ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Financial Economics

Markets understanding of asset commonality

Evidence from the syndicated loan market

Name student: Charalambos Hadjipanteli

Student ID number: 479939ch

Supervisor: Chalabi, J.

Second assessor: Smajlbegovic, E.

Date of final version: 16.08.2018

Abstract

Asset commonality is a significant contagion channel of systemic risk in the banking sector during periods of financial distress. Based on the theoretical rationale about the risk associated with the asset commonality, this paper examines whether the market prices this risk. Exposures in the same industries through syndicated loans are used to capture the risk related with asset commonality while the CDS spreads act to observe if agents want compensation for the exposure of banks in this risk. The paper finds that the 2007 financial crisis raised the awareness of investors to the asset commonality risk. Since the 2007 crisis investors demand higher CDS spreads for banks with more similar assets to other banks.

Contents

Acknowledgements

I would like to thank my supervisor for her guidance, helpful suggestions and constructive feedback. Our discussions and her comments allowed me the successful completion of this thesis. I am also grateful to my family and friends for the support.

Introduction

The recent economic history is dominated by the US mortgage crisis in 2007 and the Sovereign Crisis in Europe in the early 2010's. These two events caused the failure of a significant number of financial institutions and tested the stability of the banking system. The results were not so encouraging since the global economy entered a long period of recession and poor economic performance. The banking sector took a huge blow and several years were required to regain its stability and confidence. In several countries of Europe like Greece, Italy and Spain the banking system is still recovering.

These incidences forced a wave of regulatory actions to stabilise the banks. Regulations were focused on the equity each bank must hold, the quality of the assets and the default risk faced by each bank. These actions resulted on the reduction of bank-specific risk of the individual banks by the means of diversification. Basel III, weights different assets classes by their risk, encouraging the banks to diversify their portfolios and gain from a reduced risk weighted asset capital requirements. In the road towards diversification, banks started to hold similar portfolios causing the increase of systemic risk (Acharya, 2001; Acharya and Yorulmazer, 2005; Wagner, 2010). Banks' idiosyncratic risks were low, but they were identical. Acharya (2009) suggests that traditional capital regulations cause systemic risk through diversification and risk-shifting but prudential regulations combats this problem.

Systemic risk is the conditional probability of failure of the whole system, due to a shock during periods of distress. In the banking sector, a crisis is defined as systemic if a shock results into a failure of the banking sector. There are two types of shocks that can cause a systemic breakdown in the banking sector. The first is an idiosyncratic shock, of the form of an operational failure, high numbers of non-performing loans or fraud. The second one is an external shock. An external shock can occur on a macro-level, usually as an increase in the unemployment that can cause defaults on mortgages or asset prices bubbles. External shock on the micro-level can be a default of the counterparty that has loans with many banks. The probability of a systemic breakdown is conditional on severe economic conditions. In periods of economic distress, these shocks can cause a large number of banks to fail and the system to collapse since the risk absorption mechanisms become redundant. Under healthy conditions, banks can absorb such shocks through the interbank market, or through the equity buffer that regulation require them to hold.

This spread of the failures from one bank to another, occurs because there are three links between banks that act as contagion channels during distress. Freixas et al (2000) show the interbank market connects banks and act as a significant contagion channel. Information sharing between banks also helps in spreading the failure across the system (Chen, 1999). The third link that propagates failures is the asset commonality in the banks' balance sheets (De Vries, 2005).

Issuing syndicated loans and undertaking on similar operations are two banks actions that cause the asset side of their balance sheets to be similar to each other. Banks usually come together as a syndicate and group their money to provide a loan to a corporation. The amount of funds that each member of the syndicate supply differs, and the larger contributor is the leader. The asset side of the balance sheet of the syndicate members include the same loan, making them similar. If a shock causes the borrower to default, all banks involved in the syndicated loan will be affected providing a clear channel of contagion. The latter bank action that cause asset commonality is to invest in the same asset classes. Mortgages are the best example. Since the asset side of the balance sheet of all banks consist of a high number of mortgages, they are highly exposed to any macroeconomic shock that can cause the simultaneous default on the mortgages and a simultaneous decrease in banks' assets and a possible failure. Moreover, if an idiosyncratic shock hits one bank and fire sales of its assets is required, the increase supply of the asset will cause a price drop that will affect all the other banks, since they hold the same asset class.

Banks diversify their operations to reduce their idiosyncratic risk. However, there is a negative externality caused by the diversification. Banks hold similar assets in their balance sheets. This asset commonality acts as a contagion channel and makes the banking system vulnerable to a systemic breakdown. Banks' similar exposure to mortgage backed securities during the 2007 financial crisis, caused the contagion and the collapse of the banking system.

The missing piece

This paper focuses on the asset commonality contagion channel, a channel of high magnitude and significance and questions the pricing of the risk associated with asset commonality. The exposures to the same industries through syndicated loans are used to proxy for asset commonality. This contagion channel will be called “interconnectedness” throughout this paper. Cai et al (2018) state that the size of the syndicated loan market is large, with one trillion dollars of new syndicated loans issued every year. Sufi (2017) analyses the syndicated loan market and finds that the syndicated loans are a significant source of funding for nearly all publicly listed companies. Corporations use syndicated loans to invest on working capital and issues related to their capital structure. Moreover, Bernanke (2010) at his speech during his time as the Federal Reserve (FED) Chairman, explained that the concerns of the FED are now focusing on the interconnectedness of large financial institutions. He stresses the need for new ways to measure the concentration of risk in the system and reveals that the FED is currently collecting data on institutions’ exposure to systemic risk due to syndicated corporate loans. The significant role of Bernanke during his speech emphasizes the concerns of the regulators about the implications of contagion due to asset commonality and the attention that must be given to this contagion channel.

After the economic rationale for the risk associated with these types of loans is proven both theoretically (De Vries, 2005) and empirically (Cai et al, 2018), this paper takes a step forward. It adds to the literature by examining if market participants price the contribution of asset commonality in the systemic risk.

Why is it important

The pricing of such a risk is of high importance. Why investors should care? Firstly, an agent who invest its money in the bank should get compensated for the risk he bears. An investor is exposed at the idiosyncratic risk of the bank failing, but given its interconnectedness, the health of the bank can deteriorate, or the bank can even fail if other banks default. There contagion effect is an externality faced by the bank from other banks. So, the investor is exposed to the risk that his own bank will default due to a systemic breakdown given its asset commonality with the other banks that will fail. This extra risk is supported theoretically by De Vries (2005). The interconnectedness due to syndicated loans is highly correlated with other systemic risk measure revealing the extra risk a bank face (Cai et al, 2018).

If markets are rational and efficient, the interconnectedness risk should be priced. Failure to price it indicates that this contagion channel is completely ignored by the market participants. Banks are not penalised by increasing their exposure to common assets. Consequently, this market inefficiency will result in an unpunished increase of banks' asset commonality and the systemic risk. Given banks' thrust by the regulations to diversify and decrease their idiosyncratic risk, the banking system will become more fragile without any consequence on the banks themselves. Therefore, it is crucial to examined whether investors recognize this interconnectedness risk.

The paper test empirically if there is a relationship between the CDS spreads of banks and the asset commonality. CDS spreads are used as a vehicle to measure investors awareness. When an investor buys a banks CDS, he pays interest, the spread, every period and in exchange he gets compensation if the bank defaults. Therefore, the CDS acts as a vehicle to observe investors awareness of risk since the default risk of the bank is reflected in the CDS spread of the bank. The asset commonality measure is constructed based on Cai et al (2018). The borrowers are divided into 10 industries and the share of syndicated loans to each industry is calculated for each bank. Then, the distance between two banks is measured as the similarity of exposures to each industry. The asset commonality of each bank is measured by the weighted average distance of the bank with the rest. To sum up, the paper estimates a CDS pricing model and investigates if the asset commonality can be used to explain variations in CDS spreads.

Several CDS pricing models with different combinations of explanatory variables are estimated. The choice of the variables is motivated by the most recent bank CDS pricing literature. The empirical analysis reveals that after the 2007 financial crisis, market participants recognize that banks' asset commonality involves risk and require higher CDS spreads. Before the 2007 crisis, markets were not rational and ignored the asset commonality contagion channel. The numerous bank bailouts and defaults during the crisis raised the awareness of investors who started require compensation for this risk.

The structure of this paper is organised as follows. Chapter two gives a brief literature review of the academic papers analysing systemic risk, asset commonality, interconnectedness and syndicated loans. In chapter three the methodology and the data used are explained. Chapter four provides the empirical results of the CDS pricing models. Finally, chapter five concludes by providing some regulation suggestions.

Literature Review

The literature review is divided into three categories. At the beginning the literature on bank linkages, contagion channels, banking sector fragility and systemic risk is reviewed. Then the theoretical research by De Vries (2005), which builds a theoretical framework of asset commonality and systemic failure. The review ends with the empirical paper by Cai et al (2018) which introduces a measure of asset commonality due to syndicated loans, defined as interconnectedness. The relationship between this measure and other systemic risk measure is analysed by the authors to test empirically the risk associated with banks' interconnectedness.

Linkage, contagion channels and systemic risk

The concept of systemic risk was researched heavily in the recent years, since its importance was highlighted by the economic crises of the past decade. This is a brief overview of the academic literature on systemic risk. Firstly, there are some concepts that need to be analysed before the explanation of systemic risk can be given, such as a systemic event, the liquidity transformation of banks and the linkage in the banking sector. Then the papers giving theoretical models about contagion and systemic risk are discussed. The overview of the empirical papers follows.

De Bandt and Hartmann (2000) categorize a systemic event based on the type of shock and its outcome. A shock is in the form of "bad news" or a failure of a bank. A narrow systemic event is when a shock leads to the failure of other banks. In other words, a narrow event occurs when a shock causes a domino effect and the failure of other banks, without specifying the length of the domino chain. A broad systemic event includes in addition to the narrow systemic event, the case where there is a simultaneous shock in many banks that cause the simultaneous failure of the system. In terms of the domino effect, a broad systemic event occurs when the board where the dominoes (banks) are placed is shaken and they all fall simultaneously, without a clear domino block taking the blame. This distinction between the systemic events discussed by De Bandt and Hartmann (2000) is crucial for the analysis of the syndicated loans contribution to systemic risk. A syndicated loan shock is regarded as a broad systemic event if when the failure of the borrower to meet its obligations can cause the failure of all the partners in the syndicated loan. There is no domino effect. De Bandt and Hartmann (2000) argue that the foundations of systemic risk lie in the narrowness of the systemic event. Regulation-wise, they argue that the actions taken by the regulator to reassure the stability of the sector depends on the nature of the systemic risk. They emphasize that the nature of the systemic event must be determined before any regulatory action. The authors believe that the determination of the properties of the systemic event can solve the debate between the lender of last resort or the liquidity boost to the market (usually in the form of quantitative easing) as a measure of combating systemic threads. Systemic events play a crucial role in the analysis of systemic risk, since the event describes the trigger and the spread of the system failure. The systemic risk is determined by the harshness of the systemic event and the probability of the event happening.

The members of the banking sector also differentiate their properties from members in other sectors. One of banks' main tasks, is the liquidity transformation. This is what makes the banking sector vulnerable to systemic risk. A simple bank collects short term liquid deposits which are its liabilities and gives out long term illiquid loans which are its assets. On the asset side, they also issue equity or invest in financial assets. There is a fix rate of deposit withdrawals and the bank sets up its balance sheet to satisfy the withdrawals. However due to the mismatch of the liquidity (maturity) between assets and liabilities, a shock can cause the bank to default. If there is shock, depositors will withdraw their deposits making the bank liquidate its long-term loans with a loss. This will wipe out the equity of the bank. Also, there is a large probability that some depositors will not be able to withdraw their money because the bank will fail to recover the full amount of the loans in the short run. The theoretical model was firstly introduced by Diamond and Dybvig (1983). Freixas et al (2000) construct a theoretical model that justifies the existence of the interbank market as a solution to bank runs. The model is based on the fact that if one bank is illiquid then it can borrow from a highly liquid bank through the interbank market to cover its needs and repay when the storm calms.

Therefore, the liquidity transformation of banks causes the emergence of the interbank market, a linkage between banks. This mechanism creates a debate is similar to the capital requirement regulation debate. The interbank market reduces the individual exposure of each on bank runs but increases the linkage between them making them more vulnerable to systemic breakdowns. The same individual versus systemic risk trade-off holds also on capital requirements regulation. There are also other types of linkage between banks such as the payment settlement system (Humphrey, 1986; Folkerts-Landau, 1991).

The banking sector deviate in terms of properties and structure from the other sectors in the economy. The strong linkage between its members allows contagion during periods of economic distress. As mentioned earlier in the paper, there are three contagion channels: the interbank, the information, and the asset commonality channel. The latter channel will be discussed in more detail in the next section of the literature review

One bank is highly exposed on another bank through the interbank market (Iori et al, 2006; Boss et al, 2006; Upper and Worms, 2004). Freixas et al (2000) construct a theoretical model where the interbank market act in a contagion channel during periods of financial distress when the number of highly liquid banks decreases.

Moreover, Acharya and Yorulmazer (2008) show that adverse news about one bank cause the cost of funding of other banks to increase because the adverse new transmits information about a common systemic factor that banks share. Chen (1999) also analyses the information contagion channel.

The third contagion channel is the asset commonality. Greenwood et al (2015) demonstrate how fire sales by European banks during the sovereign debt crisis cause contagion amongst European banks. This is because banks have the same class of assets and the fire sales from one bank pushes the value of the assets of other banks down causing them problems. Allen et al (2012) develop a model where banks diversify their individual risk by sharing their assets, but the similarity of their assets cause their simultaneous default. This demonstrates how diversification can cause asset commonality and systemic risk.

Anufriev and Panchenko (2015) construct a network of the banking system and its exposures to other sectors using Australian data. They use partial correlations to direct linkage between banks, conditional on the whole network linkage. Using this approach, they estimate the various contagion channels. They find strong dependency between the top four banks of Australia. Moreover, these banks are linked with the real estate sector. They conclude that the top four banks play a significant role in the absorption and spread of shocks. This conclusion supports the existence of contagion channels.

González-Hermosillo et al (1997), estimate the determinants of bank fragility. They start by constructing a fragility index of the whole banking sector, by aggregating fragility of individual banks. Using data from Mexico, they regress the fragility index on several bank-specific characteristics, variables associated with contagion channels and macroeconomic variables. They find amongst other, a significant effect of contagion channels on the banking sector fragility. Their results prove empirically the existence of such contagion channels

For extensive reviews of the literature on systemic risk, see Bisias et al (2012), Benoit et al (2015) and Silva et al (2017). Dungey et al (2007) provides an overview of the methodologies used to examine the contagion.

Theoretical and Empirical literature on asset commonality

Another factor that links the banks directly, but not fully analysed yet, is the syndicated loans. The syndicated loans increase the commonality of the banks' asset side of the balance sheet. In period of financial distress, at the tails, the interconnectedness due to syndicated loans can cause a systemic breakdown. The inability of a large corporation to meet its obligation on a syndicated loan is a shock on all issuers of the loan. Since the banking network is linked, these shocks to the issuers can spread out to other banks causing a contagion. All members of the syndicate that issue the loan, are exposed to the same risk factor, that contributes to systemic risk. Therefore, this syndicated loan interconnectedness plays an important role in the linkage between banks, contagion and systemic failure.

De Vries (2005) examines which characteristics of the banking sector cause the banks to become more vulnerable to systemic breakdown. The author takes a more technical approach and supports theoretically the existence of contagion in the banking system due to asset commonality. The paper is statistically-focused and examines the marginal distributions of the tails of the bank's returns. Systemic risk is present in periods of distress, therefore the tail section of the distribution of bank's returns is examined. A bank on the tails of the distribution is suffering loses. The return distributions of a number of banks are combined to create a multivariate distribution. The tail of this multivariate distribution captures the situations where more than one bank fail at the same time. The marginal effect of each individual tail distribution on the multivariate distribution captures the contribution of each bank to joint failures of other banks.

De Vries is motivated by other papers focusing on the bank loss interdependencies, that support the view that diversification cause the tail distribution of return to become interdependent among banks (Estrella, 2001; De Nicolo and Kwast, 2002). These papers prove statistically the theory of contagion across banks without explicitly commenting on the types of contagion channels.

Starting with the scenario of two banks, the author shows that normal distribution can explain banks' performance at good times but fails to capture the outliers and the joint losses at the tails of the multivariate distribution. Figures 1 and 2 display this failure.

The author constructs a model where bank's portfolio is exposed to two types of risk factors. Firstly, the idiosyncratic risk factors, which are factors exclusive to the bank, for example operational failure, fraud. Secondly, the shared risk factors, which are risks shared with other banks. These share risk factors capture the exposure of banks to same risk due to asset commonality. Asset commonality is due to syndicated loans or exposure to the same class of asset, mainly mortgages and loans to corporations in the same sector. The presence of the shared risk factor in all banks' returns distribution, cause the tails of the multivariate distribution fatter. This feature of the tails is not captured by the normal multivariate distribution. If normality is assumed, there returns of the banks are asymptotically independent under the assumption of normality, there is asymptotic independence. The disappearance of the dependency rejects the systemic risk associated with asset commonality. Therefore, this common risk factor alters the distribution and increases the probability of systemic breakdown. In other words, combining several normal distributions ignores the risk associated with asset commonality. Looking at Figure 2 again, it is obvious that the actual joint distribution of returns includes the situations where asset commonality causes joint losses of the two banks. Normal distribution (Figure 1) ignores these situations.

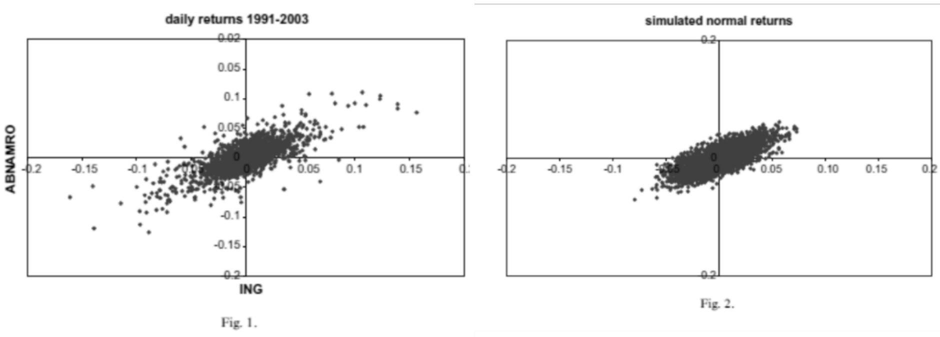

Figure 1 display the actual joint distribution of returns of ABN AMRO and ING over the period 1991-2003
Figure 2 is a simulated joint distribution based on the same period's mean and variance and normal distribution assumption.
Source: De Vries (2005)

The failure of normal distribution proven by De Vries, suggest systemic risk measure by correlation with normal distribution assumption, underestimates systemic risk. De Vries proposes a new measure of systemic risk and urges regulators to consider including tail dependencies in their calculation and application of measures. De Vries also finds that the potential of a systemic failure depends on the linearity in portfolios' exposure to risk and the marginal tail distribution of returns.

De Vries (2005) provides a clear evidence that asset commonality, captured by a shared risk factor in the banks' portfolios, makes the tails of the multivariate returns distribution fatter. Under fatter tails the probability of a systemic breakdown is more plausible. The statistical model proposed by the author, reveals a causal relationship between asset commonality and systemic risk and acts as the theoretical economic rationale of this paper.

Cai et al (2018) takes a more empirical approach in examining asset commonality as a contagion channel. The authors use data on syndicated loans to quantify the similarity of banks' assets. They construct a variable that captures the exposures of banks in to different sectors of the US economy based on syndicated loans. For each borrower, the SIC code states the industry the company operates in. Using SIC codes the common exposures can be measured. Cai et al define this variable “interconnectedness”. Interconnectedness acts as a proxy for the risk associated with asset commonality as a contagion channel, making the bank vulnerable to systemic risk.

The authors support the use of the syndicated loan market as a laboratory to examine asset commonality due to the preference of non-financial institutions to use syndicated loans as the primary funding source. Looking at the magnitude of the syndicated loan market and the number of its participants, it can be stated that the market acts as a good proxy for the whole loan market. Therefore, banks’ commonality of the syndicated loans can proxy banks’ asset commonality.

Using the interconnectedness, they analyse how banks become interconnected through syndicated loans. They find that banks and companies who worked together before, have more chances to be involved in syndication in the future. Banks tend to form syndicates with banks with more common pre-syndicate portfolio, therefore increasing the post-syndicate interconnectedness. Moreover, they examine the determinants of the interconnectedness. The main driver is diversification, which together with total assets and size have positive relation with interconnectedness. This result supports the theory that diversification-favouring regulation reduces individual bank risk but simultaneously increases systemic risk.

The authors also find a significant correlation of interconnectedness and the several systemic risk measures (SRISK, DIP, CoVaR). They also showed that interconnectedness has a causal effect on systemic risk. This causal effect is more pronounced in recession periods. These findings prove empirically that the asset commonality, as captured by the syndicated loan and supported by various theoretical papers, acts as a contagion channel and contributes towards systemic risk in the banking sector.

The paper by Cai et al (2018) provides us with an important measure of asset commonality. The relevance of this measure with systemic risk is proven by the high correlations with the several systemic risk measures.

This paper, using the "interconnectedness" measure, tries to examine the market perception of asset commonality. If the market understands that there is a contagion channel created via asset commonality, this risk should be priced.

Banks' exposure to common industries have played a significant role in several crises in the past. In the 1980s, US faced the Savings & Loans crisis. The mismatch of the maturity of the asset and liability of banks made banks vulnerable and a common shock to the interest rates cause contagion (Ho and Saunders, 1981). The 1990s financial crisis in Asia was associated with exchange rate risks. Moreover, the recent crises in Ireland and Spain was due to common exposures of their banks to real estate sector. The common exposure to real estate during the 2007–2009 financial crisis, cause a shock in house prices to spread, enforced by the several contagion channels (Cai et al, 2018; Hellwig, 1995, 2014).

Methodology and Data

The literature reviewed in the previous section provides an economic rational to the question that this paper tries to answer. The interconnectedness risk is supported theoretically (De Vries, 2005) and quantified (Cai et al, 2018), allowing us to examine if this risk is priced in the markets. The paper attempts to find evidence to support the following hypothesis:

Full pricing hypothesis*: investors understand that the commonality of a bank's assets acts as a contagion channel. Banks with more similar assets are more vulnerable to systemic breakdown and have higher CDS spreads. Under the full pricing hypothesis, interconnectedness has a positive effect on CDS spreads.*

Ignorance hypothesis*: investors fail to understand that asset commonality makes a bank vulnerable to a systemic breakdown and increases the default probability of the bank. Investors. Under the ignorance hypothesis , interconnectedness does not have a positive effect on CDS spreads.*

Market perception

The vehicle, used in this paper, to examine investors perception, is the Credit Default Swaps (CDS) of the banks. Firstly, the choice of CDS, as a vehicle, is explained and then the rationale why CDS are preferred from the other possible vehicles is given.

A CDS is a bilateral agreement in which the buyer makes a series of payments to the counterparty seller and in return accepts a one-off payment if the credit instrument defaults. The credit instrument is not necessarily a party to the contract. If the credit instrument fails to meet its obligations, the seller pays the buyer the one-off payment. The spread of the CDS is the periodic rate the CDS buyer pays on the notional amount to the CDS seller in there is no default.

CDSs are transfers of the risk of a credit event from one party to another. As such, the price of a bank's CDS reflect the perceptions of the market about the financial stability of the institution. The CDS spread of a healthy bank is expected to be lower than the spread of a bank under stress. CDS can therefore signal the financial stability of the bank to the investors and the prudential authorities.

Investors can buy and sell protection from an organization without holding any debt of the reporting organization. In other words, the owners of banks' CDS are not necessarily its shareholders. Therefore, a bank's CDS captures the market-wide understanding of the stability of the bank and the likelihood that it fails to meet its obligations. The CDS spreads simply reflects the reality, which is the health of a bank.

The cause of the default of the bank is not defined by the CDS agreement, allowing for many risks to be reflected by the CDS spread. Therefore, asset commonality can cause the default of a bank in case of a systemic shock and the seller of the CDS is obliged to make the one-off payment to the buyer. The interconnectedness risk should be incorporated in the CDS spreads, making the CDS an appropriate vehicle to examine the efficient pricing of the interconnectedness risk.

Bank's funding sources are the first methods a researcher will use to examine investors' pricing of bank's risk. The investors that fund the bank's operations are directly exposed to the risk of the bank and are the ones who will require returns for all the risk they think the bank is expose to. The main funding channels of a bank are deposits, equity issue, and long-term debt. After careful consideration of all bank's funding investors, this paper chooses the CDS spreads as the most appropriate measure of investors understanding of risk. Each funding channel is examined below and the motivation behind the preference of CDS spreads instead of the funding channels is given.

Deposit are the main funding source of banks since deposits take the largest share of banks liabilities side of the balance sheet. Deposit holders lend their money to the bank and demand return -equal to the interest rate- and banks use this money to finance the corporate loans, mortgages, syndicated loans etc. Deposit holders are subject to default risk, the risk that a lender will default, and the bank will not retrieve the full value to repay back the deposits. However, the deposits are insured in most of the developed countries by governments and are situated on the top seat in the repayment-after-liquidation hierarchy. These measures are designed by regulator to establish depositors' confidence for the banking system and therefore reduce the risk the depositors face. In addition, the returns on deposits are not simple risk compensation due to the reduced risk they bare but depend on competition in the banking market. Deposits' interest rates are firmly aligned across banks, yielding minimal cross-sectional variations. Therefore, banks' main funding channel does not provide enough information to be used in the analysis of this paper.

All banks are forced to hold equity. However, the share of equity in the banks' balance sheet is small because equity issue is regarded the most expensive source of funding. To examine if bank's shareholders demand compensation for the risk associated with the asset commonality, an approach similar to Fama and French (1992). The banks' stocks will be sorted according to the interconnectedness risk and then a portfolio long on the more risky and short on the less risky is constructed. If interconnectedness is priced by markets, then the portfolio should give significant premium. Using equity as a vehicle to examine if the asset commonality risk is priced is prone to calculation errors relative to using CDS. Moreover, if the analysis results in significant values of alpha, this is not a sure proof of the existence of the interconnectedness risk, but the interconnectedness being a proxy for another type of risk.

Another component of a bank's liabilities side of the balance sheet is long-term debt. Banks issue bonds to finance their operations. The bond holders therefore, are exposed to bank's risk making them good candidates for examining if investors price the interconnectedness risk. However, bonds are also high in the hierarchy of repayment if the bank goes into liquidation, reducing their risk exposure. In author's opinion, CDS spreads capture higher exposure on a bank's risk since they lose value automatically after a bank's failure and have no chance of avoiding loses after liquidation.

Asset commonality measure

The asset commonality of each bank's balance sheet relative to the other banks, is calculated using the approach proposed by Cai et al (2018).

Based on the SIC of the borrower, the loans are classified into 10 industries. For each bank i the total monthly loans are calculated, $W_{i,t}$. Then the share of loans to each industry j by each bank i, $w_{i,j,t}$. The Euclidian distance between two banks, i and h, in the J-dimensional space, where J is the total number of industries, is calculated given (2).

$$\sum_{j=1}^{J} w_{i,j,t} = 1 \qquad (1)$$

$$Distance_{i,h,t} = \frac{1}{\sqrt{2}}\sqrt{\sum_{j=1}^{J}\left(w_{i,j,t} - w_{h,j,t}\right)^2} \qquad (2)$$

The distance between the two banks denotes how similar is their balance sheets' asset side. The distance is normalised to unity and get a value of 1 if the banks have not issued syndicated loans to the same industries and therefore their assets are not common. A distance of magnitude 0 shows that the two banks hold very similar assets, in other words issued the same proportion of loans to the same industries.

The interconnectedness measures the asset commonality in the bank's balance sheet, relative to all other banks' balance sheets. Therefore, the interconnected is simply the average bank i's distance with all other banks, H. The measure is normalised given the equation 3 below.

$$Interconnectedness_{i,t} = \left(1 - \frac{1}{H}\sum_{h\neq 1}^{H} Distance_{i,h,t}\right) * 100 \qquad (3)$$

The interconnectedness of the lead arranger is increased when the measure approaches 100. A lower value indicates a bank that is less interconnected and less vulnerable to systemic risk through the asset commonality contagion channel. In this paper the measure is calculated as a simple equally weighted mean of distances. Interconnectedness can be also measure using a weighted average based on size and lending relationships. Size weighted interconnectedness yields higher levels of interconnectedness, supporting the theory that larger banks issue loans more similarly than smaller banks. For more information and an example of how to calculate distances and interconnectedness of banks, see Cai et al (2018).

Empirical Methodology

The objective of this paper is to estimate the investors' understanding of the risk risen by the asset commonality in banks' balance sheets. The empirical methodology for finding the investors awareness is the estimation of the following model using panel data OLS:

$$CDS_{i,t} = \beta_1 * Interconnectedness_{i,t} + B_2 * characteristics_{i,t} + b_k + c_t + e_{i,t} \quad (4)$$

Where i denotes the bank, k denotes the country the bank i is located and t denotes the month.

This paper estimates a characteristics model where the several characteristics of the bank are used to explain the monthly price of the bank's CDS. In this characteristics model, the common exposure in the asset side of the banks' balance sheets is captured by the interconnectedness risk as measured by Cai et all (2018). The interconnectedness captures the risk associated with bank's asset commonality. It is the variable of interest and any empirical results will be based on its coefficient β_1. Benkert (2004) prove Merton's (1974) model applicability to the CDS market, while Drago et al (2017) state that CDS analysis based on characteristics is acceptable in the banking sector. Characteristics is a matrix containing several control variables, divided into bank-specific characteristics, market condition characteristics and macroeconomic characteristics. For the choice of the characteristics control variables, the most recent literature on banks CDS valuation is followed (Demirguc-Kunt and Huizinga, 2013; Drago et al, 2017).

One of the bank-specific control variables is the market risk. The market risk of the bank is calculated by regressing the bank's stock returns on the market index. The estimated coefficient, beta, captures the relative volatility of the bank's stock with the market return. The estimated betas of all the banks in the sample is calculated and used in the main regression. The approach used to measure the credit risk is similar to the Fama-Macbeth two stage approach. The bank size is used to control for economies of scale. Shareholders and investors of the bank care about technological and managerial (dis-)economies of scale. Moreover, a failure of a large banks will have greater impact in the macroeconomy -too big to fail- and therefore it is more likely to be bailed out by government. The logarithm of total assets is used to measure bank size. Systemic size is captured by the ratio of total liabilities to the country's GDP. This measures how large the liabilities of the bank are compared to the country's GDP. A government is more likely to bail out of support financially a bank whose liabilities amount for more than half of the GDP. Therefore, this variable captures the likelihood of bailout in case of distress. Demirguc-Kunt and Huizinga (2013) support that the likelihood of access to government's safety net due to size and due to systemic size are independent. The quality of the bank's asset also determines the CDS spread of the bank. A bank with poor quality assets is less likely to be able to meet its obligations and has more default risk. Thus, the share of non-performing loans to total assets is used. The paper also controls for the bank's risk appetite and level of debt using the leverage ratio. The operational performance of each bank is captured by the profitability ratio (return on assets) and efficiency ratios (cost-to-income ratio). In the analysis, the share of non-interest income to total operating income is used. If non-interest income is a large share of a bank's income, suggest a bank that generates most of its income from advisory services rather than traditional lending activities. Therefore, banks with low traditional lending activities should have lower CDS spreads in times of financial distress. Bank liquidity is measured by the ratio of net loans to total assets (NL/TA) ratios. The NL/TA ratio measures how many of the assets are tied up in loans. Loans are considered illiquid assets and capture the liquidity of the banks. The last bank-specific control variable used is the credit rating of the bank from Moody's rating agency. The rating signals the overall health of the institution.

The market condition characteristics capture the overall performance of the financial markets. The stock market and volatility indices of each country are used to capture the overall climate in the financial markets.

The macroeconomic condition of the bank's host county is controlled using the term structure of interest rates and the risk-free rate. The term-structure of interest rates is used as an indicator future of economic conditions. The yield of the 10 years government bond is used as the "risk free" interest rate indicating sovereign risk. Moreover, the host county's stability and budget deficit are controlled using these two macroeconomic variables.

Variations in the CDS spread can also be explained by the liquidity of the swap contract. Liquidity is capture by the bid-ask spread of each CDS. The bid-ask spread is also affected by the transaction costs, demand and supply forces and the information asymmetry in the market.

Finally, a US dummy variable is used to capture any variation between US and non-US banks due to asymmetric information. The availability of published information, such as balance sheets and income statements, is limited and costly to US investors. Investors should require more compensation for the CDS of foreign banks compared to domestic banks whose information is easily available. This information advantage should be priced in the CDS spreads. European and Asian banks expand their operations abroad and acquire several problematic US banks after the 2008 crisis, contributing to a significant amount of non-US banks in the sample. The data sources of the control variables are summarised in table 1

There are several fixed effects that need to be considered before proceeding to the OLS regression: (i) Time fixed effects as a means to control for shocks across the sample's time period. Moreover, if the time-fixed effects are omitted, the model grasp the influence of aggregate trends and wrongfully presents a causal relationship where there is none; (ii) Country fixed effect are used to control for any cultural and constitutional differences between countries. One can argue that the high non-performing loans in the Mediterranean countries co-exist with the similar culture in these countries. Moreover, constitutional differences include the easiness of a government to bail out a bank due to laws. Different constitutions may require more time to pass a bailout law.

If investor price this asset commonality contagion channel and the exposure of the bank to a systemic breakdown then the syndicated loan exposure will have significant explanatory power in the CDS of the banks. If the interconnectedness can explain the CDS price, then this supports the full pricing hypothesis. Investors understand that the commonality of a bank's assets acts as a contagion channel and increased systemic risk due to asset commonality.

During recessions, the banking system is unstable, already occurred losses have decreased banks' capital levels and therefore the absorbing capacities for additional losses are lower. This period is exactly when banks are most exposed, so interconnectedness can easily facilitate spill overs. Therefore, the perception of investors to the interconnectedness risk is increased. The sensitivity of CDS on interconnectedness is expected to vary between the economic business cycle. Therefore, the CDS characteristics pricing model is estimated pre-crisis (2002-2007), post-crisis (2007-2016) and on the full sample (2002-2016) to capture any variation of investors risk awareness during the recessions. Market efficiency suggests that fully rational investors should require compensation for the risk associated with asset commonality throughout the sample period.

Data

Firstly, the data collection process for the syndicated loans will be explained, followed by the data on CDS and the control variables.

The data on syndicated loans is obtained from Thomson Reuters LPC DealScan database through WRDS. The primary sample includes 85,566 syndicated loans obtained by US companies from 2002 to 2016. For each loan the borrower's name, 4-digit SIC code and loan amount is reported. The banks participating in the loan syndicate are matched for each loan. The primary sample consists of 85,530 syndicated loans with an average of 5.64 banks participating in the syndicated lending.

The lead bank is the bank that initiates the loan. Before the loan issue, it collects and process information and conducts due diligence on the borrowing company, conducts due diligence.

Its evaluation of the borrower is then presented to other possible lenders. The lead bank then sells shares of the loan to the other syndication members but retains the largest share itself. The monitoring of the borrower is also a responsibility of the lead bank. Overall, the lead banks acts throughout and after the loan issue and as an agent of the syndicate. Therefore, the sample is restricted to the lead banks of each syndicated loan.

In the DealScan database, leaders of syndicated loans are assigned several titles, all corresponding to a lead bank role. This paper uses the “Admin agent” role to sort out lead banks. 78,494 of the loans (92%) have a bank with administrative role. If there is no administrative agent recorded for the loan, banks that have “prestigious” titles are chosen as lead banks (Ivashina, 2009; Standard & Poor’s, 2006; Loan Syndications and Trading Association, 2006). Standard & Poor’s (2006) classifies agents, arrangers, bookrunners, lead manager, lead arrangers and lead banks as “prestigious” titles. The hierarchy used in this paper is: Admin agent, Mandated Lead Arranger, Lead Arranger, Arranger, Syndication agent, Agent, Documentation Agent and Facility Agent. For loans with several leader banks, the loan amount is retained for all leaders. According to Ivashina (2009), the inclusion and exclusion of loans with multiple leads does not affect the analysis.

Loans where the borrower’s sic code is missing or loans that have no data on leader bank are removed from the sample. Data collected via DealScan are matched with CDS data obtained via the Bloomberg database. A gvkey identifier for 1,127 out of the 1,356 banks involved in syndicated lending as lead banks cannot be obtained so these banks cannot be matched with the Bloomberg data, reducing the number of banks in the sample to 229 banks (Sudheer and Roberts, 2008). Of those 229 banks, 56 share the same gvkey, revealing a possible change in the DealScan bank identifier but not a change in the company. For example, General Motors Acceptance Corp (GMAC) changed its name in 2008 to Ally Financial Corp but retain the same gvkey. Data on these 56 banks are aggregated. Moreover, the sample is focused on banks that serve as lead arrangers for at least 10 loans in the sample period. The purpose of the latter restriction is to exclude banks that enter the syndicated loan market as a lead arranger randomly. The banks excluded with the latter restriction are usually smaller banks that have minimal contribution to the interconnectedness. This restriction is motivated by Cai et al (2018) who find no difference

Table 1. The description and sources of the independent and dependent variables.

Variable	*Description*	Source
1.Dependent Variable		
CDS	The spread of the senior 5 years CDS expressed in US dollars and basis points	Bloomberg
2.Independent Variables		
Interconnectedness	The weighted average of bank i's Euclidian distance with banks j, where $j \neq i$	DealScan/author's calculation based on Cai et al (2018)
Market risk	The beta of the bank stock returns relative to the market	Regression output
Size[1][2][3]	$Log(Total\ Assets)$	Compustat/Orbis Bank
Systemic size[1]	$\frac{Total\ liabilities}{GDP}$	Compustat/Orbis Bank
Asset quality[2][3]	$\frac{Non-performing\ loans}{Total\ assets}$	Compustat/Orbis Bank
Leverage/Risk appetite[2][3]	$\frac{Total\ assets}{TIER\ 1\ capital}$	Compustat/Orbis Bank
Profitability[1][2]	$\frac{Net\ income}{Total\ assets}$	Compustat/Orbis Bank
Efficiency[2]	$\frac{Operational\ Expenses}{Operational\ income}$	Compustat/Orbis Bank
Non − interest income[1]	$\frac{Non-interest\ income}{Operational\ income}$	Compustat/Orbis Bank
Liquidity[2]	$\frac{Total\ loans}{Total\ liabilities}$	Compustat/Orbis Bank
Credit rating[2][3]	The credit score given by S & P	Compustat/Bloomberg
Market performance[2][3]	S&P 500, KOSPI200, NIKKEI225, EURONEXT100 and ALL-ORDINARIES indices	Bloomberg
Market volatility[2][3]	CBOE Volatility Index (VIX)	Bloomberg
Risk free rate[2][3]	10-year government bond yield	Bloomberg/FRED
Economic prospects[3]	Term structure of the interest rates $10\ \text{Years Gov. bond yield} - 2\ \text{Years Treasury bond}$	Bloomberg/FRED/ author's calculation
CDS bid − ask spread[2]	$CDS\ ask\ spread - CDS\ bid\ spread$	Bloomberg
US dummy	A dummy with value 1 if the bank is located in US and zero otherwise	Author's calculation

The number next to the control variable denotes the paper that proposed it. [1] Demirguc-Kunt and Huizinga, 2013 [2] Samaniego-Medina et al, 2016 [3] Drago et al, 2017
Data obtained from CompuStat are expressed in millions of US dollars
GDP data obtained from FRED are expressed in billions

in the interconnectedness measure with and without the exclusion of banks with less than 10 loans as lead banks in the sample.

The remaining sample consists of 47,146 loans issued by 104 banks. On average each bank is involved in 453 loans as a syndication leader in the sample period. For each bank the interconnectedness measure is calculated, following the methodology proposed by Cai et al (2018). During the financial crisis of 2007, US companies started to draw down their credit lines. These credit lines were devoted by banks in the credit-expansion pre-crisis period (Berg et al, 2016). Therefore, both syndicated loans and syndicated credit lines are used in the calculation of the interconnectedness of each bank (Cai et al, 2018)

The monthly spread of the 5-year senior CDS of each bank is obtained from Bloomberg and cover 180 months, from January 2002 to December 2016. The sample includes CDS spreads for 51 banks out of the 104 banks where data on interconnectedness is measured. Banks with limited CDS spread observations are replaced by their parent companies if their parent companies have a significantly greater number of observations. Three banks satisfy this condition. Standard Chartered Bank is replaced with its parent company Standard Chartered Holdings, with the correlation of their sample-existing CDS spread at 0.9934. RBS Holdings replaces RBS PLC (correlation = 0.9525) and Mizuho Bank replaces Mizuho Finance (correlation = 0.9400). Using this substitution, the number of observation increased without losing the ability to test for a causal relationship between interconnectedness and CDS spreads. This is because a risk of the subsidiary is also bared by the parent, the default of a subsidiary will affect the health of the parent, and therefore the higher risk of default of the subsidiary should be reflected in the parent company CDS spread. Although CDS are traded at several maturities, the 5-year maturity senior CDS since it is considered the most liquid of all and constitute the most widely held CDS in the market. (Jorion and Zhang, 2007; Demirguc-Kunt and Huizinga, 2013). This type of CDS spreads is regarded a benchmark for the CDS traders (Norden, 2017). All CDS observations are transformed in basis points.

The beta of each bank is the regression output of the bank’s stock returns on the market index. The monthly returns of the S&P 500, KOSPI200, NIKKEI225, EURONEXT100 and ALL-ORDINARIES indices are used for the US, Korean, Japanese, European and Australian based banks respectively. For the calculation of the systemic size the quarterly GDP of each country is kept constant throughout the quarter. For the country term structure, the generic 2-year and 10-year government bonds yields are used. The monthly yield of the 10-year government bond is also used as the monthly risk-free rate.

Data collection resulted in an unbalanced panel of 51 banks for the 180 months from Jan 2002 to December 2016. The descriptive statistics of each variable are presented in table 2.

Table 2. The descriptive statistics of the independent and dependent variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
CDS spread	7,287	103.8	143.2	3.207	4751
Interconnectedness	9,180	59.28	21.45	0.000	100.0
Beta	7,522	1.192	0.342	0.320	1.960
Size	8,465	13.44	1.371	9.819	19.10
Systemic size	8,371	0.001	0.001	0.000	0.011
Asset quality	2,296	0.011	0.009	0.000	0.055
Leverage	8,199	19.25	37.99	-129.0	136.2
Profitability	8,453	0.002	0.004	-0.098	0.053
Efficiency	5,651	2.039	7.531	-110.1	85.72
Non-interest income	3,051	-2.377	7.025	-112.7	25.44
liquidity	8,465	1.073	0.049	0.994	1.317
Bid-ask spread	7,278	8.783	16.29	-31.78	870.0

Empirical Results

The results of the empirical analysis are presented in table 3. The first column presents the baseline model. For this model the interconnectedness and the most traditional variables are used to explain the variations in the CDS spreads. The traditional variables are defined as the variables more frequently used in the CDS pricing literature.

The other columns include variations of the baseline model by the addition of more explanatory variables. Column 2 and 3 display the baseline model with the bank-specific variables added to it. Column 4 present the baseline model with the macroeconomic variables added to it. Finally, combinations of bank-specific and macroeconomic variables are added, and the results are presented in column 5.

Before commenting on the results, it is required to point out that this paper is not aiming to find the risk factors that are priced by the CDS spreads. The paper is using explanatory variables that help explain the banks' CDS spreads and deviate from the traditional asset pricing models, such as CAPM and Fama French 3-factor model, in the sense that there is no assumption of risk compensation. Moreover, there is no distinction between rational risk loading variables or irrational systematic behavioral biases in the variables this paper chooses. However, the analysis is a good indication of a relationship between the CDS spreads and banks characteristic and the awareness of the investors that some

Table 3. The results of the empirical analysis

	CDS spread				
	(1)	(2)	(3)	(4)	(5)
Interconnectedness	0.543*	0.465**	0.489 **	0.570*	0.474**
	(1.86)	(2.04)	(2.43)	(1.93)	(2.33)
<u>*Traditional variables*</u>					
Leverage	0.051	-0.988***	-2.072***	0.059*	-2.468***
	(1.58)	(2.86)	(3.15)	(1.78)	(2.94)
Risk free rate	4.663	-5.024	-5.887	8.307	7.572
	(0.29)	(1.34)	(1.33)	(0.50)	(0.15)
Beta	11.239	8.477	5.305	10.786	14.218
	(0.66)	(0.42)	(0.19)	(0.61)	(0.45)
Market return index	-0.009	-0.043***	-0.037***	-0.011	0.089
	(0.61)	(3.20)	(2.88)	(0.71)	(0.64)
Market volatility index	-8.008	-2.653***	-2.779***	-21.696	-3.867
	(0.91)	(2.90)	(2.69)	(1.10)	(1.49)
Bid-ask spread	6.050***	3.981***	3.777***	6.043***	3.674***
	(17.42)	(3.61)	(2.91)	(17.23)	(2.83)
<u>*Bank-specific variables*</u>					
Size		27.990***	26.196**		4.936
		(2.62)	(1.99)		(0.17)
Asset quality		811.548	-26.581		272.447
		(1.31)	(0.04)		(0.37)
Profitability		-6,558**	-8,526***		-8,088***
		(2.42)	(3.48)		(3.06)
Liquidity			-389.670		-466.168*
			(1.59)		(1.72)
Credit rating			0.609		1.397
			(0.13)		(0.31)
Efficiency			1.465*		1.538*
			(1.68)		(1.72)
<u>*Macroeconomic variables*</u>					
Economic prospects				15.913	73.631***
				(1.36)	(3.52)
Systemic size				-1,276	326,588
				(0.63)	(0.94)
_cons	175.933	-404.1***	-628.1**	569.5*	-906.3**
	(1.25)	(3.34)	(2.50)	(1.79)	(1.98)
N	5,779	1,500	1,338	5,622	1,322
Country fixed effects	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Bank clustering	YES	YES	YES	YES	YES

The dependent variable is the monthly average of daily closing credit default spreads on a 5-year contract. Leverage is liabilities divided by total assets. Risk free rate is the 10-year government bond yield. Beta is the estimated beta of the bank's stock returns relative to the market index. Market return and volatility indices are the monthly average of daily stock market indices. Bid-ask spread is the monthly average of the daily bid-ask spread of bank's CDS. Size is natural logarithm of total assets in constant 2000 US dollars. Asset quality is the share of non-performing assets to total assets. Profitability is the return-on-asset ratio. Liquidity is the share of loans to total liabilities. Credit rating is the rating given to the bank from S&P agency. Efficiency is the ratio of operating income to operating expenses. The economic prospects of the country are proxied by the term structure of the interest rate calculated by the difference in yields of the 10-year and 2-year government bond. Systemic size is the share of bank's total liabilities to country's GDP per capita in constant 2000 dollars. All regressions include country and year fixed effects. Values in bracket below the coefficients denote the resulted t-statistic of the test that the estimated coefficient is not different from zero. Stars denote significance levels (* $p<0.1$; ** $p<0.05$; *** $p<0.01$). Bank clustering corrects for serial autocorrelation of errors.

characteristics signal a high default probability. Thus, the results help to reveal any awareness of investors to asset commonality risk and a pricing of the interconnectedness risk.

The coefficient of interconnectedness is positive and significant in all pricing models estimated. These results suggest a positive relationship between banks' CDS spreads and the level of interconnectedness of each bank. This relationship is a signal that investors are aware that banks with high interconnectedness are riskier and require higher CDS spread for banks with higher asset commonality. The results support the full pricing hypothesis. Investors understand the contagion channel that is provided by the commonality of a bank's assets and require compensation for the asset commonality risk. Keeping all other variables constant, a 1 percentage point increase in the interconnectedness of the bank results in a rise in the CDS spread of 0.465-0.570 basis points.

The joint significance of the time fixed effect using an F-test is not rejected suggesting that the model requires time fixed effects. A similar joint significance test of the country fixed effects suggests the inclusion of country fixed effects in the model.

Woolridge test is run on the models to test for serial autocorrelation of the error terms. The null hypothesis of no serial correlation is rejected suggesting that the models suffer from serial autocorrelation. Since some variables are obtained in lower frequency than monthly, and are kept constant across months, observations are correlated across time. Observations within banks are correlated due to the above adjustment, but observations across banks are not correlated. For example, keeping the quarterly total assets of bank i and j constant across the three months of the quarter creates autocorrelation within the errors of bank i and j but no error autocorrelation across bank i and j. By clustering standard errors by banks, the assumption of zero correlation across banks is retained but the model allows for within-bank autocorrelation. The estimates are still unbiased, and their standard errors are corrected. Therefore, the corrected t-statistics presented in table 3 can be used to verify the statistical significance of the coefficients.

Since the choice of the control explanatory variables is taken from past literature on banks' CDS spread pricing, the best strategy to analyse and validate the results is to compare them with the results of this past literature.

Leverage is found to have significant effect on the CDS spread under models 2, 3, 4 and 5. This result is consistent with Demirguc-Kunt and Huizinga (2013) who find a significant negative effect of leverage on the CDS spreads. However, Samaniego-Medina et al (2016) and Drago et al (2017) find a significant positive effect. The deviations in the results can be explained by the different definitions of leverage used in each paper. In this paper, higher leverage ratio describes a situation where assets are financed without issuing more debt. Thus, higher leverage ratio reveals a less risky bank with lower probability of default and lower CDS spreads.

The coefficient of the risk-free rate is insignificant suggesting that it has no effect on the CDS spread. This result is consistent with Samaniego-Medina et al (2016) and Drago et al (2017) who also find an insignificant effect of the risk-free rate.

Beta captures the market risk and is found to have an insignificant and positive effect on the spread. This suggest a failure in pricing of this risk in the CDS spreads.

The effect of market performance and market volatility is found to have significant negative effect in models 2 and 3. Samaniego-Medina et al (2016) and Drago et al (2017) also find negative effect of market indices on the CDS spreads and proposed the market indices covary with the business cycle and changes in the overall economic conditions affect default probabilities.

The bid-ask spread has a positive relationship with the CDS spread, as expected. Lower contract liquidity increases the price of the contract. High bid ask spread denotes mismatch between supply and demand of the contract and therefore higher contract price. The positive effect of bid-ask spread on the CDS spread is also found by Samaniego-Medina et al (2016). Corò et al. (2013) support that liquidity risk has higher importance than individual credit risk in explaining variations in CDS spreads.

Size is found to affect positively the CDS spread, keeping all other factors constant. Diseconomies of scale as well as the too-big -to-fail effect help explain this finding. Our findings are consistent with Demirguc-Kunt and Huizinga (2013) and Samaniego-Medina et al (2016). They state that the positive effect of size is a result of the diseconomies of scale associated with large institutions.

Samaniego-Medina et al (2016) and Drago et al (2017) show that banks with lower asset quality, captured by the ratio of non-performing assets to total assets, have higher CDS spreads. Banks with high non-performing assets may not be able to meet future obligations and have higher default probability. This paper finds a positive but insignificant effect of asset quality.

Demirguc-Kunt and Huizinga (2013) and Samaniego-Medina et al (2016) find that more profitable banks have lower CDS spreads. Their results are consistent with the results shown on table 3. Higher profits are a signal of a healthy institution and retained profits can be used in the future to cover any losses and prevent default.

Samaniego-Medina et al (2016) find a positive significant coefficient of liquidity as expected. Our estimates of the liquidity effect are also positive but insignificant.

The coefficient of credit rating is positive but insignificant suggesting a zero effect. Drago et al (2017) also estimate the effect of rating on CDS spreads and finds a significant negative coefficient.

The effect of efficiency on CDS is examined by Samaniego-Medina et al (2016). Their results reveal an insignificant positive effect, similar to the results of this study.

The expectations of future economic prospects are captured by the term structure of the interest rate and are found to have a significant positive effect on CDS spreads. Therefore, high term structure signals dull country future and the country's banks have more default probability in the future. This mechanism can help explain the positive coefficient.

Demirguc-Kunt and Huizinga (2013) examine heavily the effect of the systemic size on CDS spreads. They also find an insignificant coefficient for the bank's systemic sized proxied by the liabilities-to-GDP ratio. The authors also check for a quadratic effect of systemic size, an interaction effect with bank size and used the total banking system share of liabilities to

GDP to capture the systemic size of the banking system. All their tests result in an insignificant coefficient, suggesting that the expected credit losses that the CDS spread reflects are not affected by the systemic size.

After reaching a conclusion about the pricing of the asset commonality risk by investors, it is interesting to see if there is any difference in the pricing of this risk over the years. The occurrence of the 2007 financial crisis is expected to alter the awareness of investors in systemic risk. The failure of banks caused significant spill-overs to the global economy and acted as a proof of the existence of contagion channels. The need for a stable banking system was highlighted. The 2007 financial crisis is a possible sample division event that is used to examine any change in the awareness and subsequently pricing of the asset commonality risk.

Choosing a period after the financial crisis, where years are dominated by financial instability in the banking sector, reassures that the sample is in the tails and more vulnerable to the risk imposed by syndicated loans' interconnectedness. Therefore, it is expected that the pricing of the interconnectedness risk will be higher. Table 4 displays the results of the model estimated pre-crisis and post-crisis. Columns 1 and 2 include all the banks and set the 2007 financial crisis as the sample division event. Columns 3 and 4 include only US based banks and used the 2007 financial crisis as the sample division event. Columns 5 and 6 focus on European banks. Fears about an upcoming economic crisis developed in Europe during 2009. The sovereign debt crisis in Europe started in early 2010 so 2009 is chosen as the reference point for dividing the sample. It is during 2009-2010 that European governments started bailing out banks and signalling the systemic instability in the banking sector.

Rational investors should be aware and price the asset commonality of banks. Any changes in the awareness of the asset commonality risk can be observed by differences in the coefficients of the interconnectedness measure. For the full sample, it can be concluded that investors price asset commonality risk only after the start of the 2007 crisis. This shows that the crisis informed the investors about the significant externalities and consequences of asset commonality. Considering that the blame for the crisis was thrown to the housing bubble, the high exposure of most banks on mortgages and the mortgage backed securities,

Table 4. The effect of the crisis on the pricing of interconnectedness.

	CDS spread					
	Full sample		US banks		European banks	
	'02-'06	'07-'16	'02-'06	'07-'16	'02-'08	'09-'16
Interconnectedness	-0.175	0.668*	-0.122	0.891*	-0.062	-0.049
	(1.18)	(1.88)	(0.87)	(1.79)	(0.34)	(0.14)
Leverage	-0.376	0.054	0.200	-0.968	-1.99***	0.085***
	(0.26)	(1.63)	(0.13)	(1.23)	(12.20)	(5.55)
Risk free rate	-9.588	4.702	-5.928	-87.735	-22.002	79.88***
	(1.47)	(0.27)	(0.38)	(0.69)	(0.88)	(6.42)
Beta	-54.706*	12.743	-9.602	2.402	-65.23**	225.251
	(1.91)	(0.58)	(0.37)	(0.11)	(2.17)	(1.45)
Market perf. index	0.012	-0.008	-0.185	-0.352	-0.298	2.704
	(1.41)	(0.45)	(0.67)	(0.72)	(0.46)	(1.39)
Market vol. index	-8.074	0.554	-2.651	-1.232	-0.499	34.741
	(0.78)	(0.32)	(0.74)	(0.52)	(0.14)	(1.26)
Bid-ask spread	6.619***	6.072***	8.553	6.096***	0.966	3.567**
	(3.11)	(18.73)	(5.42)***	(15.04)	(1.27)	(2.50)
Size	8.750	0.872	14.511	46.742	10.857	-144.78
	(0.71)	(0.04)	(0.71)	(0.80)	(1.02)	(1.34)
Profitability	-1,032.9	-3,521**	237.5	-3,569**	-16,802***	5,804**
	(0.54)	(2.21)	(0.16)	(2.20)	(3.89	(2.03)
Liquidity	137.820	98.460	144.030	314.431	402.265	-1,319.3
	(0.80)	(0.22)	(0.81)	(0.54)	(0.68)	(1.30)
Economic prospects	1.401	12.459	-12.844	-45.463	26.299	-25.917*
	(0.21)	(1.07)	(0.63)	(0.42)	(0.55)	(1.70)
Systemic size	-14,793***	-1,521	-447,167	-639,955	-9,655**	17,791.7
	(3.36)	(0.40)	(0.86)	(0.94)	(2.79)	(0.77)
_cons		-334.04				
		(0.67)				
N	1,453	4,140	1,160	2,927	261	458
Country FE	YES	YES	NO	NO	NO	NO
Time FE	YES	YES	YES	YES	YES	YES
Bank clustering	YES	YES	YES	YES	YES	YES

The dependent variable is the monthly average of daily closing credit default spreads on a 5-year contract. Leverage is liabilities divided by total assets. Risk free rate is the 10-year government bond yield. Beta is the estimated beta of the bank's stock returns relative to the market index. Market return and volatility indices are the monthly average of daily stock market indices. Bid-ask spread is the monthly average of the daily bid-ask spread of bank's CDS. Size is natural logarithm of total assets in constant 2000 US dollars. Profitability is the return-on-asset ratio. Liquidity is the share of loans to total liabilities. The economic prospects of the country are proxied by the term structure of the interest rate calculated by the difference in yields of the 10-year and 2-year government bond. Systemic size is the share of bank's total liabilities to country's GDP per capita in constant 2000 dollars. All regressions include year fixed effects. Values in bracket below the coefficients denote the resulted t-statistic of the test that the estimated coefficient is not different from zero. Stars denote significance levels (* p<0.1; ** p<0.05; *** p<0.001). Bank clustering corrects for serial autocorrelation of the residuals.

investors realised the externalities of banks holding assets in the same sector. Before the crisis investors did not care about banks holding similar asset as the insignificant coefficient of interconnectedness in column 1 reveals. The several bank bailouts during the crisis, raised the awareness of investors who demand more CDS spreads for banks with high asset commonality with other banks, as the positive significant coefficient of interconnectedness in column 2 reveals. Columns 3, 4, 5 and 6 show that investors priced the interconnectedness risk only for US banks after the crisis. The insignificant coefficient of interconnectedness in columns 5 and 6 suggest that the European sovereign debt crisis did not alter investors interconnectedness risk perception. The results displayed in table 4 suggests that the overall pricing of the risk associated with asset commonality started concerning investors after the 2007 financial crisis.

Comparing tables 3 and 4, it can be suggested that the pricing of this risk after the 2007 crisis is so intense that it has led to the pricing of the risk to show a significant figure for the whole period under consideration (table 3) even if table 4 shows that investors did not price this risk prior 2007.

Robustness checks are carried to check the validity of the control variables. The positive coefficient of size suggests that large banks experience diseconomies of scale and this is priced in the CDS spreads. To validate if this theory holds, a quadratic size term is added to the regression to account for the nonlinear effect of size on the performance of the banks. The addition of the quadratic term turns both size and size square coefficients insignificant (Model 1 and 2). This suggests that the positive effect of size is not due to diseconomies of scale. The positive effect can be explained by the too-big-to-fail effect. Governments are more likely to step up and bail out a problematic bank if the bank is large rather than small. Governments are fearing that a default of a large bank will have severe negative effects to the economy and the welfare of the country is higher if the bank is bailed out. This safety can force banks to take excessive risk and therefore increase their default probability. They know that if their projects fail the government will save them. The higher probability of default is priced in the CDS spreads.

In the analysis, the volatility of the market is proxied by the CBOE Volatility Index (VIX). This index is based on the US stock market. As a robustness check, it is examined if VIX is a good proxy for the stock market volatility in European and Asian countries. Model 1 estimates the

Table 5. Model variations for robustness checks.

	CDS spread			
	(1)	(2)	(3)	(4)
Interconnectedness	0.604**	0.590**	0.703*	0.180
	(2.08)	(2.02)	(1.84)	(0.49)
Leverage	0.060*	0.062**	-0.628	-0.643
	(1.89)	(2.03)	(0.96)	(0.97)
Risk free rate	8.365	10.188	-47.391	-51.309
	(0.52)	(0.65)	(1.06)	(1.23)
Beta	13.053	11.070	-5.029	-3.818
	(0.75)	(0.71)	(0.23)	(0.18)
Market performance index	-0.010	-0.011	-0.170	-0.234
	(0.70)	(0.69)	(0.92)	(1.11)
Market volatility index	-18.394	-19.613	0.257	-1.367
	(0.92)	(1.05)	(0.12)	(0.52)
Bis-ask spread	6.117***	6.156***	6.190***	6.171***
	(19.09)	(19.98)	(15.57)	(15.13)
Size	-5.903	34.565	13.566	21.338
	(0.70)	(0.42)	(0.70)	(0.95)
Profitability	-3,958.8***	-4,171.9***	-4,024.8**	-3,957.3**
	(2.74)	(2.66)	(2.48)	(2.52)
Liquidity	214.373	229.348	259.790	299.924
	(0.94)	(1.44)	(1.02)	(1.13)
Economic prospects	14.276	14.689	-9.034	-2.465
	(1.27)	(1.36)	(1.31)	(0.16)
Systemic size	1,723.600	1,418.714	-366,052	-445,618
	(0.67)	(0.65)	(1.18)	(1.32)
Size*Size		-1.539		
		(0.48)		
Crisis*Interconnectedness				0.751
				(1.36)
_cons	153.998	-89.861		
	(0.28)	(0.15)		
N	4,110	4,110	2,465	4,110
Country FE	YES	YES	NO	NO
Time FE	YES	YES	YES	YES
Bank clustering	YES	YES	YES	YES

The dependent variable is the monthly average of daily closing credit default spreads on a 5-year contract. Leverage is liabilities divided by total assets. Risk free rate is the 10-year government bond yield. Beta is the estimated beta of the bank's stock returns relative to the market index. Market return and volatility indices are the monthly average of daily stock market indices. Bid-ask spread is the monthly average of the daily bid-ask spread of bank's CDS. Size is natural logarithm of total assets in constant 2000 US dollars. Profitability is the return-on-asset ratio. Liquidity is the share of loans to total liabilities. The economic prospects of the country are proxied by the term structure of the interest rate calculated by the difference in yields of the 10-year and 2-year government bond. Systemic size is the share of bank's total liabilities to country's GDP per capita in constant 2000 dollars. Models 1,2 and 3 are estimated using the full sample. Model 4 is estimated using only US banks. All regressions include year fixed effects. Values in bracket below the coefficients denote the resulted t-statistic of the test that the estimated coefficient is not different from zero. Stars denote significance levels (* p<0.1; ** p<0.05; *** p<0.001). Bank clustering corrects for serial autocorrelation of the residuals.

model on the full sample and model 3 estimates the model on only US banks. If VIX is a good proxy for the global stock market volatility, the coefficient of Stock market volatility will not differ. Using an F-test , the hypothesis that the two coefficients are equal is rejected. Thus, the VIX is only used as an explanatory variable when only US banks are considered. Model 4 display the robustness check for the failure of pricing interconnectedness risk before the 2007 financial crisis. Table 4 reveals that investors start pricing the interconnectedness risk after 2007. Using the subsamples approach, all the variable effects have the chance to change during the recession. In table 5, model 4, a different approach is taken to test difference in pricing over time. An interaction dummy, Crisis * Interconnectedness, is used. This interaction dummy takes a value only after the 2007 financial crisis. Using the interaction term, only the interconnectedness variable is allowed to change during recessions. Results of the interaction dummy approach are presented in table 5, model 4. The effect of interconnectedness on CDS spreads is 0.180 before 2007 and 0.930 afterwards. Although both are not statistically significant, the difference in magnitude of the two effects reveals that investors perception about the interconnectedness risk alter after the 2007 financial crisis.

Conclusions

Banks whose balance sheets have similar asset sides, are exposed to the same risk factors. The high commonality of assets increases the probability of a systemic breakdown. This paper questions if investors price the risk associated with asset commonality. Using banks' CDS spreads as a vehicle to examine investors awareness, the paper finds that investors correctly price this risk.

Furthermore, the paper finds that investors were not always pricing this risk. The events that followed the 2007 financial crisis raised concerns that holding similar assets causes the banking network to fail. The concerns took a formal shape after the speech given by Ben Bernanke (2010), the FED chairman at that time. At the Conference on Bank Structure and Competition, he stated that FED is trying to compact the high interconnectedness of large financial institutions. Bernanke highlighted the risk associated with asset commonality and the attention that must be given to this contagion channel. These fears stimulated investors to demand higher CDS spreads to US banks with high asset similarity with other banks.

The pricing of this risk is also a proof of the existence of the risk. The findings emphasise the negative externalities of the diversification of banks risk through sharing of assets caused balance sheets of banks to become similar. Banks in a try to reduce their idiosyncratic risk, are getting exposed to the same risk. This makes the banking system more vulnerable to a shock and raises the systemic risk. The results can be used to motivate regulators and bank authorities to consider the externality of diversification is setting up regulations. Better design of regulatory measures can increase the stability of the banking sector. Asset classes with high bank ownership should carry a higher weight in the risk weighted capital requirements under Basel III. A design of a weight that can incorporate the concentration of banks' operations in one asset class or one industry can help reduce the asset commonality risk.

Moreover, the pricing of the asset commonality risk provide evidence on the efficient and rational behaviour of the market. Investors are considering the interconnectedness risk and behave rational in wanting compensation for this risk. Markets are efficient but the non-pricing of the risk before 2007 suggests that efficiency can be improved. Bank authorities, governments, central banks and regulators should try and inform the market participants of the banking network dynamics and mechanisms and not wait for financial crisis to raise the awareness of investors to these matters. In this way financial crises can be prevented by informing investors about the risks that can cause the crises, before the crisis occurs. If investors were aware of the interconnectedness risk before 2007, they would have priced it, and banks would have reduced their interconnectedness, reducing the negative consequences of the 2007 crisis. In author's opinion, banks need a more robust enterprise risk management framework to identify, analyse and address such risks. New regulation should also oblige banks or bank authorities to share information about the similarity of their portfolios with the investors.

References

Acharya, V., 2001. A Theory of Systemic Risk and Design of Prudential Bank Regulation. Mimeo, London Business School.

Acharya, V., 2009. A theory of systemic risk and design of prudential bank regulation. Journal of Financial Stability 5(3), 224-255.

Acharya, V., Yorulmazer, T., 2005. Limited Liability and Bank Herding. Mimeo, London Business School.

Acharya, V., Yorulmazer, T., 2008. Information Contagion and Bank Herding. Journal of Money, Credit and Banking 40, 215-231.

Allen, F., Babus, A., Carletti, E., 2012. Asset commonality, debt maturity and systemic risk. Journal of Financial Economics 104 (3), 519–534.

Anufriev, M., Panchenko, V., 2015. Connecting the dots: Econometric methods for uncovering networks with an application to the Australian financial institutions. Journal of Banking & Finance 61, Supplement 2, S251-S255.

Benkert, C., 2004. Explaining credit default swap premia. Journal of Futures Market 24, 71–92.

Benoit, S., Colliard, J., Hurlin, C., Perignon, C., 2015. Where the Risks Lie: A Survey on Systemic Risk. HEC Paris Research Paper No. FIN-2015-1088.

Berg, T., Saunders, A., Steffen, S., 2016. The total costs of corporate borrowing: Don't ignore the fees. Jounal of Finance 71(3), 1357-1392.

Bernanke, B., 2010. Speech at the Conference on Bank Structure and Competition, Chicago.

Bisias, D., Flood, M., D., Andrew, W., L., Valavanis, S., 2012. A Survey of Systemic Risk Analytics. U.S. Department of Treasury, Office of Financial Research No. 0001.

Boss, M., Elsinger, H., Summer, M., Thurner, S., 2006. Network topology of the interbank market. Journal of Quantnative Finance 4(6), 677-684.

Cai, J., Eidam, F., Saunders, A., Steffen S., 2018. Syndication, interconnectedness, and systemic risk. Journal of Financial Stability 34, 105-120.

Chen, Y., 1999. Banking Panics: The Role of the First-Come, First-Served Rule and Information Externalities. Journal of Political Economy 107(5), 946-968.

Corò, F., Dufour, A., Varotto, S., 2013. Credit and liquidity components of corporate CDS spreads. Journal of Banking and Finance 37, 5511–5525.

De Bandt, O., Hartmann, P., 2000. Systemic risk: A survey. Working Paper Series 0035, European Central Bank.

De Nicolo, G., Kwast, M.L., 2002. Systemic risk and financial consolidation: Are they related?. Journal of Banking and Finance 26, 861–880.

De Vries, C., G., 2005. The simple economics of bank fragility. Journal of Banking and Finance 29, 803-825.

Demirguc-Kunt, A., Huizinga, H., 2013. Are banks too big to fail or too big to save? International evidence from equity prices and CDS spreads. Journal of Banking & Finance 37(3), 875-894.

Diamond, D., W., Dybvig, P., H., 1983. Bank runs, deposit insurance, and liquidity. Journal of Political Economy 91(3), 401–419.

Drago, D., Di Tommaso, C., Thornton, J., 2017. What determines bank CDS spreads? Evidence from European and US banks. Finance Research Letters 22, 140-145.

Dungey, M., Fry R., González-Hermosillo B., Martin, L., V., 2007. Empirical modelling of contagion: a review of methodologies. Quantitative Finance 5(1), 9-24.

Estrella, A., 2001. Mixing and matching: Prospective financial sector mergers and market valuation. Journal of Banking and Finance 25, 2367–2392.

Fama, E., F. and French, K., R., 1992. The Cross-Section of Expected Stock Returns. The Journal of Finance 47 (2), 427.

Folkerts-Landau, D., 1991. Systemic Financial Risk in Payment Systems, in: Determinants and Systematic Consequences of International Capital Flows. IMF Occasional Paper, no.77 (Washington, DC: IMF, March), 46-67.

Freixas, X., Parigi, B., Rochet, J., 2000. Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. Journal of Money, Credit and Banking 32(3), 611-638.

González-Hermosillo, B., Pazarbaşioğlu, C., Billings, R., 1997. Determinants of Banking System Fragility: A Case Study of Mexico. IMF Econ Rev (1997) 44, 295.

Greenwood, R., Landier, A., Thesmar, D., 2015. Vulnerable banks. Journal of Financial Economics 115 (3), 471-485.

Hellwig, M., F., 1995. Systemic aspects of risk management in banking and finance. Swiss Journal of Economics and Statistics 131(4), 723–737.

Hellwig, M., F., 2014. Systemic risk and macro-prudential policy. Speech at the Nederlandse Bank's High-Level - Seminar on Making Macroprudential Policy Work in Practice.

Ho, T., S., Y., Saunders, A., 1981. The determinants of bank interest margins: theory and empirical evidence. The Journal of Financial Quantitative Analysis 16(4), 581.

Humphrey, D., B., 1986. Payments Finality and Risk of Settlement Failure, in Technology and Regulation of Financial Markets: Securities, Futures and Banking, ed. by Anthony Saunders and Lawrence J. White, pages 97-120 (Lexington, MA: Lexington Books).

Iori, G., Jafarey, S. and Padilla, G.F., 2006. Systemic risk on the interbank market. Journal of Economic Behavior & Organization 61(4), 525-542.

Ivashina, V., 2009. Asymmetric information effects on loan spreads. Journal of Financial Economics 92(2), 300-319.

Loan Syndications and Trading Association, 2006. The Handbook of Loan Syndications and Trading. The McGraw Hill Companies, Inc., New York, NY.

Merton, R., C., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance 29, 449–470.

Norden, L., 2017. Information in CDS spreads. Journal of Banking and Finance 75(C), 118-135.

Samaniego-Medina, R., Trujillo-Ponce, A., Parrado-Martínez, P., Pietro, F., 2016. Determinants of bank CDS spreads in Europe. Journal of Economics and Business 86, 1-15.

Silva, W., Kimura, H., Sobreiro, V., A., 2017. An analysis of the literature on systemic financial risk: A survey. Journal of Financial Stability 28(C), 91-114.

Standard & Poor's, 2006. A Guide to the Loan Market. The McGraw-Hill Companies, Inc., New York, NY.

Sudheer, C., Roberts, R., M., 2008. How Does Financing Impact Investment? The Role of Debt Covenants. Journal of Finance 63, 2085-2121.

Sufi, A., 2007. Information asymmetry and financing arrangements: evidence from syndicated loans. Journal of Finance 62(2), 629-668.

Upper, C., Worms, A., 2004. Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? European Economic Review 48(4), 827-849.

Wagner, W., 2010. Diversification at financial institutions and systemic crises. Journal of Financial Intermediation 19(3), 373-386.