$ is the stock market index for the EU, $Itraxx$ is the iTraxx Europe CDS index, $Vstoxx$ is the a volatility index and $Term$ is the term spread. To control for possible time variation in the exposures we run this factor model for every year in the sample separately. This way, we obtain time-varying coefficient estimates. In Section 4.3, we redo our analysis for two alternative specifications of the factor model: (i) we run the factor models including the Itraxx index as the only state variable, and (ii) we take a different choice of the regression windows, coinciding with major credit events in the CDS market. The main results remain unaltered.

The above analysis allows us to investigate whether, on a year-by-year basis, there is contagion between all bank/sovereign pairs. However, we are also interested in how this contagion evolves over time. To formally test whether changes in excess correlation are statistically significant, we make use of the Fisher transformation of (excess) correlation coefficients. We denote with $corr$ the correlation between a bank and a country (the home country or another country). The Fisher transformed correlation is then given by $corr^*$

$$corr^*_{b,c} = 0.5 \cdot \log(|\frac{(1 + corr_{b,c})}{(1 - corr_{b,c})}|)$$

The standard error or $corr^*_{b,c}$ is given by $\frac{1}{\sqrt{N-3}}$ where N is the number of observations. The test-statistic for the difference between two measures of (excess) correlation $corr^*_{b,c}$ (labeled the Z-statistic) is given by

$$Z_{t_1,t_2} = \frac{(corr^*_{t_1} - corr^*_{t_2})}{\sqrt{\frac{1}{\sqrt{N_{t_1}-3}} + \frac{1}{N_{t_2}-3}}}$$

where N_{t_1} is the number of observations during the first period, and N_{t_2} the number of observations during the second period. The Z-statistic is normally distributed, and hence significance can be assessed with the usual test statistics.

3.3. Explaining contagion

Once we have established the presence of contagion between sovereign and bank credit risk, we take the analysis a step further by investigating bank- and country-specific characteristics that could be driving this excess correlation. For each country-bank combination in our sample, we calculate excess correlations on a quarterly basis using daily CDS data[10]. This is the dependent variable of interest in our panel analysis. Throughout the analysis, we exploit the fact that we have multiple observations (i.e. excess correlations with different countries) for each bank at each point in time. This allows us to look at the impact of country-specific characteristics while making abstraction of bank-specific factors. Similarly, since we have multiple observations for each country at each point in time, we are able to analyze the impact of bank-specific characteristics on the bank-country relationship.

We start by exploring cross-sectional differences between bank-country excess correlations by focussing on bank balance sheet characteristics. For example, we hypothesize that banks with higher capital adequacy levels are better able to withstand financial shocks, lowering the expected correlation between the bank and country level. To identify the impact of bank-specific factors we regress the excess correlations on a vector of bank-specific characteristics[11] and a home/foreign country time fixed effect. By using this three-way fixed effect, we can compare the excess correlation of bank i with country j to the excess correlation of another bank k - located in the same country z as bank i - with country j at the same point in time. This way, the variation left in the country-bank correlations can only be related to bank-specific differences. The specification thus looks as follows:

$$Corr_{i,j,t} = \alpha + \beta_1 * Z_{i,t} + \eta_{z,j,t} + \varepsilon_{i,j,t} \tag{2}$$

where $Corr_{i,j,t}$ is the excess correlation between bank i and country j at time t, $Z_{i,t}$ is a vector of bank-specific variables and $\eta_{z,j,t}$ is a three-way fixed effect, which addresses differences over time at the home and foreign country level.

In a next step we use a similar setup to analyze the potential impact of country-specific characteristics. We start by analyzing whether domestic banks have a stronger relation with the sovereign, by looking at the impact of higher sovereign CDS spreads on excess correlations, and by focusing on whether bank-specific characteristics can change the impact of higher sovereign CDS spreads. We use the following specification:

$$Corr_{i,j,t} = \alpha + \beta_1 * Home_{i,j} + \beta_2 * CDS_{j,t} + \beta_3 * CDS_{j,t} * X_{i,t} + \eta_{i,t} + \varepsilon_{i,j,t} \tag{3}$$

[10]We calculate excess correlations at quarterly frequency since this is the highest frequency for which we have bank balance sheet data available. The balance sheet data is linked to correlations in a later step.

[11]More detailed information on the bank-specific variables that we use can be found below in part 3.4 Bank- and country-specific factors

where $X_{i,t}$ is a vector of bank-specific variables , $CDS_{j,t}$ is the sovereign CDS spread of country j at time t , $Home_{i,j}$ is a dummy variable, which equals one when bank i is located in country j , $\eta_{i,t}$ is a bank-time fixed effect and $\varepsilon_{i,j,t}$ is the error term. By using bank-time fixed effects, we can compare the relationship of the same bank with different countries at the same point in time. In other words, by using bank-time fixed effects we ensure that the variation left in the excess correlations can be attributed to country-specific factors. We expect the home dummy coefficient to be positive and significant for several reasons. First, banks tend to have a strong home bias in their government bond portfolios, making them more vulnerable to home country shocks. Second, when banks get into distress, the probability of a bailout of that bank increases. As bailouts are typically financed by the home country of the bank, this can cause a contagion effect. Related to this, a government in a weak fiscal position is less likely to step in when things go wrong in the banking sector, potentially increasing the credit risk of the financial institutions in the home country. Fourth, problems at the sovereign level may lead to fiscal consolidation, which, although potentially beneficial in the long term, may lead to lower economic activity in the short term, which could increase loan losses and hence bank credit risk (Avdjiev and Caruana (2012)).We also expect that higher default risk at the country level will lead to higher excess correlations. Bank default risk is more likely to be related to sovereign default risk when sovereigns are in distress situations than when default risk at the sovereign level is low. We are also interested in whether some bank business models are better in withstanding sovereign distress than others. Therefore, we also interact the sovereign CDS spread with a set of bank business model characteristics.

In a following step, we consider the actual exposures of banks towards European countries and analyze whether these exposures have a direct impact on the contagion variable. We apply a similar setup as in equation 3. We focus on sovereign debt exposures, for which we have data available from the EBA stress test reports since mid-2010. We hypothesize that a bank's default risk is more strongly correlated with a country's default risk when the bank has a higher exposure to that country.

In a last step, we focus on country-specific factors that could be driving the relationship between sovereign CDS spreads and the excess correlations. We hypothesize that a banks' default risk is more strongly correlated with countries that have higher debt-to-GDP ratios, higher government revenues in percentage of GDP, a larger banking sector (in percentage of GDP) and a less optimistic economic sentiment indicator. We again expect this effect to be stronger towards the home country, which is why we also interact each of these variables with the home country dummy. The regression specification looks as follows:

$$Corr_{i,j,t} = \alpha + \beta_1 * Home_{i,j} + \beta_2 * X_{j,t} + \beta_3 * Home_{i,j} * X_{j,t} + \eta_{i,t} + \varepsilon_{i,j,t} \quad (4)$$

where $X_{j,t}$ is a vector of country-specific variables[12]. By using bank-time fixed effects, we can compare the relationship of the same bank with different countries at the same point in time.

3.4. Bank- and country-specific factors

An important contribution of our paper is to investigate the relationship between bank/sovereign contagion and the characteristics of the banks and countries involved. For the banks in the sample, we use a variety of measures intended to capture their business model. Consequently, we focus on indicators of their retail orientation, funding structure, diversification and, especially, the banks' capital adequacy (see Baele et al. (2012), Altunbas et al. (2011), Ayadi et al. (2011)). For countries, the selected variables focus on debt sustainability and business cycle conditions. Bank-specific data is mainly taken from Thomson Reuters Worldscope database; country-specific series are taken from a range of other sources (Eurostat, Oxford Economics, ECB statistical data warehouse). Summary statistics for these variables can be found in Table 3.

The first bank-specific variable we consider is bank size, measured as the ratio of each bank‘s total assets over its home country GDP. The rationale is that large banks are more likely to be systemic institutions that may need a public bailout in case of distress. The larger the bank, the more likely it is that a bank bailout will affect confidence in the financial system (BIS (2011a)). We expect that the relative size of banks is positively related to the excess bank/sovereign correlations, especially with the home sovereign.

Capital regulation is the cornerstone of the prudential regulation of banks. Since capital serves as a buffer for unexpected losses (e.g. value losses on sovereign bonds), the higher the capital buffer, the less risky a bank is and, hence, the lower we expect the excess correlations with sovereigns to be. In general, banks with adequate capital buffers are perceived by market participants to be able to withstand shocks much better than their less capitalized peers, which is reflected, e.g., in a lower market beta (Altunbas et al. (2011); Baele et al. (2007)). In our main analysis, we focus on an unweighted capital ratio that is calculated as the sum of Tier 1 and Tier 2 capital over total assets. As a robustness check, we also consider the risk weighted Tier 1 ratio.

[12]More detailed information on the country-specific variables that we use can be found below in part 3.4 Bank- and country-specific factors

The fundamental role of a bank is to transform deposits into loans to businesses and households. Therefore the loan-to-asset ratio is a typical indicator of a bank's retail orientation. Retail banks have been perceived as less risky than their non-retail peers, especially during the financial crisis. Schepens and Vander Vennet (2009) show that European retail banks, defined as banks with a high loan-to-assets ratio as well as a high deposit-to-assets ratio, have considerably lower market betas. Moreover, when a bank is characterized by a high proportion of loans in its total assets, the relative weight of securities is lower, entailing less exposure to (sovereign) bonds. Finally, when a bank operates a profitable lending portfolio, this should serve as a generator of profits and capital, which make a bank safer over time. Consequently, we expect that banks with a relatively high loan-to-asset ratio will exhibit lower excess correlations.

To assess the relevance of banks' exposures to (foreign) sovereign risk, we include information on country exposures. This data is taken from the CEBS and EBA stress tests of 2010-2011 that were carried out to assess the financial strength of European banks under different scenarios. The CEBS/EBA stress tests were the first Europe-wide exercises of that kind and the results as well as the main data inputs where made publicly available. The exercises included 90/91 of Europe's largest banks, covering over 65% of the EU banking system total assets and at least 50% of each national EU banking sector. In the context of the stress testing exercise, data was published on banks' sovereign debt exposures to the 30 European Economic Area states and was made available at two points in time: in July 2010 (data collection either in December 2009, in March or in May 2010) and in July 2011 (data collection in December 2010). Such detailed data had never been available at the bank level before; therefore, it was not possible to analyze the direct impact of sovereign debt exposure on individual bank's credit risk in the past. Our study is one of the first ones to include sovereign exposures to investigate such link, which basically captures the above described 'asset holdings channel'.

On the liability side of the balance sheet, the composition of the funding sources is an important determinant of the risk profile of a bank. Several papers have demonstrated that banks relying on wholesale funding, predominantly through the interbank market, are perceived by market participants to be more risky than banks predominantly funded with retail deposits. Especially during the financial crisis, funding through potentially volatile sources proved to be catastrophic for some banks. Altunbas et al. (2011) and Schepens and Vander Vennet (2009) report that banks with a relatively high proportion of wholesale funding exhibit significantly higher systematic risk, measured by the market beta. Hence, when the asset quality of a bank deteriorates (in this case because of the exposure to bonds of fragile sovereigns), informed market participants (e.g., institutional depositors) will focus on the sustainability of the bank's funding structure. This may hamper access to the interbank market and increase the cost of funding in the repo or deposit markets. Such risk spillovers between sovereigns and banks are another example of transmission channels that affect the cost of funding for banks. We measure the impact of a bank‘s funding structure by including the ratio of short term and money market funding over total funding.

The degree of revenue diversification is captured by the proportion of non-interest income in total revenues (see Stiroh (2006b) and Baele et al. (2007)). When a bank is less reliant on interest income, it is supposed to be better diversified in the case of negative shocks to its interest income or funding cost. However, non-interest sources of income may be more volatile, especially in periods of financial market stress, and hence provide an imperfect hedge. As a result, the ultimate effect on bank/sovereign excess correlations is unclear a priori.

The country-specific variables attempt to capture the state of public finances as well as the importance of business cycle conditions in each of the countries concerned. The main variable of interest is the debt-to-GDP ratio, since it is the major determinant of the sovereign rating (see, e.g., Bernoth et al. (2004)). We also include the ratio of government revenues to GDP for each country as a proxy for the revenue-generating capacity that sovereigns have to deal with banking problems. Since taxes are needed to service additional debt, this is an indicator of the hard budget constraint countries are facing. The larger the banks in a country, the more problematic bank rescues may be for public finances. Therefore, we include the size of the bank sector in each country as a proportion of GDP. The bigger the relative size of the banking system, the higher we expect bank/sovereign risk spillovers to be. Further, to account for business cycle conditions, an indicator for economic sentiment is added to our analysis. We use the economic sentiment indicator provided by the European Commission, which is composed of five sectoral confidence indicators (industrial, services, consumer, construction and retail trade) with different weights, each confidence indicator being based on surveys. Including these variables, and some interaction terms, enables us to get insight into the determinants of bank/sovereign contagion.

4. Results

4.1. Excess correlations

We investigate the presence of contagion between banks and countries by examining the excess correlation, which is the correlation between bank and sovereign credit risk over and above what can be explained by fundamental factors. We start by giving an overview of the factor models used to calculate the excess correlations (see eq. 1). Table 2 reports the summary statistics of the state variables in our analysis, whereas Table 4 shows the average coefficient estimates and their significance in the bank factor models.[13] Running these models on a yearly basis allows us to analyze the evolution over time of the impact of the state variables and they eventually yield the excess correlations. We notice a sharp increase in exposure to economy-wide credit risk (measured by the iTraxx factor) during 2007 and 2008 and this exposure remains elevated until the end of the sample period. Table 4 shows that the vast majority of banks loads significantly on the iTraxx factor (up to 97% of the banks in the sample in 2007). The significance of the other coefficient estimates is much lower (below 10% for both the market factor and Vstoxx implied volatility). These results are in line with Ejsing and Lemke (2011), who use the iTraxx index of non-financial CDS premia as single common risk factor, arguing that it explains most of the variability in corporate and sovereign CDS spreads. However, including more state variables implies that we control for more possible sources of commonality, which implies that the excess country/bank correlations are estimated more conservatively[14].

In the left hand side panel of Figure 1, we investigate how the average correlation between bank and home country credit risk varies over time, whereas the right hand side panel of Figure 1 reports the corresponding correlation in residuals, i.e. excess correlation, which is our preferred contagion measure. As expected, we notice an increased correlation between sovereign and bank CDS spreads during the recent financial crisis in the left hand side panel of Figure 1. As mentioned before, an increase in correlation does not necessarily imply evidence of contagion. Instead, contagion can only be inferred from a statistically significant increase in excess correlation. The right hand side panel of Figure 1 shows the average yearly excess correlation between the sovereign CDS spread and the average CDS spread of the banks headquartered in the country. We observe that correlation in CDS spread changes are on average higher than correlation in the residuals. Table 5 indicates that the average bank/sovereign correlation in our sample is 35%, whereas

[13]For convenience, we only report the results for the banks. The results of the sovereign factor models are similar and are available upon request.

[14]In part 4.3 we discuss the robustness of our results w.r.t. an alternative specification of the factor model.

the average excess correlation is 17%. Comparing both panels in Figure 1 indicates that common factors can only partly explain the increase in correlations during the crisis; even after controlling for common factors, there is still a strong increase in correlations between sovereign and bank CDS spreads between 2006 and 2011. It are precisely these excess correlations that we try to explain using country- and bank-specific variables.

The figures show a clear increase in excess correlations over the past years. To formally test whether this increase is also statistically significant, we make use of the Fisher transformation of (excess) correlation coefficients. The left-hand side in Table 6 ('Base Year: 2007') depicts the percentage of significant bank-country excess correlations during each year compared to excess correlations in 2007; the right-hand side ('Base Year: 2008') shows the results when taking 2008 as a benchmark. Moreover, we differentiate between contagion between banks and their home country (Panel A), banks and foreign countries (Panel B) and banks and GIIPS countries (both home and foreign, in Panel C). All three panels point to significant contagion in the vast majority of our sample. For example, in 2009 and 2010 we find evidence of significant contagion for respectively 86% and 64% of the banks with their home country (base year 2007). Furthermore, we observe that, in general, evidence of contagion between banks and foreign countries is slightly lower (76% and 63% of the banks in the sample in 2009 and 2010). Finally, we also notice significant contagion between banks and the GIIPS countries, which is most pronounced in 2009. As can be seen in the table, the number of observations in 2008 is always higher than in 2007. Therefore, we verify whether the evidence of contagion is still present when taking 2008 as the base year. Our previous conclusions are confirmed, as can be seen on the right-hand side of Table 6.

To summarize, we find significant evidence of increasing contagion between banks and countries in the period covering the bank crisis as well as the sovereign debt crisis in Europe. Yet, we are particularly interested in how to explain this excess correlation. We therefore turn to the analysis of bank- and country-specific characteristics.

4.2. Explaining bank-country contagion

In this part, we study the impact of bank- and country-specific characteristics on bank-country contagion. The particular structure of our database, in which we have excess correlations for each bank in our sample with different sovereigns on a quarterly basis, allows us to disentangle the impact of bank- and country-specific characteristics. More specifically, by either comparing the relation between one bank and different sovereigns (using bank-time fixed effects) or by comparing the relationship of different banks with one country (using country-time fixed effects), we can make a distinction between the impact of bank and country variables. Except for the home country dummy, all right hand side variables in these regressions are standardized, which means that the coefficients show the impact of a one standard deviation change of the independent variables.

In a first step, we study the impact of bank-specific characteristics on the country-bank excess correlations. We do this by comparing the excess correlations of different banks from the same country with a single country at a certain point in time. In terms of the regression setup, this implies that we introduce home country/foreign country time fixed effects. By comparing banks from the same country, we prevent that sovereign relationships that are unrelated to country-bank relationships disturb our analysis. It also allows us to control for potential differences between banks due to regulatory or institutional differences at the home country level. By comparing the different banks with a single country, we make sure that the only variation left in the excess correlations is due to bank-specific factors. The first specification of Table 7 shows the impact of a set of bank characteristics on contagion. We start by regressing the excess correlations on five bank balance sheet characteristics, i.e. bank size (total assets over GDP), asset structure (loan-to-asset ratio), funding risk (short term funding over total funding), capital adequacy (total capital ratio) and income diversification (non-interest income as a percentage of total income). In general, we find that bank size, capital adequacy levels and funding structure have a significant impact on bank-country contagion. For example, the coefficient of minus 1.76 for the total capital ratio implies that a one standard deviation increase in the total capital ratio (i.e. a rise in the total capital ratio of about 2.2 percentage points, see Table 3) leads to a decrease in country-bank excess correlations of about 1.76 percentage points. For the average bank in our sample, this means a reduction in excess correlation of almost 8 percent. Furthermore, banks with a higher proportion of short-term debt in their total funding exhibit higher bank-country excess correlations. The impact of a standard deviation change in the short-funding ratio is similar to the impact of a standard deviation increase in the capital ratio. This confirms that banks with potentially volatile funding are more exposed to shocks in the quality of their assets, confirming the presence of the collateral channel (see Section 2). This result is in line with the findings of Vuillemey and Peltonen (2012), who investigate whether sovereign CDS mitigate or amplify shocks on sovereign bonds. Their main finding is that the main risk for CDS sellers is in the sudden increases in collateral requirements.

These finding stress the importance of adequate bank capital buffers for bank stability. Whereas previous studies showed a strong effect of bank capital on bank-specific risk indicators (see, e.g. Wheelock and Wilson (2000) and Altunbas et al. (2011)) our findings suggest that adequate capital levels are also an important buffer against contagion. Similarly, where Demirguc-Kunt and Huizinga (2010) find that banks increase most of their short-term funding at the cost of enhanced bank fragility, our findings point at the importance of stable funding as a feature in mitigating contagion.

In column 2 of Table 7 we interact each bank-specific variable with a home country dummy to analyze whether there is any asymmetry in the above results caused by a stronger relation with the home country. The results show that the impact of the bank-specific variables is equally strong towards the home country compared to other countries, as none of the interaction terms is significant. The impact of the size of a bank (in percentage of GDP) on the excess correlations, for example, is not statistically different when comparing the home country excess correlations with the foreign country excess correlations. This suggests that there is no direct evidence in favor of the guarantee channel in this setup. However, further results using a different setup (see Table 9) indicate that the guarantee channel is at work. Overall, bank size is positively related to excess correlations, irrespective of focussing on the relation with the home country or a foreign country.

In the third column, we add banks‘ sovereign debt exposure as an explanatory variable. Notice that this reduces the sample size, as we only have information on debt exposures from 2010 onwards. The results for this setup first of all confirm our previous findings; better capitalized banks and banks with a lower proportion of short-term debt in their total funding exhibit lower bank-country excess correlations, although the capital ratio becomes insignificant in this setup. Furthermore, the impact of the income diversification variable becomes significant. Thus, in this subsample, banks with a lower percentage of non-interest income have significantly lower excess correlations. The fact that this variable has a stronger impact in this subsample is due to the sample period.[15] As we only have data on sovereign debt exposures from 2010 onwards, this subsample covers the recent crisis period. Being a more retail-oriented bank, i.e. having a lower proportion of non-interest income, reduces bank risk (see, e.g. Altunbas et al. (2011), Baele et al. (2007)) and helps to survive the most stressful moments of the sovereign debt crisis. These results point to a change in risk perception during periods of increased sovereign distress of certain bank business models. The sovereign debt exposure variable itself is not significant in this setup. We would expect higher exposures to lead to

[15]We run the same regression as in column one on the sample for which we have EBA data (column 3) and reach similar conclusions. This confirms that the change in significance for the loan to asset ratio and the income diversification variable is due to a the change in sample period and is not caused by the introduction of the EBA exposure variable.

higher excess correlations. However, we control for home country/foreign country time fixed effects, which means that we compare the relationship of different banks from the same country with one and the same country at a certain point in time. Thus, the insignificant result for the sovereign exposure variable is most likely a reflection of the fact that the variation in exposures between banks in the same country is rather limited.[16] Column 4 of Table 7 shows that our results also hold when using the Tier 1 ratio as a capital ratio instead of the total capital ratio. Overall, our results lend support to the new prudential rules contained in Basel III, which focus both on the level and quality of bank capital as well as the need for stable funding sources.

Next, we focus on the impact of home country effects, sovereign CDS spreads and the actual sovereign bond exposures of the banks on excess correlations. We expect that excess correlations will be higher when a country‘s default risk is higher, when we consider the relation between a bank and its home country and/or when banks are more exposed to sovereigns through their bond portfolio (asset holdings channel). Our contagion variable measures the degree of excess correlation between a country and a bank, but in itself does not allow us to make any statements about the direction of the spillover. Using bank-time fixed effects allows us to compare the excess correlations of one bank with different sovereigns.This gives us a better view on how factors at the sovereign level can affect the excess correlations between sovereigns and banks. By interacting the sovereign CDS spread with bank-specific variable, we are also able to analyze which bank characteristics can act as a buffer againsts spillovers from the sovereign level.

In the first column of Table 8, we regress the contagion variable on a home country dummy, the sovereign CDS spread and an interaction terms between both while controlling for bank-time fixed effects and for a potential non-linear relationship between the sovereign CDS spread and excess correlations. We start by focusing on the relationship between a bank and its home country. We hypothesize that the contagion between a bank and its home country is stronger than between a bank and any other sovereign. This can be caused by several factors, be it a strong home bias in their bond holding portfolio, higher bailout risk or fiscal consolidation leading to lower economic activity in the short term (Avdjiev and Caruana (2012)). The first column of Table 8, corroborates the home country hypothesis. The excess correlation between a bank and its home country is on average 2.7 percentage points higher than with another country, after controlling for the impact of sovereign CDS spreads. Next, our results show that banks have higher excess correlations

[16]Furthermore, when using a different regression setup (bank-time fixed effects),we do find a significant impact for sovereign bond exposures, see Table 9 below.

with countries that have a higher level of credit risk. The squared term of the CDS spread is negative, indicating that the positive effect becomes negative when the spread gets higher. However, the impact only becomes negative for countries above the 96th percentile, which in practice means that we only measure a negative relationship with Greece. Hence, except for Greece, the expected positive relationship between sovereign CDS spreads and excess correlations holds. Also interesting is the positive and highly significant impact of the interaction term between the sovereign spread and the home dummy, indicating that the excess correlations of a bank with its home country is higher when the home country has a higher level of credit risk.

In the second column of Table 8, we test whether there is an asset holdings channel at work during the sovereign debt crisis. We do this by introducing bank-specific sovereign bond exposures, which we collect from the 2010 and 2011 EBA stress test exercises. The results in column 2 of Table 8 show that a bank with a one standard deviation higher exposure to country A than to country B has an excess correlation with country A which is about 1.5 percentage points higher. This confirms the presence of an asset holdings channel during the sovereign debt crisis. Furthermore, the positive coefficient for the interaction term between the sovereign CDS level and the exposure variable in column 3 shows that a higher sovereign CDS spread amplifies the impact of the asset holdings channel, although this interaction term is only significant at the 15% level. Overall, we find support for the asset holdings channel. Banks with a larger exposure to a country are more vulnerable to risk shocks originating from that country.

In the last three columns of Table 8, we again focus on the importance of bank-specific characteristics. More specifically, instead of looking at the direct impact of bank characteristics, which we did in Table 7, we now investigate which bank characteristics could reduce the negative impact of higher sovereign credit risk. In other words, we analyze how banks could protect themselves against increased credit risk at the sovereign level. We do this by adding interaction terms between the sovereign CDS spreads and bank-specific characteristics in our regression specification. In column 4, we focus on the sample for which we have EBA data available, in the fifth column we do the same analysis but for a broader sample and in the last column we replace the total capital ratio with the Tier 1capital ratio. Our results again stress the importance of solid capital ratios to withstand sovereign default risk. More specifically, the coefficient of -0.8 for the interaction term between the sovereign CDS spread and the total capital ratio in the fourth and the fifth column shows that a one standard deviation rise in the total capital ratio lowers the impact of a standard deviation change in sovereign credit risk on excess correlations from 1.83 percentage points to

1.15 percentage points, which is a decline of more than 35 percent. The last column in Table 8 confirms that this result also holds when using an alternative capital ratio (Tier 1 ratio). The interaction terms between the other bank-specific characteristics and the sovereign CDS spread are not significant. Overall, the results in these last three columns show that higher capital adequacy ratios not only have a direct impact on excess correlations, but also have a positive indirect effect by lowering the negative impact of higher sovereign credit risk, which underscores their importance for maintaining financial stability.

So far, the only country-specific variable we investigated is the sovereign CDS spread. We show that banks are more strongly correlated with countries that have a higher level of credit risk and that higher capital levels can reduce this negative effect. We now take this analysis one step further by studying country-specific characteristics that are expected to have an impact on the credit risk of a country and could thus be of importance for the contagion between banks and sovereigns. By again using bank-time fixed effects, we analyze the correlation of each bank in our sample with the different countries, which allows us to attribute differences in excess correlation to country-specific factors. We focus on the impact of government debt (debt to GDP ratio), government revenues (as percentage of GDP), the importance of the banking sector in a country (total bank sector size over GDP) and the overall economic sentiment.

The results in column one of Table 9 show that bank-country contagion is more pronounced for countries with a higher debt-to-GDP ratio. The positive and significant coefficient of 1.21 for the debt ratio shows that for every standard deviation change in the debt ratio, the excess correlation increases by 1.21 percentage points. Higher debt ratios reduce the probability of a bailout in the banking sector and also lead to higher bank-level credit risk through the bond portfolios of financial institutions, which explains this positive and significant effect. However, the standard deviation of the debt ratio in our sample is around 27 percent (see Table 3), hence the economic impact is rather limited in this setup. Other country-specific characteristics, such as the share of government revenues in GDP or the size of the banking sector in a country do not turn out to be statistically significant. Furthermore, even after controlling for these country-specific factors, the home-country relationship still remains an important driver of the excess correlations. The coefficient of 2.88 for the home dummy is positive and significant at the 1 percent level. The coefficient for the economic sentiment indicator is positive, which is somewhat unexpected. This could indicate that market participants base their risk assessment rather on the health of bank balance sheets than on the economic conditions in a country. Moreover, growth has been dismal in many of the countries during the sample period, which makes it more difficult to assess the potential impact of economic conditions. In the second column of

Table 9 we analyze whether the home-country effect and the country characteristics potentially reinforce each other. Interestingly, the positive and significant interaction term between the debt-to-GDP ratio and the home dummy confirms that government debt is an important contributor to the contagion between a bank and its home country. More specifically, the impact of the home country dummy more than doubles when we compare a bank operating in a country with an average debt-to-GDP ratio with a bank operating in a country that has a debt-to-GDP ratio in the 90th percentile of our sample.[17] This result is in line with the argument that banks exhibit a home bias in their bond portfolios and with the conjecture that governments in a weak fiscal position are less likely to step in to save financial institutions when needed, confirming the presence of both the asset holdings channel as well as the guarantee channel. Comparing column 1 with column 2 also shows that the influence of the debt-to-GDP ratio is most pronounced in explaining the excess correlation of banks with their home country. A one standard deviation change in the debt-to-GDP ratio adds 1.05% points to the excess correlation for foreign countries, whereas this augments to 3.04% points (1.05+1.99) for home countries. Column 3 shows that the significant impact of the debt-to-GDP ratio also holds when controlling for sovereign bond exposures. Furthermore, in this specification we also find a positive and significant coefficient for the government revenues variable. A high level of government revenues lowers the possibility to further increase taxes in future crisis situations, which will make it harder for governments to react to a crisis and could thus lead to increased credit risk. Overall, these results indicate that banks tend to be more strongly correlated with countries with less sustainable debt levels, and this effect is largest in magnitude for the home country. This confirms that worsening public finances are one of the main drivers for contagion effects between sovereigns and banks. The implication is that restoring stability in the financial system requires simultaneous efforts in the field of public finances.

4.3. Robustness

In this section we show that our main finding are robust to using alternative factor models for calculating the excess correlations and to different ways of clustering standard errors in the panel regressions. Furthermore, column 3 of Table 7 and column 5 of Table 8 already indicated that our results also hold when using an

[17] The coefficient for the home country banks becomes 2.57 (coefficient for home dummy) + 1.99*1.5 (coefficient for interaction term*standardized value of the debt to GDP ratio at the 90th percentile) = 5.5 for banks operating in a country in the 90th percentile in terms of debt ratio, whereas the coefficient for a bank operating in a country with the average debt-to-GDP ratio equals 2.57+ 1.99*0 = 2.57.

alternative capital ratio.

We start by evaluating the choice of the factor models used to calculate the excess correlations. In our main analysis, we calculate the excess correlations based on yearly factor models that include four common factors, i.e. an overall stock market index for the EU, the iTraxx Europe CDS index, the Vstoxx volatility index and the term spread. To make sure that our main results are not influenced by our choice of factor model, we calculate two sets of new excess correlations, one set based on a factor model only including the iTraxx CDS index and a set based on a factor model with the same factors, but with an alternative choice of the time periods. The iTraxx-only model is an interesting benchmark as it is a model that is frequently used in the existing CDS literature (see e.g., Ejsing and Lemke (2011) and Fontana and Scheicher (2010)). The model with alternative time periods addresses the critique that structural breaks within the yearly regression window could potentially bias our measure of contagion. To address this issue, we divide our sample period into different time windows, chosen at well specified events, to avoid structural breaks within the time windows. More specifically, we divide our sample period into 7 different periods being 2006, 2007, January 2008 until August 2008 (pre-Lehman), September 2008 - March 2009 (strong banking distress), April 2009-March 2010 (In April, the EU orders France, Spain, the Irish Republic and Greece to reduce their budget deficits, start of sovereign crisis), April 2010-March 2011 (no major events) and April 2011 - September 2011 (strong rise in default risk of Southern European countries). Both factor models confirm the results of our baseline factor model. For the model with the different time windows, the Itraxx is again the most important common factor. For both the Itraxx-only and the extended time windows model, we again find significant spillovers for the majority of the banks in our sample and a clear increase in excess correlations over the past years. The results for these factor models are available upon request.

After calculating the two sets of alternative excess correlations, we reinvestigate the impact of bank and country characteristics as done in Section 4.2. The results are shown in columns 2 and 3 of tables 10 to 12 in Appendix. The fourth column in these tables adds an extra robustness check by clustering the standard errors at either the bank level (Table 11 and 12) or at the country level (Table 10) instead of at the bank-time or at the country-time level. This alternative clustering setup allows that the error terms are correlated over time within the same bank/country, while they were only allowed to be correlated within the same bank/country at one point in time in our baseline setup. The results all confirm our main findings. Both higher capital ratios and lower money market funding decrease excess correlations (Table 10). Furthermore, higher capital ratios reduce the positive impact of higher sovereign CDS spreads on excess correlations (Table 11). The robustness checks also confirm the existence of a home country effect and the positive relation between sovereign debt exposures and excess correlations. Finally, higher debt ratios are positively related to higher excess correlations, especially when focussing on the relationship between domestic banks and the home sovereign (Table 12).

5. Conclusions

This paper provides empirical evidence on risk spillovers between banks and sovereigns during the European financial and sovereign debt crisis. Whereas there is a substantial literature exploring the determinants of bank or sovereign credit risk (measured by bond yields or CDS spreads) separately, empirical evidence exploring contagion between the two is scarce. This paper attempts to fill the gap by examining the pattern of contagion in the sovereign-bank nexus in Europe and by investigating which bank-specific and country-specific determinants drive contagion.

We define contagion as "excess correlation", i.e. correlation over and above what is explained by fundamental factors. Our preferred measure of sovereign and bank credit risk is CDS spreads. After controlling for common factors (market risk, economy-wide credit risk, term spread changes and volatility), we document significant empirical evidence of bank/sovereign contagion. In the year 2009, when the sovereign debt crisis emerged, we find significant spillovers for 86% of the banks in the sample. This number increases to 94% when only considering spillovers between the banks and the GIIPS countries. Moreover, we provide empirical evidence of a substantial home bias, confirming the expectation that contagion between banks and their home country is stronger. The close link between domestic banks and their sovereigns can be attributed to several factors. We report evidence supporting the asset holdings channel caused by the large share of domestic debt in banks' sovereign portfolios and evidence in favor of the guarantee channel caused by the fact that the presence of large banks increases the bailout pressure on governments.

We exploit the cross-sectional differences between bank/sovereign excess correlations by relating them to bank- and country-specific variables. We include a broad set of measures intended to capture the strategic choices inherent in bank business models. The capital adequacy level of banks has the most economically significant effect; we find that an increase in the total capital ratio reduces the excess bank-country correlation significantly. Furthermore, the lower the banks' reliance on short-term funding sources (measured as the proportion of short-term funding in total debt), the lower the intensity of risk spillovers between banks and sovereigns. These findings support the new regulatory Basel III framework which imposes more stringent capital adequacy ratios and new liquidity measures. At the sovereign level, we find that higher debt-to-GDP ratios significantly increase the degree of bank/sovereign contagion. The effect even becomes twice as big for countries with high debt-to-GDP ratios (in the sample, a ratio above 101%, compared to the average of 74%). This finding motivates the recommendation that public finances need to be consolidated, especially in the countries with high debt levels. A credible commitment to reduce debt levels over time will probably require efforts at the domestic level as well as enforceable coordination at the European level and, perhaps, some form of (partial) debt mutualisation.

We investigate the relationship between bank/sovereign risk spillovers and banks' holdings of sovereign debt. For that purpose, the EBA disclosures of banks' sovereign exposures prove to be particularly valuable, since they allow us to verify whether (i) banks with different holdings of sovereign debt exhibit higher excess correlations with the countries involved, and (ii) whether excess correlations are higher for the countries to which the bank is more exposed. Using different regression specifications, we confirm both hypotheses. Hence, investors differentiate rationally between countries with different levels of indebtedness and between banks with different sovereign debt exposures.

We also document that increased sovereign credit risk is in itself a driver of bank-sovereign excess correlations. We find that contagion is more pronounced when the sovereign CDS spreads are higher. Moreover, we document that the link between sovereign debt holdings and contagion is stronger when the sovereign CDS spread is higher. When we investigate country-specific determinants of excess correlations, we find that sovereign debt-to-GDP levels play a decisive role as the main determinant of bank-sovereign risk spillovers. In the period of increased stress in sovereign debt markets, we document that also the government revenue ratio reinforces the risk spillovers. These findings suggest that credible plans to put public finances on a sustainable track are a necessary ingredient of any crisis resolution attempt.

In terms of policy implications, our results suggest several actions to alleviate the contagion between bank and sovereign risk. The ambition of policymakers and supervisors should be to (1) decrease the probability of contagion and (2) when contagion occurs, decrease the intensity of the risk spillovers. In order to achieve these objectives, action in three dimensions is necessary: make banks more robust, make public finances more resilient and weaken the bank-sovereign link. On the bank side, the degree of capital adequacy turns out to be crucial. Moreover, banks should be restricted in their reliance on money market funding. Both elements are at the core of the internationally agreed Basel III rules that will be phased in gradually.

Our results lend support to these objectives and policymakers and supervisors should provide incentives to banks to adjust their business models accordingly. Since the home bias in bank bond portfolios is identified as a channel of contagion, there might be scope for concentration limits in various dimensions. On the sovereign side, making public finances more sustainable and ensuring that resolution mechanisms are in place to deal with distressed banks are important policy objectives. Finally, our results indicate that breaking the link between banks and their sovereigns should be a priority. This will require a so-called banking union at the European (or Eurozone) level, implying that not only bank supervision should be executed at the European level (e.g. by the ECB), but also that deposit insurance and bank resolution, and the associated burden sharing arrangements have to implemented on a European scale.

References

Acharya, V., Drechsler, I., Schnabl, P., 2012. A pyrrhic victory? - Bank bailouts and sovereign credit risk. NBER Working Paper 17136.

Aizenman, J., Hutchison, M., Jinjarak, Y., 2011. What is the risk of european sovereign debt defaults? Fiscal space, CDS spreads and market pricing of risk. NBER Working Paper 17407.

Allen, F., Babus, A., Carletti, E., 2009. Financial crises. theory and evidence. Available at SSRN: http://ssrn.com/abstract=1422715.

Allen, F., Babus, A., Carletti, E., 2010. Financial connections and systemic risk. NBER Working Paper 16177.

Alter, A., Beyer, A., 2012. The dynamics of spillover effects during the European sovereign debt turmoil. CFS Working Paper (13).

Alter, A., Schuler, Y., 2012. Credit spread interdependencies of European states and banks during the financial crisis. Journal of Banking and Finance (36), 3444Ű3468.

Altunbas, Y., Manganelli, S., Marques-Ibanez, D., 2011. Bank risk during the financial crisis: Do business models matter? ECB Working Paper 1394.

Anderson, M., 2011. Contagion and excess correlation in credit default swaps. Available at SSRN: http://ssrn.com/abstract=1937998.

Ang, A., Longstaff, F., 2011. Systemic sovereign credit risk: Lessons from the U.S. and Europe. NBER Working Paper 16982.

Angeloni, C., Wolff, G., 2012. Are banks affected by their holdings of government debt? Bruegel Working Paper 07.

Arezki, R., Candelon, B., Sy, A., 2011. Sovereign rating news and financial markets spillovers: Evidence from the European debt crisis. IMF Working Paper 68.

Avdjiev, S., Caruana, J., 2012. Sovereign creditworthiness and financial stability: An international perspective. Banque de France Financial Stability Review (16).

Ayadi, R., Arbak, E., De Groen, W., 2011. Business models in European banking: A pre-and post-crisis screening. CEPS Paperbacks.

Baele, L., De Bruyckere, V., De Jonghe, O., Vander Vennet, R., 2012. Do stock markets discipline U.S. bank holding companies: Just monitoring, or also influencing? Available at SSRN: http://ssrn.com/abstract=1636697.

Baele, L., De Jonghe, O., Vander Vennet, R., 2007. Does the stock market value bank diversification? Journal of Banking and finance 31 (7), 1999Ű2023.

Barrios, S., Iversen, P., Lewandowska, M., Setzer, R., 2009. Determinants of intra-euro area government bond spreads during the financial crisis. European Commission Economic Papers 388.

Bekaert, G., Harvey, C., Ng, A., 2005. Market integration and contagion. Journal of Business 78 (1), 39–69.

Beltratti, A., Stulz, R., 2012. The credit crisis around the globe: Why did some banks perform better? Journal of Financial Economics 105 (1), 1Ű17.

Berndt, A., Douglas, R., Duffie, D., Ferguson, M., Schranz, D., 2005. Measuring default risk premia from default swap rates and EDFs. BIS Working Papers 172.

Bernoth, K., von Hagen, J., Schuknecht, L., 2004. Sovereign risk premia in the European government bond market. ECB Working Paper 369.

BIS, 2011a. Global systemically important banks: Assessment methodology and the additional loss absorbency requirement. BIS Rules Text.

BIS, 2011b. The impact of sovereign credit risk on bank funding conditions. Committee on the Global Financial System Papers 43.

Bosma, J., K. M., Wedow, M., 2012. Credit risk connectivity in the financial industry and stabilization effects of government bailouts. Deutsche Bundesbank Discussion Paper (16).

Boyer, B., Gibson, M., Loretan, M., 1999. Pitfalls in tests for changes in correlations. Board of Governors of the Federal Reserve System International Finance Discussion Paper 597.

Brown, C., Dinc, I., 2011. Too many to fail? Evidence of regulatory forbearance when the banking sector is weak. Review of Financial Studies 24 (4), 1378–1405.

Calomiris, C., Kahn, C., 1991. The role of demandable debt in structuring optimal banking arrangements. American Economic Review 81 (3), 497–513.

Caporin, M., Pelizzon, L., Ravazzolo, F., Rigobon, R., 2012. Measuring sovereign contagion in Europe. Norges Bank Working Paper 05.

Constancio, V., 2012. Contagion and the European debt crisis. Banque de France Financial Stability Review 16.

Demirguc-Kunt, A., Huizinga, H., 2010. Bank activity and funding strategies: The impact on risk and returns. Journal of Financial Economics 98 (3), 626–650.

Demirguc-Kunt, A., Huizinga, H., 2011. Do we need big banks ? Evidence on performance, strategy and market. World Bank Policy Research Working Paper 5576.

Dungey, M., Fry, R., Gonzalez-Hermosillo, B., Martin, V., 2005. Empirical modelling of contagion: a review of methodologies. Quantitative Finance 5 (1), 9–24.

Eichengreen, B., Mody, A., 2000. What explains changing spreads on emerging-market debt? In: Edwards, S. (Ed.), Capital Flows and the Emerging Economies: Theory, Evidence and Controversies. University of Chicago Press.

Ejsing, J., Lemke, W., 2011. The janus-headed salvation: Sovereign and bank credit risk premia during 2008-09. Economic Letters 110 (1), 28–31.

Fontana, A., Scheicher, M., 2010. An analysis of euro area sovereign CDS and their relation with government bonds. ECB Working Paper (1271).

Forbes, K., Rigobon, R., 2002. No contagion, only interdependence: Measuring stock market comovements. Journal of Finance 57 (5), 2223Ű2261.

Gross, M., Kok, C., 2012. A mixed-cross-section GVAR for countries and banks. ECB Working Paper (forthcoming).

Huang, R., Ratnovski, L., 2011. The dark side of bank wholesale funding. Journal of Financial Intermediation 20 (2), 248–263.

Hui, C.-H., Chung, T.-K., 2011. Crash risk of the Euro in the sovereign debt crisis of 2009-2010. Journal of Banking and Finance 35, 2945Ű2955.

Kamin, S., von Kleist, K., 1999. The evolution and determinants of emerging markets credit spreads in the 1990s. BIS Working Papers 68.

Kaminsky, G., Reinhart, C., Vegh, C., 2003. The unholy trinity of financial contagion. NBER working paper 10061.

Kiyotaki, N., Moore, J., 2005. Liquidity and asset prices. International Economic Review 46 (2).

Kyle, S. C., Wirick, R., 1990. The impact of sovereign risk on the market valuation of U.S. bank equities. Journal of Banking and Finance 14 (4), 761–780.

Longstaff, F., Pan, J., Pedersen, L., Singleton, K., 2011. How sovereign is sovereign credit risk? American Economic Journal: Macroeconomics 3 (2), 75–103.

Mauro, P., Sussman, N., Yafeh, Y., 2002. Emerging market spreads: Then versus now. Quarterly Journal of Economics 177 (2).

Pan, J., Singleton, K., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads. Journal of Finance 63 (5).

Pericoli, M., Sbracia, M., 2003. A primer on financial contagion. Journal of Economic Surveys 17 (4).

Pesaran, M., Pick, A., 2007. Econometric issues in the analysis of contagion. Journal of Economic Dynamics and Control 31 (4).

Petrovic, A., Tutsch, R., 2009. National rescue measures in response to the current financial crisis. ECB Legal Working Paper 8.

Schepens, G., Vander Vennet, R., 2009. Bank risks during the crisis. Mimeo.

Stiroh, K., 2004. Diversification in banking: Is noninterest income the answer? Journal of Money, Credit and Banking 36 (5).

Stiroh, K., 2006b. New evidence on the determinants of bank risk. Journal of Financial Services Research 30 (3).

Stiroh, K., 2010. Diversification in banking. In: Berger, A. e. a. (Ed.), The Oxford Handbook of Banking. Oxford University Press, pp. 146–171.

Tang, D., Yan, H., 2010. Market conditions, default risk and credit spreads. Journal of Banking and Finance 34 (4).

Vuillemey, G., Peltonen, T., 2012. Sovereign credit events and their spillovers to the European banking system - Interplay between sovereign bonds and CDS holdings. Mimeo.

Wheelock, D., Wilson, P., 2000. Why do banks disappear? The determinants of U.S. bank failures and acquisitions. The Review of Economics and Statistics 82 (1).

6. Tables and Figures

Table 1: CDS spread changes - Summary Statistics

This table shows the summary statistics for the daily sovereign and bank CDS spread changes between the first quarter of 2006 and the third quarter of 2011 for all banks and countries in our sample. We use spreads on 5-year CDS contracts. All CDS quotes are obtained from Bloomberg, CMA. The CDS spread series are transformed into daily arithmetic returns.

Sovereign	year	MEAN	STD	MIN	MAX
	2006	-0.004	0.064	-0.250	0.344
	2007	0.012	0.123	-0.533	1.129
	2008	0.020	0.094	-0.356	1.511
	2009	-0.001	0.054	-0.382	0.989
	2010	0.004	0.046	-0.388	0.395
	2011	0.003	0.041	-0.191	0.258
Banks	year	MEAN	STD	MIN	MAX
	2006	-0.002	0.030	-0.388	0.634
	2007	0.010	0.072	-0.439	1.237
	2008	0.007	0.072	-0.560	1.109
	2009	-0.001	0.037	-0.280	0.485
	2010	0.004	0.046	-0.425	2.148
	2011	0.003	0.040	-0.361	1.229

Table 2: State variables - Summary statistics

This table shows the summary statistics for the four state variables used in our main factor model. To control for market-wide business climate changes in the European Union, we include Datastream's total stock market index for the EU. To control for market-wide credit risk, we include the iTraxx Europe index. The third common factor is the Vstoxx volatility index, capturing market expectations of volatility in the Eurozone. The fourth common factor is the term spread, which is calculated as the difference between the 10-year government bond yield for each country and the 1-year Euribor rate. All state variables are obtained from Datastream and transformed into arithmetic returns, except for the term spread, which we include in first differences.

	MARKET	**ITRAXX**	**VSTOXX**	**TERM**
MEAN	0.000	0.002	0.003	0.001
STD	0.014	0.039	0.062	0.041
MIN	-0.075	-0.278	-0.221	-0.392
MAX	0.097	0.291	0.388	0.179

Table 3: Bank and Country specific variables - Summary statistics

Statistics for the country variables are calculated at the country-time level, whereas the statistics for the bank variables are calculated at the bank-time level, which explains the differences in number of observations. The capital ratio is calculated as Tier 1 plus Tier 2 capital over total assets. Funding risk is the share of short term debt in total debt. The loan ratio is the ratio of total loans over total assets. Income diversification is calculated as the share of non-interest income over total income.

Variable	Mean	Std. Dev.	Obs.
Country variables			
Sovereign CDS spread	86.56	124.14	150
Debt to GDP ratio	74.37	27.44	150
Government revenues /GDP	45.30	6.44	150
Economic sentiment indicator	93.87	11.41	150
Bank variables			
Bank size / GDP	60.38	50.39	293
Capital ratio	6.35	2.46	293
Loan ratio	62.79	16.12	293
Funding risk	45.03	21.52	293
Income diversification	30.30	14.89	293

Table 4: State variables - Average coefficients and significance

This table reports the average coeffients for the four state variables used in the factor models for the banks. The state variables included are a EU stock market Index, the European iTraxx index, the Vstoxx volatility index and the term spread between the 10-year government bond yield for each country and the 1-year Euribor rate. For each of these variables, we report the average yearly coefficient for the banks in our sample and the percentage of banks for which the specific state variable is significant in the factor models. We also report the number of banks in the sample for each year and the average adjusted R-squared. Changes in the number of observations are due to data availability of bank CDS spreads.

	2006		2007		2008		2009		2010		2011	
	coef	% sign	coef	% sign	coef	% sign	coef	% sign	coef	% sign	coef	% sign
MARKET	-0.0436	0.00%	-0.2865	0.00%	0.0669	6.52%	-0.2347	0.00%	-0.1503	3.77%	-0.2918	0.00%
ITRAXX	0.0402	13.64%	0.7490	96.77%	0.6365	91.30%	0.4010	86.27%	0.4400	92.45%	0.4772	84.91%
VSTOXX	-0.0065	0.00%	-0.0784	0.00%	0.0705	8.70%	-0.0735	0.00%	-0.0022	5.66%	-0.0572	0.00%
TERM	0.0217	4.55%	0.0485	6.45%	-0.0784	0.00%	0.0080	5.88%	0.0126	18.87%	0.0232	32.08%
# banks	22		31		46		51		53		53	
adj. R^2	0%		32%		33%		18%		32%		29%	

Table 5: Correlations and Excess correlations - Summary statistics

This table shows the mean, standard deviation, minimum and maximum of the pairwise bank/sovereign correlations in our sample. The second row contains the summary statistics of the excess correlations, calculated as the pairwise correlations of the residuals from the bank and sovereign factor models.

	# OBS.	**MEAN**	**ST.DEV.**	**MIN**	**MAX**
Average correlation	3034	35.29	22.72	-36.10	87.70
Average Excess Correlation	3034	17.38	18.73	-55.94	84.27

Table 6: Contagion - statistical significance

The table presents the percentage of bank-country excess correlations that are significantly different from the excess correlation in a pre-defined base year for three different setups. We compare the excess correlations with two different base years, being 2007 (left-hand side) and 2008 (right-hand side). The table consists of panels A, B and C. In panel A, we focus on the relation between a bank and its home country. The panel shows the number of bank-home country correlations that are significantly different from the correlations in the base year. In panel B, we analyze the correlations between a bank and foreign sovereigns. We report the number of bank-country correlations that are significantly different from the correlations in the base year. In panel C, we focus on the relationship between a bank and the GIIPS countries (Greece, Ireland, Italy, Portugal and Spain). We again report the number of bank-country correlations that are significantly different from the base year.

BASE YEAR: 2007					BASE YEAR: 2008			
	HOME			Panel A		HOME		
	significant	total	percentage significant			significant	total	percentage significant
2007	Base year				2007	3	14	21%
2008	3	14	21%		2008	Base year		
2009	12	14	86%		2009	24	35	69%
2010	9	14	64%		2010	26	35	74%
2011	5	14	36%		2011	19	35	54%
	FOREIGN			Panel B		FOREIGN		
	significant	total	percentage significant			significant	total	percentage significant
2007	Base year				2007	45	172	26%
2008	45	172	26%		2008	Base year		
2009	130	172	76%		2009	260	467	56%
2010	108	172	63%		2010	216	467	46%
2011	67	172	39%		2011	143	456	31%
	GIIPS			Panel C		GIIPS		
	significant	total	percentage significant			significant	total	percentage significant
2007	Base year				2007	4	31	13%
2008	4	31	13%		2008	Base year		
2009	29	31	94%		2009	40	46	87%
2010	23	31	74%		2010	34	46	74%
2011	16	31	52%		2011	24	45	53%

Table 7: Excess correlations and bank characteristics

This table analyzes the impact of bank characteristics on contagion. In the first column, we regress country-bank excess correlations on a set of bank-specific characteristics and a home country/foreign country - time fixed effect. By including this fixed effect, we compare the excess correlation of bank i at time t with country j to the correlation of another bank k - located in the same country as bank i - with country j at time t. Thus, the part of the variation that is left in the bank-country correlation can only be explained by differences in bank-specific characteristics. In the second column, we do a similar analysis, but we also interact each bank-specific variable with a home country dummy. This allows us to analyze whether bank-specific variables are of different importance when considering the relationship of a bank with its home country. In the third column, we control for the impact of sovereign bond exposures. In the last column we replace the total capital ratio with the Tier 1 capital ratio. All variables are standardized, such that the coefficients indicate the impact of a one standard deviation change of the variable.

	(1)	(2)	(3)	(4)
VARIABLES	Excess Correl.	Excess Correl.	Excess Correl.	Excess Correl.
Size	1.441**	1.440**	0.462	1.710***
	(0.686)	(0.711)	(0.793)	(0.641)
Size x Home		-0.0650		-0.160
		(2.773)		(2.655)
Total Capital ratio	-1.707**	-1.758**	-0.261	
	(0.789)	(0.835)	(1.075)	
Total Capital ratio x Home		0.363		
		(2.590)		
Loan to Assets ratio	0.178	0.292	-0.0642	-0.807
	(0.547)	(0.571)	(0.765)	(0.637)
Loan to Assets ratio x Home		-1.311		-1.221
		(2.021)		(2.586)
Funding risk	1.642***	1.703***	1.867***	1.855***
	(0.474)	(0.489)	(0.541)	(0.454)
Funding risk x Home		-0.769		-0.827
		(1.951)		(1.722)
Income diversification	-0.506	-0.508	1.912***	-0.573
	(0.510)	(0.528)	(0.686)	(0.530)
Income diversification x Home		0.0351		-0.0106
		(2.070)		(2.082)
EBA Country Exposures			0.618	
			(0.951)	
Tier 1 Capital ratio				-1.696***
				(0.613)
Tier 1 Capital ratio x Home				0.0476
				(2.513)
Constant	17.57***	17.57***	17.64***	17.57***
	(5.32e-08)	(0.0158)	(0.162)	(0.0228)
Observations	3,034	3,034	1,349	3,034
R-squared	0.767	0.767	0.692	0.767
Home–Foreign-Time FE	YES	YES	YES	YES
Cluster	Home–Foreign-Time	Home–Foreign-Time	Home–Foreign-Time	Home–Foreign-Time

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Country-bank spillover effects

This table shows the impact of sovereign credit risk on excess correlations between banks and sovereigns. In each of the regressions, we control for bank-time fixed effects, which boils down to comparing the impact of credit risk of different sovereigns on one and the same bank. The first column presents the results when regressing the excess correlations on the sovereign CDS spread, a home dummy and the interaction between both. In the second column, we replace the home dummy with eba exposure data, which captures the sovereign bon exposure of a bank to the sovereign with which we are measuring the excess correlation. In the third column, an interaction term between the EBA exposure variable and the sovereign CDS spread is added. The fourth column shows the impact of bank-specific characteristics on the relationship between the sovereign CDS spreads and the excess correlations. The last two columns are two robustness checks. In the fifth column, we check whether the decrease in sample size due to using the EBA exposure data has an impact on the role of bank-specific variables. In the last column, we include the Tier 1 capital ratio as an alternative capital measure instead of the total capital ratio. The last two rows of the third, the fourth and the last column show the impact of the sovereign CDS spread when the foreign exposure variable is one standard deviation above its mean. The exposure is expressed as a percentage of the total sovereign exposure of the bank. All variables are standardized such that the coefficients indicate the impact of a one standard deviation change.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Excess Correl.	Excess Correl.	Excess Correl.	Excess Correl.	Excess Correl.	Excess Correl.
Sovereign CDS spread	1.837**	1.813**	1.790**	1.776**	1.829**	1.982**
	(0.770)	(0.853)	(0.850)	(0.846)	(0.771)	(0.833)
Sovereign CDS spread _Squared	-0.723***	-0.677***	-0.648***	-0.636***	-0.710***	-0.644***
	(0.147)	(0.160)	(0.165)	(0.164)	(0.147)	(0.164)
Home dummy	2.706***				2.726***	
	(0.839)				(0.843)	
Home x	5.361***				5.408***	
Sovereign CDS	(1.453)				(1.452)	
EBA Country Exposures		1.463***	1.243***	1.237***		1.210***
		(0.328)	(0.355)	(0.360)		(0.357)
EBA Country Exposures x			0.738	0.782*		0.639
Sovereign CDS			(0.468)	(0.467)		(0.453)
Total Capital ratio x				-0.807*	-0.795*	
Sovereign CDS				(0.485)	(0.465)	
Funding risk x				-0.282	-0.144	-0.370
Sovereign CDS				(0.269)	(0.303)	(0.277)
Loan to Assets ratio x				0.363	0.405	-0.241
Sovereign CDS				(0.488)	(0.406)	(0.466)
Income Diversificationx				0.0212	0.115	-0.125
Sovereign CDS				(0.476)	(0.394)	(0.468)
Size x				-0.449	-0.443	-0.0641
Sovereign CDS				(0.368)	(0.377)	(0.356)
Tier 1 ratio x						-0.505*
Sovereign CDS						(0.297)
Constant	18.11***	18.91***	18.85***	18.83***	18.09***	18.85***
	(0.165)	(0.114)	(0.135)	(0.132)	(0.166)	(0.134)
Observations	3,034	1,349	1,349	1,349	3,034	1,349
R-squared	0.670	0.575	0.576	0.579	0.671	0.579
Bank-time FE	YES	YES	YES	YES	YES	YES
Cluster	Bank-time	Bank-time	Bank-time	Bank-time	Bank-time	Bank-time

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Excess correlations - Impact of country characteristics

This table shows the relationship between country characteristics and bank-country excess correlations. In the first column, we regress the excess correlations on a home dummy, a set of country-specific characteristics and bank-time fixed effects. In the second column, we also interact each country-specific variable with a home country dummy. In the last column, we replace the home country dummy with a variable that contains EBA exposure data. By using bank-time fixed effects, we ensure that the only variation left in the excess correlations can be attributed to country-specific characteristics. All variables are standardized such that the coefficients represent the impact of a one standard deviation change in the variable.

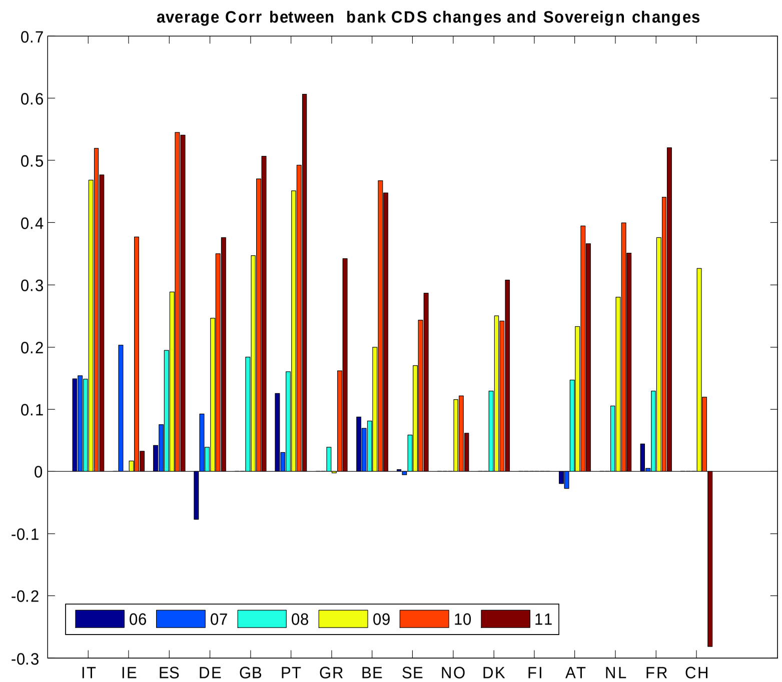
	(1)	(2)	(3)
VARIABLES	Excess Correl.	Excess Correl.	Excess Correl.
Home dummy	2.876***	2.574***	
	(0.881)	(0.925)	
Debt to GDP	1.215***	1.052***	0.919***
	(0.221)	(0.234)	(0.287)
Debt to GDP x		1.993**	
Home		(0.843)	
Government Revenues	0.0628	0.0536	1.664***
	(0.268)	(0.281)	(0.391)
Government Revenues x		-0.845	
Home		(0.861)	
Bank sector size	0.229	0.229	0.605*
	(0.229)	(0.237)	(0.322)
Bank sector size x		-0.213	
Home		(0.981)	
Economic Sentiment	1.317**	1.207**	0.489
	(0.563)	(0.563)	(0.686)
Economic Sentiment x		1.284	
Home		(1.074)	
EBA exposure			0.0954***
			(0.0182)
Constant	17.33***	17.33***	16.82***
	(0.0732)	(0.0723)	(0.353)
Observations	3,034	3,034	1,349
R-squared	0.661	0.662	0.562
Bank-Time FE	YES	YES	YES
Cluster	Bank-Time	Bank-Time	Bank-Time

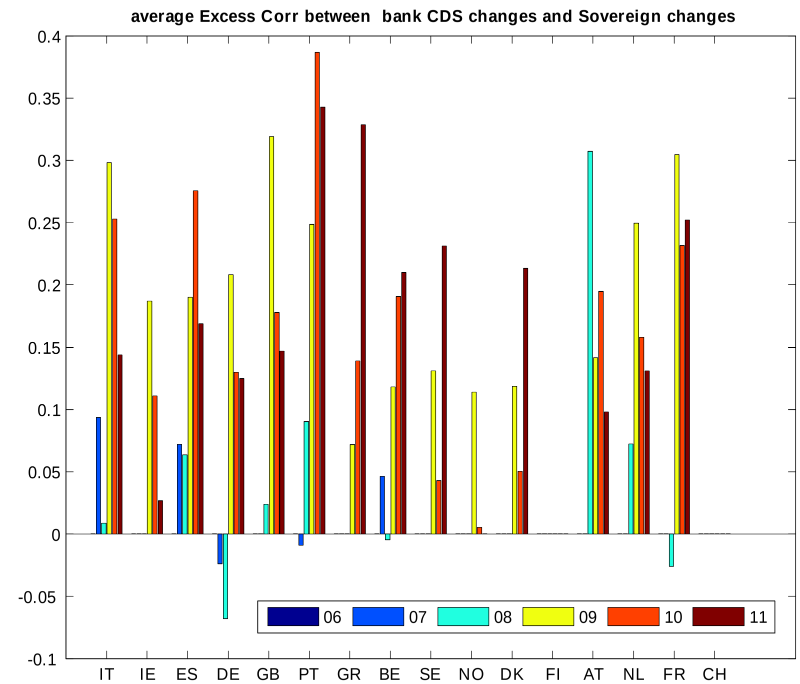
Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1: Home country - bank CDS correlations

These figures show the correlations and excess correlations between sovereign and bank credit risk on a yearly country-by-country basis. The left hand side figure shows the average yearly correlations between the sovereign CDS spread and the banks headquartered in that country for all countries in our sample. The figure on the right hand side shows the average yearly excess correlations between the sovereign CDS spread and the banks headquartered in that country for all countries in our sample. Missing observations for some years are due to limited availabilty of either liquid sovereing CDS spread or liquid bank CDS spreads.





7. Appendix

Table 10: Robustness - impact bank characteristics

This table contains robustness checks for the impact of bank-specific characteristics on excess correlations. The first column is the benchmark regression, which corresponds to column 2 in Table 7. The second and the third column focus on the robustness of our results using different factor models to calculate the excess correlations. In column 2 we use an Itraxx only factor model, whereas we use alternative time windows to calculate the excess correlations in column 3. In the last column we use the same factor model as in our baseline setup, but we cluster standard errors at the country level instead of on the country-time level.

VARIABLES	Benchmark Excess Correl.	ITraxx only Excess Correl.	Time Windows Excess Correl.	clustering Excess Correl.
Size	1.440**	1.279*	1.279*	1.440
	(0.711)	(0.746)	(0.746)	(1.600)
Size x Home	-0.0650	1.240	2.018	-0.0650
	(2.773)	(2.864)	(2.851)	(1.560)
Total Capital ratio	-1.758**	-2.179**	-2.179**	-1.758***
	(0.835)	(0.904)	(0.904)	(0.440)
Total Capital ratio x Home	0.363	1.345	1.742	0.363
	(2.590)	(2.496)	(2.757)	(0.991)
Loan to Assets ratio	0.292	0.458	0.458	0.292
	(0.571)	(0.567)	(0.567)	(0.666)
Loan to Assets ratio x Home	-1.311	-1.258	-1.496	-1.311
	(2.021)	(2.167)	(2.005)	(0.982)
Funding risk	1.703***	1.832***	1.832***	1.703**
	(0.489)	(0.502)	(0.502)	(0.716)
Funding risk x Home	-0.769	-1.037	-1.545	-0.769
	(1.951)	(2.038)	(1.993)	(1.002)
Income diversification	-0.508	0.331	0.332	-0.508
	(0.528)	(0.556)	(0.557)	(1.778)
Income diversification x Home	0.0351	-0.701	-0.761	0.0351
	(2.070)	(2.091)	(2.033)	(1.322)
Constant	17.57***	19.28***	19.24***	17.57***
	(0.0158)	(0.0231)	(0.0245)	(0.00761)
Observations	3,034	3,060	3,060	3,034
R-squared	0.767	0.759	0.762	0.767
Home–Foreign-Time FE	YES	YES	YES	YES
Cluster	Home–Foreign-Time	Home–Foreign-Time	Home–Foreign-Time	Home Country

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Robustness - impact home country and sovereign CDS

This table contains robustness checks for the impact of the home country effect, sovereign CDS spreads, and related interaction terms on excess correlations. The first column is the benchmark regression, which corresponds to column 5 in Table 8. The second and the third column focus on the robustness of our results using different factor models to calculate the excess correlations. In column 2 we use an Itraxx only factor model, whereas we use alternative time windows to calculate the excess correlations in column 3. In the last column we use the same factor model as in our baseline setup, but we cluster standard errors at the bank level instead of on the bank-time level.

VARIABLES	Benchmark Excess Correl.	Itraxx only Excess Correl.	Time windows Excess Correl.	clustering Excess Correl.
Sovereign CDS spread	1.829**	3.296***	3.282***	1.829**
	(0.771)	(0.662)	(0.660)	(0.845)
Sovereign CDS spread Squared	-0.710***	-0.982***	-0.983***	-0.710***
	(0.147)	(0.131)	(0.131)	(0.157)
Sovereign CDS x	-0.795*	-0.717	-0.752*	-0.795*
Total Capital ratio	(0.465)	(0.437)	(0.439)	(0.441)
Sovereign CDS x	-0.144	-0.163	-0.181	-0.144
Funding risk	(0.303)	(0.327)	(0.330)	(0.286)
Sovereign CDS x	0.405	0.504	0.482	0.405
Loan to Assets ratio	(0.406)	(0.462)	(0.464)	(0.255)
Sovereign CDS x	0.115	0.144	0.132	0.115
Income Diversification	(0.394)	(0.365)	(0.364)	(0.274)
Sovereign CDS x	-0.443	0.136	0.112	-0.443
Size	(0.377)	(0.400)	(0.401)	(0.330)
Home dummy	2.726***	1.899**	1.287	2.726***
	(0.843)	(0.817)	(0.816)	(0.777)
Sovereign CDS x	5.408***	4.121***	2.459*	5.408***
Home	(1.452)	(1.359)	(1.364)	(1.189)
Constant	18.09***	20.12***	20.12***	18.09***
	(0.166)	(0.147)	(0.146)	(0.145)
Observations	3,034	3,060	3,060	3,034
R-squared	0.671	0.692	0.691	0.671
Bank-time FE	YES	YES	YES	YES
Cluster	Bank-time	Bank-time	Bank-time	Bank

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12: Robustness - country characteristics

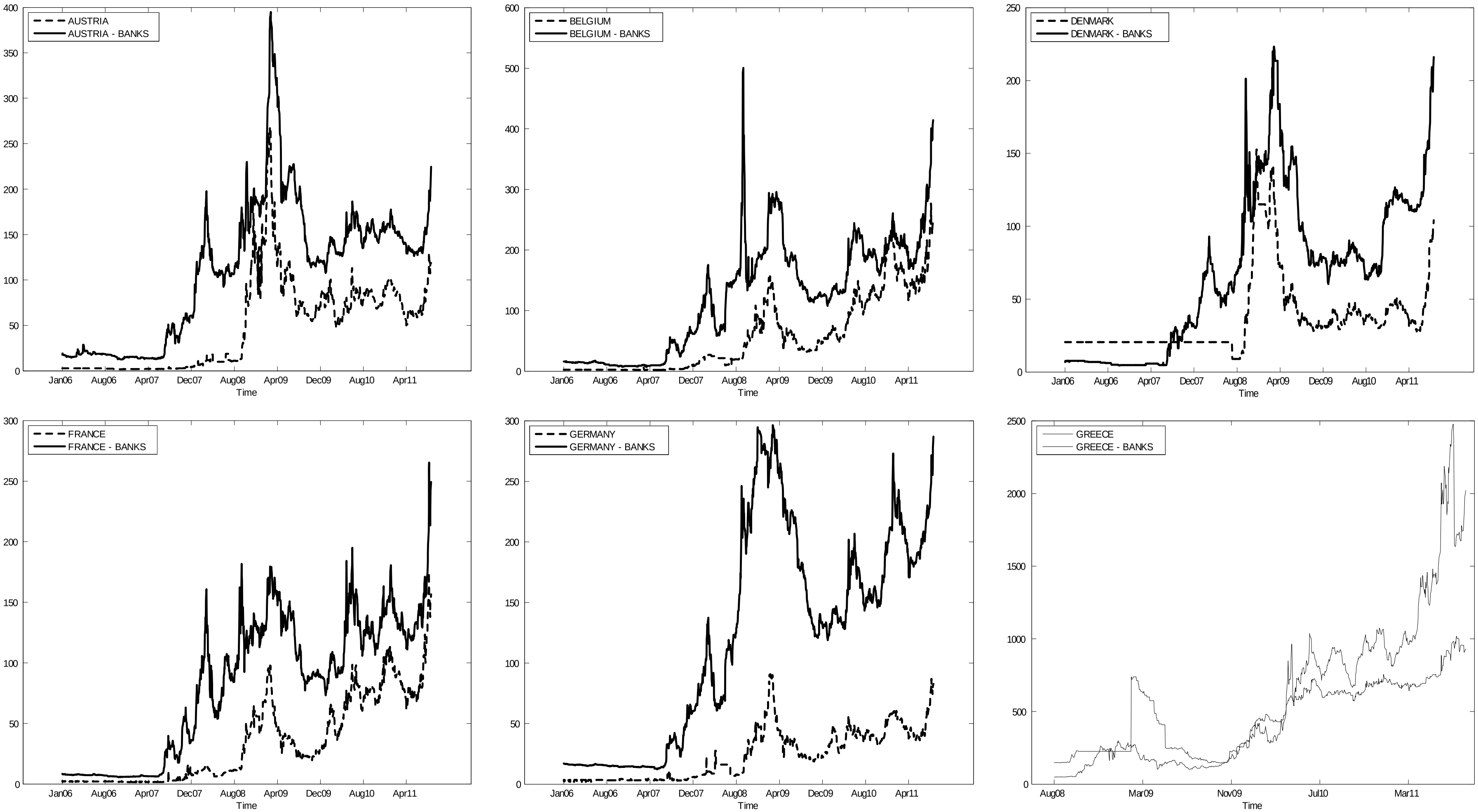
This table contains robustness checks for the impact of country-specific characteristics on excess correlations. The first column is the benchmark regression, which corresponds to column 2 in Table 9. The second and the third column focus on the robustness of our results using different factor models to calculate the excess correlations. In column 2 we use an Itraxx only factor model, whereas we use alternative time periods to calculate the excess correlations in column 3. In the last column we use the same factor model as in our baseline setup, but we cluster standard errors at the bank level instead of on the bank-time level.

VARIABLES	Benchmark Excess Correl.	Itraxx only Excess Correl.	Time Windows Excess Correl.
Home dummy	2.574***	1.756**	2.574***
	(0.925)	(0.886)	(0.878)
Debt to GDP	1.052***	0.664***	1.052***
	(0.234)	(0.242)	(0.167)
Debt to GDP x	1.993**	2.352***	1.993**
Home dummy	(0.843)	(0.823)	(0.959)
Government Revenues	0.0536	-0.496*	0.229
	(0.281)	(0.282)	(0.234)
Government Rev enues x	-0.845	-0.819	-0.213
Home dummy	(0.861)	(0.843)	(0.853)
Bank sector size	0.229	-0.126	0.0536
	(0.237)	(0.236)	(0.262)
Bank sector size x	-0.213	-0.862	-0.845
Home dummy	(0.981)	(0.962)	(0.909)
Economic Sentiment	1.207**	1.026**	1.207**
	(0.563)	(0.505)	(0.512)
Economic Sentiment x	1.284	0.357	1.284
Home dummy	(1.074)	(1.052)	(0.811)
Constant	17.33***	19.10***	17.33***
	(0.0723)	(0.0697)	(0.0750)
Observations	3,034	3,060	3,034
R-squared	0.662	0.680	0.662
Bank-Time FE	YES	YES	YES
Cluster	Bank-Time	Bank-Time	Bank

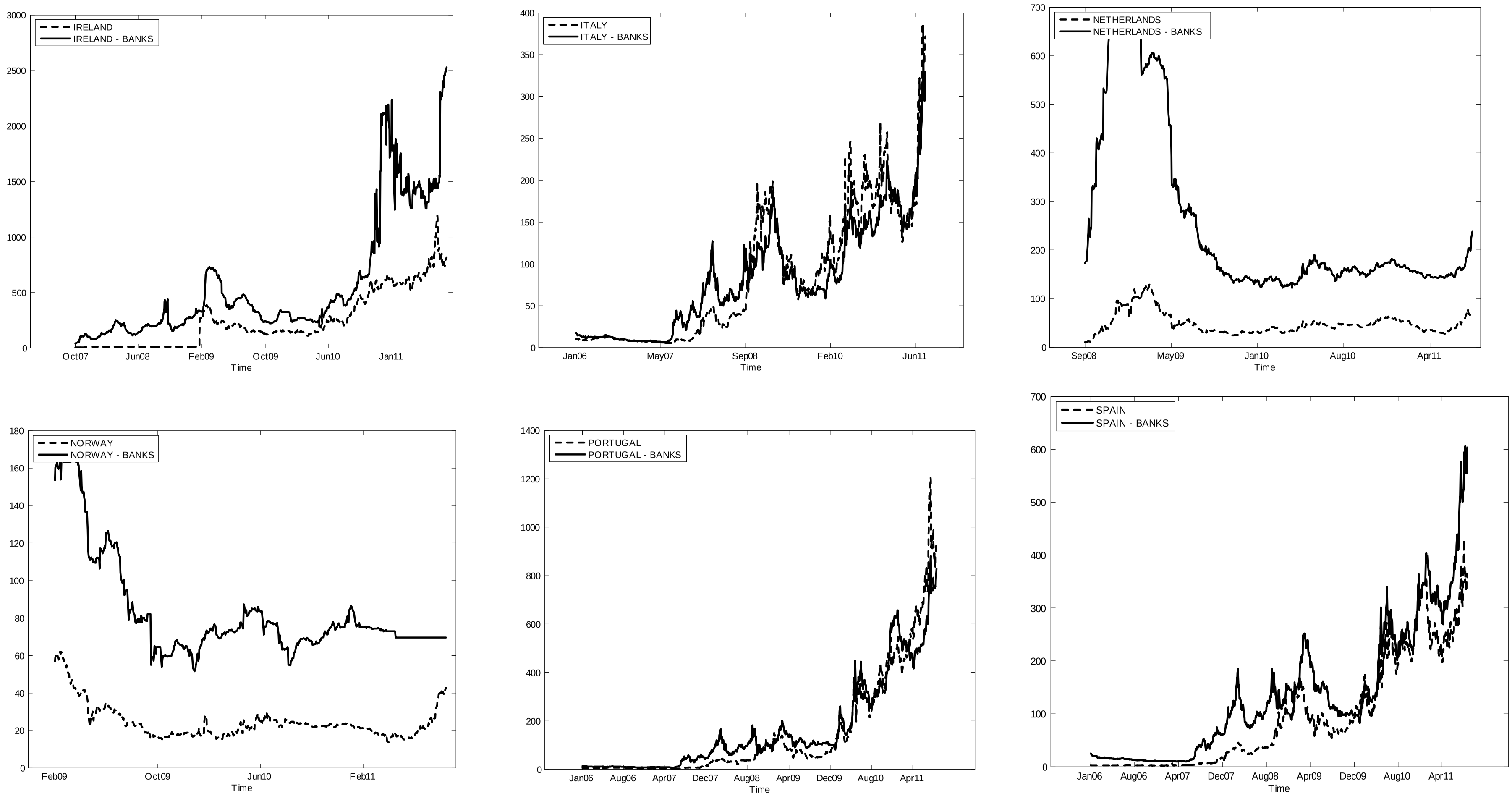
Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

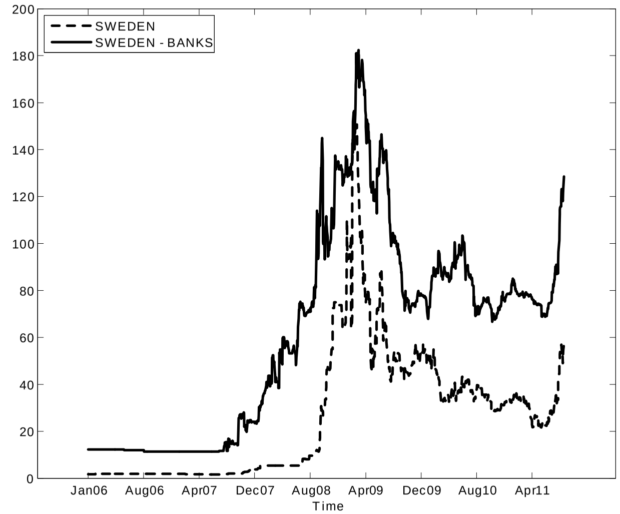
Bank and sovereign CDS spreads

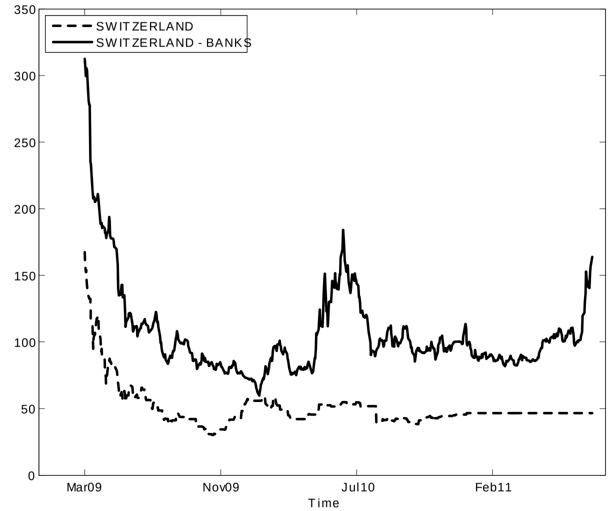


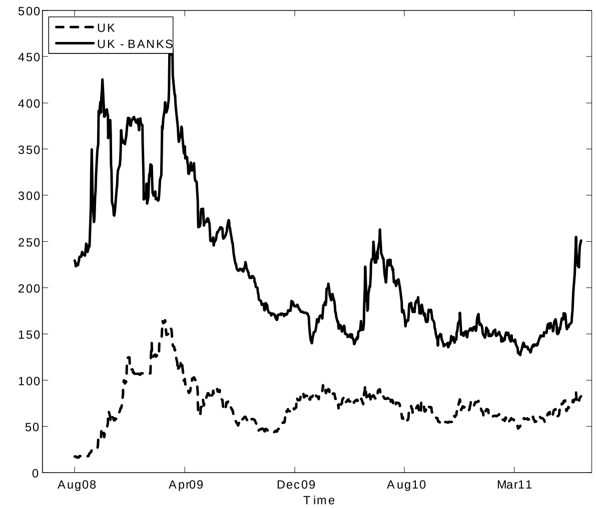
Bank and sovereign CDS spreads - continued



Bank and sovereign CDS spreads - continued







CHAPTER 5

A Network based Stress Test Tool for the European Banking Sector

A Network based Stress Test Tool for the European Banking Sector

Valerie De Bruyckere [1]

Abstract

This paper presents a network based methodology to stress test the European banking sector using publicly available information. Banks are not only exposed to shocks from common risk factors (macroeconomic risk factors, sovereign risk, financial risk and housing price risk), but also to shocks from all other banks in the system. To do so, this paper relies on Bayesian Model Averaging (BMA) of Locally Weighted Regression models. BMA allows to identify a set of relevant risk factors out of a larger set of potentially important regressors. I illustrate the power of the model in projecting future evolutions in bank equity prices. The model correctly projects the direction of 77% of bank equity price changes over an horizon ranging from one quarter to four quarters ahead. Moreover, I show that the performance of my model increases to 81% due to the use of the Locally Weighted Regression model, further illustrating the usefullness of this model as a stress test tool. Furthermore, I provide insight into the time-varying importance of risk factors, and I analyse the interconnectedness of the financial system both in terms of the strength and probability of the connections. I compute network centrality measures (degree, closeness and betweenness) and show how their relate to different states of the economy.

Keywords: financial networks, bayesian model averaging, locally weighted regression, stress testing, systemic risk, forecasting, financial stability

JEL:C52, C53, C54, C58, E44, G01, G15, G17, G18, G21

[1]Ghent University, Department of Financial Economics, Woodrow Wilsonplein 5D, Ghent, Belgium. Email-address: valerie.debruyckere@ugent.be. This paper has been written while Valerie was a Trainee in the Financial Stability Assessment Division of the ECB, DG-Financial Stability. This paper has been prepared by the author under the Lamfalussy Fellowship Program sponsored by the ECB. This paper benefited from comments from Gianni Amisano, Adrien Amzallag, Lieven Baele, Ben Craig, Co-Pierre Georg, Hans Degryse, Hans Dewachter, Domenico Giannone, Maciej Grodzicki, Marco Gross, Grzegorz Halaj, Philipp Hartmann, Iftekhar Hasan, Jérôme Henry, Christoffer Kok, Michele Lenza, Fabien Mercier, Peter Raupach, Koen Schoors, Tuomas Peltonen, Rudi Vander Vennet, David Veredas, Angelos Vouldis and other seminar participants at the Bundesbank, European Central Bank and the ECARES seminar at the Université Libre de Bruxelles.

1 Introduction

Since the start of the financial crisis, macro-prudential oversight has gained in importance and is currently a top priority in the financial stability debate. The emergence of new regulatory bodies such as the European Systemic Risk Board (ESRB) in the European Union, the Financial Stability Oversight Council (FSOC) in the US, and the creation of a single supervisory mechanism (SSM) for the oversight of credit institutions, which is a key element in the EU's plan to establish a banking union, are illustrative of this fact. The goal of macro-prudential oversight is to focus on the financial system as a whole. This implies identifying, assessing and prioritizing system-wide risks, and formulating recommendations on how to mitigate them. This paper aims to contribute to this by developing a stock market based stress test tool for the banking sector.

The identification if system-wide risks is closely related to the literature on systemic risk measures. Many empirical papers construct measures of systemic risk based on stock market information. However, current systemic risk measures have generally been limited to the measurement of exposure to market risk (examples of these include Acharya, Pedersen, Philippon, and Richardson (2010) and Van Oordt and Zhou (2010)). In contrast, this paper models bank risk exposure to the whole set of common (potential) risk factors, such as macroeconomic risk factors, sovereign risk, house price risk and financial sector specific risk. Moreover, this paper argues that financial institutions are not only sensitive to common risk factors, but also to potential shocks from other banks in the financial system. The goal of this paper is to provide a stock market based stress test tool for the European banking sector, taking into account the network structure of the financial sector as in Adrian and Brunnermeier (2009), Diebold and Yilmaz (2011) and Hautsch, Schaumburg, and Schienle (2011). At the same time, the model controls for the bank's exposure to a wide range of common risk factors. To do so, this paper relies on Bayesian Model Averaging of Locally Weighted Regression models (LOESS).

Bayesian Model Averaging (BMA) techniques allow to identify a set of relevant risk factors out of a larger set of potentially important regressors. The logic starts from the idea of "model uncertainty", meaning that a researcher is a priori uncertain about which (constellation of) risk factors affects a particular financial institution. When estimating only one model, the researcher clearly ignores the uncertainty he has about the correct model. He imposes the "right" model on the data, and the only uncertainty that is considered is parameter uncertainty, where one typically interprets the coefficients of significant variables. To address this issue of "model uncertainty", this paper uses Bayesian Model Averaging techniques. In the logic of Bayesian Model Averaging, the model space includes all model combinations which can be made out of a given set of regressors. More specifically, if there is a list of k potential explanatory variables, 2^k different model combinations can be made, where each model is defined through the inclusion or exclusion of (a subset of) the explanatory variables[2]. For each of the 2^k different models, the "posterior model probability" gives insight into how likely each model is, given the model space of all model combinations. A similar metric, labeled the "posterior inclusion probability", expresses how likely a certain regressor (for instance a bank) affects another financial institution. These bilateral *probabilities* are used to construct a Stress Matrix, indicating the probability that each bank affects another bank in the financial system. A similar Stress Matrix is constructed for the *strength* of the relationship between financial institutions. To assess the strength of the connection between banks, I use the posterior parameter estimates. In Bayesian Model Averaging, the information from all models is combined. The posterior parameter estimate is obtained as the weighted average of the parameter estimates in the different models, where the weight is given by the posterior model probability.

Locally Weighted Regression models allow to condition the estimate of bank risk exposure on the specific value of a chosen state vector. In that perspective, it is akin to tail based estimators of bank risk, such as in Hartmann, Straetmans, and de Vries (2005), De Jonghe (2010) and Van Oordt and Zhou (2010). Contrary to these measures, this model can condition the estimate of interbank relationships on a specificic realization of any chosen state vector. This can for instance be the market index being on its 5th percentile, in line with previously proposed measures of bank tail risk, but it can also be conditioned on a recession (measured by a specific value for industrial production), or any other common factor in the model. To the best of my knowledge, this is the first paper which introduces and implements a Bayesian LOESS model. This approach is especially useful from a financial stability (or stress testing) perspective, since

[2]The Bayesian approach compares all models simultaneously, as opposed to model selection criteria (such as Akaike's information criterion (Akaike (1974)), Schwarz's criterion (a Bayesian information criterion, Schwarz (1978)) or Fisher's information criteria (Wei (1992))) where only one model is retained.

the supervisor is particularly interested in bank risk exposures during times of financial market stress, during a recession, during times of money market stress, ... Modelling the dependence between financial institutions in the tail of the distribution of a specific risk factor is key in our understanding of bank risk behavior. Combining the BMA approach with LOESS regressions allows to simultaneously address issues of model uncertainty and the presence of heterogeneous effects across different realizations of a state vector. Moreover, I show that this particular feature of the model improves its performance as a stress test tool.

The usefullness of this model is illustrated with different applications. First, this paper provides insight into the time varying importance of risk factors for financial institutions, using the posterior inclusion probabilities. On the other hand, the strenght of the effect can be assessed through the time varying parameter estimates. Second, the ability of this model to correctly project future evolutions bank equity prices is assessed by analysing the percentage of correctly estimated directions of change in bank equity prices. The model correctly projects 77% of bank equity price changes over an horizon ranging from one quarter to four quarters ahead. Moreover, I show that the performance of my model increases to 81% due to the LOESS feature of the BMA set-up, further indicating the usefullness of this model as a stress test tool. Third, I illustrate how this model can be used for stress testing with three hypothetical stress test scenarios, on three stress test dates (the two CEBS/EBA stress test release dates, 1st of July 2010 and 1st of July 2011, as well as the 1st of January 2012). Fourth, I compute key indicators of network centrality (degree, closeness and betweenness), and analyse how the network structure has evolved over time. Finally, I assess the structure of the network over different realizations of state vectors (such as industrial production, stress in the money market and economy wide credit risk).

The model proposed in this paper has several advantages which are worth mentioning. *First*, the model can be used as a stress test tool for the European banking sector. One can use the model to evaluate the impact of hypothetical scenarios on the European banking sector. *Second*, the methodology allows to include any risk factor which could potentially affect bank stock returns. Additional macroeconomic risk factors, additional financial risk factors or additional risk taking institutions can be included in the model. This feature of the model differentiates it from other papers in this field (e.g. Diebold and Yilmaz (2011) and Alter and Beyer (2012)).

Third, the model allows to track how the importance of a particular risk factor (or a block of risk factors) has evolved over time. This way, we can get insight into the time evolution of risk factors in the financial system. Fourth, the results in the Stress Matrix can be used to assess which financial institutions are most central to the financial network structure, in terms of network centrality measures such as degree, closeness and betweenness. *Finally*, the algorithm used in this paper is not only useful in this specific set-up, but might also be useful to apply to other research questions where there are many potential factors affecting the dependent variable, for instance in the case of credit risk modelling.

This paper is organised as follows. Section 2 reviews and contrasts this model to the several related strands of literature. Section 3 documents on the data used in this study. Section 4 outlines the methodology, whereas Section 5 analyses the empirical results of the model and the different applications. Section 6 concludes.

2 Literature

Since the subject of this paper is very topical and since the model includes a wide range of risk factors, this paper connects to several strands of literature. First, the construction of network centrality measures from the Stress Matrix connects this paper to the literature on systemic risk measures. Second, the Stress Matrix of the financial network relates it to the literature on financial networks and measures of network centrality. Third, it connects to the macro-finance literature and the empirical banking literature using bank factor models. Finally, the proposed set-up allows to analyse the effect of hypothetical scenarios on bank stock prices, connecting it to the literature on bank stress testing.

The approach taken in this paper is related to market based measures of systemic risk, such as the CoVaR measure of Adrian and Brunnermeier (2009), the Marginal Expected Shortfall measure proposed in Acharya, Pedersen, Philippon, and Richardson (2010) or extreme value based measures of bank risk, such as in Hartmann, Straetmans, and de Vries (2005), De Jonghe (2010) and Van Oordt and Zhou (2010). Adrian and Brunnermeier (2009) and Acharya, Pedersen, Philippon, and Richardson (2010) track the relationship between individual financial institution and overall market movements. In contrast, the approach taken in this paper considers the relationship between a financial institution and all other financial institutions, while at the same time controlling for exposure to market movements (and other common factors). Hartmann, Straetmans, and de Vries (2005) derive indicators of the severity and structure of banking system risk from asymptotic interdependencies between banks' equity prices. De Jonghe (2010) also uses extreme value theory to compute systemic banking risk by the tail beta. Van Oordt and Zhou (2010) propose a related measure, the tail regression beta, which takes into account both tail dependence and tail risk in the market and the financial asset itself. Contrary to these measures, this model conditions the estimate of interbank relationships on a specificic realization of a chosen state vector. This can for instance be the market index being on its 5th percentile, in line with previously proposed measures of bank tail risk, but it can also be conditioned on a recession (measured by a specific value for industrial production), or any other common factor in the model. In Section 5, I show that the ability of the model to condition the interbankrelationships on a certain state of the economy improves the ability of the model to project future bank stock return evolutions at all horizons (ranging from one quarter ahead to two years ahead).

In order to measure the systemic importance of financial institutions, the measure must contain information on the institution's potential impact on the financial system (or on individual financial firms) in the event of failure or distress. In practice, capturing these contagion or spillover effects is a difficult task, as these can operate through different channels, and the information from different data sources only sheds light on part of the network linkages in the banking sector. Moreover, data on each of these channels is not always available (for instance, data on interbank exposure is not publicly available)[3]. Therefore, several papers assess the systemic importance of financial institutions using stock return data. Bank stock prices are particulary useful to model systemic risk, because they combine market perceptions of the firm's outlook, publicly available balance sheet and income statement data and currently available market data. Moreover, they cover the different channels through which risks can transmit within the financial sector, such as common credit exposures, interbank lending or trade of

[3]As mentioned in Cerutti, Claessens, and McGuire (2012) market participants need better information on aggregate positions and linkages to appropriately monitor and price risks. To overcome the shortcomings in the availability of bank-by-bank biletaral exposures, techniques have been developed to randomly generate interbank networks. An example of this is Halaj and Kok (2013).

derivatives. Finally, stock market data have some additional advantages over balance sheet or income statement data, in that (i) stock market data have a higher frequency, and hence allow a more timely assessment of risks, and (ii) balance sheet and income statement data is subjective to accounting discretion, such as window dressing and other earnings smoothing techniques.

In sum, the literature on systemic risk is very widespread, and a plethora of systemic risk measures has been developed. This is clearly illustrated in the first working paper of the Office of Financial Research (Bisias, Flood, Lo, and Valavanis (2012)), which provides an extensive survey of current systemic risk measures. Hence, the goal of this paper is not to develop a new measure of systemic risk, but rather to (i) provide a stress test tool to allows supervisors to assess the impact of a hypothetical scenario on the future evolution of stock returns, (ii) to get insight into the time varying importance of risk factors, and (iii) to get insight into the network structure of the financial sector based on publicly available data.

A recent strand of literature in the field of empirical banking studies the network structure of the financial sector. On the one hand, there are papers which make use of (country specific) interbank data to construct and analyse the network (for instance Karas and Schoors (2012) for Russia, Langfield, Liu, and Ota (2012) for the UK and Degryse and Nguyen (2007) for Belgium). On the other hand, a recent strand of literature models interbank relationships using publicly available data. Examples of these are Hautsch, Schaumburg, and Schienle (2011), Diebold and Yilmaz (2011), Betz, Oprica, Peltonen, and Sarlin (2012), Dungey, Luciani, and Veredas (2012). Hautsch, Schaumburg, and Schienle (2011) provide a network description of publicly traded US financial institutions, in an approach which combines both balance sheet data of the firms, macroeconomic data and bank stock returns. Diebold and Yilmaz (2011) use high-frequency intra-day data from the Trade and Quote (TAQ) database to estimate a bivariate connectedness matrix. Betz, Oprica, Peltonen, and Sarlin (2012) incorporate the approach of Hautsch, Schaumburg, and Schienle (2011) to predict events of bank distress. Dungey, Luciani, and Veredas (2012) generate a network structure of the financial sector based on correlations in volatility shocks. Furthermore, I connect to the literature on networks by computing three commonly used measures of network centrality, i.e. degree, closeness and betweenness.

The modeling of financial stock returns as a function of macroeconomic factors connects this paper to an evolving strand of literature in the field of macro-finance, linking financial sector risks and macroeconomic risks. Trichet (2009) mentioned that financial and real sectors are increasingly intertwined. Not only may a shock in the financial sector trigger a crisis in the rest of the economy, also the build-up of macroeconomic or sovereign risk will affect the evolutions in the financial sector. Therefore, this paper takes into account that financial institutions are also exposed to common factor shocks. More specifically, this model has a macroeconomic block, a sovereign block, a financial block and a housing block. It therefore connects to a growing literature in the field of macro-finance. Examples of these are Gross and Kok (2012), Alter and Beyer (2012) and Dewachter and Wouters (2012). Moreover, the use of bank factor models in the empirical banking literature is very widespread. The most common form of bank factor model is the one factor model, including a general stock market index. Baele, De Bruyckere, De Jonghe, and Vander Vennet (2013) however show that other risk factors also significantly affect bank stock returns, and their importance varies significantly over time. The suggested model can be considered as an extended bank factor model.

Finally, I illustrate how this model can be used for examining the potential impact of specific scenarios as in a stress-test context. This methodology in this paper can be classified as a market based, Top-Down stress-test, following IMF (2012). It is similar to stress tests set-ups proposed by Gray, Merton, and Bodie (2007) and Gray, Merton, and Bodie (2010)) and Segoviano and Goodhart (2009).

3 Data

The variables included in this analysis can broadly be divided into two categories. First, I allow that shocks stemming from other banks in the system are affecting every other bank. Secondly, every bank is exposed to common risk factors. These common risk factors can broadly be divided into 4 blocks: a macroeconomic block, a sovereign block, a housing block and a financial block[4].

[4]The current set-up does not include lags of the explanatory variables, i.e. I measure the contemporaneous impact of each risk factor on each bank. However, this model can easily be extended with lags of (some) variables to allow for a delayed response of a risk factor. This extension is left for future research.

The sample period ranges from the 3nd quarter of 2005 until the 3rd quarter of 2012. Table 2 contains a detailed description of the data series, the source and the data manipulations.

Banking Block

To identify the potential risk of other banks in the system, I include the stock return series of all other banks in the sample. The sample of banks included in the sample is based on a few criteria. First, I start with the banks which were included in the 2010/2011 stress tests of the European Banking Authority. I take log returns of the weekly stock prices of these banks. Then, I require at least 80% of liquid data points (liquid is defined as a nonzero stock return) within each quarter[5]. I further reduce the sample by excluding banks which have less than 5 years of consecutive liquid stock returns. I finally balance the sample by dropping all banks which have illiquid stock return series for at least one quarter between January 2005 and October 2012. This results in a sample of 34 banks from 13 countries (Austria, Belgium, Germany, Denmark, Spain, France, UK, Greece, Hungary, Ireland, Italy, Portugal and Sweden). The summary statistics of the all independent variables in this study can be found in Table 3. The complete list of banks included in the analysis can be found in Table 1.

Macro Block

To capture the potential exposure of banks to shocks in the macroeconomic environment, I include several risk factors. I include inflation, industrial production growth, the 3 Month euribor, a market index, the Vstoxx implied volatility index and the Itraxx index. Both the inflation rate and industrial production series are obtained from the ECB Statistical Datawarehouse. However, the frequency of these series is monthly. I therefore interpolate these two series with a cubic spline, to match the weekly frequency of the other regressors in the system. The market index is the total stock market index for the EU (Datastream code TOTMKEU). It mirrors all EU stock markets, not only the financial sector. The Vstoxx volatility index captures market expectations of volatility in the Eurozone (also see, e.g., Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) and Tang and Yan (2010)). This index is generally perceived as a market sentiment or investor fear indicator. Finally, I include the Itraxx index to proxy for the evolution of market-wide credit

[5] I make an exception for Dexia during the second and third quarter of 2012, since this would otherwise reduce the sample period to the 1st quarter of 2012.

risk. The Itraxx index is constructed as the equally weigthed average of the 125 most liquid CDS series in the European market. A higher iTraxx indicates a higher overall default risk in the economy, thus I expect a negative relationship between the iTraxx index and bank stock returns. Industrial production growth and inflation are included in levels, whereas the other series are included in logarithmic returns.

Sovereign Block

The recent sovereign debt crisis has indicated that bank risk and sovereign risk can become very intertwined. Studies as De Bruyckere, Gerhardt, Schepens, and Vander Vennet (2012), Alter and Schuler (2012), Alter and Beyer (2012) and Gross and Kok (2012) therefore analyse spillovers between financial institutions and sovereigns. To allow shocks in sovereign credit risk to affect financial institutions, I include the 10-year government bond yield of 13 countries (Germany, Italy, France, Spain, Portugal, Greece, Ireland, Austria, Belgium, UK, Denmark, Sweden and Hungary). The series are included in logarithmic returns.

Financial Block

I include two measures for financial sector specific risk. To measure stress in the European funding market, I include the spread between the 3 month eonia index swap and the 3 Month Euribor interest rate. Secondly, I include the Itraxx senior Financial index, which tracks the evolution of the credit risk in financial institutions in Europe. However, the Itraxx financial index is highly correlated with the Itraxx index, which is included in the macroeconomic block. Hence, I orthogonalize the Itraxx financial index with respect to the Itraxx, and take the residual series instead.

Housing Block

As a measure of the evolution of house prices, I include an EU house price index obtained from the ECB's statistical datawarehouse. The quarterly house price series is interpolated with a cubic spline to a weekly frequency. The house price index is transformed to logarithmic returns.

4 Methodology

In the next subsections, I explain the methodology used to assess the interconnectedness in the financial system. In subsection 4.1 I introduce the concept of the Stress Matrix. Subsection 4.2 explains the logic of Bayesian Model Averaging and the algorithm to browse the model space. In subsection 4.3, I introduce the Bayesian LOESS regression model. Finally, in subsection 4.4 I describe the different network centrality measures (degree, closeness and betweenness).

4.1 The Stress Matrix

To infer on the risk exposures of each bank to the range of potential risk factors, I estimate the following equation:

$$Y = \beta.X + \varepsilon \tag{1}$$

where Y is a vector consisting of the M banks in the system

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ ... \\ y_{M-1} \\ y_M \end{pmatrix} \tag{2}$$

and X is a matrix consisting of the N potential risk factors, where M is a subset of N.

$$X = \left(\underbrace{x_1 \quad x_2 \quad ... \quad x_{M-1} \quad x_M}_{BankBlock} \underbrace{x_{M+1} \quad ... \quad x_{N-1} \quad x_N}_{Common\ Factors} \right) \tag{3}$$

More specifically, I estimate the following system of equations:

$$\left\{ \begin{array}{c} y_1 = \beta_{1,2}x_2 + \beta_{1,3}x_3 + ... + \beta_{1,M}x_M + \beta_{1,M+1}x_{M+1} + ... + \beta_{1,N}x_N + \varepsilon_1 \\ y_2 = \beta_{2,1}x_1 + \beta_{2,3}x_3 + ... + \beta_{2,M}x_M + \beta_{2,M+1}x_{M+1} + ... + \beta_{2,N}x_N + \varepsilon_2 \\ y_3 = \beta_{3,1}x_1 + \beta_{3,2}x_2 + ... + \beta_{3,M}x_M + \beta_{3,M+1}x_{M+1} + ... + \beta_{3,N}x_N + \varepsilon_{31} \\ ... \\ y_M = \beta_{M,1}x_1 + \beta_{M,2}x_2 + ... + \beta_{M,M-1}x_{M-1} + \beta_{M,M+1}x_{M+1} + ... + \beta_{M,N}x_N + \varepsilon_M \end{array} \right\} \tag{4}$$

where each bank is exposed to shocks from other banks in the system, and to shocks from the common factors (macroeconomic, sovereign, financial sector specific and house price shocks). Concentrating only the connections between the banks, I introduce the concept of the *Stress Matrix*, both in terms of the strength of the connection, as in terms of the probability of a connection.

Stress Matrix (strength of connection) **Stress Matrix (probability of connection)**

$$\begin{bmatrix} . & \beta_{1,2} & \beta_{1,3} & ... & \beta_{1,M} \\ \beta_{2,1} & . & \beta_{2,3} & ... & \beta_{2,M} \\ \beta_{3,1} & \beta_{3,2} & . & ... & \beta_{3,M} \\ ... & ... & ... & ... & ... \\ \beta_{M,1} & \beta_{M,2} & \beta_{M,3} & ... & . \end{bmatrix} \qquad \begin{bmatrix} . & P_{1,2} & P_{1,3} & ... & P_{1,M} \\ P_{2,1} & . & P_{2,3} & ... & P_{2,M} \\ P_{3,1} & P_{3,2} & . & ... & P_{3,M} \\ ... & ... & ... & ... & ... \\ P_{M,1} & P_{M,2} & P_{M,3} & ... & . \end{bmatrix} \tag{5}$$

The Stress Matrix introduced in this paper is similar in nature to the Connectedness Table in Diebold and Yilmaz (2011) and the Spillover Matrix in Alter and Beyer (2012). The Connectedness Table in Diebold and Yilmaz (2011) is constructed based on variance decompositions, whereas the Spillover Matrix in Alter and Beyer (2012) is constructed based on Generalized Impulse Responses. The contribution of this approach is that Bayesian Model Averaging is able to accomodate a much larger set of potential risk factors (in casu banks), such that the Stress Matrix can be larger. In Alter and Beyer (2012), the size of the spillover matrix is $20x20$, allowing for spillovers between 11 countries and the banking sectors of 9 countries, whereas the dimension of the (bank specific) spillover matrix is $13x13$ in Diebold and Yilmaz (2011). Since I included stock returns of 34 financial institutions in this study, the dimension of the Stress Matrix is $34x34$ (including the common factors, the dimension of the model is $34x56$). However, the model can easily be extended with other banks (as long as (liquid) stock return data are available). Moreover, the Stress Matrix measures both the strength of the relationship and its probability. The strength of the relationship is given by the *posterior parameter* estimate, whereas the probility is computed based on the *posterior inclusion probability* of each bank.

4.2 Bayesian model averaging

To analyse the probability that each bank affects another bank in the system, and the strength of that relationship, this paper use Bayesian Model Averaging. Bayesian Model Averaging was first developed by Leamer (1978), and has since then been used in several disciplines, ranging from statistics (Raftery, Madigan, and Hoeting (1997) and Hoeting, Madigan, Raftery, and Volinsky (1999)), to the large literature on cross-country growth regressions (Fernandez, Ley, and Steel (2001b), Brock and Durlauf (2001) and Sala-I-Martin, Doppelhofer, and Miller (2004) among others) and finance (Cremers (2002), Avramov (2002) and Wright (2008)). In the logic of Bayesian Model Averaging, the model space includes all model combinations which can be made out of a given set of regressors. More specifically, if there is a list of k potential explanatory variables, 2^k different model combinations can be made, where each model is defined through the inclusion or exclusion of (a subset of) the explanatory variables[6]. For each of the 2^k different models, the *posterior model probability* gives insight into how likely a specific model is, given all other models in the model space.

To indicate the different models estimated for each bank in the system, I add a superscript

[6] The idea to use variable selection techniques to model drivers of stock return data, can also be found in Hautsch, Schaumburg, and Schienle (2011) and Adrian, Moench, and Shin (2010). Hautsch, Schaumburg, and Schienle (2011) propose a systemic risk beta as a measure for financial companies' contribution to systemic risk, given network interdependence between firm's tail risk exposures. In fact, the authors use the Least Absolute Shrinkage and Selection Operator (LASSO) to identify the set of relevant tail risk drivers for each financial institution. The selection technique allows to shrink the number of relevant risk drivers from a high-dimensional set of possible cross-linkages between all financial firms. Adrian, Moench, and Shin (2010) use the same idea, although in a somewhat different context. The authors investigate the predictive power of financial intermediary balance sheet aggregates for excess returns on a broad set of equity, corporate and Treasury Bond portfolios. They use the Least Angle Regression (LAR) technique (a generalization of the Least Absolute Shrinkage Selection Operator LASSO) and find that security broker-dealer leverage and the shadow bank asset growth are selected as the best predictors. However, the advantage of Bayesian Model Averaging over selection methods is that the information from all models is combined in the final estimation. Whereas variable selection approaches define a threshold up to which covariates are considered relevant, Bayesian Model averaging weights the different models according to their informativeness, i.e. the results of all models are weighted with their corresponding posterior model probability.

k. This modifies the system of equations in (4) to

$$\left\{\begin{array}{c} y_1 = \beta^{1,k}x^{1,k} + \varepsilon_1^k \\ y_2 = \beta^{2,k}x^{2,k} + \varepsilon_2^k \\ y_3 = \beta^{3,k}x^{3,k} + \varepsilon_3^k \\ ... \\ y_M = \beta^{M,k}x^{M,k} + \varepsilon_M^k \end{array}\right\} \tag{6}$$

where for instance $x^{1,k}$ indicates the regressors in model M^k for bank 1.

In Bayesian Model Averaging, the researcher has a prior belief about model k, summarized in the model prior $p(M^k)$, where every model is indicated with subscript k. The posterior probabilty of model k is given by

$$p(M^k|y) = \frac{p(y|M^k)p(M^k)}{\sum_{m \in M} p(y|M^m)p(M^m)} \tag{7}$$

where $p(y|M^k)$ is the marginal likelihood of model M^k, and $p(M^k)$ is the prior on model M^k.

Whereas the posterior model probability in equation 7 gives insight into how likely a specific model is, the more interesting metric expresses how likely a certain regressor should be included in the model. This is captured by the *posterior inclusion probability.* Following Leamer (1978) and Doppelhofer and Weeks (2009), it is calculated as the sum of the posterior model probabilities of the models which include the specific variable. The posterior inclusion probability of variable i for bank j is given by

$$PIP_{i,j} = \sum_{k=1}^{2^{56}} p(M^{j,k}|y_j) \cdot I(x_i \in X|y_j, M^{j,k}) \tag{8}$$

These posterior inclusion probabilities for $i = 1, ..., M$ and $j = 1, ..., M$ form the entries of the elements in the Stress Matrix of probabilities in equation 5.

To obtain posterior estimates of risk exposure, Bayesian Model Averaging combines the information from all models. The posterior parameter estimate is obtained as the weighted average of the parameter estimates in the different models, where the weight is given by the posterior model probability.

$$E(\beta^j|y_j) = \sum_{k=1}^{2^{56}} p(M^{j,k}|y_j) \cdot E(\beta^{j,k}|y_j, M^{j,k}) \tag{9}$$

These posterior estimates for $j = 1, ..., M$ form the rows of the Stress Matrix and express the strength of the connection between banks in equation 5.

The model prior $p(M)$ used in this paper is a prior on the number of regressors. The maximum number of regressors is set to 7, whereas lambda is set to 3. The model prior follows a *poisson* distribution,

$$p(M^k) = \frac{\lambda^{l^k} e^{-\lambda}}{l^k!}$$

where l^k is the number of regressors in model M^k. Moreover, I assess the robustness of my results to the commonly used *Binomial model prior*, assuming equal prior probability for all models (but still constrained to models with a maximum dimension of 7), more specifically

$$p(M^k) = \frac{1}{2^{56}} \tag{10}$$

The correlation in posterior parameter estimates and posterior inclusion probabilities between both sets of results is always above 99%, and the minimum correlation is never below 96%.

The set of potential risk factors affecting each bank is too big to estimate every model in the model space. Given the set of 56 potential regressors, this means the model space contains 2^{56} (72057594037927900) models. Even constraining the dimension of the models to maximum 7 only reduces the model space to 268602259. Hence, some numerical technique is necessary to approximate the model space. I therefore use a shochastic search algorithm to jump between models of the same or different dimensionality. I use a Markov Chain Monte Carlo algorithm to simulate a Markov chain consisting of different models M_k. I use the recently proposed Subspace Carlin and Chib (SCC) algorithm of Athanassios and Dellaportas (2012). The authors show that this algorithm avoids some pitfalls and performs better than existing algorithms (such as the Carlin and Chib algorithm, the Metropolised Carlin and Chib, Shotgun Stochastic Search, Reversible Jump, ...).

As with any posterior simulator, it is important to verify convergence of the algorithm. I follow the suggestion of Fernandez, Ley, and Steel (2001a). Based on a reduced set of models, calculate the posterior model probability analytically (using equation 7) and using the SCC algorithm. If the algorithm has converged, then both ways of calculating the posterior model probabilities should give the same result. Fernandez, Ley, and Steel (2001b) suggest the correlation between the analytical posterior model probabilities and the model probabilities of the algorithm to exceed 0.99. Already with 1000 burn-in draws and 15000 iterations, this result is achieved for most banks in the sample.

4.3 Bayesian Locally Weighted Regression (LOESS)

To allow the estimated network structure to depend on the state of the economy (measured by a specific realization of a state vector), I make use of the locally weighted regression technique, as in Cleveland (1979) and Cleveland and Devlin (1988). The idea is to condition the estimates of stock returns of bank j on a certain state of the economy, for instance measured by industrial production being on its 25th percentile. The LOESS technique is a frequentist econometric technique (as opposed to Bayesian econometrics), but this method is adjusted to a *Bayesian* LOESS to integrate it into the Bayesian Model Averaging framework. To the best of my knowledge, this is the first paper which develops and implements a Bayesian Locally Weighted Regression Model.

To specify that the exposure of bank j to certain risk factors is conditional on a certain choice for x, equation 11 specifies the relationship between stock returns of bank j to the set of risk factors (in x_j).

$$y_{j,t} = g(x_{j,t}) + \varepsilon_{j,t} \tag{11}$$

The function $g()$ is conditional on a choice for x (x_t), for instance the economy being in a specific adverse state. I will refer to a particular choice x_t as a gridpoint. The estimate $\hat{g}(x_{j,t})$ is the coefficient estimate of the locally weighted regression. The locally weighted regression operates through two channels. First, the locally weighted regression uses only a number of neighbouring observations closest to the gridpoint. The number of neighbouring observations q is determined by the fraction f, where $f = q/n$, with n the total number of observations in the sample. The choice of q determines the *proportion* of observations in the neighbourhood of x_t which is taken into account in the locally weighted regression. In this paper, f is chosen and set at $1/3$, implying that one third of the observations in the neighbourhood of a specific gridpoint are taken into account[7]. The second way in which the estimate $\hat{g}(x_t)$ conditions on a specific gridpoint, is

[7] The sample period ranges from $2005Q3$ until $2012Q3$. With weekly stock returns, this implies that 127 weekly

by assigning weights to the q observation vectors which are closest to x_t. To assign weights to observations, the *tricube weight function* is used:

$$W(u) = \begin{Bmatrix} (1-u^3)^3 & \text{if } 0 \leq u < 1 \\ 0 & \text{otherwise} \end{Bmatrix} \tag{12}$$

The weight function W is applied to the relative distance of the observation w.r.t. the q-th nearest observation to x_t, as follows:

$$w_t(x) = W\left(\frac{\rho(x, x_t)}{d(x)}\right)$$

where $d(x)$ is the distance between x and the qth nearest observation x and $\rho(x, x_t)$ is the Euclidian norm. Note that the x and x_t should be normalized prior to measuring the Euclidian distance.

The Bayesian locally weighted regression is obtained by imposing the Normal-Gamma natural conjugate prior on the coefficients, using Zellner's g-prior where $g = n$ (the number of observations). Details of this approach can be found in the Appendix to this paper. The bottomline is that the estimator is a function of the *weighted* OLS estimator for β where the weights W are given by the weight matrix in equation 12.

$$\hat{\beta} = (X'WX)^{-1}X'Wy$$

4.4 Network Centrality Measures

To study the network properties of the interbank network, I use three classic network centrality measures (degree, closeness and betweenness). The network is composed of vertices (banks), which are connected to each other through edges.

Degree centrality Degree centrality equals to the number of ties a vertex has with other vertices. To classify whether a bank has a tie with another bank, a threshold is imposed on

stock returns are used for each gridpoint (380/3). In the analysis over moving windows (of 6 or 8 quarters) (for instance subsection 5.1) , I set $f = 1$, implying that all observations in the window are used. The LOESS feature of the model then only comes from the weights assigned to neighbouring observations.

the stress matrix. More specifically, I consider a bank to be connected to another bank if the posterior inclusion probability is larger than 50%. Moreover, since the stress matrix is a *directed* matrix, both the *indegree* and the *outdegree* can be constructed. To compute the indegree, I sum over the columns of the Stress Matrix of probabilities, whereas I sum over the rows to compute the outdegree. The indegree of bank i is given by

$$\text{Indegree}_i = \sum_{j=1}^{N} I(PIP_j > 50\%)$$

whereas the outdegree of bank j is given by[8]

$$\text{Outdegree}j = \sum_{i=1}^{N} I(PIPi > 50\%)$$

where $I()$ is an indicator function equal to one if the PIP is greater than 50%, and zero otherwise. Generally, banks with a higher outdegree have a greater capacity to influence other banks, whereas banks with a greater indegree are more exposed to shocks from other banks in the system.

Closeness A more sophisticated centrality measure is closeness (Freeman (1979)) which emphasizes the distance of a vertex to all others in the network. Closeness can be regarded as a measure of how long it will take information to spread from a given vertex to others in the network. Again, as the Stress Matrix is a directed matrix, both in- and out-closeness can be computed:

$$\text{Closeness(in)}_i \sum_{j=1}^{N} \frac{1}{d(i,j)}$$

$$\text{Closeness(out)}_j = \sum_{i=1}^{N} \frac{1}{d(i,j)}$$

where the distance $d(i,j)$ between bank i and bank j is defined as $1 - PIP(i,j)$.

Betweenness centrality. Betweenness centrality is based on the number of shortest paths passing through a vertex. Vertices with a high betweenness play the role of connecting different banks. In financial networks, vertices with high betweenness are typically the brokers and

[8] I keep the terminology in terms of bank i and bank j to stress that the direction of summation is different (columns versus rows).

connectors who bring others together. Being between means a vertex has the ability to control the flow of knowledge between most others. As in the case of the degree centrality, I specify a threshold on the posterior inclusion probability of 50% to consider a link between bank i and bank j.

5 Empirical Results

This Section describes the empirical results of the BMA LOESS model. Before presenting the Stress Matrix, I describe in subsection 5.1 the results of the model over rolling windows of respectively 6 and 8 quarters. The goal is to get insight into the time varying importance of risk factors. In subsection 5.2 I illustrate the power of my model to project future evolutions of bank stock prices. In subsection 5.3 I show how this model can be used to project bank stock prices using three hypothetical stress test scenarios on three dates. Finally, I show in subsecion 5.4 how the three measures of network centrality (degree, closeness and betweenness) have changed over time, and how they relate to different realizations of the common factors.

5.1 Time varying importance of blocks

To analyse how the importance of certain risk factors has changed over time, I run the model over rolling windows of 6 quarters ($1,5$ years), rolling forward every quarter. In this part of the paper, I do not use the LOESS feature of the model, as estimating the model over every 6 quarter period already implies that I am centering the estimations on a specific point (in time). The sample period starts in the second quarter of 2005, so the first estimate is obtained for the third quarter of 2006. Presenting the results of all 56 regressors would be infeasable, and therefore I summarize the results per block. Figure 1 shows the maximum posterior inclusion probability of the regressors in each block. Already in the third quarter of 2007, the PIP of the bank sector jumps to 50%, indicating the stress in the bank sector. The underlying results indicate that this maximum is due to Dexia, just as the second spike in the second quarter of 2008. Panel B of Figure 1 shows the median and the interquartile range of the PIPs in the banking block. This graph indicates that the median (and also the mean) hide considerable cross sectional heterogeneity.

In general, the importance of shocks to house prices in Europe is relatively low (below 5%). Macroeconomic risk factors have in general a PIP of below 30%, except at the very end of the sample period, where they increase to 42%. Panel A in Figure 2 shows that this is due to the increased importance of inflation risk in the second and third quarter of 2012. Sovereign risk reaches its maximum importance in the first and the third quarter of 2009 (with a PIP of 31%). Panel B of Figure 2 presents the PIPs of the GIIPS countries' sovereign bond yields. The maximum of 31% is due to the sovereign debt problems in Ireland. Note that the importance of the risk factors is averaged across the banks, meaning that the sovereign debt problems of Ireland had the largest effect on the bank stock prices in the sample[9]. The importance of financial sector specific risks is in general also low (below 10%), except for the first quarter of 2009, where the maximum importance was 20%. To show that these conclusions are robust to a longer time window (8 quarters instead of 6), I include in Panel A of Figure 3 the same PIPs of the macroeconomic risk factors for rolling windows of 8 quarters. Panel B of Figure 3 provides insight into the two financial sector specific risk factors, and indicates that the jump in the financial sector PIP in the first quarter of 2009 was due to financial sector specific credit risk (Itraxx financial series).

5.2 Out-of-sample Projections

To verify whether this model is useful as a stress test tool, I assess the ability of the model to correctly project the direction of future bank stock prices. More specifically, I assume for every equation in (4) the realized path. In other words, I assume that history is realized to assess how well a hypothetical scenario would project the future stock price evolution. I assess the performance of the model for periods of one to eight quarters ahead.

Label with H the number of correct positive signals, F the number of false positive signals, Z the number of correct negative signals and M the number of false negative signals, then the proportion of correct signals can be calculated as

$$PC(\%) = \frac{H + Z}{H + F + Z + M} \tag{13}$$

[9] The fact that this sample contains more banks of certain countries, and that banks have been shown to have a strong home bias in their sovereign bond portfolios (see De Bruyckere, Gerhardt, Schepens, and Vander Vennet (2012)), might affect the conclusions here.

Panel A of Figure 4 shows the time varying ratio PC for projection horizons from one to four quarters ahead. The two, three and four quarter ahead PC ratios do not reach the end of the sample period, as these data are necessary to assess the projection accuracy. The PC ratio is compared to the 50% threshold. The Figure shows that the PC ratio exceeds the thresholds in most periods. It is below 50% during the last quarter of 2008 (this means over the period $2006 - 2008$) for two and four quarter ahead projections (respectively 41% and 44%). The PC ratio also drops below 50% towards the end of the sample period. The average PC ratio over all time windows is 73%, 75%, 77% and 74% for projections one to four quarters ahead. Panel B of Figure 4 compares the PC ratio over projected windows of one to four quarters ahead, using estimation windows of 6 versus 8 quarters. The Figure shows that the projection accuracy is always higher when the estimation window is 8 quarters (instead of 6). Moreover, the projection accuracy is highest for projections 3 quarters ahead (77% of the directions of bank stock prices is correctly projected). Finally, Panel C of Figure 4 shows the RMSE over the estimation windows (8 quarters). The RMSE of the model is largest in the second quarter of 2008, suggesting that this period of the financial crisis what most unpredictable.

Finally, I illustrate the usefullness of the Bayesian LOESS model in Figure 5. This bar chart compares the projection accuracy (measured with the PC ratio) of BMA using a standard bayesian linear model versus the Bayesian LOESS model for projection horizons ranging from one to eight quarters ahead. The LOESS estimates are centered around the last value of industrial production in each estimation window (8 quarter windows). The proportion of the window that is used is 100% (i.e. f equals 1), implying that the LOESS feature of the model is only due to the weighting scheme. The projection accuracy of the LOESS model is higher than that of the standard linear model for every projection horizon. For horizons 3 quarters ahead, the PC ratio equals 81% with the LOESS model, as compared to 77% with a standard linear model[10]. This suggests that the LOESS feature of the model improves the projection accuracy, and makes it

[10] The model does not include lags of the explanatory variables. However, inspection of the Durbin Watson statistics over the rolling windows suggests that for some banks, during some quarters, there is still autocorrelation left in the residuals. From an econometric point of view, this implies that the coefficient estimates are unbiased and consistent, but not efficient. Including lags of the explanatory variables could improve the efficiency, and could potentially even further improve the projection accuracy. This is left for future research.

an interesting tool for stress test purposes[11].

5.3 Stress Testing the European Banking Sector

To illustrate how this model can be used in a stress test context, I assess the future evolution of bank stock prices on three stress test dates, for three hypothetical scenarios. The three stress test dates are the 1st of July 2010 and 2011 and the 1st of January 2012. The first two dates coincide with the release of the CEBS/EBA stress test results. The three scenarios describe current risks in the financial and sovereign debt crisis.

1. An aggravation of the euro area sovereign debt crisis.
2. A deterioration in the credit quality due to a weakened economic environment.
3. Further fragmentation and distress in bank funding markets.

These scenarios are translated into specific "paths" for (some of) the explanatory variables. More specifically, I assume (i) a downward movement in (all) bank stock prices and (ii) an upward movement in (all) sovereign bond yields over a one quarter horizon for the first scenario[12]. To allow for different degrees of severity in the scenarios, I assign a number from 1 to 6. The Worst Case Scenario (WCS) is labeled by 1, whereas the Best Case Scenario (BCS) is labeled by 6. To assume realistic scenarios, I use the observed sample period to assign a value for the scenarios. More specifically, 1 (WCS) corresponds to the maximum drop in bank stock stock returns over a quarterly horizon, 2 corresponds to the 20th percentile, 3 to the 40th percentile, 4 to the 60th percentile, 5 to the 80th percentile, and 6 to the maximum observed quarterly observed stock return. As an increase in sovereign bond yields corresponds to the adverse scenario, I reverse the numbers for the sovereign risk factors. For the other risk factors, I assume that they remain constant. To proxy for the second scenario, a deterioration in the credit quality due to a weakened economic environment, I assume a path for the Itraxx index, keeping the value of all other regressors constant. For the third scenario, I assume a path for the Vstoxx, the spread, and the Itraxx financial index. More specifically, I assume increased volatility in de market,

[11] Ideally, the supervisor would want to center the estimate around the expected value of industrial production.

[12] Note that the path of the scenario does not matter, i.e. it does not matter whether I assume the scenario to be realized over the first week of the quarter, or whether I assume it to realize gradually over the quarter.

increased money market stress, and increased financial sector specific credit risk. To project the future evolution of bank stock prices, I use the 8 quarter window of data to do the estimation (I do not use the LOESS feature of the model here, i.e. the results are based on the BMA of the linear bayesian model).

Figure 6 plots the projected evolution in bank stock prices over the next quarter for the three projection dates, and the three hypothetical scenarios. The last value of all stock prices is 100. To show the dispersion across the 34 banks in the sample, I plot the median and the interquartile range. Panel A in Figure 6 shows the results of the three scenarios on the first stress test day (1st of July 2010). The figure shows that the 1st (WCS) to 3rd path for the first scenario would have predicted a downward trend for the interquartile range of the banks. In the WCS, the median bank's stock return is projected to drop from 100 to 36 over the next quarter. On the second and third stress test day (Panel B and C in Figure 6), the effect for the median bank is much less severe (for the median bank, the model projects a drop to respectively 45 and 43). The effects of the second scenario is much less severe than the first on the third projection date. The median bank would see no change in its stock price (and remain at 100), although for some banks there is a negative effect. On the second projection day however, an increase in credit risk in the economy would have had a much larger effect on the banks. This result can be explained by the increased credit risk in the economy in the period prior to the 1st of July 2011. Finally, the projected effects of the third scenario are very dispersed over the cross section of banks, and between the three projection days. On the first and third projection day, no significant effect is be projected. On the 1st of July 2011 however, the effect of a fragmentation in bank funding markets would have had more severe effects on bank stock price evolutions. In the WCS, the median bank's stock return is projected to drop to 91, whereas the 25th bank's stock return would decrease by half. The results suggest that the state of the economy on the 1st of January 2012 was much more resilient to a deterioration in the credit quality (scenario 2) and distress in funding markets (scenario 3) than it was on the previous second stress test date. The model projects that further a further aggravation of bank and sovereign risks (scenario 1) would have had an adverse negative impact on the banking systems's equity valuations on the 1st of January 2012.

5.4 Measures of Network Centrality

Figure 7 visualizes the financial network structure centered around two values of industrial production. The figure on the left hand side takes the lowest value of industrial production in the sample (the value at the end of April 2009) as the gridpoint in the LOESS estimation, whereas the figure at the right hand side takes the maximum (in sample) value of industrial production (end of May 2010) as a gridpoint. The graph only visualizes connections between banks when the PIP is larger than 50 percent. The probability of the connection (the PIP) is connected to the darkness of the lines. All banks in the graph get equal size (the red circle). The location of the banks on the graph is an approximation of their geographical location in Europe. However, it is hard to draw strong conclusions about the interconnectedness of the system from this graph. Therefore, I compute the network centrality measures discussed in Section 4.4.

Figure 8 summarizes how the degree, closeness and betweenness vary over moving windows of 8 quarters. Panel A shows that the average degree (the average number of connections a bank has in the system) reached a maximum of 3.7 in the last quarter of 2010. The estimation window for the value ranges from $2008Q1$ until $2010Q4$, which is exactly the period with the highest market tensions within the financial system. Panel B of Figure 8 confirms that the closeness was also at its highest value during that quarter. This means that information was spreading very fast between banks during this period. The graph shows that there is a spike in the network centrality in the third quarter of 2011 for all three measures. The LTRO program launched by the ECB in the fourth quarter could be a possible explanation for the decline afterwards. Moreover, the three graphs show the decline in network centrality from then until the end of the sample period. The network centrality measures indicate that the stress between banks in the system has declined over time. Indeed, credit risk in the financial sector has become more bank specific, and the sovereign debt problems of certain European countries have dominated the news more than before.

To get insight into how these network centrality measures relate to certain values of the common factors, I estimate the BMA LOESS model conditional on specific values for the level of 5 common factors: industrial production, the Vstoxx implied volatility index, the total market index (totmkeu), the Itraxx and the spread. Figure 9 shows the values of the three network centrality measures (degree, closeness and betweenness, in Panel A to C) for 5 values of the common factors. The 5 values are the values at equally spaced intervals between the minimum and the maximum (in the levels) of the common factor. The observed patterns are not always monotonous, but some patterns can be observed.

At the lowest level of industrial production, the average number of connections a bank has with other banks is slightly higher. This means that some banks seem to affect other banks more during recessions. In line with intuition, the degree and the closeness of the system are higher when the Itraxx is higher. For the betweenness, this relationship is not there. This can be explained by the fact that information may also be spreading rapidly over the financial system in times of low credit risk. Exactly the opposite pattern can be found for the stock market index. At high values of the stock market index, the degree and closeness are lower. The Vstoxx does not seem to be meaningfully related to the degree and betweenness, although the closeness of the system is higher for extreme volatility as compared to extremely low volatility in the market. Finall, in line with intuition, the interconnectedness of the financial system is higher when the spread is higher. This relationship holds for all three measures of network centrality, although the middle gridpoints are not always linearly related to the outer ones.

6 Conclusion

This paper presents a methodology to stress test the European banking sector using publicly available data. Banks are not only exposed to shocks from common risk factors (macroeconomic risk factors, sovereign risk, financial risk and housing price risk), but also to shocks from all other banks in the system. To do so, this paper relies on Bayesian Model Averaging (BMA) of Locally Weighted Regression models. BMA allows to identify a set of relevant risk factors out of a larger set of potentially important regressors. The goal of this paper is to (i) provide a stress test tool to allows supervisors to assess the impact of hypothetical scenarios on the future evolution of stock returns, (ii) to get insight into the time varying importance of risk factors, and (iii) to get insight into the network structure of the financial sector.

Several contributions of this model are worth mentioning. First, this paper provides insight into the time varying importance of risk factors for financial institutions, using the posterior inclusion probabilities. On the other hand, the strenght of the effect can be assessed through the time varying parameter estimates. Second, ability of this model to correctly project future evolutions bank equity prices is assessed by analysing the percentage of correctly estimated directions of change in bank equity prices. The model correctly projects 77% of bank equity price changes over an horizon ranging from one quarter to four quarters ahead. Moreover, I show that the performance of my model increases to 81% due to the LOESS feature of the BMA set-up, further indicating the usefullness of this model as a stress test tool. Third, I illustrate how this model can be used for stress testing with three hypothetical stress test scenarios, on three stress test dates (the two CEBS/EBA stress test release dates, 1st of July 2010 and 1st of July 2011, as well as the 1st of January 2012). Fourth, I compute key indicators of network centrality (degree, closeness and betweenness), and analyse how the network structure has evolved over time. Finally, I assess the structure of the network over different realizations of state vectors (such as industrial production, stress in the money market and economy wide credit risk).

The questions addressed in this paper are important from a policy perspective, as assessing empirically the impact of a hypothetical (stress test) scenario has clear implications for crisis management, i.e. crisis resolution at the individual bank level versus macro-oriented stabilisation policies.

The approach in this paper offers interesting possibilities for future research. The Bayesian nature of this set-up offers interesting opportunities to incorporate other sources of information. Hartmann, de Bandt, and Peydro-Alcalde (2009) stress that financial systemic risk is characterized by both a cross-sectional and a time series dimension. This idea is also exploited in Schwaab, Lucas, and Koopman (2010). In the specification of the prior on the parameters, I have used relatively uninformative priors so far. Hence, it could be interesting to see whether the incorporation of balance sheet based characteristics of banks would allow to further improve the projection performance, by centering the parameter prior around the posterior estimate of similar banks (in terms of balance sheet characteristics). Moreover, the same idea could be used along the time series dimension of the data, incorporating information from the previous time window into the new parameter prior. Incorporating usefull sources of other information could potentially improve the projection performance of this model even further.

References

Acharya, V., L. H. Pedersen, T. Philippon, and M. Richardson, 2010, "Measuring Systemic Risk," *AFA 2011 Denver Meetings Paper.*

Adrian, T., and M. Brunnermeier, 2009, "CoVar," *Federal Reserve Bank of New York Staff Report Nr 348.*

Adrian, T., E. Moench, and H. Shin, 2010, "Financial Intermediation, Asset Prices, and Macroeconomic Dynamics," *Federal Reserve Bank of New York Staff Report NÂř 422.*

Akaike, H., 1974, "New Look at Statistical-Model Identification," *Ieee Transactions on Automatic Control*, Ac19(6), 716–723.

Alter, A., and A. Beyer, 2012, "The Dynamics of Spillover Effects during the European Sovereign Debt Turmoil," *CFS Working Paper Number*, 2012/13.

Alter, A., and Y. Schuler, 2012, "Credit spread interdependencies of European states and banks during the financial crisis," *Journal of Banking and Finances*, 36(12).

Athanassios, P., and P. Dellaportas, 2012, "An MCMC model search algorithm for regression problems," *Journal of Statistical Computation and Simulation*, pp. 1–19.

Avramov, D., 2002, "Stock return predictability and model uncertainty," *Journal of Financial Economics*, 64(3), 423–458.

Baele, L., V. De Bruyckere, O. De Jonghe, and R. Vander Vennet, 2013, "Model Uncertainty and Systematic Risk in US Banking," *Working Paper.*

Berndt, A., R., D. Douglas, M. Duffie, M. Ferguson, and Schranz, 2005, "Measuring default risk premia from default swap rates and EDFs," *BIS Working Papers*, 172.

Betz, F., S. Oprica, T. A. Peltonen, and P. Sarlin, 2012, "Predicting Bank Distress and Identifying Interdependencies among European Banks," *Working Paper.*

Bisias, D., M. Flood, A. L. Lo, and S. Valavanis, 2012, "A Survey of Systemic Risk Analytics," *Office of Financial Research, Working Paper*, 1.

Brock, W. A., and S. N. Durlauf, 2001, "Growth empirics and reality," *World Bank Economic Review*, 15(2), 229–272.

Cerutti, E., S. Claessens, and P. McGuire, 2012, "What Can Available Data Tell Us and What More Data Are Needed?," *BIS Working Paper*, 376.

Cleveland, S., 1979, "Robust Locally Weighted Regression and Smoothing Scatterplots," *Journal of the American Statistical Association*, 74(1), 829–836.

Cleveland, S., and S. J. Devlin, 1988, "Locally Weighted Regression: An Approach to Regression Analysis by Local Fitting," *Journal of the American Statistical Association*, 83(403), 596–610.

Cremers, M., 2002, "Stock Return Predictability: A Bayesian Model Selection Perspective," *Review of Financial Studies*, 15(4), 1223–1249.

De Bruyckere, V., M. Gerhardt, G. Schepens, and R. Vander Vennet, 2012, "Bank /sovereign risk spillovers in the European debt crisis," *National Bank of Belgium Working Paper Series*, 232.

De Jonghe, O., 2010, "Back to the basics in banking? A Micro-Analysis of Banking System Stability," *Journal of Financial Intermediation*, 19(3), 387–417.

Degryse, H., and G. Nguyen, 2007, "Interbank Exposures: An Empirical Examination of Contagion Risk in the Belgian Banking System," *International Journal of Central Banking*, 3(2), 123–171.

Dewachter, H., and R. Wouters, 2012, "Endogenous risk in a DSGE model with capital-constrained financial intermediaries," *National Bank of Belgium Working Paper Series*, 235.

Diebold, F., and K. Yilmaz, 2011, "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms," *NBER Working Paper*, (17490).

Doppelhofer, G., and M. Weeks, 2009, "Jointness of Growth Determinants," *Journal of Applied Econometrics*, 24(2), 209–244.

Dungey, M., M. Luciani, and D. Veredas, 2012, "Ranking systemically important financial institutions," *Working Paper*.

Fernandez, C., E. Ley, and M. F. J. Steel, 2001a, "Benchmark priors for Bayesian model averaging," *Journal of Econometrics*, 100(2), 381–427.

——— , 2001b, "Model uncertainty in cross-country growth regressions," *Journal of Applied Econometrics*, 16(5), 563–576.

Freeman, L. C., 1979, "Centrality in social networks: Conceptual clarification, Social Networks," *Social Networks*, 1(3), 215–239.

Gray, D. F., R. C. Merton, and S. Bodie, 2007, "A New Framework for Measuring and Managing Macrofinancial Risk and Financial Stability," *NBER Working Paper*, 13607.

——— , 2010, "United States: Technical Note on Stress Testing," *IMF Country Report Number 10/244*, Section IV.

Gross, M., and C. Kok, 2012, "A mixed-cross-section GVAR for sovereigns and banks," *First Draft*.

Halaj, G., and C. Kok, 2013, "Assessing Interbank Contagion Using Simulated Networks," *Working Paper*.

Hartmann, P., O. de Bandt, and J. L. Peydro-Alcalde, 2009, "Systemic Risk in Banking: An Update," *In: Oxford Handbook of Banking*, ed. by A. Berger, P. Molyneux and J. Wilson.

Hartmann, P., S. Straetmans, and C. de Vries, 2005, "Bank System Stability: a Cross-Atlantic Perspective," *NBER Working Paper*, 11698.

Hautsch, N., J. Schaumburg, and M. Schienle, 2011, "Financial Network Systemic Risk Contributions," *Working Paper Humboldt-Universitat zu Berlin*.

Hoeting, J. A., D. Madigan, A. E. Raftery, and C. T. Volinsky, 1999, "Bayesian model averaging: A tutorial," *Statistical Science*, 14(4), 382–401.

IMF, 2012, "Macrofinancial Stress Testing - Principles and Practices," *Monetary and Capital Markets Department*.

Karas, A., and K. Schoors, 2012, "Bank Networks, Interbank Liquidity Runs and the Identification of banks that are Too Interconnected to Fail," *Working Paper*.

Langfield, S., Z. Liu, and T. Ota, 2012, "Mapping the UK interbank system," *Working Paper*.

Leamer, E. E., 1978, "Specification Searches: Ad Hoc Infererence with Nonexperimental Data," *Wiley*, New York.

Raftery, A., D. Madigan, and J. A. Hoeting, 1997, "Bayesian Model Averaging for linear regression models," *Journal of the American Statistical Association*, 92, 179–191.

Sala-I-Martin, X., G. Doppelhofer, and R. I. Miller, 2004, "Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach," *American Economic Review*, 94(4), 813–835.

Schwaab, B., A. Lucas, and S. J. Koopman, 2010, "Systemic Risk Diagnostics," *Tinbergen Institute Discussion Paper*, 10/104 DSF 2.

Schwarz, G., 1978, "Estimating Dimension of a Model," *Annals of Statistics*, 6(2), 461–464.

Segoviano, M. A., and C. Goodhart, 2009, "Banking Stability Measures," *IMF Working Paper*, WP/09/4.

Tang, D., and H. Yan, 2010, "Market conditions, default risk and credit spreads," *Journal of Banking Finance*, 34(4).

Trichet, J.-C., 2009, "Clare Distinguished Lecture in Economics and Public Policy," Clare College, University of Cambridge.

Van Oordt, M., and C. Zhou, 2010, "Systematic Risk under Extremely Adverse Market Conditions," *DNB Working Paper*.

Wei, C. Z., 1992, "On Predictive Least-Squares Principles," *Annals of Statistics*, 20(1), 1–42.

Wright, J., 2008, "Bayesian Model Averaging and Exchange Rate Forecasts," *Journal of Econometrics*, 146(2), 329–341.

7 Tables

Table 1: List of banks included in the sample

This table lists the 34 banks included in the banking block, along with the home country of the bank. The selection is based on the 91 banks included in the 2010 stress test, further reducing this sample by only considering stock listed banks, and applying stringent liquidity criteria.

Nr	Country	Bank Name
1	AT	Erste Bank Group (EBG)
2	BE	DEXIA
3	BE	KBC BANK
4	DE	DEUTSCHE BANK AG
5	DE	COMMERZBANK AG
6	DK	DANSKE BANK
7	DK	Jyske Bank
8	DK	Sydbank
9	ES	BANCO SANTANDER S.A.
10	ES	BANCO BILBAO VIZCAYA ARGENTARIA S.A. (BBVA)
11	ES	BANCO POPULAR ESPAÑOL, S.A.
12	ES	BANCO DE SABADELL, S.A.
13	FR	BNP PARIBAS
14	FR	CREDIT AGRICOLE
15	FR	SOCIETE GENERALE
16	GB	ROYAL BANK OF SCOTLAND GROUP plc
17	GB	HSBC HOLDINGS plc
18	GB	BARCLAYS plc
19	GB	LLOYDS BANKING GROUP plc
20	GR	EFG EUROBANK ERGASIAS S.A.
21	GR	ALPHA BANK
22	GR	PIRAEUS BANK GROUP
23	HU	OTP BANK NYRT.
24	IE	ALLIED IRISH BANKS PLC
25	IE	BANK OF IRELAND
26	IE	IRISH LIFE AND PERMANENT
27	IT	INTESA SANPAOLO S.p.A
28	IT	UNICREDIT S.p.A
29	IT	BANCA MONTE DEI PASCHI DI SIENA S.p.A
30	IT	UNIONE DI BANCHE ITALIANE SCPA (UBI BANCA)
31	PT	Banco BPI, SA
32	SE	Nordea Bank AB (publ)
33	SE	Skandinaviska Enskilda Banken AB (publ) (SEB)
34	SE	Swedbank AB (publ)

Table 2: Summary table of the regressors in the model

This table summarizes the different regressors in the model. The regressors are grouped into different blocks: a banking block, a macoreconomic block, a sovereign block, a house price price block and finally a financial block. The table indicates the source of the data, the data transformation(s) and the frequency of the series. Series with a frequency lower than weekly are transformed to a weekly frequency using a cubic spline interpolation.

			Source	Data Transformation	Frequency
BANKING BLOCK					
	Bank stock prices	34 stock listed banks in the EBA stress test sample of 2010	Bloomberg	log returns	weekly
MACRO BLOCK					
1	Industrial production	Euro area 17 (fixed composition) - Industrial Production Index, Annual rate of change	ECB SDW	cubic spline + level	monthly
2	HICP inflation	Euro area (changing composition) - HICP - Overall index, Annual rate of change	ECB SDW	cubic spline + level	monthly
3	ST interest rate	3 month EURIBOR rate	ECB SDW	log returns	weekly
4	Default spread	iTraxx Europe Benchmark Index	DS	log returns	weekly
5	Market index	total EU market index (mnemonic TOTMKEU)	DS	log returns	weekly
6	VSTOXX	option implied volatility index (mnemonic VSTOXXI)	DS	log returns	weekly
SOVEREIGN BLOCK					
1	Sovereign bond yield (10 year maturity)	10 year government bond yield	Bloomberg	log returns	weekly
HOUSING					
1	Real estate	The EU ECB house price index	ECB	cubic spline +log returns	quarterly
FINANCIAL BLOCK					
1	Stress in interbank market	Spread between the 3 month eonia index swap and the 3 month euribor	Bloomberg	level	weekly
2	Bank specific credit risk	iTraxx Europe Financial Sector Index, orthogonalized w.r.t. the iTraxx Europe Financial Sector Index	Bloomberg	logreturns	weekly

Table 3: Summary statistics of the regressors in the model

This table contains the summary statistics (mean, standard deviation, minimum, maximum, skewness and kurtosis) of the regressors in the model. The frequency of all regressors is weekly, and the time period ranges from the second quarter of 2005 until the third quarter of 2012.

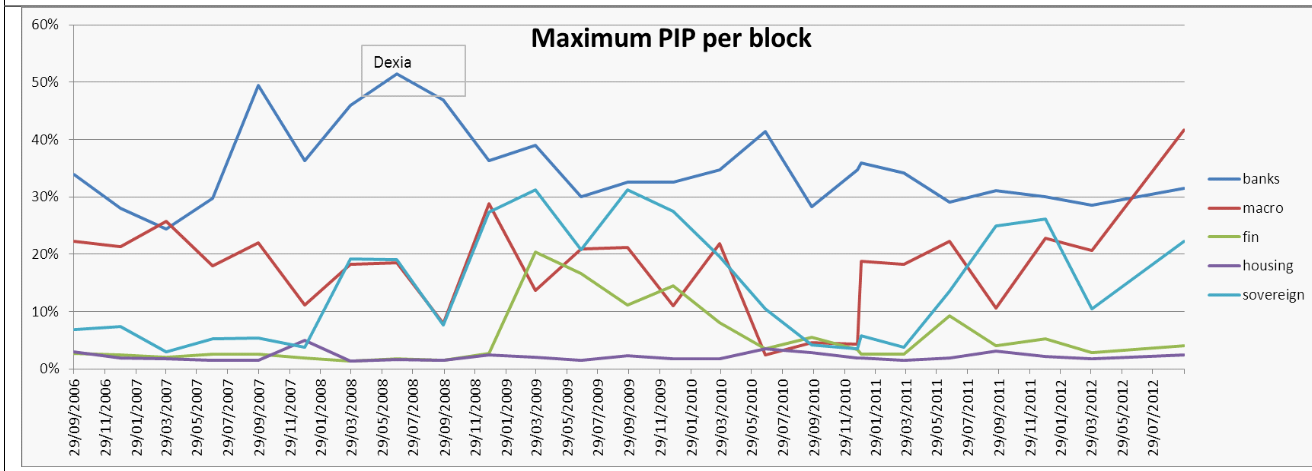
	MEAN	ST.DEV.	MIN	MAX	SKEWNESS	KURTOSIS
BANKING BLOCK						
banks	-0.0044	0.0766	-1.4887	0.7286	-0.6212	11.6337
MACRO BLOCK						
infl	2.1117	0.9691	-0.6000	4.0303	-0.7146	3.5826
ip	0.2573	7.2780	-21.2900	9.7865	-1.4103	4.2146
euribor3m	-0.0060	0.0282	-0.1735	0.0692	-1.6869	8.2686
vstoxx	0.0016	0.1220	-0.3654	0.6774	0.6969	6.1511
totmkeu	-0.0001	0.0369	-0.2543	0.1211	-1.3795	10.2072
itraxx	0.0033	0.0860	-0.2870	0.4868	0.6154	6.9414
FINANCIAL BLOCK						
spread	0.4052	0.3584	-0.0080	1.8640	1.4221	5.5571
itraxx_fin	0.0000	0.0589	-0.2395	0.4835	1.4736	16.7982
SOVEREIGN BLOCK						
DE	-0.0022	0.0433	-0.1775	0.1806	-0.1218	5.8889
IT	-0.0011	0.0326	-0.1246	0.1283	-0.2933	5.2887
FR	0.0010	0.0297	-0.1930	0.0966	-1.1099	10.1016
ES	0.0016	0.0359	-0.1972	0.1150	-0.9929	8.5740
PT	0.0023	0.0445	-0.3013	0.2013	-0.5447	11.1475
GR	0.0045	0.0616	-0.6984	0.3286	-4.5444	58.0086
IE	0.0013	0.0415	-0.2457	0.3066	1.3913	21.4691
AT	-0.0013	0.0354	-0.1659	0.1682	0.1857	8.3290
BE	-0.0007	0.0353	-0.2320	0.2034	-0.2437	11.2843
UK	-0.0025	0.0370	-0.1676	0.1543	0.0030	5.8136
DK	-0.0025	0.0462	-0.2574	0.2242	-0.3365	11.9814
SE	-0.0020	0.0428	-0.1999	0.1929	-0.1709	6.8492
HU	0.0003	0.0397	-0.1202	0.2578	1.2142	9.4775
HOUSE PRICE BLOCK						
house pric	0.0003	0.0008	-0.0014	0.0017	-0.3194	2.3591

8 Figures

Figure 1: Maximum PIP per block and interquartile range banking block over rolling windows of 6 quarters

This Figure shows for each quarter the maximum PIP in each block (Panel A) and the interquartile range of the bank block (Panel B). The length of one window is 6 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the third quarter of 2006.

Panel A: Max PIP per block



Panel B: Interquartile range and median PIP (bank block)

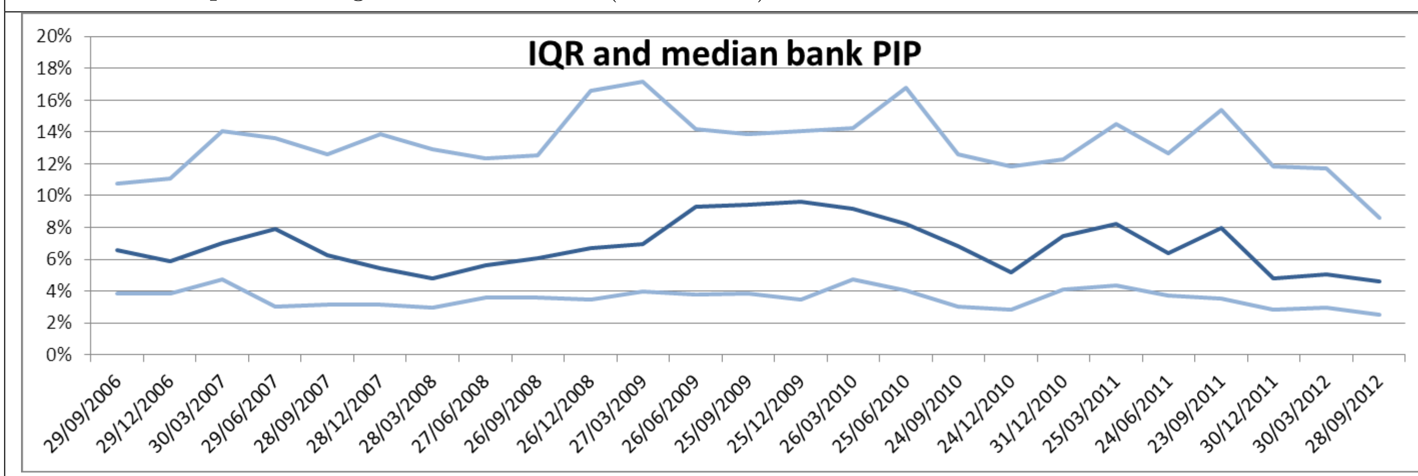
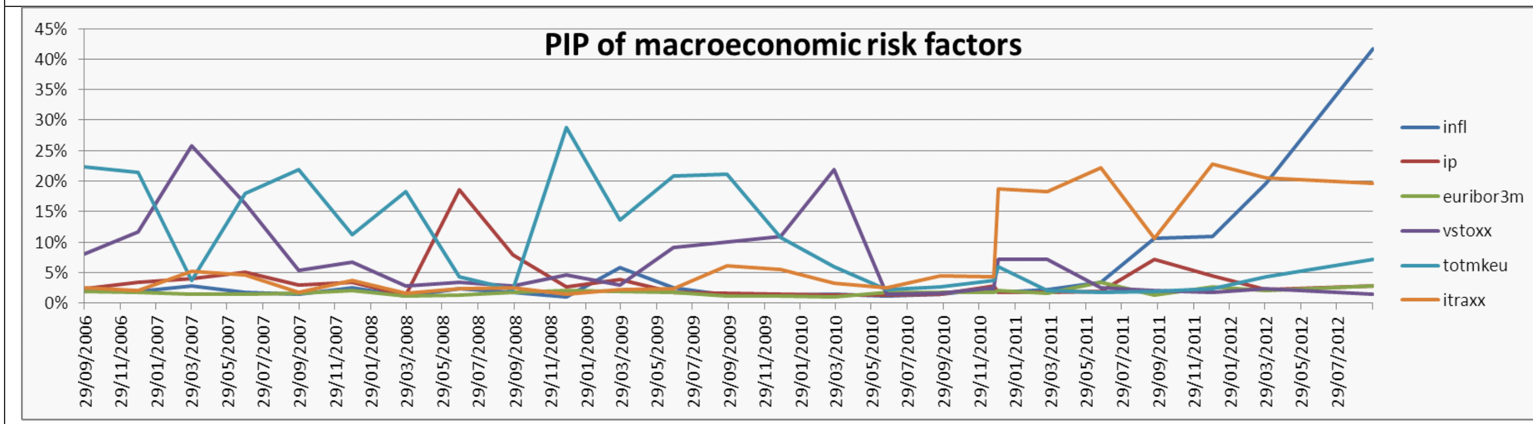


Figure 2: PIP of macroeconomic risk factors and GIIPS countries sovereign bond yields

This Figure shows for each quarter the PIP of the components of the macroeconomic block (Panel A) and the GIIPS countries sovereign bond yields (Panel B). The length of one window is 6 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the third quarter of 2006.

Panel A: PIP for macroeconomic risk factors



Panel B: PIP of GIIPS countries sovereign bond yields

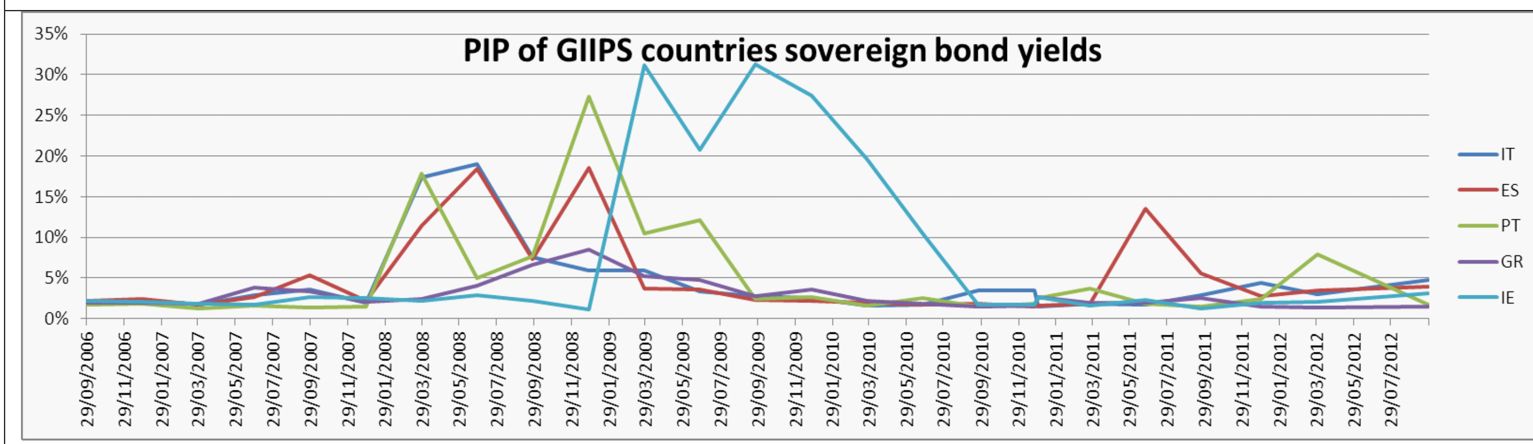
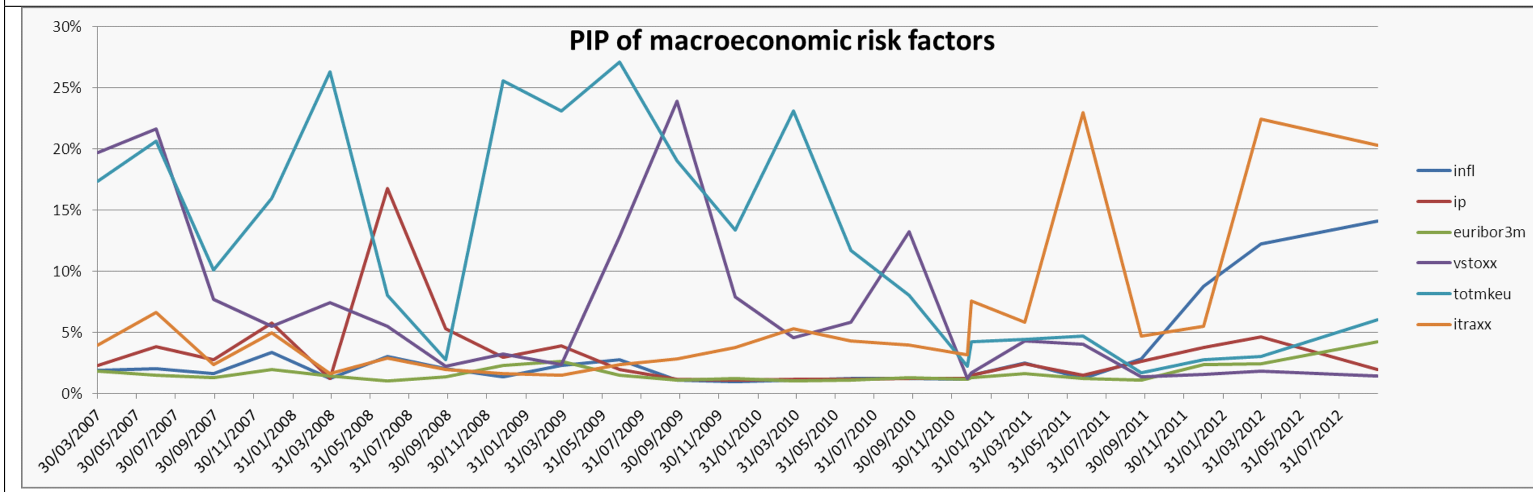


Figure 3: PIP of macroeconomic and financial sector risk factors over rolling windows of 8 quarters

This Figure shows for each quarter the PIP of the components of the macroeconomic block (Panel A) and the PIP of the financial sector risk factors (Panel B). The length of one window is 8 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the first quarter of 2007.

Panel A: PIP for macroeconomic risk factors (8 quarter window)



Panel B: PIP of financial risk factors (8 quarter window)

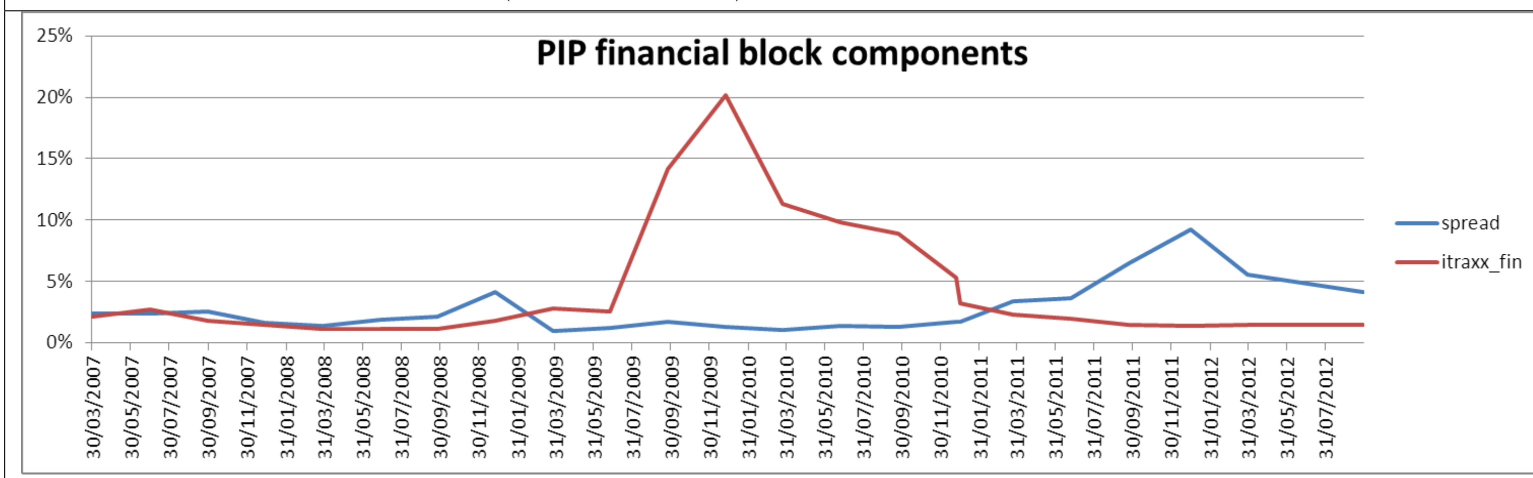
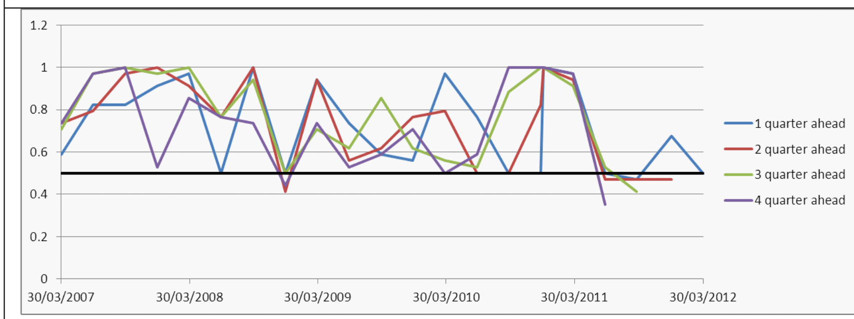


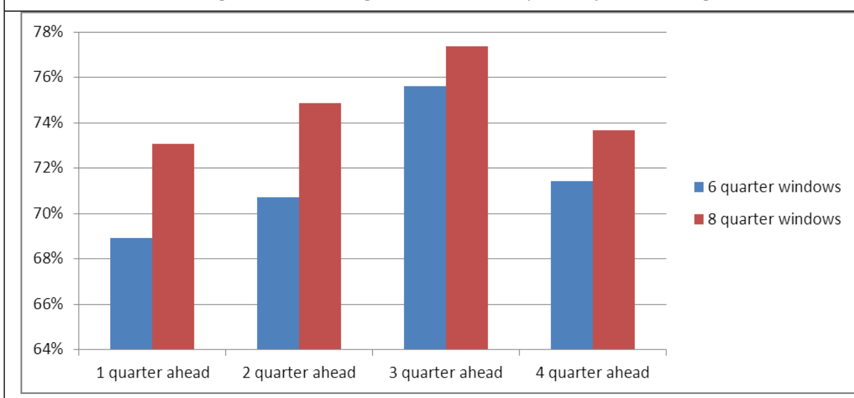
Figure 4: Projection Accuracy

This Figure shows different aspects of the projection accuracy of the model. Panel A shows the percentage of correctly projected signs of bank stock returns (PC) for different projection horizons (1quarter ahead to 4 quarters ahead). Panel B compares the PC for windows of 6 versus 8 quarters, whereas Panel C shows the RMSE of the 8 quarter rolling windows.

Panel A: Percentage of correctly projected signs of bank stock prices



Panel B: Average percentage of correctly projected signs of bank stock prices



Panel C: RMSE over 8 quarter rolling windows

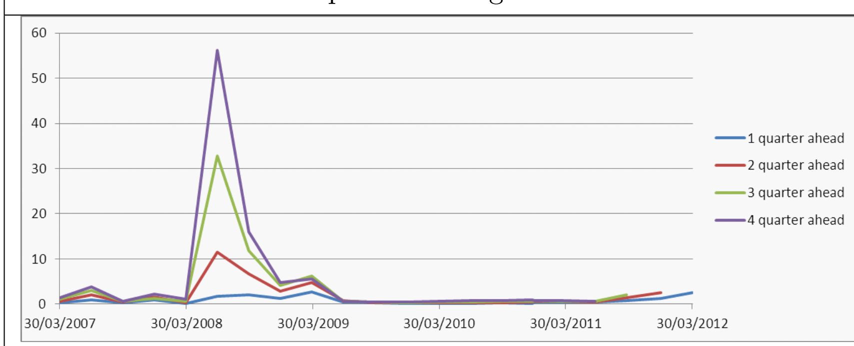


Figure 5: Projection Accuracy of standard BMA versus LOESS BMA

This bar chart indicates the projection accuracy (measured with the PC ratio) of BMA using the bayesian linear model versus the bayesian LOESS model. The results summarize the projections over horizons ranging from one to 8 quarters ahead. The estimation window is 8 quarters. The parameter f is set to 1 for the Bayesian LOESS model, and the estimates are centered around the last value of industrial production in each estimation window.

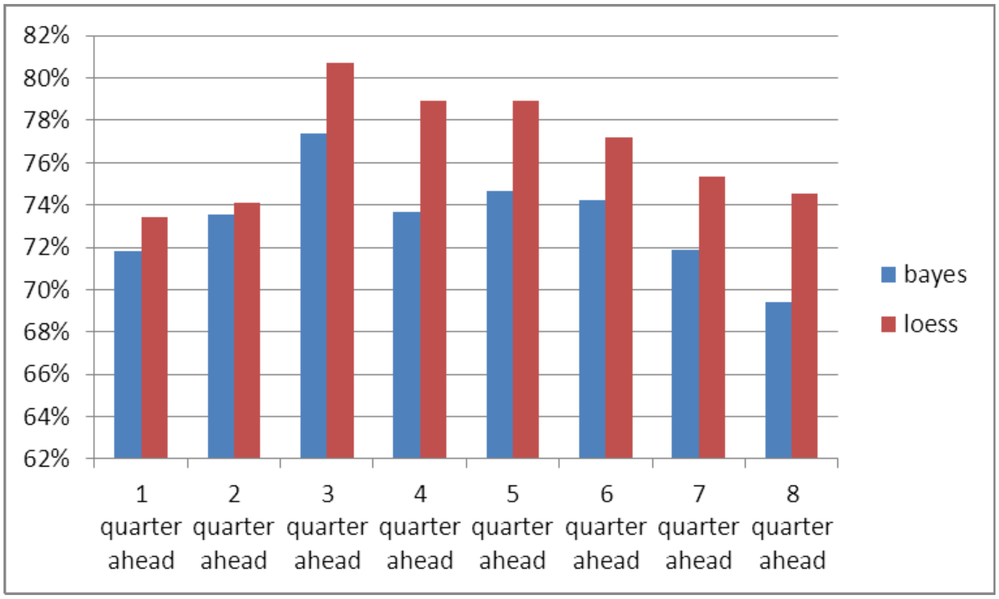
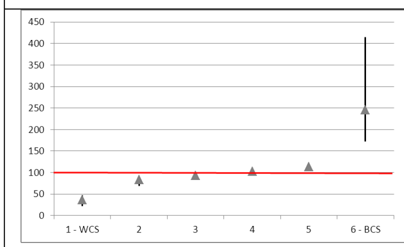


Figure 6: Projected Bank Stock Prices for 3 Stress Test Scenarios on three dates

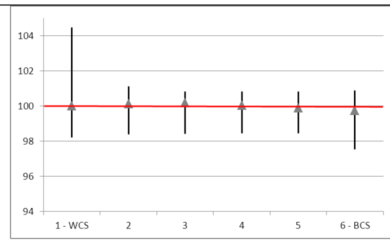
This graph shows the projected evolution of bank stock prices on three stress test dates (1st of July 2010 and 2011 and 1st of January 2012) for three scenarios. The severity of the scenario is indicated by the number ranging from 1 (Worst Case Scenario) to 6 (Best Case Scenario). The projection horizon is one quarter. The end of period bank stock price is 100.

Projection Day 1 (July 1st 2010)

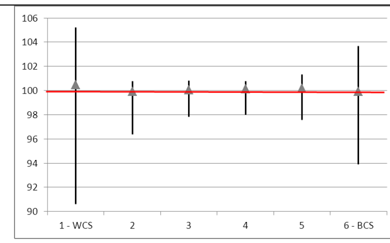
Scenario 1



Scenario 2

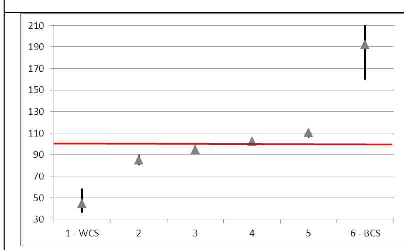


Scenario 3

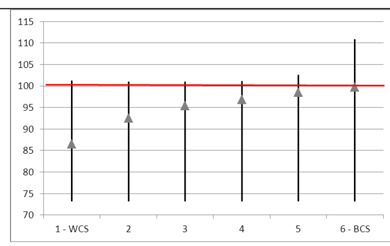


Projection Day 2 (July 1st 2011)

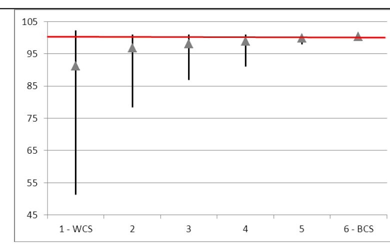
Scenario 1



Scenario 2

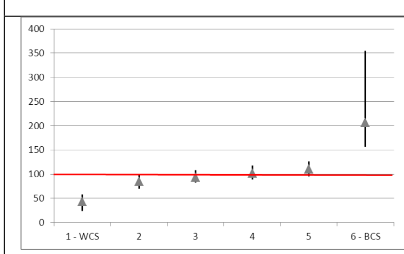


Scenario 3

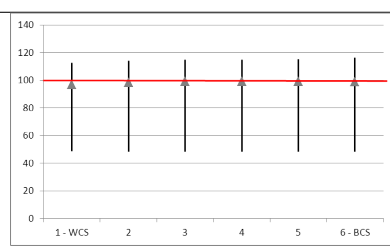


Projection Day 3 (January 1st 2012)

Scenario 1



Scenario 2



Scenario 3

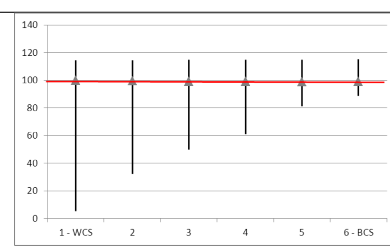


Figure 7: Visualisation of the Financial Network for two gridpoints of industrial production

This Figure visualizes the financial network structure centered around two values of industrial production. The figure on the left hand side takes the lowest value of industrial production in the sample (the value at the end of April 2009) as the gridpoint in the LOESS estimation, whereas the figure at the right hand side takes the maximum (in sample) value of industrial production (end of May 2010) as a gridpoint. The graph only visualizes connections between banks when the PIP is larger than 50 percent. The probability of the connection (the PIP) is connected to the darkness of the lines. All banks in the graph get equal size (the red circle). The location of the banks on the graph is an approximation of their geographical location in Europe.

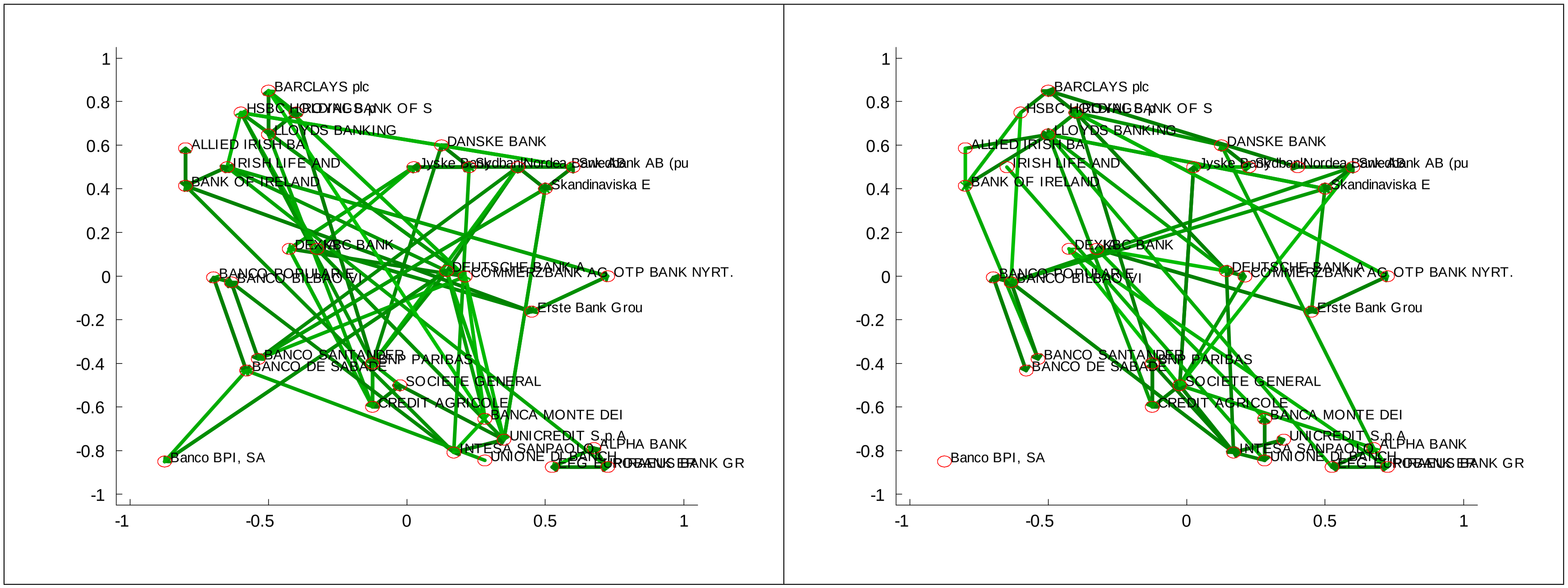
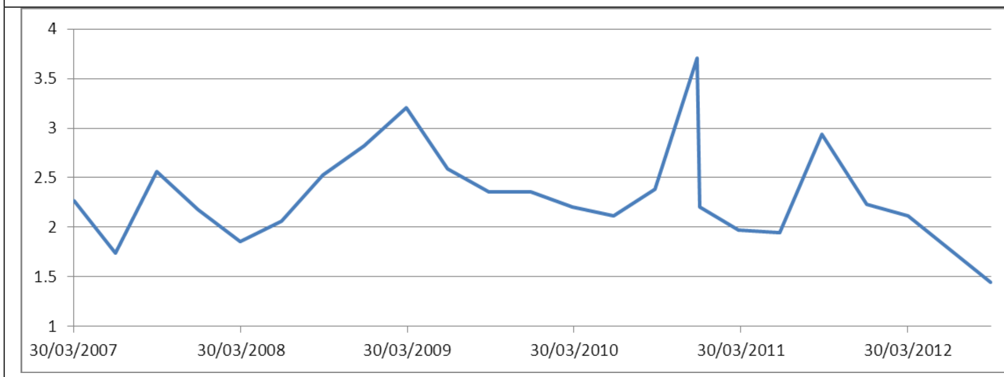


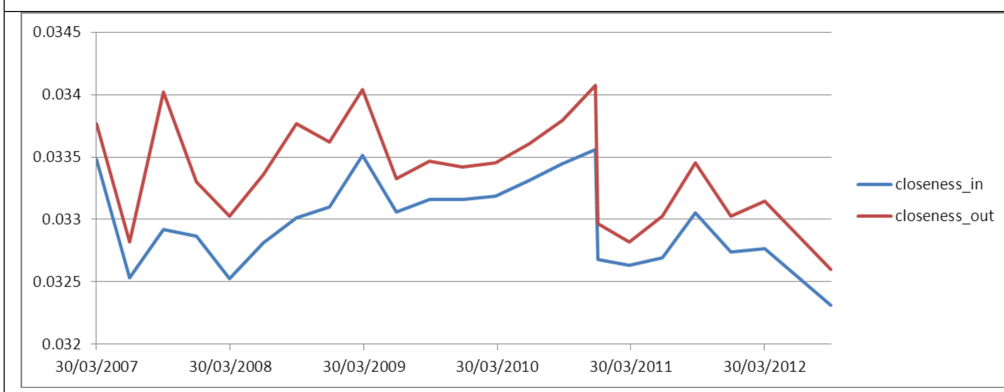
Figure 8: Network Centrality Measures over time

This graph shows how the three measures of network centrality (degree, closeness and betweenness) have evolved over time. I use 8 quarter rolling windows for the estimations.

Panel A: Degree Centrality (mean) over time



Panel B: Closeness



Panel C: Betweenness

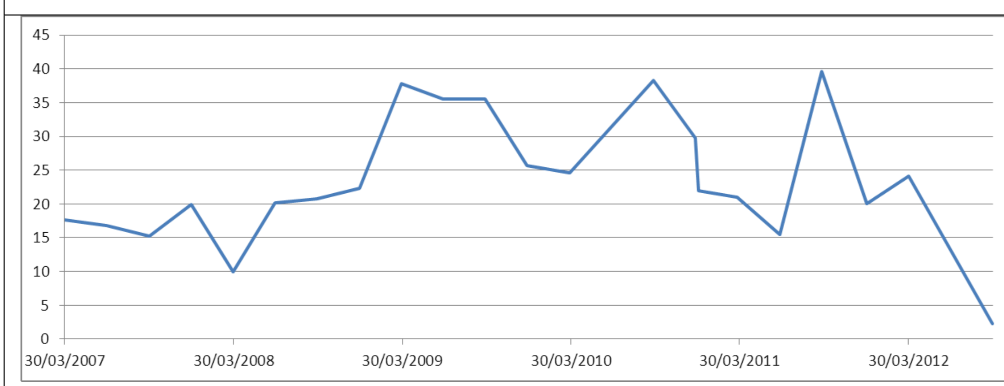
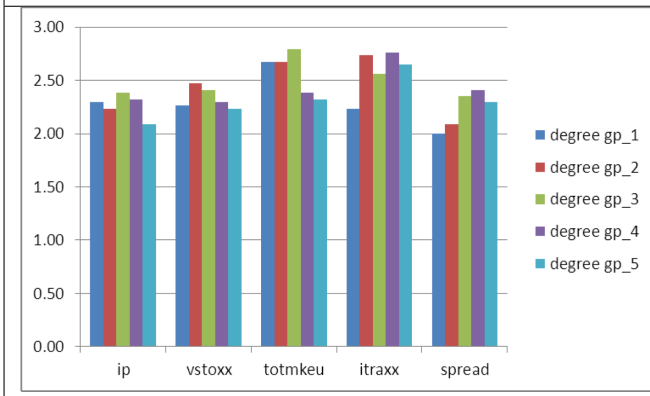


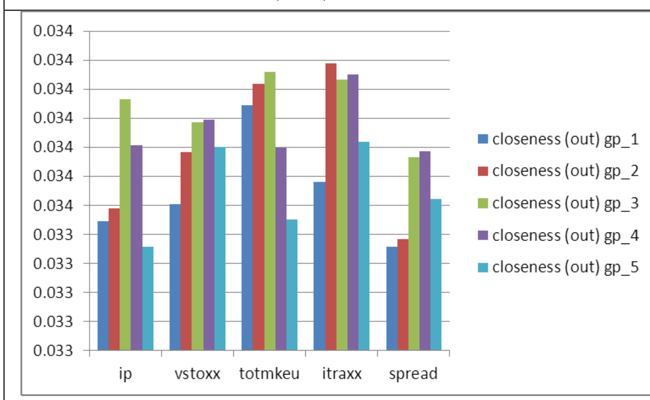
Figure 9: Network Centrality Measured over different values of the common factors

This graph shows how the degree, closeness (out) and betweenness vary for did’erent values of industrial production, market volatility (vstoxx), the stock market index (totmkeu), the itraxx and the spread. The gridpoints range from 1 to 5 (1 is the lowest value, 5 is the highest value in sample).

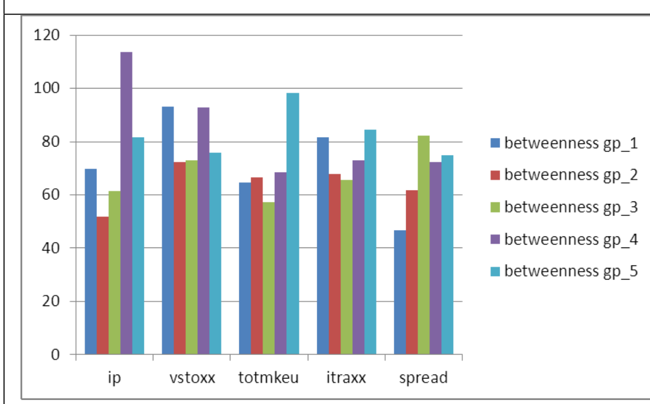
Panel A: Degree



Panel B: Closeness (out)



Panel C: Betweenness



9 Appendix: The Bayesian LOESS

The Bayesian locally weighted regression is obtained by imposing the Normal-Gamma natural conjugate prior on the coefficients, together with Zellner's g-prior where $g = n$. More specifically,

$$\beta | h \backsim N(\mathring{\beta}, h^{-1}\mathring{V})$$

where $\mathring{\beta}$ is a vector of zeros, and

$$\mathring{V} = g(X'X)^{-1}$$

where g is Zellner's prior, and specified as $g = n$. The prior for h follows the Gamma distribution, with hyperparameter $\mathring{s}^{-2}$ set at 1*10^{-3} and $\mathring{v}$ set at 1.

$$h \backsim G(\mathring{s}^{-2}, \mathring{v})$$

With this choice of priors on the parameters, the posterior has the following form:

$$\bar{\beta} = \bar{V}(\mathring{V}^{-1}\mathring{\beta} + X'X\hat{\beta})$$

$$\bar{V} = (\mathring{V}^{-1} + X'X)^{-1}$$

where $\hat{\beta}$ corresponds to the weighted OLS estimator for β with the weighting matrix given by equation 12 above.

$$\hat{\beta} = (X'WX)^{-1}X'Wy$$

The marginal likelihood of model M_j is obtained as

$$p(y_j|M_j) = c_j \left(\frac{|\bar{V}_j|}{|\mathring{V}j|} \right)^{1/2} (\bar{v}_j \bar{s}_j^2)^{-\bar{v}_j/2}$$

where

$$c_j = \frac{\Gamma\left(\frac{\bar{v}_j}{2}\right)(\mathring{v}_j \mathring{s}_j^2)^{\mathring{v}_j/2}}{\Gamma\left(\frac{\mathring{v}_j}{2}\right)\pi^{n/2}}$$

with $\bar{v}_j = \mathring{v}_j + n$ and $\bar{s}_j^2$ implicitly defined through

$$\bar{v}_j \bar{s}_j^2 = \mathring{v}_j \mathring{s}_j^2 + v_j s_j^2 + (\hat{\beta}_j - \mathring{\beta}_j)[\mathring{V}j + (X_j'X_j)^{-1}]^{-1}(\hat{\beta}_j - \mathring{\beta}_j)$$

where $v_j = n - k_2$ and s_j^2 is the usual OLS quantity defined as:

$$s_j^2 = \frac{(y - X\hat{\beta})'(y - X\hat{\beta})}{v_j}$$

I take the following values for the hyperparameters: Zellner's g-prior is defined by $g = n$, I set $\mathring{s}_j^2$ at 1 (which is larger than the empirical variance of the standard errors of a small subset of the models), and I set $\mathring{v}_j$ at 0.001, which is very small as compared to the sample size n, hence this implies a large uncertainty around the prior value of $\mathring{s}_j^2$.This choice of hyperparameters ensures a relatively noninformative prior on the coefficients.