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Essays on risk management and systematic risk

Silva Buston, C.F.

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Consuelo Silva Buston

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Consuelo Fernanda Silva Buston

geboren op 26 juli 1984 te Santiago, Chili.

PROMOTIECOMMISSIE:

PROMOTOR:	prof. dr. Wolf Wagner
OVERIGE LEDEN:	prof. dr. Thorsten Beck
	prof. dr. Hans Degryse
	prof. dr. Vasso Ioannidou
	prof. dr. Augustin Landier
	prof. dr. Ian Marsh

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Chapter 1

Introduction

Through the creation of the Financial Stability Board (FSB), G20 members have committed to regulate the financial sector across the globe in order to enhance the resilience of the system. Two important points in this agenda are the regulation of OTC derivatives, such as Credit Default Swaps (CDS) and the regulation of Systemically Important Financial Institutions (SIFIs). The first two chapters of this thesis relate to the first point. These papers study the effects of the use of CDS at banks on banks' behavior and stability. The last chapter of the thesis addresses the second point. This chapter discusses the proper assessment of systemic risk, and the characteristics and performance of systemically important banks based on this assessment. Each chapter is summarized in turn.

The first paper investigates whether, and through which channel, the active use of credit derivatives changes bank behavior in the credit market, and how this channel was affected by the crisis of 2007-2009. Our principal finding is that banks with larger *gross* positions in credit derivatives charge significantly lower corporate loan spreads, while banks' *net* positions are not related to loan pricing. We argue that this is consistent with banks passing on *risk management* benefits to corporate borrowers but not with alternative channels through which credit derivative use may affect loan pricing. We also find that the magnitude of the risk management effect remained unchanged during the crisis period of 2007-2009. In addition, banks with larger gross positions in credit derivatives cut their lending by less than other banks during the crisis and have consistently lower loan charge-offs. In sum, our study is suggestive of significant risk management benefits from financial innovations that persist under adverse conditions – that is, when they matter most.

In the second paper, we analyze the net impact of two opposing effects of active risk management at banks on their stability: higher risk-taking incentives and better isolation of credit supply from varying economic conditions. We present a model where banks actively manage their portfolio risk by buying and selling credit protection. We show that anticipation of future risk management opportunities allows banks to operate with riskier balance sheets. However, since they are better insulated from shocks than banks without active risk management, they are less prone to failure. Empirical evidence from US bank holding companies broadly supports the theoretical predictions. In particular, we find that active risk management banks were less likely to fail during the crisis of 2007–2009, even though their balance sheets displayed higher risk-taking. These results provide an important message for bank regulation, which has mainly focused on balance-sheet risks when assessing financial stability.

Finally, in the third paper we show that the interbank correlation of stock returns can be decomposed into two components that have different implications for financial stability. The first arises from diversification activities at banks, while the second is due to systemic risk. Estimation of both components for U.S. BHCs shows that diversification has increased resilience to the crisis of 2007-2009 but that systemic risk is not robustly associated with crisis performance. We also find that diversification benefits are rapidly declining with bank size and that large banks display very high levels of correlation due to systemic risk. Large banks are thus exposed to a high degree to the undesirable part, but to a lesser degree to the desirable part of bank correlation. Overall, our results emphasize that it is important to distinguish between different sources of interbank correlations when judging systemic risk exposures of banks.

Chapter 2

Financial innovation and bank behavior: Evidence from credit markets

2.1. Introduction

Financial innovations are at the centre of the debate on how to shape the future global financial system. The dominant view prior to the crisis of 2007-2009 was that financial innovations are beneficial for the financial system. The experience of the crisis has led to an – at least partial – reassessment of this view. Many policy makers now argue that the use of financial innovations needs to be restricted or prohibited. There is also general concern that financial innovations, while beneficial under normal economic conditions, may amplify shocks in times of crisis. Whether this concern is justified depends on why and how these innovations are used in the financial system. If, for instance, the innovations are employed by financial institutions to improve risk measurement and risk control, they may serve to insulate the financial system against negative shocks. The use of financial innovations may, however, also encourage risk-taking by financial institutions and cause dependence on their continued availability. This can result in greater vulnerability in times of stress.

Despite the importance of this issue, there is relatively little evidence on the channels through which financial innovations may affect the behavior of financial institutions and on how these channels are operating under adverse conditions. In this paper we analyze the key innovation in credit markets of recent decades – credit derivatives. Specifically, we examine whether, and through which channel, the active use of credit derivatives changes bank behavior in the credit market, and how this channel was affected by the crisis of 2007-2009. Credit derivatives – unlike traditional debt instruments, such as bonds and loans – make it relatively easy to hedge or source credit risk. Banks are major players in the credit derivative market and the market has grown dramatically over the last decade. The outstanding amount at the peak of the market in 2007 was estimated at $50 trillion by the BIS and has declined to $28 trillion by the end of 2011. It should be noted that unlike some other credit markets (such as the market for structured securitization products), the market for credit derivatives did not break down during the crisis.

Studies that examine banks' use of financial innovations show that under normal economic conditions these instruments facilitate the extension of credit and result in more favorable lending conditions for borrowers. In particular, lower borrowing costs are observed for loans intended for subsequent sale (Guener (2006)) or securitization (Nadauld and Weisbach (2011)).[1] Hirtle (2009) shows that greater credit derivative use by banks increases the credit supply to large firms and lowers corporate loan spreads on average. Ashcraft and Santos (2009) document that firms with a higher default risk face higher loan spreads after they become traded in the CDS market. Ashcraft and Santos argue that this effect is driven by reduced incentives for banks to monitor the default risk of these firms. These studies all analyze the pre-crisis period. In addition, in the interpretation of the results they focus on one particular channel through which credit derivative use may affect credit markets – they do not consider several channels simultaneously. This makes it difficult to obtain a view about the dominant channel and how this channel operates under different market conditions.

Our paper aims to fill this gap by examining various channels through which banks' use of credit derivatives may influence the pricing of syndicated corporate loans – both in normal times and in times of crisis. In addition, to further the understanding of the relevant channel, we complement the loan pricing analysis with an analysis of the lending behavior of banks active in the credit derivative market. We investigate four different channels. Credit derivatives may provide benefits that can be passed on to borrowers if banks use these instruments to i) hedge credit risk, to ii) reduce economic or

[1] There is also evidence that loan sales (Cebenoyan and Strahan (2004)) and Collateralized Debt Obligations (Franke and Krahnen (2005)) lead to an increase in lending at banks.

regulatory capital, or to iii) actively manage the credit risk of their loan portfolios. Credit derivatives can also increase borrower risk (and result in higher spreads) if the transfer of risk leads to iv) incentive problems at banks. In order to identify the channel we develop hypotheses about the link between either a bank's *gross position* in credit derivatives (the sum of protection bought and sold) or its *net position* (the difference of protection bought and sold) and loan pricing. The key prediction is that the risk management channel is the only channel which can operate through banks' gross positions. For example, a risk managing bank may reduce exposures arising from their lending business by buying protection but at the same time source credit risks on underrepresented risks through a sale of protection. All other channels require the bank to take a positive net position in credit derivatives.

Our dataset is based on loan-level information from the LPC DealScan database and bank-level information from the Call Reports covering the period from 1997 to 2009. The principal result from regression analysis is that, after controlling for lender, loan and bank characteristics, banks' gross positions in credit derivatives are significantly negatively related to the loan spread they charge to the average corporate borrower. By contrast, banks' net positions in credit derivatives do not display any association with loan spreads. This result provides support for the risk management channel but is inconsistent with the other channels through which credit derivatives may affect loan pricing. The effect is robust – in particular it is still present when we control for the use of other derivatives and take into account various endogeneity concerns. The effect is larger for borrowers that are more likely to be actively traded in credit derivative markets. The estimates for firms that are rated investment grade imply that a one-standard deviation increase in the banks' gross credit derivative position lowers their loan spread by 18% (46 bps). We also find that the risk management benefits extend to firms that are unlikely to be traded in the credit derivative market: their spread is reduced by 5% (13 bps).[2] Significant risk management benefits are thus passed on to the entire portfolio of borrowers and not only the borrowers that can be easily traded. This suggests that risk management reduces a bank's overall marginal cost of risk-taking. It may also reflect pseudo pricing – the practice at banks to price non-traded credit exposures using correlated traded credit exposures.

[2]The implied annual savings per loan are still in excess of $127.000.

We then turn to the analysis of loan pricing during the crisis of 2007-2009. If banks use credit derivatives to properly manage risks, we would expect that their pricing advantage relative to other banks is not eroded during the crisis. We first document that loan spreads increased for all banks during the crisis, reflecting the fact that the crisis was driven by systemic factors that cannot be diversified away using credit derivatives. Second, consistent with effective risk management, we find that banks active in credit derivatives still charge loan spreads that are lower than those of other banks – in fact, the loan spread difference is essentially unchanged compared to the pre-crisis period. We also investigate the relationship between credit derivative use and the characteristics of lending at the bank level. Effective risk management would suggest that banks are less likely to face constraints under adverse conditions (Froot, Scharfstein and Stein (1993)). Consistent with this argument, we find that risk management banks cut lending back by significantly less than other banks. Risk managing banks also do not seem be more aggressive as their pre-crisis lending levels are comparable to other banks. There is thus no evidence for increased risk-taking arising from credit derivative use. Furthermore, we expect banks that actively manage their credit risks to have lower loan risks and not to suffer more from the financial crisis than other banks. In accordance with this, we find that banks with a larger gross position in credit derivatives have lower charge-offs than other banks and that this difference is not eroded (even partially) during the crisis.[3]

Our paper contributes to the literature on financial innovations, risk management, banking and corporate finance. Taken together, the analysis provides consistent evidence that banks use credit derivatives to improve their management of credit risks.[4] There is no evidence in support of other channels through which credit derivatives may affect loan spreads. Corporate borrowers benefit from risk management through lower spreads and these benefits do not seem to be limited to the borrowers whose risks can be directly managed using the derivatives. Our results also show that the benefits extend to the crisis period – not only through more favorable lending conditions but also through a more stable supply of credit. All in all, our results contain a positive message about the benefits of this type of financial innovation – even in circumstances where markets are

[3]We also find that over the entire sample period the volatility of the average loan spreads charged by the group of active banks is about half of the spread volatility of the other banks. This further speaks to risk management benefits.

[4]Our results on financial innovations complement recent evidence on the link between risk management, control and performance of US bank holding companies (Ellul and Yerramilli (2010)).

under great stress.

The remainder of the paper is organized as follows. In Section 2 we develop hypotheses that allow us to identify the channel through which credit derivatives might affect corporate loan spreads. In Section 3 we describe the data. In Section 4 we outline the empirical strategy and present the results. Section 5 concludes.

2.2. Hypotheses

Related studies and evidence from the banking industry suggest different channels through which credit derivatives (and risk transfer activities in general) may affect bank lending behavior. Subsequently, we briefly summarize the key channels. We also explain our approach to identifying the channels empirically.

Credit derivatives allow banks to transfer risk exposures to third parties by hedging exposures through the purchase of protection. This may reduce banks' incentives to screen and monitor borrowers (e.g., Morrison (2005)). We refer to this as the *Incentives Channel*. Ashcraft and Santos (2009) provide evidence for this channel. They investigate the effect of a firm being traded in the CDS market on the spread it has to pay on its loans. Ashcraft and Santos argue that once a firm is traded in the CDS market, banks can hedge their exposure to this firm. This may, in turn, lower banks' incentives to monitor. The firm's borrowing cost should then increase – as it becomes riskier. Consistent with this, Ashcraft and Santos find that riskier and informationally opaque firms, who benefit the most from bank monitoring, face higher spreads after the onset of trading in the CDS market.[5]

Credit derivatives may also affect bank lending through the *Risk Management Channel*. According to this channel, credit derivatives allow banks to better manage the risk in their credit portfolios. Banks can buy protection on overrepresented exposures and sell protection on underrepresented exposures. Banks can also use credit derivatives to keep the overall risk of their portfolio close to the target level. Among others, such risk management in form of active credit portfolio management provides benefits as it reduces the likelihood of financing constraints becoming binding. Risk management benefits may

[5]Marsh (2006) finds that the announcement effect of a new bank loan is weakened when a bank actively uses securitization techniques to transfer the risk – consistent with reduced bank incentives.

also obtain indirectly: the use of credit derivatives may induce banks to measure and price their credit risks more rigorously. An increased awareness of risks may make banks more efficient in their lending behavior. Empirical research provides evidence that risk management benefits enable banks to extend larger loan volumes (Franke and Krahnen (2005)) or to pass on the benefits to their borrowers through lower spreads (see Cebenoyan and Strahan (2004) for loan sales). If this channel is operative, we would expect banks that are actively trading credit derivatives to reduce the interest rate charged to borrowers. Hirtle (2009) examines this hypothesis. Controlling for bank and loan characteristics, Hirtle finds that for large borrowers, the net position of credit derivatives held by banks has a negative effect on loan spreads, and argues that this finding is consistent with banks managing credit risk. Global survey evidence confirms that large international banks have been following active credit portfolio management with credit derivatives for many years (Beitel et al. (2006)).

There are two additional channels through which credit derivatives may influence loan pricing. Both channels suggest a negative effect on loan spreads. According to the *Hedging Channel,* banks hedge their exposures by purchasing protection in derivatives markets.[6] Nadauld and Weisbach (2011) study whether this channel is operative for loan pricing. Nadauld and Weisbach examine the spreads of loans that are subsequently securitized. They provide comprehensive evidence that loans that were later included in a CLO exhibit lower spreads when they are issued. Another channel, closely related to the hedging channel, is the *(Regulatory) Capital Relief Channel*. This channel is based on the idea that bank lending is constrained because of the scarcity of regulatory bank capital. Credit derivatives can be used to alleviate this constraint by buying protection from third parties, thus releasing bank capital for new lending. This allows banks to grant new loans and to price loans more aggressively. Broadly consistent with this channel, Loutskina and Strahan (2006) show that securitization diminishes the impact of bank financial conditions on loan supply.

While most of the studies have focused on one channel, our paper considers these channels jointly and aims to identify the key channel(s) through which credit derivatives

[6] There is no universally accepted definition of hedging and risk management in the literature. In this paper we take hedging to mean the simple shedding risk using financial instruments, while risk management goes beyond this and requires banks to actively control the risk of their portfolio, which also involves the acquisition of new risks through derivatives.

influence corporate loan spreads. We note that the channels vary with their prediction regarding the impact on loan spreads (a spread reduction is suggested by the risk management, hedging and capital relief channel; a spread increase is consistent with the incentive channel). However, the key innovation in our paper that ultimately allows us to identify the dominant channel is that we separately consider the effect of the *gross* and the *net* position in credit derivatives on loan spreads (the gross position is the sum of protection bought and sold, while the net position is the difference between protection bought and sold). We argue that all channels except the risk management channel require the bank to take a positive net position in credit derivatives (i.e., to be a net protection buyer). Under the hedging channel, risk is only reduced if the bank sheds risk net, that is, buys more protection than it sells. Similarly, regulatory capital relief only occurs if the bank reduces its risk overall, again requiring the bank to take a net buy position. The incentive channel also requires banks to buy protection – but not to sell. The only channel that can become operative, without requiring the bank to be a net buyer, is the risk management channel. For example, diversifying the portfolio by shedding risk on overrepresented borrowers and assuming risk on underrepresented exposures can be achieved without taking a net position. Improvement of the measurement of risks requires regular use of credit derivatives but not to take a net position. We thus argue that finding an association between gross positions and loan spreads supports the risk management channel.[7] Moreover, the absence of a relationship between the net position and the spread would be evidence against the presence of each of the three other channels.

2.3. The data

Our analysis is based on individual loan transaction data from the LPC DealScan database and bank level data from the US Call Reports. From the first database we obtain information on loan characteristics of syndicated loans, such as loan spread over LIBOR, loan maturity, loan amount, currency, loan purpose and loan type. We also ob-

[7] It is important to point out that risk management can also take place by taking a one-sided position (i.e., with a gross of zero). Hence, the absence of a relationship between gross positions and spreads cannot be taken to imply that there are no risk management benefits.

tain borrower characteristics such as industry, sales, rating and stock market listing. We only consider completed term loan transactions. The database also provides information about the lead arrangers that are involved in the syndicate. In addition, we consider only loans with a single lead arranger, as in the case of multiple lead arrangers it is difficult to attribute the effects of credit derivative use of individual banks to the spread offered by the lending syndicate[8]. We match the lead arranger with bank-level data from the Call Reports. From the Call Reports we obtain quarterly bank balance sheet and income statement information. We also collect information about banks' off-balance sheet activities from these reports. From these we construct our main variables of interest: the outstanding volume of credit derivatives purchased and sold by the bank in each quarter. Note that credit derivatives are mostly in the form of credit default swaps (CDS), which are dominated by single-name CDS on large corporate borrowers. Thus our variable of interest captures the same type of firms as observed in the syndicated lending market. The sample covers the period from the first quarter of 1997 (when reporting requirements for credit derivatives started) until the fourth quarter of 2009. The final sample comprises a total of 2566 loan observations and 76 banks.

Table 1 reports summary statistics for our sample (loan spreads, gross and net positions are winsorized at 2.5%). The average (all-in) loan spread in our sample is 259.12 basis points and varies between 30 and 455 basis points. Our main variables of interest are banks' gross and net credit derivative positions. The gross position (the outstanding sum of protection bought and sold) is on average around 40% of total assets. The net position (the difference of outstanding bought and sold protection) is only 2% of assets on average (but varies widely between banks). Figures 2.1(a) and 2.1(b) depict the evolution of the quarterly averages of the gross and net credit derivatives positions over time[9]. It can be seen that, starting from the first quarter of 1997, the gross position held by banks increases over time. The net position fluctuates between -1% and 4% of assets. We can also see that starting from the end of 2005, banks increased their net purchase of protection, presumably in anticipation of a higher share of problem loans. Moreover, the coefficient of variation (mean divided by standard deviation) of the gross and net posi-

[8]This is not a concern regarding the sample selection since from the entire sample of loans from DealScan database, about 80% are made by a single lead arranger.

[9]These figures exclude the Bank of America, which bought very large amounts of protection in 2005 and 2007.

tion is comparable (0.49 and 0.42), suggesting that the measures exhibit similar overall variation. The rank correlation between both metrics is positive but rather low (0.20).

Figure 2.2 compares the loan spreads charged by banks that are active in credit derivative markets with those of banks that are not. For this figure we consider a bank being "active" from the moment it either purchases or sells protection for the first time. We can see that throughout the sample period, active banks tend to charge lower spreads than passive banks.[10] The mean difference in the spread of active and passive banks is 44.73 bps and this difference is significant (t-statistic of 9.79). We also note that during the sample period there does not seem to be any trend in the spread differences among the group of banks. This is first evidence for credit derivatives use being associated with a persistently lower loan spread. In addition, the figure suggests that the spreads of the active banks are more stable over time compared to their passive counterparts, consistent with risk management effects.

2.4. Empirical method and results

2.4.1. The empirical strategy

We estimate a loan-spread model that controls for loan, borrower and bank characteristics. We proxy banks' credit derivative use with the gross and net positions of credit derivatives scaled by (total) assets. A significant negative relationship between the gross position and the loan spread supports the risk management channel. A negative significant coefficient on the net position would provide evidence for the hedging or capital relief channel, while a positive relationship would be consistent with credit derivatives leading to incentive problems. The various channels also lead us to expect that the impact of credit derivative use may depend on the borrower type and whether banks operate under adverse circumstances. In a second step, we also study whether the loan-spread impact differs among borrowers and whether it changes during the crisis of 2007-2009.

In order to investigate whether credit derivative use has an effect on loan spreads, we estimate a standard loan pricing model (see Harjoto et al. (2006)), which we augment by

[10]In the figure, for some quarters averages for passive banks are missing since there were no loans originated by these banks.

adding banks' gross and net positions in credit derivatives as main explanatory variables:

$$\begin{aligned} spread_{b,f,l,t} \;=\; & \alpha + \sum_{b=1}^{B} \beta_{1b} bank_b + \sum_{t=1}^{T} \beta_{2t} year_t + \beta_3 grossCD_{b,t} + \beta_4 netCD_{b,t} + \sum_{i=1}^{K} \phi_i F_{i,f,t} \\ & + \sum_{i=1}^{K} \gamma_i L_{i,b,f,l,t} + \sum_{i=1}^{K} \delta_i B_{i,b,t} + \epsilon_{b,f,l,t}, \end{aligned} \tag{2.1}$$

where b denotes the bank, f the borrower (firm), l the loan and t time. In (2.1) *spread* is the loan spread, *bank* is a set of bank dummies and *year* is a set of time dummies. The term $grossCD$ denotes the sum of credit protection sold and purchased by a bank and $netCD$ is the difference between credit protection purchased and credit protection sold. The terms F_i denote borrower characteristics. These include dummies indicating the industry group of the borrower and the logarithm of the sales in US dollars. We expect firms with more sales to have lower spreads since large firms are more likely to have built a reputation and are less likely to suffer from problems of informational asymmetries. We also include a dummy indicating whether the borrower is listed on the stock market (*ticker*). We expect a negative association between this dummy on one side, and the loan spread on the other side. This is because public firms are likely to face lower informational asymmetries. Further we control for a set of dummies that indicate the S&P senior debt rating of the borrower (using non rated firms as the omitted category). Within the set of ratings, we expect higher rated firms to be charged lower spreads.

The terms L_i refer to loan characteristics. Following Harjoto, Mullineaux and Yi (2006), these controls include two dummy variables that indicate whether the database denotes a loan as *secured* and whether it denotes a loan as *unsecured* (the omitted category are loans for which securitization information is missing). It is not clear what sign to expect for these dummies. Safe borrowers may use collateral to signal their type to the lender (Besanko and Thakor (1987) and Chan and Kanatas (1985)). If this is the case, secured loans should be associated with lower spreads. However, there is evidence suggesting that lenders require collateral for riskier borrowers, which would lead to higher spreads (Berger and Udell (1990) and Berger, Frame and Ioannidou (2011)). We also include among the controls the logarithm of the loan amount in US dollars ($log(amount)$). Again, the loan amount coefficient can be positive or negative. Larger and safer firms usually demand larger loans, hence we should expect lower spreads for such loans. However, larger loans also have a higher probability of default and may in addition result in overexposures in banks' credit portfolios, suggesting higher spreads. The next set of variables contains dummies for the loan maturity: *shortmaturity* for term loans with maturity of less than two years, *intermediatematurity* for term loans with maturity between two and five years, and *longmaturity* for term loans with a maturity exceeding five years. The expected sign on these dummies is also ambiguous. There is some evidence of longer maturity loans being associated with higher spreads (Dennis, Nandy and Sharpe (2000)) but other studies show that short maturity loans exhibit higher spreads (Strahan (1999)). We further include a set of loan purpose dummies (*corporatepurposes*, *acquisitions*, *backupline*, and *debtrepayment*). Finally, we consider dummies for the tranche type. $TERM$ indicates terms loans without a tranche structure and $TERMA$, $TERMB$, $TERMC+$ indicate whether a loan is designated to tranche A, B, C or higher, respectively (for details, see also Nadauld and Weisbach (2011)).

The terms B_i stand for bank characteristics. We include as a proxy for bank size the logarithm of assets. We expect this coefficient to be negative given that larger banks are expected to have a lower cost of funds due to better access to debt markets. We also include a measure of a bank's liquidity equal to cash plus securities over assets (*Liquid Assets*/TA). We expect this coefficient also to be negative, reflecting that also liquid banks find it cheaper to fund loans. Further we include as additional controls the return on assets (ROA), the amount of charge-offs over assets ($Chargeoff/TA$), subordinated debt over assets (*Subdebt*/TA), loan loss provisions over assets (*LoanLossProv.*/TA) and equity over assets (*Equity*/TA).

2.4.2. Credit derivative use and loan spreads

Table 2 reports the results of regressions that relate loan spreads to banks' credit derivative positions. All regressions include borrower controls, loan controls and dummies for industry, loan purpose and year. Standard errors are clustered at the bank level. Regression 1 includes the bank controls next to the gross and the net positions. The coefficient of the gross position takes a negative value (-8.86) and is significant at the 1%-level. The coefficient of the net position is not significant. This result provides support for the risk management channel but not for the other channels. The magnitude of the effect for the gross position indicates economic significance. It implies that a one standard-deviation increase in the ratio of the gross position over (total) assets decreases loan spreads by about 8 basis points. Given a mean spread of 259 bps this implies spreads fall on average by 3%. The implied annual savings for borrowers are about \$127.000 per loan as the average loan size is \$159 mln in our sample. This is a considerable impact – in particular since this is the impact on the *average* borrower in the syndicated loan market (many of these borrowers are not actively traded in the credit derivative market). Also note that the gross and net position exhibit approximately the same relative variation compared to their mean (coefficient of variation), indicating that there is no bias in favor of finding a significant effect on one or the other measure.

Among the borrower controls, we can see that larger firms are charged lower spreads. The same is found for firms which have a stock exchange listing – but the significance is only marginal. Various rating category dummies turn also out to be significant (the insignificance of the other rating dummies is due to the fact that for these ratings there are only few observations). Among the significant rating categories, loan spreads are found to decline with the firm's S&P rating – as expected. Turning to the loan controls, we find that there is a negative and significant association between loan amount and loan spreads. This may reflect the tendency for large loans to be given to larger, established, firms. Secured loans have significantly higher, and unsecured loans have significantly lower, spreads. This is explained by banks being more likely to require collateral for lending to risky firms (see Berger, Frame and Ioannidou (2011)). Among the maturity variables, the long-term dummy enters with a negative sign and is weakly significant (at the 10% level). The loan tranche indicators are positive and significant. Since the omitted category is loans without a tranche structure, this indicates that tranched loans are more risky and consequently command higher spreads. From the bank controls only the charge-offs are significant. They enter with a positive sign. This result likely reflects that banks that have many problem loans in their book incur higher costs and pass these costs on to their borrowers.

Regression 2 includes bank fixed effects instead of bank controls. The coefficient on the gross position increases in absolute value to -10.35. The net position remains insignificant. The other coefficients in the model are mostly unchanged. We take this model to be our baseline model. There is the concern that the insignificance of the net position is driven by a potential multicollinearity between net and gross positions. However, the correlation among these variables is not very high (0.22). To be sure, regression 3 reports results where the gross position is excluded. The net position remains insignificant. The impact of the net position may conceivably also depend on whether the net is positive or negative. We thus modify the baseline model by including separate terms for positive and negative net-positions (unreported). These terms are each insignificant and the gross position remains significant.

Some of the previous results suggest that loan characteristics and loan spreads are jointly determined. In regression 4 we follow the literature by estimating a model that excludes the loan controls. The coefficient of the gross position now increases in absolute value to -13.69. This surely reflects that some of the loan controls are correlated with credit derivative use at banks. However, the coefficient on the gross position remains significant and that on the net position stays insignificant. The key result is thus robust to the exclusion of potentially endogenous loan controls.

A key concern at this stage is that banks also have means for risk management other than through credit derivatives. Use of these means is conceivably correlated with credit derivatives. The gross credit derivative position may hence also proxy for general sophistication in bank risk management. In this case, our estimated effects cannot (exclusively) be attributed to credit derivatives. To address this issue, regression 5 controls for the stock of other derivatives used for hedging (these derivatives include interest rate, foreign exchange, equity, and commodity derivatives). The coefficient on the gross position is essentially unchanged and the other derivatives turn out to be insignificant. We have also estimated a version of regression 5 where instead of including the sum of all other derivatives we include each derivative separately. The results for our variables of interest are essentially unchanged (not reported here). This result suggests that the risk management benefits do indeed come through credit derivatives. Among the other derivatives all are insignificant except the commodity derivatives (which are significant at the 10% level).

Another important issue is the potential endogeneity of the gross credit derivative position. A bank that pursues a risky strategy may simultaneously underprice in the syndicated lending market and write protection in the CDS market. Alternatively, a bank that faces good lending opportunities may have low lending rates and hedge the additional amount of loans using credit derivatives. However, this type of endogeneity affects the net position of credit derivatives. It is more difficult to conceive how endogeneity may affect gross positions. Endogeneity problems are also limited in our setting since we control for bank fixed effects and time effects. Nonetheless, we also employ an IV-estimation to account for remaining endogeneity. Our instruments for the gross position are other derivatives held for trading purposes.[11] Banks typically start hedging activities in derivatives following trading in derivatives. We thus expect derivatives for trading to be a good explanatory variable for credit derivatives (Minton, Stulz and Williamson (2009) find that use of credit derivatives is highly correlated with the trade of other derivatives). At the same time, we do not expect trading of derivatives to have a direct independent effect on the lending business of banks. Trading is typically done in response to short-term profit opportunities and it is difficult to conceive of how this should affect a bank's lending strategy. In addition, in most banks trading activities and lending activities are carried out in separate organizational entities that do not communicate. Regression 6 reports results from an IV-regression where the gross credit derivative position is instrumented with the various other derivatives held for trading (interest rate, foreign exchange, equity and commodity derivatives). The F-test of 636.38 in the first stage of the IV regression indicates that trading derivatives are good instruments as they are highly correlated with credit derivatives. The J-test has a p-value of 0.40. This indicates absence of endogeneity for the instruments, confirming that non-credit derivatives trading activities are not related to loan pricing. The coefficient of the gross position is still significant. The size of the coefficient decreases in absolute size, but only slightly so (to -9.22).

One could argue that our instruments are capturing other bank characteristics, such as manager sophistication or good IT system, which would also lead to lower spreads. To control for this, we run our model restricting the sample to sophisticated banks (not reported). For this, we define a bank as being sophisticated from the quarter it starts using derivatives for hedging purposes. The gross position remains negative and significant. To further test for this identification concern, we re–estimate our baseline model restricting the sample to the top 50 banks in the sample[12] (not reported). Our

[11] The Call Reports distinguish derivatives held for trading for all derivatives except credit derivatives.

[12] We take this information from a Federal Reserve Statistical Release in the FED's website, reporting the largest commercial banks in the US.

results remain unchanged.Finally, we have also included borrowers fixed effects. This would be a good solution to control for borrower's unobserved characteristics. However, we do not have a panel structure in our data, therefore we do not observe many borrowers more than once in our sample. This leads to a much more restricted sample when using borrower fixed effects. When estimating our model in this case, our results turn not significant. This may be the result of the mentioned data constraints.

A specific type of endogeneity may arise from a contemporaneous dependence of gross positions on demand or supply side considerations. In regression 7 we thus include the one-year lagged gross position – instead of the contemporaneous one. The coefficient now increases in absolute size (to -11.50) and is significant at the 1% level. We conclude that our results are not driven by endogeneity problems associated with banks' gross positions in credit derivatives.

Call Report data does not differentiate between credit derivatives used for trade and not for trade. This opens up the possibility that our results are influenced by market-making activities of banks. In a robustness check we hence exclude dealer banks from the sample. Following Hirtle (2009) we define dealer banks as banks that have more than $10 billion in credit derivatives at some point in our sample and banks that are among the two largest credit derivatives users in a given period. Column 8 shows that the coefficient increases in absolute value and remains negative and significant (the effect remains economically significant; a one standard-deviation increase in the gross position decreases loan spreads by about 2.6%).[13] We have also run other robustness checks, such as allowing for group-specific trends for active and passive banks, clustering at the firm level and scaling variables by loans instead of assets (not reported here). These do not show any noteworthy change in our variables of interest. Furthermore, there might be some heterogeneity across banks with respect to the effect of the different channels on loan spreads. For instance, one concern may be that the capital relief channel affects only banks with equity levels closer to minimum requirements. We have tested for this by including an interaction term of the net position with a dummy which indicates whether a bank is close to minimum requirements. The effect remains not significant. One could also argue that the effect of the risk management channel differs for different

[13]We have also estimated our model using the approach in Minton et al. (2009) to exclude dealers from the sample, which is only to include banks with a (strictly) positive net position. The results are similar.

diversification levels. We have tested this by including an interaction term of the gross position and different diversification measures[14]. We found that the effect of the risk management channel does not vary with diversification levels. This may reflect that the benefits from risk management go beyond diversification, and they extend also through indirect benefits: the use of these derivatives leads banks to measure and price risk more accurately. Hence, this makes banks lending behavior more efficient.

In sum, the evidence in this section suggests a stable and negative association between banks' gross credit derivative positions and loan spreads. The effect is robust to controlling for various forms of biases that may arise in the context. No association between net positions and loan spreads can be found. The results thus lend support to the hypothesis that banks use credit derivatives to manage risks more effectively and pass on gains to borrowers. By contrast, there is no support for other channels through which credit derivative may affect loan spreads.

2.4.3. Loan spreads by borrower type

The baseline analysis shows that borrowers at banks active in credit derivatives benefit from lower loan spreads. In this section we analyze whether this effect is uniform across borrowers, or whether specific types of borrowers benefit more. Since the universe of liquid credit derivatives mainly consists of large, investment-grade rated corporate borrowers, our expectation is that risk management gains are the largest for these firms.

For this we add interaction terms between gross positions and borrower types to the baseline model. Table 3 reports the results. Regression 1 shows the results of a specification that looks at whether the credit derivative effect is different for large firms. The dummy variable *Large* indicates whether a firm belongs to the 25% largest percentile of our sample in terms of sales. The interaction term of this variable with the gross amount in credit derivatives captures the difference in the effect of risk management for these firms. The coefficient of the interaction term is negative and significant, indicating that the largest firms benefit more from risk management at banks.

Regression 2 studies whether investment grade rated firms experience a different loan spread effect. We include interaction terms with dummies indicating whether the firm

[14] These measures include the non interest income share (as in Baele et al. (2007)), the correlation between the ROA of a given bank and the annual average ROA of the sample (as in Silva Buston (2012)), and revenue diversity (as defined in Laeven and Levine (2007)).

is a low risk entity (i.e., the S&P rating of its senior debt is A or better) or a high risk entity (i.e., the S&P rating is BBB or worse). The omitted category are unrated firms. The low risk interaction term obtains a very high coefficient in absolute values (-42.24) but is only weakly significant. The low significance most likely reflects limited rating coverage in our sample (low risk firms represent only a fraction of 0.7% in the sample while high-risk firms are 16%; the remaining 83.3% are unrated firms). The combined coefficient from the interaction term and the non-interacted gross position is -52.76. Thus, a one-standard deviation increase in gross positions at banks results in a loan spread for firms rated low-risk that is 46 bps lower (equivalent to a spread reduction of 18%).

We also study whether firms listed at the stock market benefit more from banks' use of credit derivatives. Stock market listing – after controlling for the presence of a rating – is likely to be unrelated to a firm's presence and liquidity in the credit derivative market. Consistent with this we find that the interaction term of stock market listing and the gross credit derivative position is insignificant (see regression 3).

Regressions 1-3 have considered whether firms more likely to be actively traded experience different credit derivative effects. In the respective regressions, the non-interacted gross-position coefficient stays significant. This result suggests that firms less likely to be actively traded also benefit from enhanced risk management. In regression 4 we address this question directly. We constrain our sample to the set of firms that are unrated (and hence are very unlikely to have active credit derivatives trading). The effect on the gross position is significant and the coefficient (-13.23) is of similar magnitude to the one in the baseline model. This suggests that risk management benefits also extend to the firms for which the bank cannot directly manage risks using credit derivatives. This is consistent with risk management (balancing risks within the portfolio, keeping total risks close to the desired levels and improved measurement of risks) that reduces the banks' *overall* (marginal) cost of taking on risk. It may also partially reflect *pseudo-pricing* – the practice of banks to price untraded exposures using correlated traded exposures – which allows banks to reduce risks on exposures for which credit derivatives do not exist.

In sum, the evidence in this section suggests that firms generally seem to benefit from credit derivative use at banks, but firms that are more likely to be actively traded in the credit derivative market are the largest beneficiaries.

2.4.4. Loan spreads during the crisis of 2007-2009

It has been argued that financial innovations, while beneficial in normal times, may amplify the effects of crises. While this is likely to be the case under (for example) the incentive channel, the presence of a risk management channel suggests that benefits continue to be present under adverse circumstances. We note that the risk management channel, unlike the incentives, hedging and capital relief channel, is likely to be persistent over time. This is because banks' decision to engage active credit portfolio management is typically a one-time decision, and bank risk culture tends to be a stable characteristic (see Ellul and Yerramilli, 2010; Fahlenbrach, Prilmeier and Stulz, 2011). In this section we investigate whether the difference in loan pricing between active and passive banks persists during the crisis of 2007-2009. For this purpose, we re-estimate the baseline model allowing the coefficient of interest and the intercept to differ after the onset of the financial crisis.

Table 4 presents the results. Regression 1 includes a dummy indicating the crisis period (which we take to start in the last quarter of 2007). This dummy is significant and its coefficient indicates that loan spreads increase during the crisis period by 42.66 bps. Regression 2 includes the interaction term between the gross position of credit derivatives and the crisis dummy. The non-interacted gross position term stays significant and obtains a coefficient of -12.19. The interacted gross position term is insignificant. This result suggests that the benefits of credit derivative use remain unchanged after the onset of the financial crisis.

A concern with regression 2 is that banks may have changed their credit derivative activities in response to the crisis. The crisis interaction term in regression 2 relates to the contemporaneous gross position. It thus does not directly measure benefits from risk management prior to the crisis. In regression 3 we look at how loan spreads change for banks depending on their credit derivative activity prior to the crisis. We thus include an interaction term of the crisis dummy with banks' gross position in the third quarter of 2007. We find that the interaction term remains negative and insignificant. The persistence of the loan spread benefit is thus not driven by banks' responses to the crisis but by prior engagement in credit derivative markets.

We finally consider whether net positions in credit derivative markets lead to different loan spreads in the crisis. We thus include the net position and the net position interacted with the crisis dummy. The interaction term is insignificant. We also note that our prior results are unchanged as the non-interacted net term also remains insignificant.

In conclusion, the evidence suggests that even though loan spreads generally increased after the onset of the financial crisis, the benefits of borrowing from banks' engaging in risk management via credit derivatives persist during the crisis.

2.4.5. Credit derivative use and bank lending

The evidence from the loan-level regressions supports the hypothesis that banks use credit derivatives for risk management purposes. In this section we look at banks' lending characteristics in general. If banks successfully manage their risks, we would expect banks active in credit derivative markets to experience lower losses on loans. In addition, we would expect these banks to be less likely to be constrained when credit risks in the economy worsen and also to exhibit more stable lending behavior.[15]

Specifically, we relate in this section lending characteristics at the bank level to banks' use of credit derivatives. First, we study whether charge-offs on commercial and industrial loans are related to credit derivative use and whether this effect changes during the crisis. Second, we study how the lending volume of banks before and during the crisis depends on the credit derivative activities. For this analysis we use yearly bank level data from the Call Reports. We include in our sample observations for the years 2006 to 2010. We estimate two models:

$$\begin{aligned} Netchargeoffs/TA_{b,t} &= \alpha + \beta_1 Crisis_t + \beta_2 GrossCD_{b,t} + \beta_3 Crisis_t * GrossCD_{b,t} \\ &\quad + \sum_{i=1}^{K} \phi_i B_{i,b,t} + \epsilon_{b,t} \end{aligned} \tag{2.2}$$

$$\begin{aligned} CommercialLoans/TA_{b,t} &= \alpha + \beta_1 Crisis_t + \beta_2 GrossCD_{b,t} + \beta_3 Crisis_t * GrossCD_{b,t} \\ &\quad + \sum_{i=1}^{K} \phi_i B_{i,b,t} + \epsilon_{b,t} \end{aligned} \tag{2.3}$$

In the first model, the dependent variable is the sum of net charge-offs (charge-offs minus

[15] Figure 2 already suggested that the loan pricing behavior of active banks is more stable than that of passive banks (the standard deviation of the quarterly spreads of the active banks is nearly 50% less than that of the passive banks).

recoveries) of commercial and industrial loans minus the net gains of credit derivatives scaled by assets. We include the gains on credit derivatives in order to capture potential risk management benefits: if a bank effectively manages its risk, charge-offs (recoveries) of loans should be off-set by gains (losses) in credit derivatives holdings. The terms B_i stand for other bank characteristics. These include: subordinated debt, equity, liquid assets, total loans and commercial loans (scaled by assets). We also include the logarithm of assets and the ROA.

If credit derivative use extends risk management benefits, we should see that banks with larger gross amounts of credit derivatives face a lower level of net charge-offs in a given period. We hence expect the coefficient on the gross amount of credit derivatives to be negative in the first model. The crisis regressions have shown that (although spreads increased across the board) the loan spread differential between banks active on both sides of the credit derivative market and other banks persisted during the crisis. This result suggests that banks with active risk management did not encounter larger losses than other banks. Accordingly, we expect the interaction term of the gross position and the crisis dummy in the model to be insignificant or even negative.

The dependent variable in the second model are commercial loans scaled by assets. We include the same set of bank controls but exclude the dependent variable. Banks that successfully manage their risk should be less constrained under adverse conditions. They should have more stable lending and possibly be able to expand lending activities (relative to passive banks) in times of crisis. We thus expect the interaction term of the gross derivative position with commercial lending to be non-negative or even positive.

Table 5 displays the results of both models. In both regressions standard errors are clustered at the bank level. Regression 1 displays the results for the net charge-off regression. We see that banks with higher gross positions have significantly lower charge-offs as indicated by the coefficient of the gross positions. The coefficient on the crisis dummy is positive and significant – indicating that charge-offs increased during the crisis. The interaction term of the crisis dummy with the gross position is insignificant. Thus, the advantage (in terms of lower charge-offs) of banks active on both sides of the credit derivative market persists during the crisis.

Regression 2 estimates the lending volume model. We find that the coefficient for the gross position in credit derivatives is not significant in this regression, indicating that active users of credit derivatives do not extend more commercial and industrial loans than other banks. The negative sign on the crisis dummy shows that the volume of commercial and industrial loans extended by banks overall decreases during the crisis. The interaction terms of the crisis dummy and the gross position is positive and significant. Thus, banks active on both sides of the market increased their lending volume relative to passive banks. This is consistent with risk management stabilizing the lending activities of these banks.

Summarizing, the bank-level regressions suggest that banks active on both sides of the credit derivative market face lower charge-offs in both normal times and in times of crisis. In addition, they are able to expand their lending relative to passive banks in crisis times. These findings are consistent with risk management benefits from credit derivative use.

2.5. Conclusions

The debate on the costs and benefits of financial innovations is still ongoing. There is no consensus about whether their impact on the financial system is broadly a positive one or not. To a significant extent this is owed to the fact that we have little knowledge about the channels through which financial innovations affect the behavior of players in the financial system. In this paper we have investigated financial innovations and their role in the economy by studying their impact on loan pricing. We focus on credit derivatives – probably the most significant financial innovation of the past decade. There are several potential channels through which credit derivatives may impact lending behavior and affect economic activity. We derive hypotheses that relate these channels to loan pricing and use a new empirical strategy that allows us to identify the key channel.

We estimate a standard pricing model for syndicated loans that includes information on banks' use of credit derivatives and controls for loan, borrower and bank characteristics. Our key result is that a bank's gross position in credit derivatives has a significantly negative and robust effect on corporate loan spreads. We argue that this indicates that banks use credit derivatives for risk management purposes and pass the arising benefits (at least partly) on to borrowers. Such benefits include a better risk-balance within the loan portfolio, an improved ability to keep risk-levels at target ratios but also banks becoming more sophisticated in the measurement and control of their credit risks. We also find that the benefits from risk management persist after the onset of the financial crisis. In addition, banks that actively manage their risks with credit derivatives exhibit lower losses and have a more stable supply of loans during the financial crisis. Taken together, our paper provides consistent evidence on significant real effects of financial innovations that are present independent of economic conditions. While our analysis indicates risk management benefits at the individual bank- and borrower-level we leave the analysis of systemic and macroeconomic implications of banks' use of credit derivatives for future research.

2.6. Tables

Table 1: Descriptive statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
Loan characteristics				
Spread (in bps)	259.120	108.591	30	455
Log(amount)	18.133	1.307	13.081	21.821
Secured	0.446	0.497	0	1
Unsecured	0.054	0.227	0	1
Short Maturity	0.093	0.291	0	1
Intermediate Maturity	0.481	0.499	0	1
Long Maturity	0.363	0.481	0	1
TERM	0.518	0.499	0	1
TERM A	0.119	0.324	0	1
TERM B	0.332	0.471	0	1
TERM C	0.029	0.169	0	1
Borrower characteristics				
Log(sales)	19.232	1.732	0.693	25.710
Ticker	0.426	0.494	0	1
AAA	0.0003	0.019	0	1
AA	0.0007	0.027	0	1
A	0.008	0.090	0	1
BBB	0.047	0.211	0	1
BB	0.104	0.306	0	1
B	0.159	0.366	0	1
CCC	0.027	0.164	0	1
CC	0.001	0.033	0	1
C	0	0	0	0
Bank characteristics				
Gross CD/TA	0.404	0.817	0	3.988
Net CD/TA	0.021	0.050	-0.039	0.225
Derivatives not for trade/TA	0.302	0.330	0	1.263
Log(assets)	19.216	1.996	9.998	21.566
ROA	0.006	0.005	-0.043	0.068
Sub Debt/TA	0.331	0.140	0.0006	0.848
Liquid Assets/TA	0.196	0.112	0	0.991
Charge-offs/TA	0.002	0.003	0	0.072
Equity/TA	0.094	0.099	0.051	0.961
Loan Loss Prov./TA	0.0024	0.0030	-0.004	0.031

Table 2: Credit derivative use and loan spreads

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gross CD/TA	-8.865***	-10.35***		-13.69***	-10.19***	-9.225**		-22.29***
	(2.333)	(2.131)		(1.893)	(2.085)	(4.676)		(7.341)
Net CD/TA	29.29	18.13	4.622	24.16	17.45	16.66		37.94
	(42.50)	(31.76)	(29.69)	(31.64)	(31.80)	(46.14)		(64.40)
Derivatives					2.404			
not for trade/TA					(9.249)			
Gross CD/TA lag							-11.50***	
							(3.558)	
Net CD/TA lag							-20.01	
							(20.72)	
Log(sales)	-6.060***	-6.043***	-5.964***	-13.59***	-6.044***	-6.035***	-5.653***	-4.743***
	(1.476)	(1.498)	(1.495)	(2.241)	(1.497)	(1.593)	(1.590)	(1.595)
AAA	-58.14***	-66.70***	-72.59***	-88.81***	-67.30***	-67.34***		-67.53***
	(12.78)	(14.19)	(14.17)	(14.08)	(13.57)	(14.71)		(12.93)
AA	-39.75	-51.51	-52.98	-38.49	-51.83	-51.67	-47.54	68.00***
	(80.63)	(84.51)	(84.02)	(84.38)	(84.65)	(83.44)	(85.82)	(11.30)
A	-70.06**	-68.00**	-68.31**	-81.97**	-68.13**	-68.04**	-66.01*	-82.59**
	(32.22)	(32.78)	(33.51)	(35.14)	(32.68)	(26.90)	(38.06)	(31.24)
BB	-7.82*	-7.235*	-6.946*	5.922	-7.242*	-7.204	-5.876	-5.707
	(4.053)	(3.673)	(3.685)	(4.340)	(3.678)	(6.361)	(4.329)	(6.885)
B	29.59***	30.40***	30.79***	50.07***	30.38***	30.44***	31.10***	24.47***
	(6.79)	(6.247)	(6.194)	(7.592)	(6.235)	(5.888)	(7.255)	(8.200)
CCC	81.92***	81.58***	81.78***	104.5***	81.62***	81.60***	92.58***	82.08***
	(6.879)	(6.874)	(6.908)	(9.091)	(6.825)	(12.33)	(7.400)	(7.071)
CC	176.9***	178.7***	180.8***	186.8***	178.0***	178.9***	177.4***	164.1***
	(46.27)	(45.00)	(44.00)	(39.45)	(45.31)	(41.06)	(43.48)	(46.69)
Ticker	-12.71*	-9.228	-9.682	-11.15	-9.236	-9.277**	-11.47*	-11.61
	(7.01)	(6.588)	(6.622)	(6.857)	(6.591)	(4.326)	(6.248)	(8.838)
Log(amount)	-15.62***	-16.87***	-16.78***		-16.87***	-16.86***	-16.01***	-15.79***
	(2.325)	(2.452)	(2.431)		(2.459)	(2.225)	(2.796)	(2.499)
Secured	17.16**	16.79***	16.48***		16.82***	16.76***	12.83**	15.43**
	(5.336)	(5.255)	(5.294)		(5.247)	(4.607)	(5.615)	(7.309)
Unsecured	-59.61***	-59.41***	-60.21***		-59.38***	-59.50***	-59.23***	-59.77***
	(7.481)	(7.898)	(7.956)		(7.937)	(8.046)	(9.595)	(10.04)

Table 2: Credit derivative use and loan spreads (cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interm. maturity	-8.87	-10.66	-11.18		-10.64	-10.72*	-10.31	1.420
	(8.907)	(8.745)	(8.826)		(8.722)	(6.001)	(7.634)	(7.638)
Long maturity	-11.36	-8.677	-8.986		-8.657	-8.710	-8.629	-3.077
	(7.979)	(7.595)	(7.634)		(7.597)	(6.608)	(9.142)	(11.93)
TERM A	27.78***	25.20***	25.78***		25.16***	25.26***	24.14***	25.03***
	(5.788)	(5.120)	(5.331)		(5.097)	(5.869)	(5.903)	(6.081)
TERM B	59.96***	55.60***	56.31***		55.59***	55.68***	53.12***	56.94***
	(6.333)	(6.924)	(6.900)		(6.923)	(5.535)	(7.259)	(9.597)
TERM C	43.84***	38.58***	40.53***		38.61***	38.79***	31.49***	44.25***
	(9.619)	(9.454)	(9.340)		(9.451)	(10.84)	(10.34)	(16.14)
ROA	-265.08							
	(373.05)							
Subdebt/TA	-11.40							
	(33.26)							
Liquid Assets/TA	-30.63							
	(24.41)							
Chargeoff/TA	1,451.6***							
	(389.88)							
Log(assets)	-3.12							
	(2.759)							
Equity/TA	-4.406							
	(26.878)							
Loan Loss Prov./TA	-9.935							
	(1,004.3)							
F-stat IV						636.38		
J-test p-value						0.40		
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose Dummies	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,487	2,566	2,566	2,566	2,566	2,566	2,289	1,860
R-squared	0.350	0.386	0.383	0.306	0.386	0.386	0.371	0.391

The dependent variable is the all-in loan spread in basis points. All models are estimated using OLS with clustered robust standard errors at the bank level (in parentheses). ***, ** and * denote significance at the 1%, 5% and 10% level respectively. Model (5) uses IV estimation.

Table 3: Loan spreads by borrower type

	(1)	(2)	(3)	(4)
Gross CD/TA	-6.386***	-10.52***	-10.52***	-13.23***
	(2.048)	(2.455)	(3.310)	(2.777)
Large	-15.49*			
	(9.088)			
Gross CD/TA*large	-7.191***			
	(2.447)			
Low risk rated		-46.71		
		(43.90)		
High risk rated		1.860		
		(3.937)		
Gross CD/TA*low risk rated		-42.24*		
		(23.27)		
Gross CD/TA*high risk rated		0.157		
		(2.097)		
Ticker	-8.080	-10.60	-9.366	-8.597
	(6.845)	(6.485)	(7.164)	(11.44)
Gross CD/TA*ticker			0.507	
			(3.673)	
Borrower Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,566	2,566	2,566	1,672
R-squared	0.389	0.363	0.385	0.374

The dependent variable is the all-in loan spread in basis points. All models are estimated using OLS with clustered robust standard errors at the bank level (in parentheses). ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 4: Loan spreads during the crisis of 2007-2009

	(1)	(2)	(3)	(4)
Crisis	42.66***	45.14***	45.39***	45.70***
	(13.84)	(14.29)	(13.49)	(14.34)
Gross CD/TA		-12.19***	-12.10***	-12.38***
		(1.974)	(1.933)	(2.157)
Gross CD/TA*crisis		-0.349		-3.124
		(3.081)		(4.731)
Net CD/TA				25.68
				(26.39)
Net CD/TA*crisis				127.4
				(165.4)
Gross CD 07/TA*crisis			-0.472	
			(2.363)	
Borrower Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,730	2,524	2,524	2,524
R-squared	0.421	0.389	0.389	0.389

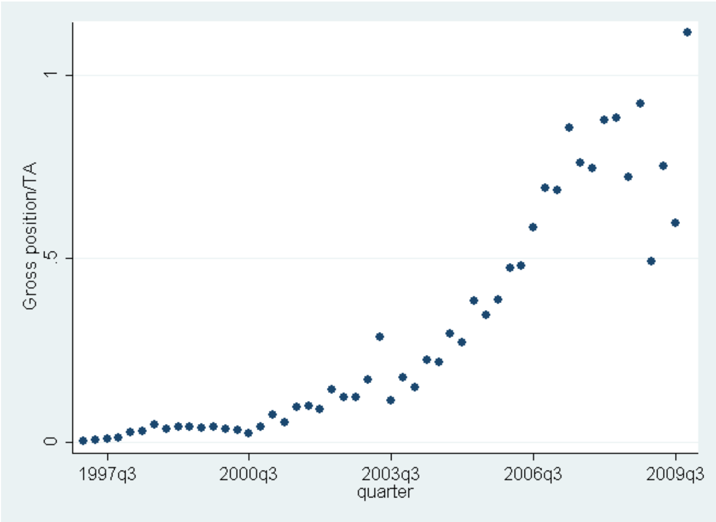
The dependent variable is the all-in loan spread in basis points. All models are estimated using OLS with clustered robust standard errors at the bank level (in parentheses). ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

Table 5: Credit derivative use and bank lending

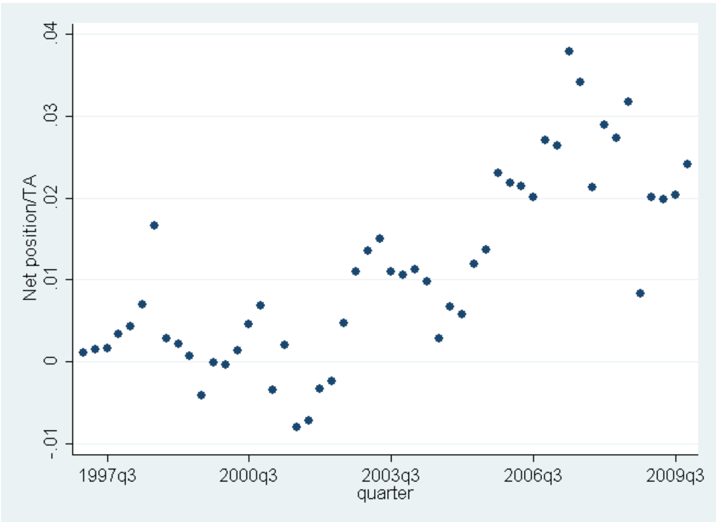
	(1)	(2)
Variables	Charge-offs commercial/TA	Commercial loans/TA
Crisis	0.000383***	-0.0307**
	(4.97e-05)	(0.0127)
Gross CD/TA	-0.300***	-12.57
	(0.104)	(19.89)
Gross CD/TA*crisis	0.120	41.93**
	(0.113)	(19.79)
Sub debt/TA	9.82e-05	-0.0769***
	(0.000158)	(0.0254)
Liquid assets/TA	0.000517***	0.0979***
	(0.000181)	(0.0325)
Equity/TA	0.000566**	-0.00101
	(0.000264)	(0.0405)
Log(assets)	9.72e-05***	0.00989***
	(1.39e-05)	(0.00212)
Total loan/TA	0.000887***	0.221***
	(0.000177)	(0.0321)
Commercial loans/TA	0.00305***	
	(0.000242)	
ROA	-0.0357***	-0.144
	(0.00205)	(0.253)
Constant	-0.00217***	-0.174***
	(0.000278)	(0.0489)
Observations	1,984	1,984
R-squared	0.358	0.145

The dependent variable in model (1) is the net charge-offs minus CDS gains scaled by total assets. The dependent variable in model (2) is the total volume of commercial loan extended scaled by total assets. All models are estimated using OLS with clustered robust standard errors at the bank level (in parentheses). ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

2.7. Figures



(a) Gross credit derivative positions



(b) Net credit derivative positions

Figure 2.1: Gross and Net derivative positions.

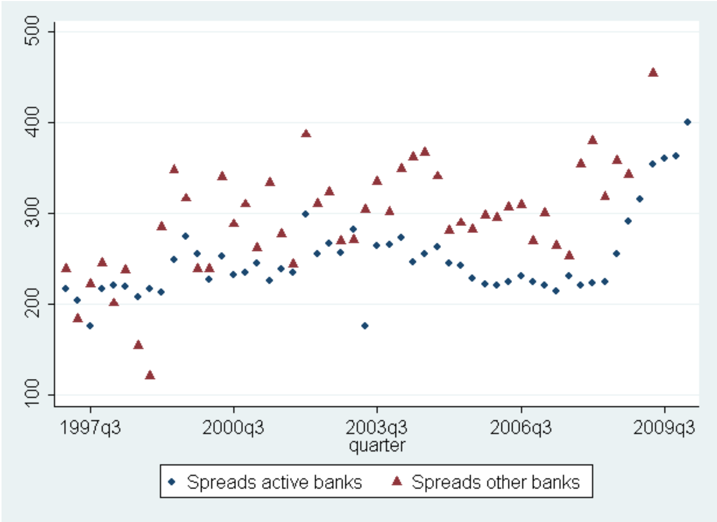


Figure 2.2: Spreads (all-in) of active versus other banks.

2.8. Appendix

Description of Variables

Gross CD/TA: Sum of credit derivative protection bought and sold divided by assets.
Net CD/TA: Difference between credit derivative protection bought and sold divided by assets.
Derivatives not for trade/TA: Total amount of derivatives used for hedging divided by assets. Equal to the sum of commodities, interest rate, equity and foreign exchange derivatives.
Log(Assets): Natural logarithm of the book value of total assets.
ROA: Net income by assets.
Sub Debt/TA: Subordinated debt divided by assets.
Liquid Assets/TA: Cash plus securities divided by assets.
Charge-offs/TA: Total charge-offs divided by assets.
Equity/TA: Bank equity divided by assets.
Loan loss Prov./TA: Loan loss provisions divided by assets.

Chapter 3

Active Risk Management and Banking Stability

3.1. Introduction

Financial innovations have played an important role during the last decade. This is mainly because their use for risk transfer and portfolio risk management, among other purposes, has increased exponentially during this period. According to data from the Bank for International Settlements (BIS), the use of credit default swaps (CDS)[16], one of the main financial innovations, increased from an outstanding gross notional amount near \$7 trillion at the end of 2005 to its peak level of around \$28 trillion in the second half of 2007. In the aftermath of the crisis, the outstanding gross notional amount in the banking sector slightly declined, reaching \$8 trillion in the second half of 2011. However, the turmoil of 2007–2009 highlighted the limited understanding of the use of these innovations in the financial system, the lack of reliable information about their use, and, most importantly, their effect on financial stability[17]. Thus, a key focus of current research is to understand and gather information on these innovations in order to shape the regulation to enhance the financial stability of the banking system.

The literature has identified several mechanisms through which financial innovations may affect the stability of the financial system[18]. On the one hand, financial innova-

[16] A credit default swap (CDS) is a contract where one party, the protection buyer, agrees to make periodic payments to the other party, the protection seller, in exchange for protection in the event of default of the reference entity (the borrower). If default occurs, the protection seller pays the amount of the loss to the protection buyer.

[17] For a review of credit risk transfer activity see BIS (2008). The importance of the use of credit derivatives for risk management and their effects on financial stability is highlighted in Geithner (2006).

[18] See Duffie (2008) for an overview of credit risk transfer with financial innovations and its potential

tions have been blamed for reducing banks' stability because they increase risk-taking incentives at banks (Santomero and Trester (1998), Duffee and Zhou (2001). Cebenoyan and Strahan (2004) and Loutskina and Strahan (2006) provide empirical evidence in this regard). Moreover, the transfer of risk from the banks' portfolios may reduce their incentives to screen and monitor their borrowers, leading them to hold a riskier pool of loans (Morrison (2005); Ashcraft and Santos (2009) provide empirical evidence). On the other hand, some researchers have pointed out that financial innovations enhance financial stability since they allow institutions to diversify their risk in a better way (Wagner and Marsh (2006)). The use of innovations for diversification may also induce banks to assess credit risk more accurately. Furthermore, risk management enables financial institutions to isolate financing and investment conditions from shocks (Froot et al. (1993); empirical evidence is given by Norden et al. (2012)). In addition, innovations may allocate risks in the financial system more efficiently, since the risk may be passed on to more stable financial institutions (Wagner and Marsh (2006)). In the process of transferring the risk, stability may also increase as a result of the greater liquidity in the system (Santomero and Trester (1998), Wagner (2007)).

There is little theoretical and empirical work on the net impact of financial innovations on banking stability. Most of the existing literature has focused on the effects on risk-taking. Furthermore, this literature has considered only the effects of the transfer of risk from banks' portfolios. However, CDS notional amounts reported in the banking sector show that banks sell nearly as much protection as they buy in CDS markets. This suggests that banks do not use CDS only to transfer risk out of the portfolio, but also to source new risks. The contribution of this paper is then twofold. First, in contrast to previous theory papers, we capture this behavior of banks in our model: instead of considering only risk shifting from the banks' portfolios, we study the impact of *active* credit risk management. That is, we model banks buying *and* selling protection in the CDS market. Second, we contribute by providing a theoretical model and empirical evidence for the net effect of the active use of CDS at banks on banking stability. We examine two opposing effects of CDS on stability: a negative effect caused by increased risk-taking incentives at banks, and a positive effect that arises from the isolation of banks' credit supply from varying economic conditions[19].

effects on financial stability.

[19]Estrella (2002) and Loutskina and Strahan (2006) study the effects of securitization on the smoothing

We consider a representative bank subject to capital requirements. These requirements determine the maximum level of risk allowed for a given level of capital. The portfolio risk varies because of shocks to the borrowers' repayment probability, which we interpret as varying economic conditions. The bank can trade CDS on its borrowers' loans in order to adjust the risk to the target level determined by the requirements.

We show that the possibility of adjusting the risk using CDS reduces the cost of risk for the bank, thus increasing risk-taking incentives[20]. However, access to CDS allows banks to react to economic shocks and thus to avoid cutting lending ex ante (see Froot et al. (1993)). We show that the negative effects of higher risk-taking are offset by the positive effects of higher revenues from performing loans and lower risk management costs in adverse economic conditions, leading to increased banking stability.

We test the model's theoretical predictions using data on bank holding companies (BHCs) from the US Call Reports covering the period from 2005 to 2010. We study risk-taking incentives at banks estimating a model for commercial loans at the bank level. We define risk management banks to be those banks that have the possibility to use CDS in the future. Therefore, we proxy risk management activity by a dummy variable that is equal to one from the moment the bank either buys or sells protection in the CDS market. For small banks we find clear evidence that CDS use leads to more risk-taking. The results suggest that the anticipation of risk management possibilities increases the ratio of corporate loans (C&I loans) to total assets by two percentage points[21]. We do not find significant evidence of an increase in the C&I loan ratio for large banks. This difference between small and large banks is consistent with the fact that small and large BHCs have different risk and diversification profiles (Demsetz and Strahan (1997)). Large banks generally tend to have a more diversified portfolio. They lend in different regions, to different types of businesses, and they have lower securitization costs. Therefore, we expect the marginal benefit of CDS use at these banks to be smaller, which may explain why the CDS dummy estimates are not significant for this group[22]. These results hold

of credit cycles. They show evidence suggesting that securitization activities limit the effects of monetary policy on lending at banks. The Global Stability Report of IMF (2006) highlights the importance of this channel in the case of credit derivatives and their effects on stability.

[20] As in Froot et al. (1993) and Froot and Stein (1998), increasing costs of raising external funds leads banks to behave in a risk-averse fashion, underinvesting in the risky asset ex ante.

[21] This is economically significant since the yearly average of this ratio is 10%.

[22] Additional evidence supports this interpretation. We show first that the ROA of large banks is significantly more correlated with the market than is that of small banks. Second we show that when we split our sample into banks with low and high correlation, the relationship holds only for the low-

when we control for alternative mechanisms that might be driving our results.

We then turn to the analysis of whether banks using CDS are more isolated from shocks than other banks. Our key prediction is that banks, via transactions in the CDS market, are able to rebalance the risk in their portfolios, and hence they can avoid adjustment of their portfolios via cuts in lending. Consistent with this prediction, we find that lending at small banks that use CDS is less procyclical than at other banks. We find evidence that small banks using CDS cut lending by less during the 2007–2009 crisis. In line with the previous result in risk-taking, we did not find significant evidence for a reduction in procyclicality for large banks[23].

In the last part of the paper, we address the question of the net effect of risk management on bank stability. We investigate which effect dominates: the negative effect of higher risk-taking or the positive effect of the isolation of the credit supply via CDS use. According to our theoretical model, we expect the benefits from risk management to offset negative risk-taking effects, increasing stability. To test this proposition, we look at the relationship between CDS use and the probability of bank failure. For small banks we find evidence supporting our prediction, consistent with our previous results. Small banks managing risk via CDS transactions have a lower probability of failure than do other banks. Specifically, active risk management reduces the probability of failure over six years by 1.2 percentage points[24].

This paper provides positive evidence for the net effect of banks' use of CDS. Banks using CDS indeed increase risk-taking, but at the same time they are less procyclical than other banks. Overall, our results show that risk management banks are more stable, facing a lower probability of failure than banks not using CDS. These results provide an important message for bank regulation, which has mainly focused on balance-sheet risks when assessing financial stability. However, this does not of course preclude other negative effects that might arise from CDS use, such as reduced incentives to monitor or higher opacity in the banking system. The evidence shown in this paper highlights the importance of measurement of banks' overall risk. High risk-taking as indicated by a

correlation sample.

[23]In this paper we focus on credit risk management with CDS. In a recent paper, Cornet, et al. (2011) study liquidity risk management and banks' lending during the crisis. They find that banks with a larger share of securitized assets increased their holdings of liquid assets during this period, at the expense of cuts in credit supply.

[24]The average probability of failure in this sample for this period is 2%.

high level of loans on the balance sheets should not be detrimental for banks' stability if accompanied by proper risk management. Thus, regulatory policies should aim to ensure proper risk management in the banking system and to encourage progress in this area.

The remainder of the paper is organized as follows. Section 2 discusses the related literature. In Section 3 we develop the basic setup of our theoretical model to study the effects of CDS transactions on risk-taking. We first consider a benchmark bank that decides its risk-taking without access to risk management possibilities. Subsequently, we allow this bank to engage in risk management activities and study the effects on risk-taking decisions. Section 4 studies how risk-taking decisions differ in these two scenarios when economic conditions change. In Section 5 we look at the net effect on financial stability. In Section 6 we present the empirical evidence. This section contains the data description, the methodology, and the results of the empirical models. Finally, Section 7 concludes.

3.2. Related Literature

Recent theoretical and empirical papers have studied the relationship between financial innovations and banks' risk-taking. In the theoretical literature, authors have shown that banks that shed risk from their portfolios by either selling loans (Santomero and Trester (1998), Duffee and Zhou (2001)) or hedging with derivatives (Duffee and Zhou (2001)) hold a larger share of risky assets in their portfolios. This result has also been proved empirically: authors have shown that banks transferring risk using different types of financial innovations increase their loans extended. Different reasons have been presented to explain this evidence; some authors argue that loan hedging decreases the cost of capital. Others point to regulatory capital constraints, arguing that transferring risk releases capital to be lent (Franke and Krahnen (2005), Loutskina and Strahan (2006)). Others claim that it is the result of a more diversified portfolio that allows a bank to increase the risk taken (Goderis et al. (2007)). The literature however has focused on studying the effect of credit risk transfer via innovations. Little work has been done on the effects of active risk management using innovations, i.e., to shed and source new risk in order to keep it at a desired level. Cebenoyan and Strahan (2004) provide some empirical evidence in this regard. They find a positive relationship between banks buying and selling loans and the share of risky assets.

There is limited theoretical work on the net impact of the use of financial innovations on financial stability. Wagner and Marsh (2006) and Wagner (2007) study the effect of selling loans on risk-taking and financial stability. In the first paper, the authors argue that financial stability increases because, in spite of increased risk-taking, risk aversion leads banks to diversify their portfolios and to shift risks out of the financial system. The second paper studies the effects of increased liquidity arising from loan sales, arguing that the benefits from higher liquidity are offset by increased risk-taking, leading to a reduction in banking stability. Instefjord (2005) studies the effects on stability of hedging activities with credit derivatives at banks. He considers the effects of higher risk-taking incentives and enhanced risk sharing. He shows that the former effect is dominant at high levels of competition, and it destabilizes banks. Finally, Hakenes and Schnabel (2010) show that credit risk transfer activities increase aggregate risk when information about the quality of the loans is not publicly available. This is because reduced monitoring incentives at banks increase their extension of unprofitable loans.

In this paper, we also consider the net impact of financial innovations on stability. However, instead of considering only risk shifting from the banks' portfolios, we study active risk management at banks. We consider banks buying and selling protection in the CDS market to keep the risk in the portfolio at a desired level. Additionally, as in the previous papers, we analyze two opposite effects of financial innovations on stability. Stability is decreased by higher ex ante risk-taking incentives. But, it is increased by the lower procyclicality of loan supply caused by the ability to react to shocks, which isolates a bank from varying economic conditions (see Froot et al. (1993)).

There is mixed empirical evidence on the effect of credit risk transfer activities and risk management on stability. For European data Franke and Krahnen (2007) show a positive relationship between CDO issuance announcement and bank betas. They also considered the effect on stock returns, but they did not find any significant evidence for this relationship. In contrast, Ellul and Yerramilli (2010) study the effect of risk management on different measures of bank risk. They construct a risk management index based on several bank characteristics and find a positive relationship between this index and the stock return. They also document a negative relationship between active risk management and downside risk, tail risk, and aggregate risk. They also provide empirical evidence for the effect of active risk management on bank stability. We investigate this relationship by looking at the probability of bank failure.

3.3. The Model

We build a model in which a bank has the possibility to react to economic shocks by actively managing its portfolio risk by buying and selling protection in CDS markets. This technology can be thought of as the result of the bank having risk-analysis expertise, i.e., an understanding of the distributions and correlations of the risky assets[25]. We first introduce in Section 3.3.1 a benchmark model, where the bank decides its optimal level of lending and it is not able to use CDS to manage its portfolio. In Section 3.3.2, we allow the bank to rebalance its portfolio using credit derivatives once a shock to the risk of the portfolio is realized.

3.3.1. Benchmark Bank

Consider a bank in a three-period model, $t = 0, 1, 2$. At $t = 0$ the bank decides its level of investment in the risky asset (loans), denoted by L, and how much to keep as liquid assets (cash). Since the balance sheet is normalized to one, the liquid asset is given by $(1 - L)$. Loans are repaid at $t = 2$. There is a regulator that requires the bank to meet capital requirements in every period. These requirements are positively related to the riskiness of the portfolio, which depends on the risk taken L and the probability of loan default. Therefore, for a given level of capital there is a maximum amount of risk that can be held consistent with this regulation.

At $t = 1$, the system is hit by a shock to the probability of loan default and this shock modifies the regulatory capital requirements. If the risk taken by the bank at $t = 0$ exceeds the maximum risk consistent with the new requirements, the bank must pay a cost c per unit of risk exceeding the new maximum. This involves raising new capital, which is costly because of the asymmetric information in capital markets. At $t = 2$, the parties are compensated. The model is formalized below.

[25] As also described in Hakenes (2004).

Loans: Loans pay an interest rate $r(L)$, where $r_L < 0$. This is, the bank faces a downward-sloping demand curve, meaning that it has some degree of monopoly power in the market for loans. This market power can be understood as the result of informational advantages about its clients' worthiness.

The return on loans is uncertain. With probability $p_\epsilon = \bar{p} + \epsilon$ the borrower defaults, where $p_\epsilon \in [0,1]$. $\bar{p}$ is the unconditional probability of default, which is exogenous and known in every period. The error term ϵ is the source of uncertainty in the model and denotes a shock to the probability of default, which is realized at $t = 1$. Moreover, ϵ is uniformly distributed on $\epsilon \sim u[\underline{\epsilon}, \bar{\epsilon}]$ and $\underline{\epsilon} = -\bar{\epsilon}$, so $E(\epsilon) = 0$. If the borrower defaults, the bank loses the interest $r(L)$ and a fraction $\lambda \in [0,1]$ of the principal. Therefore, the bank receives $(1 + r(L))$ from a fraction $(1 - p_\epsilon)$ and recovers $(1 - \lambda)$ from the fraction p_ϵ of defaulted loans.

Liability side: The bank raises short-term deposits each period, where d is the deposits and $(1 - d)$ is the capital. The depositors require a return equal to 1. We assume noninsured deposits, which are made after the optimal level of risk of the bank is decided. Therefore, in both periods deposits pay an interest rate i that compensates depositors for their expected losses[26].

Regulatory Capital: The bank has to meet capital requirements in all periods, except period $t = 2$, when the parties are compensated. To compute these capital charges, we assume that the capital requirements are a positive function of the riskiness of the portfolio, along the lines of the standardized approach of Basel II. The riskiness of the portfolio is determined by a linear weight function, $\theta(p_\epsilon) := a(\bar{p} + \epsilon)$, where $a > 0$. We assume that the difference of capital and risk-weighted assets cannot be lower than a given value, say τ. Then at $t = 0$, the capital requirements, $\hat{k}$, are given by

$$\hat{k} - \theta(\bar{p} + E(\epsilon))L \geq \tau.$$

These requirements cannot exceed the exogenously given amount of capital, $\hat{k} \leq (1 - d)$. Given this capital $(1 - d)$ and since $E(\epsilon) = 0$, the maximum risk that the bank

[26]This is equivalent to assuming fully insured deposits with fairly priced premiums.

can hold at $t = 0$ consistent with these requirements is

$$\hat{L} = (1 - d) - \theta(\bar{p}) - \tau. \tag{3.1}$$

At $t = 1$, when the shock is realized, the maximum risk allowed by these requirements is given by

$$L_{max} = (1 - d) - \theta(\bar{p} + \epsilon) - \tau. \tag{3.2}$$

If the level of risk held by the bank exceeds this maximum level, the bank will have to pay the cost c per unit of excess risk. This excess is defined as $e(L, \epsilon) := L - L_{max} = (L - ((1 - d) - \theta(\bar{p} + \epsilon) - \tau))$.

Now we turn to the optimal choice of the risky asset L^* at $t = 0$ that maximizes the expected return on equity. If the return on equity is negative, $\Pi < 0$, the bank goes into bankruptcy, and because of limited liability the return on equity is zero. If the bank does not go into bankruptcy, at $t = 2$ the return on equity is

$$\begin{aligned} \Pi &= \left[(1 - p_\epsilon)(1 + r(L)) + p_\epsilon(1 - \lambda)\right] L + (1 - L) - c\left[max(e(L, \epsilon), 0)\right] - (1 + i)d \\ &= \left[r(L) - (\bar{p} + \epsilon)(\lambda + r(L))\right] L + (1 - d) - c\left[max(e(L, \epsilon), 0)\right] - id. \end{aligned} \tag{3.3}$$

The return on equity is then the sum of the excess return of the loans extended $(r(L) - (\bar{p} + \epsilon)(\lambda + r(L)))\, L$ and the equity $(1 - d)$, minus the cost paid for the excess risk and the interest payments to the depositors id. The cost of the excess risk will be paid only when $e(L, \epsilon) > 0$. Thus, this cost is given by $c\left[max(e(L, \epsilon), 0)\right]$. Since $\frac{\partial \Pi}{\partial \epsilon} < 0$, as expected, the larger the shock the smaller the profit.

We get the critical shock for avoiding bankruptcy from

$$\Pi(L, \epsilon_c^B, i(L, \epsilon_c^B)) = 0, \tag{3.4}$$

which is given by

$$\epsilon_c^B = \epsilon_c^B(L). \tag{3.5}$$

Using (3.5), we can write the expected return on equity at $t = 0$ as

$$E(\Pi) = \int_{\underline{\epsilon}}^{\epsilon_c^B} \left[(r(L) - (\bar{p} + \epsilon)(\lambda + r(L)))\, L + (1 - d) - c[max(e(L, \epsilon), 0)] - id \right] \phi(\epsilon)\, d\epsilon. \tag{3.6}$$

If the shock is lower than ϵ_c^B, the bank does not go into bankruptcy and the depositors receive full payment. Otherwise, they receive the residual assets on the balance sheet, which using (3.3) can be written as

$$A_B = (1 + i)d - (\epsilon - \epsilon_c^B)(\lambda + r(L))L - ca(\epsilon - \epsilon_c^B).$$

Given that the depositors require a return equal to 1, their expected payment must be equal to the deposits made at the beginning of the period. Therefore, i must satisfy

$$\begin{aligned} &\int_{\underline{\epsilon}}^{\epsilon_c^B} (i + 1)d\phi(\epsilon)\, d\epsilon \\ &\quad + \textstyle\int_{\epsilon_c^B}^{\bar{\epsilon}} \left[(1 + i)d - (\epsilon - \epsilon_c^B)(\lambda + r(L))L - ca(\epsilon - \epsilon_c^B) \right] \phi(\epsilon)\, d\epsilon = d. \end{aligned} \tag{3.7}$$

Thus, the interest payment to the depositors is given by

$$id = \int_{\epsilon_c^B}^{\bar{\epsilon}} \left((\epsilon - \epsilon_c^B)(\lambda + r(L))L + ca(\epsilon - \epsilon_c^B) \right) \phi(\epsilon)\, d\epsilon. \tag{3.8}$$

Assuming that the shareholders are risk-neutral, the optimum for the risk taken at $t = 0$ is the level that maximizes the expected return on equity, subject to the maximum risk allowed at $t = 0$ consistent with the capital requirements. We can rewrite the expected return on equity using (3.6) and (3.7). Hence, at $t = 0$ the bank solves

$$MaxE(\Pi) = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \left[(r(L) - (\bar{p} + \epsilon)(\lambda + r(L)))\, L + 1 - c\,(max(e(L, \epsilon), 0)) - d \right] \phi(\epsilon)\, d\epsilon \tag{3.9}$$

s.t.

$$L \leq \hat{L}.$$

Let the probability that L is larger than the maximum allowed at $t = 1$ be $q(L)$.

Using the definition of $\theta(p_\epsilon)$,

$$q(L) = p(L_{max} < L) \\ = p(f(L) < \epsilon) \\ = \int_{f(L)}^{\bar{\epsilon}} \phi(\epsilon)\, d\epsilon \tag{3.10}$$

where $f(L) = \frac{(\hat{L}-L)}{a}$. Thus, we can write the FOC for L as[27]

$$\frac{\partial E(\Pi)}{\partial L} = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \left[(r_L - (\bar{p}+\epsilon)r_L)L + r(L) - (\bar{p}+\epsilon)(r(L)+\lambda)\right]\phi(\epsilon)\, d\epsilon - c\left(-f_L e(L, f(L)) + q(L)\right) = 0.$$

Then, the optimal L^* solves

$$r(L^*) - \bar{p}(r(L^*)+\lambda) + (r_L - \bar{p}r_L)L^* = c\left(-f_L e(L^*, f(L^*)) + q(L^*)\right). \tag{3.11}$$

The LHS of this equation is the marginal benefit of one unit of risk. The first term represents the expected return of one unit of risk, and the second term represents the decrease in interest rate since there is a downward-sloping demand curve. The RHS of the equation represents the marginal cost of one unit of risk, related to the payment of the excess risk. This expression equals the increase in the domain for which the bank pays this cost ($f_L < 0$), i.e., the increased probability of incurring the excess cost $e(L^*, f(L^*))$ plus the marginal increase in the excess, which is equal to one, weighted by the probability of having to pay the increase, $q(L^*)$. Finally, the amount lent by the bank is given by

$$L^B = min[L^*, \hat{L}] \tag{3.12}$$

i.e., the minimum between the maximum risk allowed by the capital requirements at $t = 0$ and the optimal level of risk.

[27] Notice that $\int_{\underline{\epsilon}}^{\bar{\epsilon}} max(e(L,\epsilon), 0)\phi(\epsilon)\, d\epsilon = \int_{f(L)}^{\bar{\epsilon}} e(L,\epsilon)\phi(\epsilon)\, d\epsilon$.

3.3.2. Bank with Active Risk Management

Now we turn to the case where the bank has the technology available to rebalance its portfolio once the shock is realized at $t = 1$ (the RM case). The RM bank can use derivatives to reduce the risk of its portfolio and avoid paying the cost that arises from the capital requirement constraint. Furthermore, if the risk taken at $t = 0$ is lower than the maximum allowed after the shock is realized at $t = 1$, the bank can use derivatives to adjust the portfolio and source new risk in the second period. Therefore, after observing the shock the bank decides its protection position in credit derivatives. We describe the credit derivative instrument next.

Credit Derivatives: We model a derivative instrument that follows the structure of a credit default swap (CDS). A CDS is a contract between the protection buyer and the protection seller that insures the buyer against losses arising from the default of the reference entity linked to the CDS, the borrower of a given loan. Hence, in this model, the instrument pays the losses $(r(L) + \lambda)$ with probability $p_\epsilon = \bar{p} + \epsilon$ at $t = 2$, where p_ϵ is the probability of default of the reference entity. Notice that the default probabilities of loan and derivative reference entities are perfectly correlated. Denote the protection bought/sold by the bank by S, where $S \in [-1, 1]$. When $S < 0$ the bank is buying protection, and when $S > 0$ it is selling protection.

The price of \$1 of protection is denoted w. We assume that the elasticity of the derivative supply is infinite[28]. Therefore, the bank is able to sell and buy all the derivatives it requires at this price. We assume that there are trading frictions in the CDS market and these costs are incurred by the buyer of protection[29]. Therefore, the price of protection is equal to the expected payment of losses $(\bar{p} + \epsilon)(r(L) + \lambda)$, plus a compensation γ that reflects these transaction costs. Then, at $t = 1$ the price of one unit of

[28] This can be understood as outside agents such as insurance companies being the major traders of protection. For simplicity, we do not model these traders' decisions and the counterparty risk associated with the transaction of a CDS. Furthermore, we focus on the stability implications for a representative bank, abstracting from systemic aspects arising from the use of CDS.

[29] There is evidence that CDS prices do not solely reflect credit risk but are also the result of high transaction costs during some periods of the day (Fulop and Lescourret (2009)), and that sellers of protection in the CDS market receive illiquidity compensation on top of their default risk compensation since sellers are more aggressive than buyers because they have more wealth, a lower risk aversion, or shorter horizons (Bongaerts et al. (2011)).

protection is

$$w = (\bar{p} + \epsilon)(r(L) + \lambda) + \gamma. \tag{3.13}$$

The total protection sold/bought by the bank is SL. The price of this protection is

$$wSL = (\bar{p} + \epsilon)\,(r(L) + \lambda)SL + \gamma SL.$$

The model is solved by backward induction. Therefore, we first find the optimum for the decision taken at $t = 1$, i.e., the position in credit derivatives taken by the bank, S, taking L as given. Since the bank has to meet the capital requirements in all periods, $(1 - d)$ is given, and L is given from period $t = 0$; the bank can choose S^* to adjust the risk in the portfolio and meet the requirement determined by the new probability of default that results once the shock is realized.

The risk of the new portfolio containing the loans extended at $t = 0$, L, and the credit derivative position taken at $t = 1$, $S(L, \epsilon)L$, cannot be larger than the maximum risk allowed at $t = 1$. Hence, the new portfolio must satisfy

$$L_{max} \geq (L + LS(L, \epsilon)). \tag{3.14}$$

First, consider the case where once the shock is realized the risk allowed at $t = 1$ is higher than the level of risk held by the bank, $L_{max} > L$. The bank is then able to sell protection and increase the risk in the portfolio. Since the net present value (NPV) of the derivative is positive because it is sold with a premium, $w - (\bar{p} + \epsilon)(r(L) + \lambda) = \gamma > 0$, it is always profitable for the bank to sell protection in the CDS market. Hence, it is optimal for the bank to sell the maximum protection allowed, until restriction (3.14) is binding. Thus, the optimal protection sold will be

$$\begin{aligned} S^*(L, \epsilon)_s &= \frac{(L_{max} - L)}{L} \\ S^*(L, \epsilon)_s &= \frac{-e(L, \epsilon)}{L} \end{aligned} \tag{3.15}$$

where $\frac{\partial S^*(L,\epsilon)_s}{\partial \epsilon} < 0$. The more negative the shock the more protection sold.

Now consider the case where once the shock is realized the risk allowed at $t = 1$ is lower than the level of risk held by the bank, $L_{max} < L$. In this case, the bank does not meet the capital requirements. Therefore, it can either buy protection in the CDS market to reduce the risk of the portfolio or pay the cost of exceeding the maximum risk allowed. The optimal amount of protection bought will be then where the cost of buying this protection equals the cost c of the extra risk, subject to constraint (3.14). Thus,

$$\begin{aligned} ce(L,\epsilon) &= -wS(L,\epsilon)L + (\bar{p}+\epsilon)(r(L)+\lambda)S(L,\epsilon)L \\ S(L,\epsilon)_b &= -\frac{c}{\gamma}\frac{e(L,\epsilon)}{L} \end{aligned} \tag{3.16}$$

where $\frac{\partial S(L,\epsilon)_b}{\partial c} < 0$. The higher the cost of exceeding the risk given by the capital requirements, the more negative $S(L,\epsilon)_b$, i.e., the more protection is bought. On the other hand, $\frac{\partial S(L,\epsilon)_b}{\partial \gamma} > 0$. The higher the net cost of the credit derivative the less negative $S(L,\epsilon)_b$, i.e., the less protection is bought.

Since reducing the risk in the portfolio is costly, the bank will never buy more protection than that needed to fulfill the capital requirements. Therefore, subject to the binding constraint (3.14), the optimal protection bought by the bank is

$$S(L,\epsilon)_b^* = -min\left[\left|\frac{c}{\gamma}\frac{(L_{max}-L)}{L}\right|, \left|\frac{(L_{max}-L)}{L}\right|\right] \tag{3.17}$$

where $\frac{\partial S^*(L,\epsilon)_b}{\partial \epsilon} < 0$. The higher the shock, i.e., the larger the increase in the probability of default, the larger $S^*(L,\epsilon)_b$ in absolute value, i.e., the more protection is bought.

If $\gamma < c$, i.e., the premium of the derivative is lower than the cost of the excess risk, the second term of the minimum function in (3.17) will be lower, hence it will be optimal to buy protection until the capital requirements are met. If $\gamma > c$ the bank's optimal decision tends to that of the benchmark case, and in the extreme case when $\gamma \to \infty$ the bank does not buy CDS; in both cases the bank pays the cost c. Therefore, we focus in the following on the interesting case where $\gamma < c$.

Thus, considering the corresponding optimum of protection bought $S^*(L,\epsilon)_b$ and protection sold $S^*(L,\epsilon)_s$, the optimal protection position $S^*(L,\epsilon)$ taken by the bank at $t = 1$ is

$$S^*(L,\epsilon) = \int_{\underline{\epsilon}}^{f(L)} \frac{-e(L,\epsilon)}{L}\phi(\epsilon)\, d\epsilon + \int_{f(L)}^{\bar{\epsilon}} \frac{-e(L,\epsilon)}{L}\phi(\epsilon)\, d\epsilon.$$

The first term corresponds to the protection sold and the second term corresponds to the protection bought in CDS markets. This expression equals

$$S^*(L,\epsilon) = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \frac{-e(L,\epsilon)}{L}\phi(\epsilon)\,d\epsilon, \tag{3.18}$$

which is the optimal position taken by the bank in credit derivatives at $t = 1$.

Now we turn to the decision taken at $t = 0$, i.e., the optimal amount of the risky asset in the portfolio, L^*, that maximizes the expected return on equity. If the bank does not go into bankruptcy, at $t = 2$ the return on equity will be

$$\begin{aligned}\Pi &= [(1-p_\epsilon)(1+r(L)) + p_\epsilon(1-\lambda)]\,L + S^*(L,\epsilon)L\gamma + (1-L) - (1+i)d \\ &= [r(L) - (\bar{p}+\epsilon)(\lambda + r(L)) + S^*(L,\epsilon)\gamma]\,L + (1-d) - id. \end{aligned} \tag{3.19}$$

As in the benchmark case, the return on equity will be equal to the sum of the excess return of the loans made $(r(L) - (\bar{p}+\epsilon)(\lambda + r(L)))L$ and the equity $(1-d)$, minus the interest payments to the depositors id. In this case, instead of the cost of the excess risk, we have the premium (cost) derived from the protection position held, $S^*(L,\epsilon)L\gamma$.

As in the previous section, from

$$\Pi(L, \epsilon_c^{RM}, i(L, \epsilon_c^{RM})) = 0 \tag{3.20}$$

we obtain the maximum shock for the bank not going into bankruptcy, $\epsilon_c^{RM} = \epsilon_c^{RM}(L)$. The expected return on equity in this case is

$$E(\Pi) = \int_{\underline{\epsilon}}^{\epsilon_c^{RM}} [(r(L) - (\bar{p}+\epsilon)(\lambda + r(L)) + S^*(L,\epsilon)\gamma)\,L + (1-d) - id]\,\phi(\epsilon)\,d\epsilon. \tag{3.21}$$

Using (3.19) the residual assets can be written as

$$A_{RM} = (1+i)d - (\epsilon - \epsilon_c^{RM})(\lambda + r(L) + \gamma a)L.$$

Then i must satisfy

$$\int_{\underline{\epsilon}}^{\epsilon_c^{RM}} (i+1)d\phi(\epsilon)\,d\epsilon + \int_{\epsilon_c^{RM}}^{\bar{\epsilon}} \left[(1+i)d + (\epsilon_c^{RM} - \epsilon)(\lambda + r(L) + \gamma a)L\right]\phi(\epsilon)\,d\epsilon = d. \tag{3.22}$$

Therefore, the interest payments are

$$id = \int_{\epsilon_c^{RM}}^{\bar{\epsilon}} (\epsilon - \epsilon_c^{RM})(\lambda + r(L) + \gamma a)L\phi(\epsilon)\, d\epsilon. \tag{3.23}$$

Using (3.21) and (3.22), we can rewrite the expected return on equity. Then, the optimum for the risk taken at $t = 0$ in the RM case is the level that maximizes

$$MaxE(\Pi) = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \left[(r(L) - (\bar{p} + \epsilon)(\lambda + r(L)) + S^*(L, \epsilon)\gamma)\, L + 1 - d \right] \phi(\epsilon)\, d\epsilon \tag{3.24}$$

s.t.

$$L \leq \hat{L}.$$

The FOC for L is given by

$$\frac{\partial E(\Pi)}{\partial L} = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \left[(r_L - (\bar{p} + \epsilon) r_L)L + r(L) - (\bar{p} + \epsilon)(r(L) + \lambda) - \gamma \right] \phi(\epsilon)\, d\epsilon = 0.$$

Then, the optimal L^* solves

$$r(L^*) - \bar{p}(r(L^*) + \lambda) + (r_L - \bar{p} r_L)L^* = \gamma. \tag{3.25}$$

As in the benchmark case, the LHS of this equation is the expected marginal benefit of one unit of risk. The RHS is the expected marginal cost of one unit of risk, which in this case is the price of the derivative, γ.

Finally, the amount lent by the bank is

$$L^{RM} = min[L^*, \hat{L}]$$

i.e., the minimum between the maximum amount allowed by the capital requirements at $t = 0$ and the optimal level of risk.

Proposition 1 shows that under certain conditions, in anticipation of having risk management possibilities in the second period, the bank increases risk-taking in the first period.

Proposition 1: *For high levels of competition in the loan market, risk management possibilities increase risk-taking incentives:*

$$L^{*B} < L^{*RM}. \tag{3.26}$$

Proof. See the Appendix. *Q.E.D.*

Therefore, in anticipation of risk management possibilities once the shock is realized, the bank takes ex ante a higher level of risk. In contrast, in the benchmark case, in expectation of having to pay the cost of the excess risk in the second period, the bank adjusts the risk in its portfolio by reducing the loans extended ex ante.

This result holds only for sufficiently high levels of competition. This is because the marginal cost of the bank in the RM case does not depend on the level of risk, whereas the marginal cost in the benchmark case increases with the level of risk. This is because the probability of having to pay the cost c increases as the level of risk in the portfolio increases. When competition decreases, the decrease in the marginal benefits is the same in both cases for every level of risk. Let z be the slope of the demand curve. There is a maximum slope $\tilde{z}$ where Proposition 1 holds (see Eq. (3.33) in the proof of Proposition 1). Above $\tilde{z}$ the optimum in both cases will be in the range where the marginal cost in the benchmark case is lower than that in the RM case, and therefore the optimal level of risk in the former case will be larger.

3.4. Risk-Taking and Business Cycle

In this section we study for each case how the optimal risk-taking differs as the economic conditions change. Since in the RM case the bank is able to react to the shock in the second period, we expect it to be more isolated from business cycle fluctuations in this case. We consider the state of the economy to be represented by the expected shock to the probability of loan default, $E(\epsilon)$. Thus, a higher expectation of default represents a deterioration in the state of the economy. Hence, we analyze how the optimal risk-taking L^* varies in response to an increase in the expected shock $E(\epsilon)$. For this purpose, we relax the assumption that $E(\epsilon) = 0$. Hence, $\epsilon \sim u[\underline{\epsilon}, \bar{\epsilon}]$ where $\underline{\epsilon} \neq -\bar{\epsilon}$, so $E(\epsilon) \neq 0$. The

FOC in the benchmark case becomes

$$r(L^*) - (\bar{p} + E(\epsilon))(r(L^*) + \lambda) + (r_L - (\bar{p} + E(\epsilon))r_L)L^* = cq(L^*, E(\epsilon)).$$

Notice that $e(L^*, f(L^*)) = 0$. The FOC in the RM case becomes

$$r(L^*) - (\bar{p} + E(\epsilon))(r(L^*) + \lambda) + (r_L - (\bar{p} + E(\epsilon))r_L)L^* = \gamma.$$

The RHS term in each FOC is the expected marginal cost of risk-taking. Notice that the expected marginal benefits (the LHS terms) are the same in both cases. Therefore, to consider the effect on risk-taking decisions it suffices to compare the impact of an increase in $E(\epsilon)$ on the marginal cost. It is easy to see that in the RM case an increase in $E(\epsilon)$ will not affect the marginal cost. In the benchmark case, an increase in $E(\epsilon)$ leads to an increase in the marginal cost of $c\frac{\partial q(L^*,E(\epsilon)}{\partial E(\epsilon)}$. Comparing these two effects, Proposition 2 shows that when the bank has the possibility to manage its risk, it reduces risk-taking by less when $E(\epsilon)$ increases.

Proposition 2: *Risk management allows banks to cut risk-taking by less under adverse economic conditions:*

$$\left|\frac{dL^{*RM}}{dE(\epsilon)}\right| < \left|\frac{dL^{*B}}{dE(\epsilon)}\right|. \tag{3.27}$$

Proof. See the Appendix. *Q.E.D.*

Therefore, compared to the benchmark case, the RM bank is better isolated from business cycle fluctuations. The intuition behind this result is that a higher expectation of the shock will increase the expected marginal cost of reducing risk in the portfolio in the benchmark case. This is because the probability of having to pay the excess risk $q(L, E(\epsilon))$ at $t = 1$ increases. However, the marginal cost in the RM case does not depend on the expected shock because the bank can offset any shock at $t = 1$ via transactions in the CDS market. Therefore, when facing a higher expectation of default the bank cuts lending in both cases. However, because of the decrease in the marginal benefit of risk, it cuts lending by less in the RM case.

3.5. Risk Management and Banking Stability

One question that arises from the previous findings is how risk management possibilities affect banking stability. On the one hand, with risk management possibilities, the bank is taking more risk. On the other hand, the bank is able to react to shocks by adjusting the risk in its portfolio via CDS transactions. It is thus better isolated from economic fluctuations. In this section we compare the two cases with respect to the probability of default, which is measured as

$$p(\epsilon_c < \epsilon) = \int_{\epsilon_c}^{\bar{\epsilon}} \phi(\epsilon)\, d\epsilon. \tag{3.28}$$

This is the probability of the shock being larger than the critical shock, defined previously as the shock that makes the return on equity equal to zero. Notice that the larger ϵ_c, the smaller the probability of default and therefore the safer the bank. Prediction 1 shows that the probability of bankruptcy is lower in the RM case.

Prediction 1: *Risk management increases banking stability:*

$$\epsilon_c^B < \epsilon_c^{RM}. \tag{3.29}$$

Proof. See the Appendix. *Q.E.D.*

There are three effects involved in this result. First, at the optimum, the cost of managing the extra risk in the second period is lower in the RM case, which implies higher stability for the bank in this case. Second, risk-taking has two direct effects on banking stability: a positive effect, i.e., for significant levels of competition, total revenues increase with the level of risk-taking; and a negative effect, i.e., higher risk-taking increases total losses in the event of default. This prediction shows that the negative effect of risk-taking is offset by its positive effect and the benefits arising from the lower cost of managing the extra risk in the second period. This leads to greater stability compared to the benchmark case.

In conclusion, we have shown in this model that the bank takes ex ante a higher level of risk due to risk management possibilities. The bank does so because it is able to rebalance the risk in its portfolio if economic conditions, and hence the riskiness of its loans, change. In contrast, without risk management the bank can adjust the risk in its portfolio only by reducing the loans extended ex ante. Furthermore, we have shown that even though the bank acquires more risk by extending more loans, as a result of this technology, it is more stable. We empirically test these predictions in the next section using bank-level data for regulated BHCs in the US.

3.6. The Empirical Evidence

In this section we test our theoretical predictions about the effects of active risk management at banks. Specifically, we test whether banks actively managing their risks increase risk-taking by looking at their volumes of commercial loans. We also test whether their credit supply is less procyclical, i.e., we test whether these banks extend a more stable flow of loans under varying economic conditions. To do this, we investigate how these banks behaved during the crisis period. Finally, we test whether as a result of this lower procyclicality these banks are more stable, by looking at their probability of failure one year ahead.

3.6.1. Data

The analysis is based on bank-level data from the US Call Reports. These reports contain quarterly balance-sheet data and income-statement information for all regulated BHCs in the US. We obtain from this data our main dependent variable needed to test the first two hypotheses, the outstanding amount of commercial loans scaled by total assets[30]. We also collect from this source off-balance-sheet data. We use the outstanding amount of CDS held by the bank to identify banks managing their risk using these derivatives. We look at commercial loans (instead of total loans) and credit derivatives, because CDS directly reflect the credit risk of corporate borrowers. Hence, banks can easily hedge or source credit risk in their corporate loan portfolios using these derivatives. Finally, we take annual averages of all variables, from 2005 to 2010. We exclude from the sample those banks that we observe for less than three years. The final sample consists of an

[30]This is a common measure used in the literature for credit risk-taking. See e.g. Cebenoyan and Strahan (2009), Hirtle (2009).

unbalanced panel containing 7,253 observations and comprising 2,276 banks.

We have defined RM banks as banks that expect to be able to use credit derivatives to manage their portfolio risks in the future. Therefore, active risk management in this context does not relate to the actual use of credit derivatives in a given period but to the ability to use these derivatives if necessary. We hence define active RM banks using a dummy variable, CD, which is equal to one from the first period the bank either buys or sells protection in the CDS market. We assume that if the bank has bought or sold protection in the CDS market in some period, the bank can use these derivatives again in a later period.

Table 1 presents the summary statistics of the sample. The average amount of commercial loans is about 10% of the total assets, and this percentage ranges from 0.9% to 30%. We construct our variable of interest, CD, using off-balance-sheet data. The average of this variable in our sample is around 5%.

A first inspection at the means of commercial loans indicates that when CD is equal to one, the mean of the ratio of commercial loans to total assets is higher than when this dummy is equal to zero, specifically 11.3% versus 10.1%. This difference is significant at 5% of confidence level (t-test equals 3.87). This suggests that banks using CDS may be taking more risk in their portfolios than other banks do.

Our third hypothesis relates risk management to banking stability. The dependent variable in this model indicates whether the BHC failed in a given year. To identify the failed BHCs, we use information from the list of failed commercial banks on the FDIC website. This list contains all the commercial banks that failed during this period. We then manually check which BHCs went bankrupt after their commercial banks did. We also include two mergers, Wachovia and National City, since these banks would likely have failed if they had not been taken over by the government or FED. We also consider as failed banks those banks for which an enforcement action has been taken by the FED during our sample period to improve the health of the bank. To identify these banks, we use information from the press releases on the FED website. The site provides information about all banks that have signed a written agreement with the FED for every year. Our final sample then contains 439 failed banks. A first look at the means of the failure dummy shows that banks using CDS to manage risk may fail less than other banks: the mean of the failure dummy for banks not using CDS is 2.5%, while that for banks using CDS is 2.1%. However, the difference is not significant at the 5% level.

We describe the empirical models in detail in the next sections.

3.6.2. Risk Management and Risk Taking

In Section 3.2, we have shown that an RM bank takes ex ante a higher level of risk in anticipation of its ability to adjust its portfolio when a shock is realized. In this section, we test this proposition by looking at how commercial loans extended by RM banks compare to other banks' loan levels. We expect a positive relationship of the risk management dummy with the commercial loan amount, reflecting the higher risk taken by these banks. We estimate the following panel data model at the bank level for commercial loans:

$$C\&I/TA_{b,t} = \alpha + \sum_{b=1}^{B} \beta_{1b} bank_b + \sum_{t=1}^{T} \beta_{2t} year_t + \beta_3 CD_{b,t} + \sum_{i=1}^{K} \phi_i B_{i,b,t} + \epsilon_{b,t} \quad (3.30)$$

where b denotes the bank and t is the time. In this model $C\&I/TA_{b,t}$ is the annual average of the ratio of commercial loans to assets of bank b at year t. $CD_{b,t}$ corresponds to a dummy variable that is equal to one from the moment the bank either buys or sells protection in the credit derivatives market. The B_i terms are the bank characteristics. These characteristics include as a proxy for bank size the logarithm of assets, a measure of a bank's liquidity equal to cash plus securities over assets ($liquid\ Assets/TA$), and real estate activities ($Real\ estate/TA$). We include as additional controls the return on assets (ROA), subordinated debt over assets ($subdebt/TA$), equity over assets ($equity/TA$) and two measures of the riskiness of the loans, the amount of net charge-offs over assets ($Net\ chargeoff/TA$) and the loan loss allowance over assets ($Allowance/TA$).

There are significant differences in the risk and diversification profiles of small and large BHCs (Demsetz and Strahan (1997)). Specifically, large banks are better diversified and they hold larger commercial loan portfolios. They lend in different regions, to different types of businesses, and they have lower securitization costs. Given that we are interested in studying how credit supply is affected by economic shocks for RM banks, differences in diversification profiles are likely to play a role. Therefore, to account for these differences we split the sample into two according to bank size. We consider small banks to be those at or below the 50th percentile in terms of the logarithm of the assets. This split allows us to avoid collinearity problems arising from the interaction terms. Table 2 shows the results of this model. Columns (1)–(3) show the results for the models with all banks. Columns (4)–(6) present the results for small banks and columns (7)–(9) present the results for large banks. All these models are estimated using panel data models with bank and time fixed effects to control for unobserved time-invariant bank characteristics and unobserved time-variant characteristics. The standard errors are clustered at the bank level. Regression 1 includes the dummy for risk management, CD, and the bank controls. The coefficient of our variable of interest, CD dummy, is positive (0.0097), but it is not significant. Among the bank controls, all the significant variables have the expected sign. Lower loan levels are extended by banks with more liquid assets, those extending a larger amount of real estate loans, those holding higher capital ratios, and those that are more leveraged. There is a positive relationship between higher profitability and commercial loans.

The coefficient changes slightly and remains not significant when we control for loan risk in column (2). In this model we add loan loss allowance over assets ($Allowance/TA$) and the amount of net charge-offs over assets ($Net\ chargeoff/TA$). The other coefficients in the model are also mostly unchanged. Regarding the loan risk measures, $Net\ chargeoff/TA$ is significant and negatively related to commercial loans, so banks with larger losses reduce their lending, while the coefficient of $Allowance/TA$ is not significant. We take this model to be our baseline model.

The use of credit derivatives is likely to be correlated with the use of other derivatives for risk management purposes. Therefore, our estimates for credit derivatives might be also capturing the effect of the use of other derivatives for risk management, but not only the effect of credit risk management via CDS transactions. Therefore, we include the dummy variable $Derivatives\ not\ for\ trade$, which is equal to one if the bank uses other types of derivatives not for trading. These derivatives include interest rate, foreign exchange, equity, and commodity derivatives. This model is shown in regression 3. The coefficient of the credit risk management dummy remains unchanged and not significant for the entire sample, while the dummy for the use of other derivatives is negative and not significant.

The next three columns in Table 2 present the models for small banks. For these banks the dummy for credit derivatives is positive and highly significant, in this case at the 1% level. The coefficient increases in comparison with the full-sample models to 0.024. The rest of the coefficients remain similar to those in the previous regressions. This result provides support for RM banks holding more risk in their portfolios. The effect of risk management on commercial loan level is also economically significant. The use of credit derivatives increases the ratio of loans extended to total assets by 2 percentage points, which, considering the average of this ratio, implies an annual increase of 0.002.

As for the entire sample, in regression 5 we control for loan risk. The coefficient slightly increases to 0.027 and remains significant. We also control in the subset of small banks for the use of other derivatives for risk management. In this model, the coefficient for the use of CDS remains significant and positive when we control for the use of other derivatives. This result suggests that the increase in the ratio of commercial loans to total assets indeed comes through credit risk management via transactions in CDS and not from the use of other derivatives.

It is important to note that endogeneity concerns are limited in this model to the extent that we are controlling for any source of biases arising from time-invariant heterogeneity at banks by including bank fixed effects. One remaining endogeneity concern may be that a bank might extend a larger volume of loans and remove this risk by buying protection in the CDS market. If this were the case, our estimate would be capturing the effect of the transfer of this risk by the bank. However, we are interested in the effect of a bank actively managing the risk in the portfolio by both buying and selling protection in the CDS market. To address this concern, we re-estimate our baseline model excluding the banks that only buy protection in the CDS market. The results (not reported here) show that for this subset of banks the results still hold, showing that the possibility of using CDS has a positive and significant impact on the volumes of commercial loans extended. Therefore, the positive effect of the CD dummy is driven by being at both sides of the market and not only by purchasing protection to remove risk from the portfolio. This test also rules out some other alternative mechanisms that might be driving our results. Banks may use CDS to release regulatory capital to be lent or to hedge their exposures by buying protection in the CDS market. Both mechanisms would lead to higher lending when using CDS at banks. However, both of these mechanisms require banks to reduce the risk in the portfolio, hence to buy but not to sell protection in this market. Therefore, the results of this test support our hypothesis that *active* risk management increases risk-taking at banks and rules out the possibility that our results are driven by other alternative mechanisms [31].

The last three columns of Table 2 contain the results for the subset of large banks. The coefficient of CD is not significant at the 5% level for these banks, and the coefficient is close to that for the entire sample (0.008). This result is unchanged when we control for loan risk and the use of other derivatives in columns (8) and (9) respectively. In these regressions, $Net\ chargeoff/TA$ and the dummy $Derivativesnotfortrade$ turn not significant. Therefore, we have not found any significant evidence for large banks. As mentioned earlier, the reason behind this result may be that large banks have also other means to manage their risk: they can issue securities at a lower cost, they lend in different regions, and to different types of businesses. Therefore, although large banks use CDS to a large extent, they have a lower marginal benefit from the use of credit derivatives in terms of the ability to isolate their portfolio of loans from economic conditions. Therefore, we do not observe a significant difference in the volume of loans extended by banks using CDS among large banks[32].

We have shown in Proposition 1 that the effect of risk management on credit supply is conditional on the level of competition in the loan market. Specifically, as competition increases the positive effect of risk management on risk-taking increases. We now test this conditionality. To address this question we construct a dummy variable, $lowHHI$, which is based on the Hirschman–Herfindahl index calculated at the state-year level for the commercial loan market[33][34]. The dummy equals one when HHI is lower than 0.10, which is the accepted cut-off point in the banking-competition literature below which

[31] Call Reports do not report separately credit derivatives used for hedging and trading purposes. This fact arises the possibility that our results might be driven by marker making activities. To account for this possibility, we follow Hirtle (2009) and define dealer banks as banks that have more than \$10 billion in credit derivatives at some point in the sample and banks that are among the four largest credit derivatives users in a given period. We find that we do not have this group of banks in our sample of small banks. Therefore, our results are not driven by market makers transactions

[32] This evidence is consistent with that in other literature looking at securitization benefits for large banks. See for example Loutskina (2011) for the relation between securitization and bank liquidity, Lepetit et al. (2008) for the relationship between diversification and bank risk for different bank sizes, and Demsetz and Strahan (1997) for a discussion of diversification and bank size.

[33] The banking-competition literature does not agree on the best proxy for market competition, and the research results are mixed. However, the HHI index is one of the most common measures. We also estimated this model using the Lerner index at the bank-year level as a proxy for competition, but because of collinearity problems we did not obtain reliable results.

[34] This HHI index applies to the level of competition in the state of the loan origination. The correct measure would be to construct an HHI index for the borrower's state. However, this is not possible to measure due to data limitations. Nonetheless, since our results hold for small banks it is reasonable to assume that the bank and the borrower are located in the same state.

a market is competitive (see e.g., Degryse and Ongena (2005)). To capture differences in the effect of risk management for different competition levels, we add to our baseline model the interaction term of the competition dummy and the risk management dummy, $lowHHI * CD$. According to our theoretical prediction, we expect this interaction term to be positive. Table 3 presents the results; they remain significant only for the small banks. The coefficient of the interaction term is positive and significant, indicating that the positive effect of risk management on credit supply is higher in more competitive markets.

In summary, we have found a positive relationship between the use of credit derivatives and the ratio of commercial loans to assets for small banks. The effect is also economically significant. This effect holds when controlling for bank heterogeneity by including bank fixed effects, and it is robust to the inclusion of different bank controls and tests for possible sources of bias. The evidence also suggests that our results are not driven by alternative mechanisms through which CDS use may affect loan supply. Thus, these results are consistent with RM banks taking more risk ex ante as a result of their ability to manage the risk in their portfolios.

3.6.3. Risk Management and the Business Cycle

Proposition 2 shows that banks using CDS are better isolated from economic shocks. RM banks can use CDS to adjust the risk in their portfolios. They can remove risk by buying protection and source new risk by selling protection in the CDS market. Thus, these banks need not adjust the risk in their portfolios by modifying their stock of C&I loans, and hence they can maintain a more stable flow of loans than other banks can. In this section, we test this prediction by looking at how RM banks reacted during the crisis period in comparison with other banks. To do this, we add to our baseline model a crisis dummy that we expect to be negatively related to C&I loans. We also include the interaction term of this dummy and the dummy for CDS use, $Crisis * CD$. This variable captures the impact of the crisis on lending for RM banks. We expect this variable to be positive, reflecting a lower procyclicality of C&I loans for these banks.

The results of these models are shown in Table 4. The first column shows the effect of the crisis for the entire sample. As in the previous models, the CD dummy is positive and not significant. The crisis dummy is negative and significant at the 1% level, in line with our expectations. The interaction term $Crisis * CD$ is not significant for this sample.

Column (2) presents the results for small banks. The coefficient of CD slightly decreases (0.0207) and remains significant at the 1% level. As for the entire sample, the crisis variable is negative and significant at the 10% level, as expected. However, in this case the interaction term $Crisis * CD$ is positive and significant at the 5% level. This result indicates that for small banks, RM banks' commercial loans are less procyclical than those of other banks. This evidence is consistent with the hypothesis that banks buy and sell CDS to adjust the risk in their portfolios. This rebalancing of portfolios via CDS transactions avoids the need to adjust risk by varying their stock of commercial loans.

The last column shows the results for the large banks. The coefficient of the CDS dummy in regression (3) slightly decreases (0.007) in comparison with the previous section and remains positive and not significant. The crisis dummy is again negative and significant. In line with our results in the previous section, the interaction term $Crisis*CD$ is not significant for this set of banks. This result is consistent with these banks being less procyclical even when CDS are not used.

Overall, we have found evidence that for small banks the use of credit derivatives enables them to isolate from the economic conditions and thus, maintain a more stable flow of loans. For large banks, we have not found evidence supporting less procyclicality for RM banks. This might be a result of smaller marginal benefits from the use of CDS, since large banks manage their risk by other means even in the absence of CDS use.

3.6.4. Risk Management and Banking Stability

The evidence from the previous sections shows that small banks using CDS extend a larger amount of loans than do other banks. Furthermore, we have found evidence that supports the hypothesis that these banks are better able to isolate themselves from economic conditions using these derivatives. One question that arises from these findings is whether these banks are overall more stable. Prediction 1 suggests that even though the RM bank increases risk-taking, the ability to rebalance its portfolio leads to greater banking stability. In this section, we test this proposition by studying whether banks that used CDS in the past are less likely to fail one year ahead. We expect a negative relationship between CDS use and the probability of failure, lending support to the hypothesis of greater stability for these banks. The model for bank failure prediction we estimate in this section closely follows that of Knaup and Wagner (2012). As in their paper, we drop failed banks from the sample. In addition, the estimation is carried out using probit models. The model we estimate is as follows:

$$Failure_{b,t} \quad = \quad p(CD_{b,t-1}, \sum_{i=1}^{K} \phi_i B_{i,b,t-1}) \tag{3.31}$$

where $Failure_{b,t}$ is a dummy variable that is equal to one if the BHC failed at year t. $CD_{b,t-1}$ is a dummy variable that represents whether the bank used credit derivatives in the previous year, i.e., $t-1$. $B_{i,b,t-1}$ is a set of bank controls, and all these variables are also lagged by one year.

In the set of bank controls we include loan risk measures such as nonperforming loans over total loans (NPL/TL_{t-1}), loan loss allowance over total loans ($Allowance/TL_{t-1}$), and net charge-offs over loans ($Netchargeoffs/TL_{t-1}$). We also control for asset quality by including the return over assets (ROA_{t-1}) and the annual loan growth ($Loangrowth_{t-1}$). Finally, we include general characteristics of the bank, such as subordinated debt over assets ($subdebt/TA_{t-1}$), the logarithm of the assets ($Log(assets)_{t-1}$), the loans over assets ($Loan/TA_{t-1}$), and real estate activities ($Real\ estate/TL$).

Table 5 reports the results of the failure-probability model estimation. Column (1) shows the regression for the entire sample of banks. Consistent with our results in the previous sections, this model shows that the use of credit derivatives is not significant in explaining bank failure one year ahead for the entire sample. In regressions (2) and (3), we show that the same is true when we control for quality of assets and general bank characteristics.

The model in column (4) contains the estimation for small banks. The (marginal) coefficient for the use of credit derivatives in this case is significant, and it has the expected negative sign. The (marginal) coefficient of CD_{t-1} is negative (-0.0062), and it is significant at the 1% level. This is in line with banks using CDS to manage their risk being more stable than other banks. This effect is robust for the other specifications. In column (5) when we control for asset quality, the coefficient decreases in absolute value to -0.0047 but remains negative and significant. The results are similar when we control for general bank characteristics in column (6): the coefficient is equal to -0.002 and remains statistically significant. This effect is also economically significant: an RM bank has a probability of failing one year ahead that is 0.2 percentage points lower. Thus, over the entire period (six years), the decrease in the probability of failure is 1.2 percentage points. This effect is considerable since the average probability of failure for the small banks is 2%.

The last three columns in the table present the results for large banks. As for the entire sample, the use of CDS at large banks does not have explanatory power for the probability of failure one year ahead. This also holds when we control for asset quality and general bank characteristics in columns (8) and (9), respectively. These results are in line with those of the previous sections. Large banks using CDS do not seem to extend a larger volume of loans or to be less procyclical than other large banks, probably reflecting the lower marginal benefit of the use of CDS for these banks. Similarly, we do not find significant support for large banks using CDS failing less often than other large banks.

In summary, we find a negative and significant relationship for small banks between the use of CDS and the probability of failure one year ahead. In contrast, consistent with our previous results, we do not find any such evidence for large banks. This result lends support to the hypothesis that at small banks the use of CDS to manage risks increases banking stability.

One question at this point concerns the reason underlying the differences in the results for large and small banks. As argued previously, we suspect that this difference reflects the higher degree of diversification at large banks. If large banks are already better diversified, the marginal benefit of CDS use to isolate them from shocks is lower. We now study the role of diversification in our results more directly. We test whether the effect of risk management using CDS depends on the diversification profile. We expect this effect to be present only for less-diversified banks, as suggested by our previous results.

Diversifying idiosyncratic risks increases the similarity between banks since they end up exposed to similar risks (see e.g., Wagner (2010)). Hence, as a proxy for diversification, we calculate the correlation between the return over assets of each bank, ROA, and the annual average ROA of the sample[35]. Less-diversified banks will display a lower

[35] Univariate analysis shows that large banks are significantly more correlated with the market ROA

correlation with the market average return over assets. Following the literature (see e.g., Hawkesby et al. (2007)), we consider a low correlation to be lower than 0.4. We thus estimate our baseline models by splitting the sample according to this criterion. The results are shown in Table 6. Columns (1) and (2) present the relationship between CDS and risk-taking for low-correlation and high-correlation set of banks, respectively. In line with our expectations, the relationship between CDS use and risk-taking is positive and significant only for the low-correlation sample of banks (column (1)).

We next test whether RM banks are better isolated from shocks. Columns (3) and (4) present the results. The interaction term $Crisis * CD$ in column (3) shows that for the low-correlation set of banks, CDS use does not have a significantly different effect during the crisis. This is probably because on average these banks increased the commercial loans extended during this period, as indicated by the coefficient of the crisis dummy. For the high-correlation set of banks in column (4), we do not find any positive effect of CDS use, as expected.

Finally, we test whether CDS use reduces the probability of failure. We do not split the sample in this case to maximize the variability of the dependent variable, the dummy $Fail$. Instead, we add the interaction term between the dummy variable for low correlation and the CDS-use dummy, $Low\ corr * CD_{t-1}$. The results are displayed in column (5). The single term CD_{t-1} is not significant in this case, indicating that high-correlation banks do not exhibit a lower probability of failure as a result of CDS use. In contrast, low-correlation banks using CDS have a lower probability of failure one year ahead, as indicated by the negative and significant coefficient of the interaction term, consistent with our previous results.

These results show that the effects of risk management using CDS are reduced when diversification increases. This evidence lends support to the hypothesis that differences in the results for small and large banks are driven by differences in their diversification profiles.

than small banks are. They are therefore more diversified.

3.7. Conclusions

The rapid increase in the use of financial innovations has led to a lively discussion of their potential effects on financial stability. In this paper, we study the effect on stability of two opposing effects: increased risk-taking incentives and the ability to isolate from economic shocks through risk management. We consider a model where a bank has the possibility to manage its risk, taking positions on both sides of the CDS market. We show that the bank takes more risk, increasing the supply of credit. However, overall, banking stability increases as the result of the bank's ability to rebalance its portfolio when economic conditions change.

We test these predictions using data for US BHCs. The results show that banks using CDS extended a larger share of commercial loans than other banks. Moreover, their credit supply was less affected during the 2007–2009 crisis. We find statistically and economically significant evidence for this result for small banks, for which the marginal benefit of CDS use may be higher. In line with this evidence, we show a negative and significant relationship for small banks between the use of CDS and the probability of failure one year ahead. We argue that this evidence is consistent with small banks benefiting from enhanced stability as a result of their risk management via CDS.

The results of this paper suggest that an increase in banks' credit supply should not be considered detrimental to stability, if it is accompanied by successful risk management practices. This suggests that regulation should focus on the overall riskiness of the bank when assessing bank's stability and shape a system for proper risk management practices.

3.8. Appendix

Proof of Proposition 1. Given that the marginal revenues are the same in both cases, it suffices to compare the marginal costs of each case. If the difference between the marginal cost in the benchmark case and that in the RM case is greater than zero, then the bank takes a lower risk at $t = 0$ when it does not have the ability to manage its risk. When $c > \gamma$ the difference between the marginal costs is

$$c\left(-f_L e(L, f(L)) + q(L)\right) - \gamma > 0$$
$$L > -\bar{\epsilon}a + \frac{2\gamma}{c}\bar{\epsilon}a + \hat{L}.$$

Therefore, $L^{*B} > -\bar{\epsilon}a + \frac{2\gamma}{c}\bar{\epsilon}a + \hat{L} \implies L^{*RM} > L^{*B}$. In addition, to avoid a corner solution we need $c > 2\gamma$. Define $r(L) = x - zL$. Furthermore, from (3.11) we have

$$L^{*B} = \frac{x(1-\bar{p}) - \bar{p}\lambda - c(1/2 - \hat{L}/2a\bar{\epsilon})}{2z(1-\bar{p}) + c/2a\bar{\epsilon}}. \tag{3.32}$$

Then,

$$\frac{x(1-\bar{p}) - \bar{p}\lambda - c(1/2 - \hat{L}/2a\bar{\epsilon})}{2z(1-\bar{p}) + c/2a\bar{\epsilon}} > -\bar{\epsilon} + \frac{2\gamma}{c}\bar{\epsilon}a + \hat{L}$$
$$\frac{x(1-\bar{p}) - \bar{p}\lambda - \gamma}{2(\hat{L} - \bar{\epsilon}a + 2\frac{\gamma}{c}\bar{\epsilon}a)(1-\bar{p})} > \tilde{z}. \tag{3.33}$$

Since z represents the slope of the demand curve for loans, for high levels of competition $L^{*RM} > L^{*B}$. *Q.E.D.*

Proof of Proposition 2. We consider the case where $c > \gamma$ and set the FOC of the RM case to zero. The partial derivative with respect to $E(\epsilon)$ is

$$\frac{\partial FOC}{E(\epsilon)} = -(r(L^*) + \lambda) - r_L L^*.$$

In the benchmark case

$$\frac{\partial FOC}{E(\epsilon)} = -(r(L^*) + \lambda) - r_L L^* - c\frac{\partial q(L^*, E(\epsilon))}{\partial E(\epsilon)}.$$

Given that the impact on the expected marginal benefit is the same in both cases, it suffices to compare the impact on the expected marginal costs. If the impact on the expected marginal cost in the benchmark case is higher than that in the RM case, the bank decreases risk-taking by less when the expected value of the shock increases in the RM case. Thus,

$c\frac{\partial q(L^*,E(\epsilon))}{\partial E(\epsilon)} > 0 \implies |\frac{dL^{*RM}}{dE(\epsilon)}| < |\frac{dL^{*B}}{dE(\epsilon)}|.$

This always holds since $\frac{\partial q(L^*,E(\epsilon))}{\partial E(\epsilon)} > 0$. Therefore, $|\frac{dL^{*RM}}{dE(\epsilon)}| < |\frac{dL^{*B}}{dE(\epsilon)}|$. *Q.E.D.*

Numerical Proof of Prediction 1. For $c > \gamma$, solving Eq. (3.20) shows that the critical shock for the RM case is

$$\epsilon_c^{RM} = \sqrt{\left[(r(L) - \bar{p}(\lambda + r(L)))L - (L - \hat{L})\gamma + (1-d)\right]\frac{4\bar{\epsilon}}{(\lambda + r(L))L + a\gamma}} - \bar{\epsilon}.$$

When $\epsilon > \tilde{\epsilon} = \frac{\hat{L}-L}{a}$, the term $max(e(L,\epsilon), 0) = e(L,\epsilon)$. We assume for now, and check later, that this condition holds for the optimal level of risk L^{*B} and the critical shock ϵ_c^B, which we obtain by solving Eq. (3.4):

$$\epsilon_c^{B} = \sqrt{\left[(r(L) - \bar{p}(\lambda + r(L)))L - c(L - \hat{L}) + (1-d)\right]\frac{4\bar{\epsilon}}{(\lambda + r(L))L + ca}} - \bar{\epsilon}.$$

If the critical shock in the RM case is larger than that in the benchmark case, the bank is more stable in the former case. We demonstrate graphically the higher stability of the RM bank using a numerical example. We are interested here in the case where $L^{*B} < L^{*RM}$, so we restrict our calculations to the set of parameters where this relationship holds, i.e., $\gamma < c/2$ and $z < \tilde{z}$.

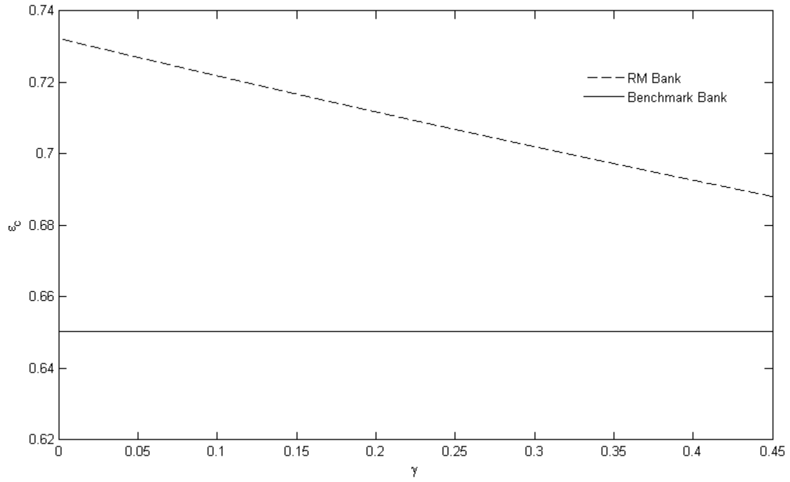


Figure 3.1: ϵ_c as a function of γ.

The figure is drawn with the parameters $x = 1, \lambda = 0.25, d = 0.5, \bar{p} = 0.3, \bar{\epsilon} = 0.10, a = 0.15, \tau = 0.08, z = 0, c = 0.9$, and $\gamma \in [0, c/2)$. Moreover, $\epsilon_c^B > \tilde{\epsilon}$.

Figure 1 depicts the critical shocks of each bank with respect to the premium of the derivative γ. We know that $L^{*B} < L^{*RM}$ holds for high levels of competition and in particular for perfect competition. Therefore, defining $r(L) = x - zL$, we assume that $z = 0$, i.e., the demand curve for loans is perfectly elastic[36]. When this is the case, if $x - \bar{p}(\lambda + x) \geq \gamma$, the RM bank will lend the maximum allowed at $t = 0$, $\hat{L}$. We also have $L^{*B} = \hat{L} - a\bar{\epsilon} + \frac{x(1-\bar{p})-\bar{p}\lambda}{c/2a\bar{\epsilon}} < \hat{L}$[37].

The figure shows that $\epsilon_c^{RM} > \epsilon_c^B$, i.e., the bank is more stable in the RM case for every level γ in this domain. When the price of the derivative γ increases, the bank buys less protection and pays the cost of the excess risk. Hence, as the price of the derivative increases the bank tends to the benchmark case. As expected, the critical shock of the bank decreases as γ increases, i.e., it becomes less stable and closer to the critical shock of the benchmark case.

To complement the comparative statistics, Fig. 2 shows the critical shocks with respect to the level of competition, z. Notice that as z increases, the level of competition decreases. We restrict this parameter to the range where $L^{*B} < L^{*RM}$, i.e., $z < \tilde{z}$.

[36] The relationship between the critical shocks of the banks and z is not monotonic. This relationship arises because of the nonmonotonic relationship between total revenues and losses and the levels of competition determined by z. Specifically, for high levels of competition (z low) the net effect of a decrease in competition on total revenues is positive (increasing the critical shock) and the net effect on losses is positive (decreasing the critical shock). Both of these effects are reversed as competition decreases (z increases). The effect of z on costs is monotonic and positive.

[37] Notice that $\gamma \leq x - \bar{p}(\lambda + x) < c/2$.

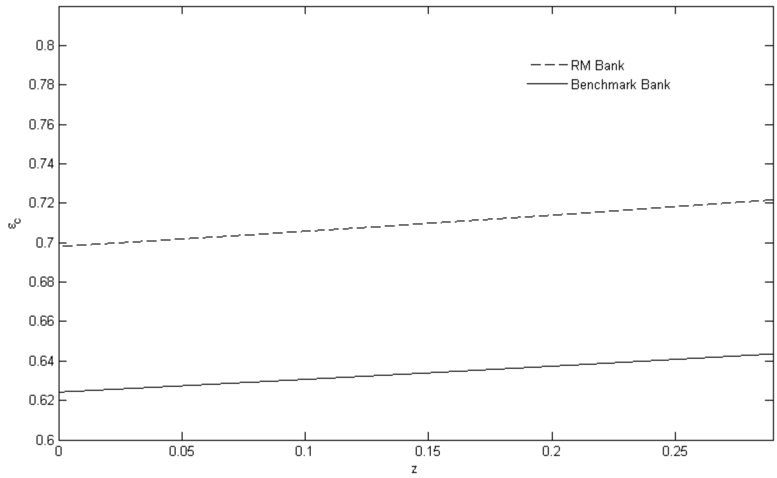


Figure 3.2: ϵ_c as a function of the level of competition, z.

The figure is drawn with the same parameters as in Fig. 1, except $\gamma = 0.3$ and $z \in [0, \tilde{z}]$. Moreover, $\epsilon_c^B > \tilde{\epsilon}$.

The figure shows that for every level of competition in this range, $\epsilon_c^{RM} > \epsilon_c^B$, i.e., the bank is more stable in the RM case. Both critical shocks increase as the level of competition decreases, i.e., z increases. This is the result of lower risk-taking as competition decreases and the corresponding positive effect on interest rates. In our example, as competition decreases, the negative effect of higher total losses is offset by the positive effect of higher total revenues and the lower total cost. Thus, stability increases when competition decreases. *Q.E.D.*

3.9. Tables

Table 1: Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
C&I/TA	0.101	0.061	0.009	0.304
CD	0.051	0.219	0	1
Log(assets)	13.825	1.377	10.188	21.569
ROA	0.004	0.004	-0.007	0.016
Sub debt/TA	0.130	0.104	0.001	0.991
Liquid assets/TA	0.234	0.119	0.002	0.911
Equity/TA	0.089	0.039	-0.163	0.797
Real estate/TA	0.516	0.149	0	0.937
Allowance/TA	0.010	0.004	0	0.024
Net chargeoffs/TA	0.002	0.002	-0.0003	0.012
Derivatives not for trade	0.437	0.496	0	1

Table 2: Risk management and risk-taking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Banks			Small Banks			Large Banks	
CD	0.0097	0.0095	0.0096	0.0244***	0.0270***	0.0267***	0.0085	0.0085	0.0085
	(0.0068)	(0.0068)	(0.0068)	(0.0023)	(0.0029)	(0.0030)	(0.0074)	(0.0074)	(0.0074)
Liquid assets/TA	-0.325***	-0.324***	-0.324***	-0.370***	-0.369***	-0.368***	-0.266***	-0.266***	-0.266***
	(0.0206)	(0.0205)	(0.0204)	(0.0335)	(0.0332)	(0.0330)	(0.0232)	(0.0233)	(0.0233)
Sub debt/TA	-0.0456***	-0.0436***	-0.0432***	-0.0359*	-0.0354*	-0.0347*	-0.0551***	-0.0551***	-0.0552***
	(0.0138)	(0.0141)	(0.0141)	(0.0204)	(0.0202)	(0.0202)	(0.0178)	(0.0184)	(0.0184)
ROA	0.536***	0.530***	0.531***	0.679***	0.566*	0.568*	0.462***	0.428***	0.427***
	(0.126)	(0.158)	(0.158)	(0.237)	(0.291)	(0.290)	(0.141)	(0.165)	(0.165)
Log(assets)	-0.0035	-0.0031	-0.0028	-0.0024	-0.0018	-0.0012	-0.0043	-0.0043	-0.0044
	(0.0034)	(0.0035)	(0.0034)	(0.0061)	(0.0061)	(0.0061)	(0.0049)	(0.0050)	(0.0050)
Equity/TA	-0.0536**	-0.0487*	-0.0490*	-0.0150	-0.0111	-0.0111	-0.109***	-0.109***	-0.109***
	(0.0251)	(0.0253)	(0.0253)	(0.0431)	(0.0443)	(0.0441)	(0.0343)	(0.0347)	(0.0347)
Real estate/TA	-0.325***	-0.327***	-0.327***	-0.383***	-0.385***	-0.385***	-0.242***	-0.243***	-0.242***
	(0.0252)	(0.0252)	(0.0252)	(0.0394)	(0.0388)	(0.0388)	(0.0291)	(0.0294)	(0.0294)
Allowance/TA		0.381**	0.378**		0.478*	0.458*		0.0112	0.0113
		(0.175)	(0.175)		(0.252)	(0.251)		(0.233)	(0.233)
Net chargeoffs/TA		-0.466**	-0.472**		-0.800**	-0.799**		-0.0945	-0.0939
		(0.234)	(0.234)		(0.348)	(0.348)		(0.301)	(0.301)
Derivatives			-0.0014			-0.0030*			7.52e-05
			(0.0010)			(0.0018)			(0.0012)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,253	7,253	7,253	3,591	3,591	3,591	3,662	3,662	3,662
R-squared	0.37	0.37	0.37	0.47	0.47	0.47	0.30	0.30	0.30

The dependent variable in these models is the total volume of commercial loans extended scaled by total assets. All panel data models are estimated bank and time fixed effects with clustered robust standard errors at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 3: Risk management and competition

	(1)	(2)	(3)
	All Banks	Small Banks	Large Banks
CD	0.0096	0.0273***	0.0091
	(0.006)	(0.002)	(0.007)
lowHHI*CD	7.61e-05	0.0101***	-0.0053
	(0.0055)	(0.0031)	(0.0075)
lowHHI	0.0001	-0.0014	0.0016
	(0.001)	(0.001)	(0.001)
Liquid assets/TA	-0.325***	-0.367***	-0.269***
	(0.0207)	(0.0335)	(0.0236)
Sub debt/TA	-0.0445***	-0.0387*	-0.0539***
	(0.0143)	(0.0202)	(0.0188)
ROA	0.541***	0.561*	0.452***
	(0.159)	(0.292)	(0.165)
Log(assets)	-0.0032	-0.0018	-0.0046
	(0.0035)	(0.0063)	(0.0052)
Equity/TA	-0.0488*	-0.0159	-0.109***
	(0.0263)	(0.0444)	(0.0370)
Real estate/TA	-0.328***	-0.382***	-0.246***
	(0.0255)	(0.0391)	(0.0298)
Allowance/TA	0.394**	0.471*	0.0364
	(0.177)	(0.253)	(0.234)
Net chargeoffs/TA	-0.507**	-0.846**	-0.150
	(0.236)	(0.349)	(0.306)
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	7,123	3,550	3,573
R-squared	0.38	0.47	0.30

The dependent variable in these models is the total volume of commercial loans extended scaled by total assets. All panel data models are estimated bank and time fixed effects with clustered robust standard errors at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 4: Risk management and business cycle

	(1)	(2)	(3)
	All Banks	Small Banks	Large Banks
CD	0.0080	0.0207***	0.0074
	(0.0071)	(0.0036)	(0.0076)
Crisis*CD	0.0030	0.0051**	0.0026
	(0.0033)	(0.0026)	(0.0036)
Crisis	-0.0025***	-0.0025*	-0.0032**
	(0.0009)	(0.0015)	(0.0013)
Liquid assets/TA	-0.334***	-0.379***	-0.277***
	(0.0207)	(0.0337)	(0.0237)
Sub debt/TA	-0.0237*	-0.0181	-0.0339*
	(0.0137)	(0.0201)	(0.0178)
ROA	0.144	0.257	-0.0146
	(0.144)	(0.259)	(0.158)
Log(assets)	-0.0003	0.0012	-6.66e-05
	(0.0027)	(0.0044)	(0.0039)
Equity/TA	-0.0423	-0.0022	-0.103***
	(0.0259)	(0.0452)	(0.0354)
Real estate/TA	-0.319***	-0.383***	-0.230***
	(0.0253)	(0.0388)	(0.0296)
Allowance/TA	0.170	0.278	-0.207
	(0.171)	(0.240)	(0.228)
Net chargeoffs/TA	-0.379	-0.694**	-0.0158
	(0.235)	(0.348)	(0.305)
Bank FE	Yes	Yes	Yes
Observations	7,253	3,591	3,662
R-squared	0.36	0.46	0.28

The dependent variable in these models is the total volume of commercial loans extended scaled by total assets. All panel data models are estimated fixed effects with clustered robust standard errors at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 5: Risk management and banking stability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Banks			Small Banks			Large Banks	
CD_{t-1}	-0.0019	-0.0007	-0.0012	-0.0062***	-0.0047 ***	-0.0029**	-0.0003	-0.0015	-0.0003
	(0.0033)	(0.0027)	(0.0018)	(0.0014)	(0.0013)	(0.0012)	(0.0033)	(0.0027)	(0.0022)
NPL/TL_{t-1}	0.568***	0.308***	0.198***	0.418***	0.225***	0.126**	0.686***	0.375***	0.217***
	(0.067)	(0.055)	(0.048)	(0.083)	(0.070)	(0.056)	(0.1007)	(0.081)	(0.068)
$Allowance/TL_{t-1}$	-0.1257	-0.0956	0.0166	0.0121	0.0258	0.1002	-0.257	-0.203	-0.034
	(0.146)	(0.128)	(0.098)	(0.181)	(0.171)	(0.129)	(0.211)	(0.175)	(0.116)
Net chargeoffs/TL_{t-1}	1.140***	0.219	0.138	0.851***	0.174	0.141	1.2678***	0.163	0.095
	(0.2238)	(0.214)	(0.165)	(0.291)	(0.291)	(0.199)	(0.318)	(0.295)	(0.201)
ROA_{t-1}		-1.576***	-0.9256***		-1.202***	-0.658***		-1.761***	-0.920***
		(0.219)	(0.205)		(0.297)	(0.233)		(0.298)	(0.257)
$Loangrowth_{t-1}$		0.0025	-0.0023		0.0020	-0.0031		0.0019	-0.0008
		(0.0072)	(0.0065)		(0.0119)	(0.0096)		(0.0088)	(0.0079)
Sub debt/TA_{t-1}			0.0139***			0.0203**			0.0106**
			(0.0047)			(0.0090)			(0.0044)
$Log(assets)_{t-1}$			0.0008*			0.0034*			0.0009
			(0.0004)			(0.0021)			(0.0005)
$Loan/TA_{t-1}$			0.0228***			0.0144**			0.0252***
			(0.0051)			(0.0071)			(0.0069)
Real estate/TL_{t-1}			0.0136***			0.0028			0.0170***
			(0.0039)			(0.0049)			(0.0051)
Observations	8,392	7,893	7,893	3,451	3,115	3,115	4,942	4,778	4,778
pseudo R-squared	0.31	0.35	0.38	0.32	0.34	0.37	0.31	0.35	0.39

The dependent variable in these models is the bank-specific failure indicator for each year. All regressions report marginal effects and are estimated with clustered robust standard errors at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 6: Risk management effect and diversification

Variables	(1) C&I/TA Low Correlation	(2) C&I/TA High Correlation	(3) C&I/TA Low Correlation	(4) C&I/TA High Correlation	(5) Failure
CD	0.0151***	0.0080	0.0202***	0.0056	0.0057
	(0.0039)	(0.0074)	(0.0054)	(0.0078)	
Crisis*CD			-0.0066	0.0037	
			(0.0050)	(0.0037)	
Crisis			0.0076***	-0.0093***	
			(0.0028)	(0.0014)	
CD_{t-1}					-0.0001
					(0.0013)
Low corr* CD_{t-1}					-0.0014**
					(0.0005)
Low $corr_{t-1}$					-0.0016***
					(0.0006)
Bank Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	No
Observations	1,864	5,389	1,864	5,389	6184
R-squared	0.31	0.40	0.31	0.40	0.35

The dependent variable in models (1)–(4) is the total volume of commercial loans extended scaled by total assets. The dependent variable in model (5) is the bank-specific failure indicator for each year. All panel data models are estimated with clustered robust standard errors at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Chapter 4

The two faces of interbank correlation

The recent crisis has made systemic risk a priority on the agenda of policy makers. While systemic risk can arise from a variety of sources, a common consequence is that it increases the vulnerability of the financial system to shocks. Broadly, two different channels can be distinguished. First, since financial institutions are heavily interconnected, a shock to one part of the financial system can easily spill to other parts.[38] Second, financial institutions tend to undertake similar activities, or display homogeneity in other dimensions (such as their risk management systems), which may amplify the impact of common shocks.[39] Notably both channels are particularly pronounced at large banks as these banks tend to be more connected and can also be a direct source of common shocks due to their importance for the financial system.

In order to avoid a repeat of the crisis, regulators are now redesigning financial regulation to take into account systemic risk.[40] A major challenge for this is the proper measurement of such risk. Since there is a large number of potential causes of systemic risk, a popular approach is to focus on an institution's overall systemic risk as reflected in market prices. A key input in such market-based measures is the correlation of a bank with other banks in the system. For example, in an early contribution, De Nicolò and

[38]Such spillovers may arise (among others) from asset prices contagion (e.g., Allen and Gale (1998)), mutual credit exposures (e.g., Freixas, Parigi and Rochet (2000)) or interbank market contagion (e.g., Aghion, Bolton, and Dewatripont (2000)).

[39]In this context, systemic risk has been shown to result from common investments (e.g., Acharya and Yorulmazer (2007)), strategic complementarities on the liability side (e.g., Farhi and Tirole (2012)) but also from common value-at-risk constraints (Persaud (2000)) and Danielsson and Zigrand (2008)).

[40]For example, Basel III includes a capital surcharge for institutions that are deemed systemically important.

Kwast (2002) propose to directly use pair-wise correlations as a systemic risk indicator. Other widely-used measures of systemic risk (such as the *CoVaR*, the *Marginal Expected Shortfall* or the *Distressed Insurance Premium*[41]) are indirectly based on correlations of individual banks with the system.

We argue that one has to be careful in equating interbank correlations with systemic risk. The reason for this are diversification activities at banks. To see the issue, suppose that all banks in the economy are fully diversified and hence invest in the same portfolio (the market portfolio). Interbank correlations will then obviously be one – but this is neither due to the presence of spillovers among banks nor due to any banking sector-specific homogeneity. This simple example illustrates a bigger issue: interbank correlations are partly driven by the diversification characteristics of banks.

We propose a methodology that allows isolating the part of the interbank correlation that is not due to diversification. The method is based on the concept of *minimum commonality.* The minimum commonality is the degree of commonality at banks that is unavoidable given their degree of diversification. From this one can define a bank's *excess correlation* (the systemic part of interbank correlation) as the part of a bank's interbank correlation that exceeds the one implied by its minimum commonality.

The decomposition of interbank correlation is conceptually important. Each component arises for different reasons and is expected to have different implications for financial stability. Excess correlation measures pure systemic risk since it arises when there are spillovers across institutions or when banks display homogeneity not present in other sectors of the economy. It should thus be of concern to regulators and attract higher capital charges. By contrast, standard portfolio theory suggests that diversification at banks enhances their resilience to shocks. Direct application of this theory would thus suggest no reason for regulators to discourage diversification.[42] In particular, since subsequent Basel accords have permitted a capital relief for diversified portfolios, consistency dictates that one should not "punish" correlation that is entirely due to diversification.

We apply our methodology to U.S. BHCs. The results strengthen the view that it is important to distinguish between the different sources of bank correlation. First, we find

[41] Adrian and Brunnermeier (2010), Acharya et al. (2011) and Huang, Zhou, and Zhu (2009), respectively.

[42] Recent literature (Wagner (2010) and Allen et. al (2012)), however, suggests that diversification at banks can also be a source of systemic risk.

that a large part of the (cross-sectional) variation in interbank correlations is due to diversification: before the crisis, about 84% of a bank's average correlation with other banks can be explained by its minimum commonality. The systemic component in interbank correlations is hence of only modest importance[43]. Second, the two components have different implications for the resilience of banks during the crisis of 2007-2009. While banks with a higher minimum commonality (indicating more diversification) performed better during the crisis, banks with more systemic correlation did not systematically perform differently than other banks.[44] Third, the distinction between both correlation components matters especially for large banks, which are of special importance for financial stability. These banks – even though they have high minimum commonality – have high excess correlation. Large banks are hence particularly exposed to the undesirable part of correlation.

While the primary focus of our paper is on the decomposition of interbank correlation, a second contribution is the development of a market-based measure of diversification. Prior literature on diversification at firms (financial or non-financial) had to deal with the challenge that it is not easy to quantify a firm's overall diversification since diversification can arise from a variety of different sources.[45] In addition, construction of comprehensive diversification measures is often constrained by the fact that accounting data only provides very limited information on diversification activities.

Our diversification measure is computed from the commonality of a firm with the market portfolio. It is based on the idea that the more diversified a firm is, the closer it becomes to the market portfolio and the higher should be its correlation with the latter.[46] The advantage of this measure is that it captures overall diversification and hence encompasses a variety of diversification sources. As the only (firm-specific) input it requires stock returns; it is hence an easily computable measure.

The diversification measures computed for BHCs exhibit some interesting properties.

[43]This figure falls to 80% during the crisis. As expected, the variance of the interbank correlation that is explained by the diversification component decreases since diversification profiles across banks are more stable, while spillover effects increase in crisis periods.

[44]The latter result may reflect various forms of government bailouts.

[45]Besides asset-side diversification (such as through geographical or functional diversification), diversification also arises on the liability side. For example, using different sources of funding (e.g., market-funding and bank loans) reduces exposure to funding shocks. At banks the measurement of diversification is particularly complex since banks undertake a plethora of diversifying activities, many of them also off-balance sheet (for instance, securitization and the buying and selling of credit protection).

[46]While we use correlations of market returns, an alternative are balance-sheet based correlation measures (for instance, the correlation of a firm's profits or sales with the ones in the economy).

Among others, they suggest quickly declining benefits from diversification. While at small banks increases in size are associated with substantial increases in diversification, these gains are quickly eroded. For medium-size and large banks increases in size only lead to modest improvements in diversification. Taken together with the result that large banks display a high degree of excess correlation, this suggests that these banks have a high amount of the undesirable part of correlation, but a low amount of the desirable part.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 explains our methodology for separating interbank correlation into a diversification and a systemic part. Section 4 presents the empirical analysis. Section 5 concludes.

4.1. Related Literature

The measurement of systemic risk has advanced rapidly in recent years. An important strand of the literature quantifies systemic risk using information compounded in the market prices of financial institutions. These measures, directly or indirectly, uses interbank correlations as an input. While early work has quantified systemic risk directly through interbank correlations (e.g., De Nicolò and Kwast (2002)), recent contributions have refined measurement by looking at what are essentially different aspects of interbank correlations or covariates. The *CoVaR* (Adrian and Brunnermeier (2010)), for instance, estimates the covariance of a bank and the banking sector conditional on the bank experiencing a tail event. Acharya et al. (2011) propose to measure systemic risk through the *Marginal Expected Shortfall* (MES), which is the expected loss to a financial institution conditional on a set of banks performing poorly. Huang, Zhou, and Zhu (2009) combine default probabilities from CDS with stock return correlations to calculate a *Distressed Insurance Premium* (DIP), which is the insurance premium required to cover distressed losses in the banking system. In a recent paper, Billio et al. (2012) characterize systemic risk by measuring correlation through principal components analysis. The results in our paper suggest that one has to be careful with interpreting these (and other) systemic risk measures since the correlations that underlie them may partly be driven by diversification activities (which may, or may not, be harmful for financial instability). In order to arrive at a "pure" measure of systemic risk, these measures should be alternatively computed isolating the effect of diversification. Our paper suggests a methodology for how this can be done.[47]

The second interest of our paper relates to extant work on the relationship between diversification and firm performance. Although the evidence is mixed, the majority of contributions suggest that diversification is detrimental to the performance of financial institutions.[48] Owing to data constraints, many papers focus on functional diversification, measured by the share of non-interest rate activities at banks. Stiroh (2006) finds that U.S. BHCs with higher non-interest rate income have higher risk but do not earn higher returns. Laeven and Levine (2007) find that functional diversification into non-loan activities leads to a valuation discount; a similar result is obtained in Schmid and Walter (2009). In contrast, Baele et al. (2007) show that functional diversification increases valuation and can reduce risk at European banks and Elsas et al. (2010) find a diversification premium for a sample of developed countries. DeLong (2001) studies M&As and finds that mergers that increase focus in terms of activity and geography enhance stockholder value, whereas mergers that induce more functional diversification do not create value.[49] Acharya et al. (2006) examine Italian banks, for which detailed data on the industrial and sectoral composition of lending portfolios is available. They overall find mixed results for the relationship between diversification and bank return and risk. However, for riskier banks diversification seems to reduce performance.

Our study differs in two respects from prior work. First, we employ a new measure of diversification. As a market-based measure it captures *overall* diversification of a bank, including all potential on-balance sheet and off-balance sheet diversification activities. It also measures *effective* diversification as it will be influenced by the extent of correlation among different activities (which accounting-based measures will ignore). Second, we do

[47]Applying our methodology to these systemic risk measures is relatively straightforward since in its empirical implementation it amounts to including only the part of interbank correlations that is orthogonal to the correlation with the market.

[48]The literature on non-financials mostly arrives at a negative link between diversification and firm performance as well (Lang and Stulz (1994), Berger and Ofek (1995) and Servaes (1996)); however, it also identifies various methodological hurdles (see Maksimovic and Phillips (2002), Campa and Kedia (2002), Graham et al. (2002)).

[49]A potential explanation for the predominantly negative effects of functional diversification (in U.S. studies) may be that non-interest income has an inferior risk-return trade-off than traditional lending activities. Evidence for this is provided in Stiroh and Rumble (2006) and Demirgüc-Kunt and Huizinga (2010).

not focus on bank performance in normal times, but in times of crisis. Specifically, controlling for a variety of alternative factors, we find that diversification reduces a bank's vulnerability to the crisis of 2007—2009, consistent with standard theory suggesting that diversification makes banks less exposed to shocks.[50] Together with extant evidence that diversification is detrimental in normal times, this may suggest that diversification benefits mainly materialize in downturns. An alternative explanation is that diversification benefits are specific to the type of diversification considered. For instance, while functional diversification may be detrimental to bank performance, overall, diversification may still be beneficial. More work seems warranted on this question.

4.2. Methodology

In this section we describe how interbank correlation can be decomposed into a diversification part and an excess (systemic) correlation part. Suppose that there are two banks, A and B, and two assets, X and Y. The assets are identically and independently distributed and of equal supply in the economy. The economy's market portfolio hence consists of identical units of the assets.

Consider first the case where both banks are fully diversified. Denoting the share of funds bank i ($i = A, B$) invests in asset X with w_i ($w_i \in [0, 1]$), we have $w_A = w_B = \frac{1}{2}$. Banks are then fully correlated with each other – but this is entirely due to their diversification strategies. We say that in this case there is zero excess correlation. Consider next a situation where banks are investing in the same asset, say, asset X ($w_A = w_B = 1$). Banks are still fully correlated with each other. However, this correlation is not due diversification (as banks are undiversified) but due to the fact that banks specialize in the same asset. Interbank correlation hence consists entirely of excess correlation (full excess correlation). Note that in this case banks are only modestly correlated with the market portfolio, while in the diversification case the correlation is one.

Let us now analyze arbitrary portfolio choices w_A and w_B. We first define a concept of commonality and diversification.

[50]Brunnermeier, Dong and Palia (2012) examine the non-interest income at banks. In contrast to our study they find that a higher share of such income (a proxy for functional diversification) is negatively related to performance during the crisis of 2007-2009.

Definition 4.1. *The **degree of commonality** between banks A and B is given by*

$$s(w_A, w_B) = 1 - |w_A - w_B| \,. \tag{4.1}$$

Similar to interbank correlation, the degree of commonality will be zero in case banks specialize in different assets (e.g., $w_A = 1$ and $w_B = 0$) and it will be one if banks hold the identical portfolios ($w_A = w_B$).

Definition 4.2. *The **degree of diversification** at bank i ($i \in \{A, B\}$) is given by*

$$d_i(w_i) = 1 - 2\left|w_i - \frac{1}{2}\right| . \tag{4.2}$$

Diversification will be zero if the bank is undiversified ($w_i = 0$ or $w_i = 1$) and it will be one if the bank is fully diversified ($w_i = \frac{1}{2}$).

The degree of commonality can be decomposed as follows. We first calculate the commonality that is unavoidable to reach a degree of diversification identical to the one in the banking sector, which we call *minimum commonality.* For average banking sector diversification d ($d := \frac{d_A+d_B}{2}$), minimum commonality is defined as follows:

Definition 4.3. *The **minimum commonality** $s^{\min}(d)$ is the lowest commonality s that can implement banking sector diversification d. Formally we have:*

$$s^{\min}(d) := \min_{w_A, w_B} s(w_A, w_B), \ s.t. \ \frac{d_A(w_A) + d_B(w_B)}{2} = d \ and \ 0 \leq w_A, w_B \leq 1. \tag{4.3}$$

From this we can define excess commonality:

Definition 4.4. ***Excess commonality** $e(w_A, w_B)$ is the difference between actual and minimum commonality:*

$$e(w_A, w_B) := s(w_A, w_B) - s^{\min}(d(w_A, w_B)). \tag{4.4}$$

In our simple example, excess commonality can be easily computed. For given diversification, the least possible commonality obtains when banks specialize as much as possible in different assets. For average banking sector diversification d ($d := \frac{d_A+d_B}{2}$), it is easy to see that an allocation that minimizes commonality arises when bank A invests a fraction $\frac{d}{2}$ in asset X and bank B invests a fraction of $\frac{d}{2}$ in asset Y ($w_A^{\min} = \frac{d}{2}$ and $w_B^{\min} = 1 - \frac{d}{2}$).[51] The resulting commonality is then $s^{\min}(d) = 1 - \left| w_A^{\min}(d) - w_B^{\min}(d) \right| = d$. Thus, the minimum commonality required to achieve a certain level of diversification is given by the degree of diversification itself. It follows that

Proposition 4.1. *In the two bank-two asset economy, excess commonality $e(w_A, w_B)$ is given by the difference between actual commonality $s(w_A, w_B)$ and diversification $d(w_A, w_B)$.*

In an empirical implementation we face various challenges. First, we do not have information on bank portfolio shares w_i, which are needed for calculating commonality. However, we can approximate commonality directly by the interbank correlation of bank stock returns. Observing that diversification is effectively a measure of commonality with the market portfolio, we can in addition approximate diversification by the correlation of a bank with the market portfolio. At this point, it is important to properly define which is the relevant market for a given bank. According to our theoretical model, the market portfolio will be defined as identical units of the assets that a given bank has available to invest in. In this paper, we focus on US banks, therefore we define the US as being the relevant market. We use then the S&P 500 as market index. For European banks for instance, because of the high degree of cross-border banking across countries, banks can lend (or invest) in other countries in the European Union. Therefore, in this case it would be reasonable to take the entire Europe as the relevant market[52].

Second, we have to adapt the commonality measures for more than two banks. If there are at least three banks, commonality becomes bank-specific. We can then calculate the commonality of an individual bank by its average correlation with all other banks, or, alternatively, by its correlation with a banking sector index. In this paper we take the later option, we calculate the correlation with the S&P 500 banking sector price index. This index follows a modified market capitalization weight methodology. Therefore, larger banks will have a larger weight. This is consistent with our theoretical model, since larger banks will also invest larger amounts in the different assets and hence, increasing their commonality.

Third, the simple property that excess correlation equals commonality minus diversification (Proposition 1) only holds for the special case of uncorrelated assets and when

[51] Since the portfolio shares enter linearly into the commonality measure, there are many other portfolios that lead to the same minimum commonality.

[52] One could take, for instance, the MSCI Europe as market index.

the number of assets is at least as large as the number of banks.[53] Excess correlation will still be a negative function of the diversification degree; however, the exact functional form will depend on what is assumed about the set of investable assets in the economy. In our empirical implementation we will hence estimate excess correlation. For this we will take excess correlation to be the regression residual from a regression of interbank correlation on diversification. In this regression, proposition 1 then will hold if the constant coefficient is close to zero and the diversification coefficient is not significantly different from one. Effectively, this excess correlation measures whether a bank has higher correlation than the one that is predicted for its diversification degree.

4.3. Empirical Analysis

4.3.1. Data

Our analysis focuses on Bank Holding Companies' (BHCs) in the US. We use bank-level data from the US Call Reports. These reports contain quarterly data about on and off balance-sheet and income-statement information for all regulated BHCs in the US. We focus our analysis on the 200 largest BHCs in 2006 that are classified as commercial banks and are listed in the US. Summary statistics of these variables are shown in Table 1 (Panel A).

We combine this data with daily share price data for BHCs – as well as for the S&P 500 price index and the S&P 500 banking sector price index – collected from Datastream. From this data we compute two of our main variables, the interbank correlation and the diversification measure. Interbank correlation for bank i, denoted $\rho_{i,b}$, is taken as the correlation between bank $i's$ share price return and the return on the S&P 500 banking sector index. For this we use weekly returns (winsorized at 1% level) over the three years preceding the subprime crisis (January 2004 - December 2006).[54] Similarly, diversification component, $\rho_{i,m}$, is calculated as the correlation between the bank return

[53]If the number of assets is less than the number of banks, it is not possible for banks to all specialize in (pair-wise) different assets. As a result, the minimum commonality associated with a certain degree of diversification rises, and excess correlation falls. Similarly, when assets are (positively) correlated, banks will be correlated even if they invest in different assets, again leading to lower excess correlation.

[54]Excluding the crisis period is warranted to avoid biases arising from calculating correlations in high volatility periods (see e.g. Forbes and Rigobon (2002)).

i and the S&P 500 index return.

Figure 1 depicts the relationship between the interbank correlation and the diversification component for the banks in our sample. The figure shows a clear positive relationship between these two variables. The R-squared of a regression of interbank correlation on diversification is 0.84. This supports our argument that interbank correlation is to a considerable extent driven by correlation with the market, and hence diversification. The figure also shows that some highly diversified banks have very high interbank correlation. Figure 2 provides a closer look at these banks. We can see that the top three banks in terms of interbank correlation are Bank of America, Wells Fargo & Co. and Wachovia. Furthermore, 13 out of the 20 largest banks in the sample appear in this figure. This suggests that size plays a role in interbank correlation levels. The line in figure 2 depicts the regression line based on the entire sample. Most banks appear clearly above the line, showing that their interbank correlation seems to be much larger than what can be justified by diversification – suggesting that these banks pose excess systemic risk.

4.3.2. Decomposition of Interbank Correlation

The next step is to separate interbank correlation into the part that comes from diversification, and systemic correlation. The approach we take here is to treat systemic correlation as the part of the interbank correlation that cannot be explained by diversification, and hence has to be the result of other bank characteristics that cause correlatedness. Specifically, we run the following cross-sectional regression[55]:

$$\rho_{i,b} = \alpha + \beta \rho_{i,m} + \epsilon_i \tag{4.5}$$

where $\rho_{i,b}$ is the interbank correlation of bank i and $\rho_{i,m}$ is the diversification measure for bank i. A bank's systemic correlation is taken to be its predicted residual from this regression, $\hat{\epsilon_i}$. Systemic correlation is hence the increase interbank correlation for bank i relative to the one that is predicted by bank $i's$ market correlation. Note that systemic correlation can be negative – in which case a bank has a lower correlation relative to

[55]We have also fit a non-linear relationship by including the square of the diversification variable. This does not affect our results.

what is predicted based on its diversification measure[56].

Table 1 (Panel B) presents the summary statistics of the three correlation measures. The average interbank correlation is about 27% and ranges from -19% and to 83%. The diversification measure has a mean equal to 32%, with the lowest value being equal to -11% and a maximum of 69%. The mean of the systemic correlation (which is a regression residual) is zero, as expected. It varies between -18% to 33%. The two largest values are obtained for Bank of America and Wells Fargo & Co.

4.3.3. Determinants of Bank Diversification and Excess Correlation

In this section we examine how excess correlation and diversification relate to various bank characteristics. For this purpose, we estimate the following cross-section model:

$$Y_i = \alpha + \sum_{k=1}^{K} \phi_k B_{k,i} + \epsilon_i \tag{4.6}$$

where Y_i is either diversification $\rho_{i,m}$ or excess correlation $\hat{\epsilon}_i$ and the term B_k are different bank characteristics in 2006. These bank characteristics, first, include general bank information such as subordinated over assets (*Sub. Debt/Assets*), loans over assets (*Loans/Assets*), real estate loans over loans (*Real estate/Loans*) and size (*Log*(*Assets*)). We also allow for a non-linear relationship with size by including the square of the size variable. Second, we consider various proxies of asset quality: annual loan growth (*Loan growth*),[57] profitability (*ROA*), and interest income from loans over loans (*Interest from loans/Loans*). We also include the share of non-performing loans over loans (*NPL/Loans*) as a measure of lending risk.

Finally, we include various variables that capture credit risk transfer and derivative activities. Such activities are obvious candidates for determining bank level diversification – but they may also be drivers of excess correlation since they tend to increase interconnectedness among banks. To measure securitization activities, we consider mortgage-backed securities (*MBS held to maturity/Assets*) and total securitized assets (*Securitization/Assets*) both relative to assets. To capture derivative activities, we include total derivatives (consisting of commodity, foreign exchange, equity and inter-

[56] The coefficient for the diversification variable in this regression is not significantly different from one and the constant coefficient is close to zero. Therefore, we can argue that proposition 1 holds.

[57] Loan growth has been found to reduce lending quality (see Foos, Norden and Weber (2010)).

est rate derivatives) used for hedging over assets (*Derivatives not for trade/Assets*).[58] We also include two variables measuring the use of credit derivatives: the gross position on credit derivatives over assets held by the banks (*Gross position CD/Assets*), which equals the sum of the protection bought and sold in the credit derivatives market, and the net position on credit derivatives over assets (*Net position CD/Assets*), which equals the difference between the protection bought and sold by the bank. The distinction between gross and net aims to capture the difference between a pure transfer of credit risk (net-position) and the simultaneous buying and selling of risk (gross-position). These activities are expected to have different implications for diversification and systemic risk.

Diversification

We first analyze how the diversification component, $\rho_{i,m}$, relates to various sets of bank characteristics. For this we initially investigate sets of control variables separately in order to reduce problems arising from multicollinearity. Table 2 presents the results.

Column (1) contains the estimation of the relationship between the diversification measure and general bank characteristics. The share of loans is found to be negatively related with diversification. This result implies that a higher proportion of non-traditional activities at banks (non-loan business) is associated with more diversification, consistent with previous literature that uses loan shares as an (inverse) proxy for functional diversification (see e.g. Laeven and Levine (2007)). Size is positively and significantly related to diversification, while the squared size-term is negatively and significantly related to diversification. Taken together, this indicates an inverted U-shape relationship between diversification and size. This interesting property of the data can also be directly appreciated from figure 3, which plots diversification against size (proxied by the log of assets). The figure shows that for smaller and medium-sized banks, increases in bank size are associated with substantial improvements in diversification. However, for larger banks there is no strong increase in diversification. This picture is consistent with marginal benefits from diversification that are declining rapidly. In particular, it suggests that diversification opportunities are already reasonably well reaped at medium-sized banks.

Column (2) focuses on the relationship between asset quality and diversification.

[58] Since a large part of bank derivative activities consists of trading activities that are unrelated to credit risk transfer, it is advisable to only include the part of derivatives that are related to hedging.

Loan growth is found to be positively related to diversification. Presumably, fast growing banks have to expand to new business areas, leading to higher diversification. Profitability, measured by ROA, is also positively related to diversification. This result is somewhat unexpected as one may have thought that there is a trade-off between diversification and return.[59] It may be explained, however, if diversification into non-traditional activities (such as to fee generating income) leads to higher returns.

Column (3) reports results for the model that includes securitization proxies. It shows a positive and significant relation between securitized assets and diversification. This is explained by the fact that securitization enables banks to improve diversification by offloading overrepresented exposures in their lending portfolios.[60]

In column (4) we analyze the role of different derivatives activities. We find a positive and significant relation for both the derivatives for hedging and the gross position held in credit derivatives. As with securitization, this result is consistent with the notion that credit risk transfer leads to more diversification (Nijskens and Wagner (2011), for example, show that credit derivative usage at banks reduces the volatility of their share prices). Notably, the net credit derivative position does not enter significantly (while the gross position does), indicating that a pure shedding of risk does not contribute to diversification.

We are also interested in studying how our market-based diversification measure relates to other diversification proxies. For this, we compare our measure with functional diversification proxies (as constructed, for instance, in Laeven and Levine (2007)). These proxies are either based on assets or revenues. Denoting with w_L the share of loans to assets, asset diversification is calculated as $Asset\ Diversity = 1 - |2w_L - 1|$. Similarly, for revenue diversity we have $Revenue\ Diversity = 1 - |2w_R - 1|$, where w_R is the share of non-interest income. In column (5) and (6) we include either of these proxies. As expected, both functional diversification proxies are positively related to our diversification measure.

The last column of table 2 include all variables jointly (except the alternative diversification proxies). Three of the bank variables turn insignificant (loan growth, derivatives

[59]Consistent with such a trade-off, Stiroh and Rumble (2006) find a negative relationship between diversification and profitability using accounting data.

[60]Diversification may also be improved because following a transfer of risk, banks take on new (and possibly less correlated) risks, see Franke and Krahnen (2005) and Loutskina and Strahan (2006)).

for hedging and the gross position held in credit derivatives). In addition, interest income becomes negatively and significantly related to diversification (consistent with a diversification-specialization trade-off), while the coefficient of total securitization becomes negative and significant.

Size is an important factor in explaining variations in diversification. This can be appreciated by the fact that the R-squared in a model that only includes the two size terms is 0.56 (not reported), while the R-squared in the model that includes the full set of variables (column (7)) is only marginally higher (0.62).

Excess Correlation

Table 3 presents the results for various models that relate excess correlation $\hat{\epsilon}_i$ to bank characteristics. Column (1) shows the results for general bank characteristics. Bank size shows up negative and significant, while squared bank size relates positively to excess correlation. There is hence a U-shape relation between excess correlation and size. This relation also shows in figure 4, which plots excess correlation against size. Medium size banks thus have the lowest excess correlation, while small and large banks display relatively large excess correlation. The result for large banks is unsurprising. Large money center are systemic banks and hence are expected to display significant comovement with the banking sector. The result for small banks is more surprising but can be explained by the fact that small banks are very undiversified (figure 3), hence their interbank correlation *conditional* on diversification is expected to be high. High levels of correlation among small banks may also be the result of herding incentives arising from too-many-to-fail policies (Acharya and Yorulmazer, 2007). Such incentives are expected to be more pronounced for small banks – since larger banks already enjoy bailout guarantees due to too-big-to fail policies.

Column (2), which includes the asset quality proxies, shows that the share of interest income from loans is significant and positively related to the excess correlation. This is surprising since one may have expected non-traditional activities to be perceived as more systemic by the market (and hence lending activities less). It is however consistent with the experience of the systemic crisis of 2007-2009, which was caused by common investments in subprime mortgages. Column (3), which considers securitization activities, shows that total securitization is positively related with excess correlation. This is expected since securitization activities tend to make banks more interconnected.

Column (4) presents the results for derivatives use. As in the diversification case, only derivatives for hedging and the gross notional amount of credit derivatives have a positive and significant relation with excess interbank correlation. This finding is interesting and reaffirms the often expressed concern that financial innovation contributes to systemic risk in the financial sector. The potential for financial innovation to create system risk is especially apparent in the case of banks that build up gross-positions in derivatives, as those will result in banks being interlinked with each other through counterparty-risk without necessarily creating any benefits arising from a (net) shedding of risks out of the banking sector.

Finally, in column (5) we present the results of the estimation including all sets of controls. The size terms still have the same sign, however, all other controls are now insignificant. The U-shaped influence of size is hence a key characteristic of excess correlation. The importance of size is also demonstrated by the fact that a regression with only the two size terms yields an R-squared of 0.33, which is not much lower than the R-squared in column (5) that is 0.41.

Taken together, the results in this and the previous subsection show that size plays a crucial role for either component of interbank correlation. The very large banks, in particular, have high excess interbank correlation and are less diversified than what their size would indicate. Our analysis thus suggests that these banks have undesirable systemic characteristics in two different dimensions.

4.3.4. Interbank Correlation and Bank Performance during the Crisis

Interbank correlation is a commonly used indicator for the extent of systemic risk in the banking sector. In this section we study its impact on bank performance during the subprime crisis, separating out the diversification and the excess correlation component. For this we relate banks' overall share price returns during the subprime crisis to their pre-crisis correlation measures, and other bank characteristics. Specifically, we estimate the following model:

$$SharePerf_{i,07-09} = \alpha + \beta_1 \rho_{i,m} + \beta_2 \hat{\epsilon}_i + \sum_{k=1}^{K} \phi_k B_{k,i,06} + \mu_i \qquad (4.7)$$

where $SharePerf_{i,07-09}$ is the share price return of bank i between January 2nd 2007 and December 31st 2009,[61] $\rho_{i,m}$ and $\hat{\epsilon}_i$ is the diversification measure and excess correlation measure of bank i computed using pre-2007 data, respectively. The terms $B_{k,i}$ are the same sets of control variables included in the previous sections, again taken from 2006.

Table 4 shows the results from various models.[62] The model in column (1) includes the two components of interbank correlation alongside general bank characteristics. The coefficient is positive for each component and significant at the 1% level. In particular, the excess correlation obtains a coefficient of 0.723; the coefficient for the diversification measure is 0.354. The sign for the coefficient is in line with theory that more diversified banks are likely to have better risk management and hence are better equipped to withstand crises (see e.g. Froot et al. (1993) and Silva-Buston (2012)). By contrast, the positive relation between the excess correlation and share performance is somewhat puzzling. One would have expected more correlated banks to perform worse during a systemic crisis. However, a potential explanation for the finding are higher bailout expectations for more correlated banks, an issue to which we return below. The other bank controls all have the expected sign whenever significant: more leveraged banks and banks with more loans had a worse performance during the crisis period.

Column (2) shows next the results when we include the ratio of real estate loans over loans, loan risk controls, as well as the asset quality controls. The positive and significant relationship for both correlation component remains, but the size of the effect decreases somewhat for the diversification part. As to be expected, real estate loans and higher loan growth prior to the crisis lead to lower performance in 2007-2009. In addition, higher profitability in 2006 is related to higher performance during this period. This indicates that more profitable banks are more resilient to downturns. Finally, the term capturing interest income from loans is negatively related to share performance during the crisis, which is in line with the poor performance of mortgage loans during the crisis.

Regression results when securitization controls are included are contained in column (3). The coefficients for the main variables remain positive and significant at 1% and 5%

[61] The starting point is motivated by the fact the banking sector price index began to decline already in the first half of 2007.

[62] Since the focus in this table is on whether the interbank correlation measures explain subprime performance over and above other variables, we subsequently enlarge the set of control variables as we progress (this is in contrast to Tables 2 and 3 where we include separate blocks of variables each time in order to mitigate potential problems arising from multicollinearity among the bank characteristics).

level. Among the other variables included, the term for MBS held to maturity is significant but only weakly so. In column (4) we add the derivatives controls. The coefficients of our variables of interest slightly decrease, but remain positive and significant. The derivatives controls are both insignificant.

An explanation for the positive relationship between excess correlation and bank performance are bail-out expectations. If the market perceives bail-outs to be more likely for correlated banks due to a "too-many-to-fail" policy, this may lead to a higher share price performance for correlated banks relative to their peers. To investigate this possibility, we include a dummy variable which indicates whether a given bank received TARP aid during the sample period. The results of the model are shown in column (5). The estimates for both components remain significant and positive. Thus, bailout expectations do not seem to be behind the positive relation between excess correlation and bank performance. The coefficient for the TARP dummy is negative and significant at 5%, which can be explained by fact that banks that received TARP are banks that are especially hit by the crisis and hence also had a bad share price performance.

We account for alternative controls of bank risk in two additional regressions. In column (6), we control for systematic risk by including share price betas estimated from 2006 data. The estimate for the beta is negative and not significant. The coefficients for correlation components remain significant with the same sign. Finally, in column (7) we control for default risk by including the Z-score[63] in 2006. The excess correlation term loses its significance, while the diversification component remains positive and significant. The Z-score itself enters positive and significant at 1% level. This result suggests that the positive relationship between excess correlation and bank performance found in the previous regression is due to the omission of bank insolvency risk as a control.

The coefficient on the diversification measure is fairly stable across the various regressions and its size suggests economic significance. For example, using the coefficient from column 7 (0.304), one can calculate a standard deviation increase in bank diversification to raise share performance during 2007-2009 by 6.5 percentage points, which corresponds to an increase of 0.2 standard deviations.

In sum, in this section we have found a positive relationship between bank diversifica-

[63]The Z-score equals $\bar{R} + 1/\sigma_R$, where $\bar{R}$ is the average return and σ_R is the standard deviation of share price returns in 2006.

tion (measured prior to the crisis) and bank performance during the crisis. In contrast, we have not found a stable relationship between excess correlation and bank performance. The results suggest that it is important to separate out the different components of interbank correlation when evaluating the systemic vulnerability of a bank. While diversification has the potential to increase resilience to crises, this is not the case for excess correlation.

Excess Correlation and other measures of Systemic Risk: the Marginal Expected Shortfall and CoVaR

An interesting question at this point is how our measure of systemic risk relates to other measures developed in the literature. In this section we address this question. We turn to compare our results from the previous section with the results obtained when using the Marginal Expected Shortfall (MES, Acharya et al. (2011)) and the CoVaR (Adrian and Brunnermeier (2010)) as a measure of systemic risk. For both measures we compute the standard measure as developed in the literature, and an *adjusted* version in order to account for the diversification component of banks' returns.

The MES computes the losses of a financial institution in the tail of the banking sector loss distribution. Following Acharya et al. (2011), empirically we compute the MES by taking the 5% worst days of the banking sector weekly returns in the three years prior to the crisis. We then compute the average weekly return of a given bank for these days. Using this measure we study how banks performed during the crisis and compare this with our measure predictions. Results are reported in columns (1)–(4) in table 5. In line with the results found in Acharya et al. (2011), we have also found that banks with a larger MES prior to the crisis performed worse during the crisis in 2007-2009.

We turn next to compare these results with an *adjusted* MES. We adjust this measure to take into account the fact that part of the variance in the banking sector returns is driven by diversification decisions at banks. Therefore, to capture this, instead of using the 5% worst days of the banking sector weekly returns, we identify the 5% worst days of the regression residuals from a regression of the banking sector weekly return on the market index weekly return for the three years previous to the crisis. As for the MES, we then proceed to compute the average return of a given bank for these days. Results for this measure are reported in columns (5)–(8) in table 5. Consistent with our results for the systemic part of interbank correlation in the previous section, we do not find a stable significant relationship between the *adjusted* MES and bank performance during the crisis.

We study now how our methodology applies to CoVaR. This measure estimates the VaR of the banking sector conditional on a bank experiencing a tail event. Following Adrian and Brunnermeier (2010), to estimate the CoVaR we run first a quantile regression (5%) of the weekly returns of a given bank on the weekly returns of the market index. To be consistent with our previous studies, we consider for this estimation data for the three years prior to the crisis. The average fitted value of this regression for these three years is the VaR of a given bank. These are the predicted bank returns in distressed periods. Next, we estimate a quantile regression (5%) of the banking sector weekly returns on the bank weekly returns. The CoVaR then will be the fitted values of this regression when replacing the bank weekly returns by the VaR of the bank. This is, the predicted returns of the banking sector conditional on a given bank being in distress. As for our previous studies, we analyse how banks' CoVaR before the crisis relate to their performance during the crisis period. Results for these models are shown in columns (1)–(4) in table 6. Banks which returns in tail events follow the market closely before the crisis performed better during the crisis. According to our intuition, this means that more diversified banks performed better during the crisis period, in line with our previous results.

We turn next to compare these results with an *adjusted* CoVaR. For this, we take for the VaR of a given bank the residuals of the regression of the bank returns on the market index returns, instead of the fitted values of this regression. In this way, we remove the share of the variance of the bank returns which is explained by the diversification component. The results for the models for bank performance when using this measure are shown in columns (5)–(8) in table 6. There is a negative relationship between the *adjusted* CoVaR and bank performance during the crisis. In line with our intuition, this result indicates that banks with a higher share of the returns' variance not explained by diversification and a higher co-movement with the banking sector, underperformed during the crisis in 2007-2009.

We have shown that the intuition behind our theoretical model is also applicable to other measures of systemic risk. More importantly, we have shown that when doing this, evidence shows the different implications for bank regulation, highlighting the importance of taking into account the diversification component for the computation of measures of systemic risk.

4.4. Conclusion

Higher correlation across banks is typically taken to imply systemic risk. Consistent with this, interbank correlations are either used as a direct measure of systemic risk or enter systemic risk measures indirectly, such as through the covariance of bank returns and banking sector returns.

In this paper we have argued that interbank correlations consist of two parts. One part is indeed due to systemic risk, but there is also second one that arises due to diversification activities. While banks that display high correlation in the first dimension should clearly alert regulators, this is less obvious for banks that have high correlation in the second dimension.

We have proposed a way to conceptually disentangle both parts based on the *minimum commonality* induced by diversification. An empirical application to U.S. BHCs has shown that variation in interbank correlations comes predominantly from the diversification component; the importance of the systemic component is much smaller. In addition, banks that displayed high correlation due to diversification performed better during the subprime crisis. Taken together this sheds doubt on the appeal of using straight correlation measures as input into systemic risk assessments and suggests that regulators should take into account the different sources of bank correlation.

4.5. Figures

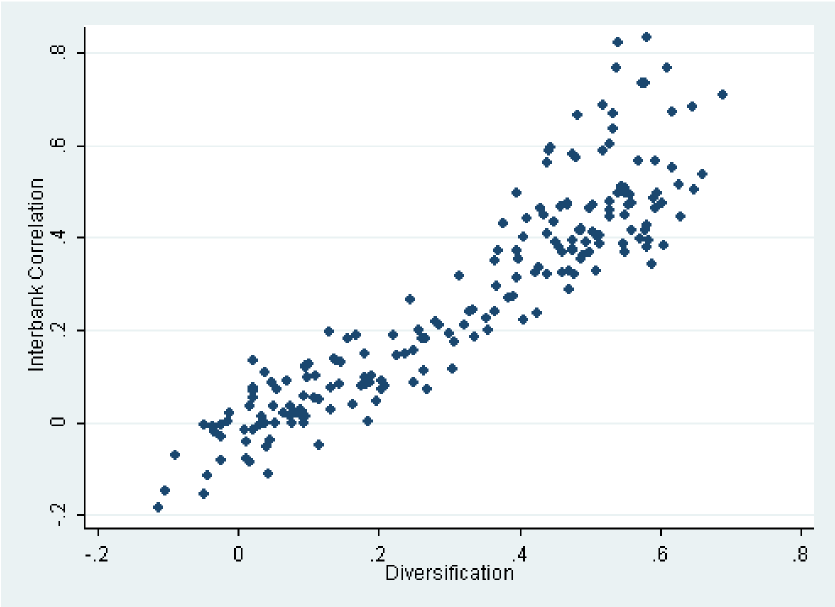


Figure 4.1: Interbank Correlation and Diversification

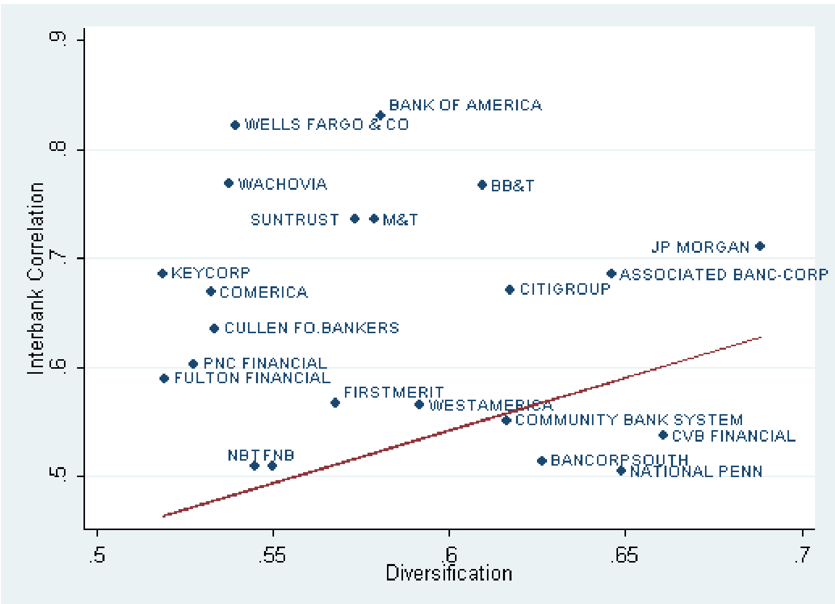


Figure 4.2: High Correlation Banks

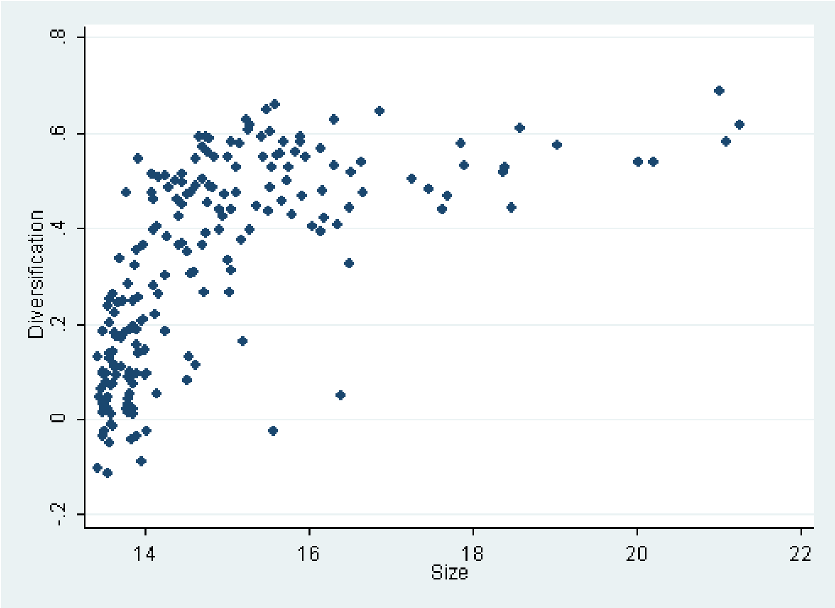


Figure 4.3: Diversification and Bank Size

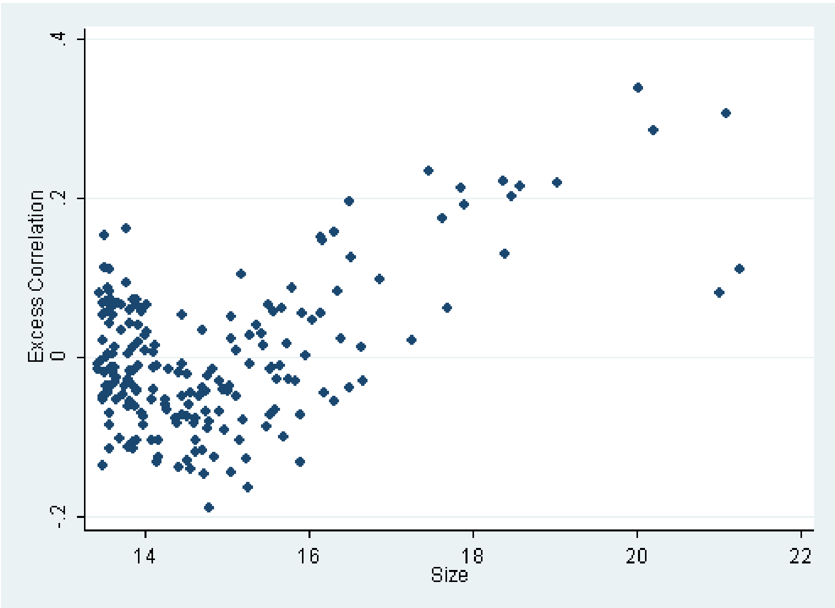


Figure 4.4: Systemic Correlation and Bank Size

4.6. Tables

Table 1: Descriptive statistics

Variables	Mean	Std. Dev.	Min	Max
Panel A: Bank Characteristics				
Sub. debt/Assets	0.156	0.096	0.005	0.654
Loans/Assets	0.692	0.113	0.313	0.854
Log(Assets)	14.828	1.524	13.407	21.257
Real estate/Loans	0.733	0.141	0.214	0.948
Loan growth	0.026	0.051	-0.172	0.253
ROA	0.006	0.002	-0.004	0.012
Interest from loans/Loans	0.049	0.008	0.020	0.091
NPL/Loans	0.007	0.008	0.00002	0.055
MBS held to maturity/Assets	0.006	0.018	0	0.086
Securitization/Assets	0.018	0.084	0	0.743
Derivatives not for trade	0.031	0.049	0	0.147
Gross position CD/Assets	0.0004	0.002	0	0.012
Net position CD/Assets	0.0002	0.004	-0.040	0.041
Panel B: Correlation Measures				
Interbank Correlation	0.267	0.228	-0.185	0.831
Diversification	0.316	0.215	-0.112	0.688
Systemic Correlation	0	0.092	-0.188	0.338

Table 2: Diversification and Bank Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sub. Debt/Assets	-0.0803						0.128
	(0.142)						(0.138)
Loans/Assets	-0.281***						-0.279**
	(0.0939)						(0.112)
Log(Assets)	0.855***						0.924***
	(0.0882)						(0.145)
Log(Assets)^2	-0.0235***						-0.0260***
	(0.00270)						(0.00469)
Real estate/Loans	0.0324						0.0431
	(0.0803)						(0.0771)
Loan growth		0.572**					0.162
		(0.274)					(0.223)
ROA		22.29***					12.54**
		(7.281)					(5.449)
Interest from loans/Loans		-1.543					-4.221**
		(2.188)					(1.880)
NPL/Loans		-1.287					-0.967
		(1.667)					(1.018)
MBS held to maturity/Assets			0.292				-1.113*
			(0.853)				(0.649)
Securitization/Assets			0.394**				-0.276***
			(0.168)				(0.0952)
Derivatives				0.888***			0.166
not for trade/Assets				(0.322)			(0.264)
Gross position				14.82***			10.26
CD/Assets				(3.958)			(11.31)
Net position				-0.238			-0.655
CD/Assets				(0.525)			(1.292)
Asset Diversity					0.308***		
					(0.0797)		
Revenue Diversity						0.453***	
						(0.0811)	
Observations	200	197	200	200	200	200	197
R-squared	0.581	0.082	0.024	0.094	0.071	0.134	0.622

The dependent variable is the correlation between the bank and S&P500 index returns. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 3: Systemic Correlation and Bank Characteristics

	(1)	(2)	(3)	(4)	(5)
Sub. Debt/Assets	-0.0540				-0.106
	(0.0724)				(0.0787)
Loans/Assets	0.0860				0.0621
	(0.0555)				(0.0709)
Log(Assets)	-0.171**				-0.189*
	(0.0705)				(0.104)
Log(Assets)^2	0.00636***				0.00693**
	(0.00221)				(0.00341)
Real estate/Loans	0.0333				0.0277
	(0.0387)				(0.0407)
Loan growth		-0.140			-0.164
		(0.123)			(0.119)
ROA		3.051			-0.0911
		(2.754)			(2.578)
Interest from loans/Loans		2.072**			0.310
		(0.856)			(0.815)
NPL/Loans		0.807			0.273
		(0.804)			(0.813)
MBS held to maturity/Assets			-0.194		0.206
			(0.282)		(0.274)
Securitization/Assets			0.366**		0.0841
			(0.171)		(0.0863)
Derivatives				0.428***	0.195
not for trade/Assets				(0.152)	(0.150)
Gross position CD/Assets				16.28***	-3.877
				(3.091)	(7.275)
Net position CD/Assets				-1.726	-1.024
				(1.068)	(1.482)
Observations	200	197	200	200	197
R-squared	0.355	0.063	0.114	0.273	0.395

The dependent variable is the excess interbank correlation, measured as the residual of a cross section OLS regression of the interbank correlation on the correlation between the bank and S&P500 index returns. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 4: Share Price Performance and Interbank Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Systemic Correlation	0.723***	0.729***	0.719***	0.661***	0.656***	0.706***	0.393
	(0.257)	(0.233)	(0.233)	(0.238)	(0.236)	(0.240)	(0.254)
Diversification	0.354***	0.269**	0.298**	0.249**	0.261**	0.287**	0.304**
	(0.134)	(0.121)	(0.122)	(0.125)	(0.127)	(0.124)	(0.123)
Sub. Debt/Assets$_{06}$	-1.116***	-0.522**	-0.578**	-0.628**	-0.632**	-0.656***	-0.644***
	(0.253)	(0.262)	(0.250)	(0.246)	(0.249)	(0.244)	(0.244)
Loans/Assets$_{06}$	-1.465***	-1.363***	-1.244***	-1.277***	-1.224***	-1.267***	-1.247***
	(0.188)	(0.187)	(0.203)	(0.208)	(0.207)	(0.210)	(0.199)
Log(Assets)$_{06}$	-0.0398	-0.0807***	-0.0877***	-0.0803***	-0.0702**	-0.0851***	-0.0777***
	(0.0246)	(0.0249)	(0.0251)	(0.0281)	(0.0285)	(0.0285)	(0.0271)
Real estate/Loans$_{06}$		-0.583***	-0.629***	-0.640***	-0.656***	-0.667***	-0.570***
		(0.139)	(0.142)	(0.141)	(0.135)	(0.145)	(0.138)
NPL/Loans$_{06}$		-3.141	-3.584*	-3.392	-3.385	-3.265	-3.317
		(2.193)	(2.149)	(2.182)	(2.275)	(2.184)	(2.112)
Loan growth$_{06}$		-0.759**	-0.938***	-0.921**	-0.836**	-1.057***	-0.842**
		(0.354)	(0.356)	(0.360)	(0.368)	(0.392)	(0.341)
ROA$_{06}$		29.36***	27.33***	30.21***	29.91***	28.22***	29.14***
		(9.055)	(9.281)	(9.275)	(9.164)	(9.357)	(8.866)
Interest from		-6.668***	-6.210**	-7.300***	-7.335***	-8.665***	-6.669***
loans/Loans$_{06}$		(2.552)	(2.511)	(2.661)	(2.662)	(2.726)	(2.553)
MBS held			1.991*	1.872*	1.553	1.867*	1.806*
to maturity/Assets$_{06}$			(1.094)	(1.055)	(1.031)	(1.033)	(1.080)
Securitization/Assets$_{06}$			0.291	0.249	0.211	0.253	0.296
			(0.219)	(0.233)	(0.217)	(0.244)	(0.253)
Derivatives				0.621	0.606	0.734*	0.649*
not for trade/Assets$_{06}$				(0.400)	(0.415)	(0.405)	(0.392)
Gross position				-10.62	-10.54	-9.482	-10.84
CD/Assets$_{06}$				(11.05)	(11.19)	(11.49)	(10.84)
Net position				-0.494	-0.308	-0.241	-0.715
CD/Assets$_{06}$				(4.279)	(4.436)	(4.149)	(4.233)
TARP					-0.0890**		
					(0.0395)		
Betas$_{06}$						-0.0278	
						(0.0496)	
Zscore$_{06}$							0.00487***
							(0.00115)
Observations	199	196	196	196	196	194	196
R-squared	0.269	0.409	0.422	0.429	0.447	0.441	0.476

The dependent variable is the bank's share price performance over the period 2 January 2007 until 31 December 2009. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 5: Share Price Performance and MES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MES	-7.224***	-6.961***	-7.643***	-5.726***				
	(1.577)	(1.575)	(1.758)	(1.544)				
Adjusted MES					2.262	1.451	2.747	2.831*
					(1.707)	(1.799)	(1.672)	(1.557)
Sub. Debt/Assets$_{06}$	-0.599**	-0.604**	-0.578**	-0.604**	-0.659***	-0.663**	-0.690***	-0.647***
	(0.258)	(0.262)	(0.259)	(0.253)	(0.253)	(0.257)	(0.250)	(0.245)
Loans/Assets$_{06}$	-1.174***	-1.136***	-1.160***	-1.199***	-1.270***	-1.237***	-1.267***	-1.257***
	(0.202)	(0.197)	(0.207)	(0.185)	(0.205)	(0.201)	(0.206)	(0.190)
Log(Assets)$_{06}$	0.0521*	0.0587**	0.0514*	0.0366	-0.0465**	-0.0316	-0.0468**	-0.0464**
	(0.0274)	(0.0274)	(0.0279)	(0.0267)	(0.0226)	(0.0244)	(0.0232)	(0.0216)
Real estate/Loans$_{06}$	-0.500***	-0.518***	-0.510***	-0.478***	-0.632***	-0.640***	-0.659***	-0.571***
	(0.137)	(0.133)	(0.138)	(0.134)	(0.143)	(0.139)	(0.146)	(0.138)
NPL/Loans$_{06}$	-3.940*	-3.935	-4.216*	-3.940*	-3.743	-3.662	-3.713	-3.941*
	(2.366)	(2.463)	(2.505)	(2.273)	(2.469)	(2.574)	(2.459)	(2.313)
Loan growth$_{06}$	-0.542	-0.482	-0.720*	-0.520	-0.983***	-0.910**	-1.083***	-0.813**
	(0.344)	(0.351)	(0.375)	(0.331)	(0.356)	(0.364)	(0.388)	(0.335)
ROA$_{06}$	37.67***	37.37***	38.59***	36.46***	33.59***	33.31***	31.61***	33.31***
	(9.056)	(9.031)	(9.149)	(8.832)	(9.342)	(9.223)	(9.343)	(8.972)
Interest from	-8.804***	-8.845***	-9.432***	-8.389***	-8.126***	-8.161***	-9.304***	-7.801***
loans/Loans$_{06}$	(2.487)	(2.501)	(2.782)	(2.404)	(2.497)	(2.496)	(2.635)	(2.448)
MBS held	1.235	0.975	1.298	1.240	1.760*	1.468	1.714*	1.608
to maturity/Assets$_{06}$	(1.151)	(1.152)	(1.142)	(1.177)	(1.061)	(1.052)	(1.033)	(1.081)
Securitization/Assets$_{06}$	0.121	0.0880	0.172	0.139	0.197	0.170	0.173	0.181
	(0.212)	(0.205)	(0.225)	(0.232)	(0.215)	(0.209)	(0.225)	(0.235)
Derivatives	0.925**	0.907**	0.920**	0.884**	0.803**	0.782*	0.913**	0.795**
not for trade/Assets$_{06}$	(0.384)	(0.394)	(0.402)	(0.389)	(0.395)	(0.408)	(0.407)	(0.398)
Gross position	-28.06**	-27.89**	-28.93***	-28.15***	-12.27	-13.48	-11.62	-15.64
CD/Assets$_{06}$	(10.98)	(11.23)	(11.05)	(10.80)	(10.37)	(10.52)	(10.55)	(10.27)
Net position	-1.026	-0.864	-1.752	-0.656	-1.939	-1.766	-1.553	-1.101
CD/Assets$_{06}$	(6.073)	(6.206)	(6.185)	(5.847)	(4.839)	(5.103)	(4.777)	(4.745)
TARP		-0.0756**				-0.0805*		
		(0.036)				(0.041)		
Betas$_{06}$			0.0365				-0.0387	
			(0.0553)				(0.0512)	
Zscore$_{06}$				0.00355***				0.00495***
				(0.00120)				(0.00108)
Observations	196	196	194	196	196	196	194	196
R-squared	0.468	0.480	0.472	0.493	0.415	0.428	0.425	0.468

The dependent variable is the bank's share price performance over the period 2 January 2007 until 31 December 2009. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 5: Share Price Performance and CoVaR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CoVaR	8.145*	8.389**	9.010**	8.325**				
	(4.227)	(4.140)	(4.228)	(4.158)				
Adjusted CoVaR					-7.847*	-8.073**	-8.692**	-8.045**
					(4.089)	(3.993)	(4.077)	(4.012)
Sub. Debt/Assets$_{06}$	-0.702***	-0.700***	-0.741***	-0.687***	-0.690***	-0.687***	-0.728***	-0.674***
	(0.257)	(0.260)	(0.256)	(0.250)	(0.257)	(0.260)	(0.255)	(0.250)
Loans/Assets$_{06}$	-1.253***	-1.200***	-1.247***	-1.248***	-1.250***	-1.196***	-1.244***	-1.244***
	(0.209)	(0.209)	(0.210)	(0.193)	(0.209)	(0.209)	(0.211)	(0.194)
Log(Assets)$_{06}$	-0.0576**	-0.0470*	-0.0580**	-0.0551**	-0.0575**	-0.0469*	-0.0579**	-0.0551**
	(0.0247)	(0.0251)	(0.0257)	(0.0237)	(0.0247)	(0.0251)	(0.0256)	(0.0237)
Real estate/Loans$_{06}$	-0.623***	-0.642***	-0.644***	-0.563***	-0.623***	-0.642***	-0.644***	-0.564***
	(0.145)	(0.140)	(0.148)	(0.139)	(0.145)	(0.140)	(0.148)	(0.139)
NPL/Loans$_{06}$	-3.243	-3.231	-3.093	-3.348	-3.233	-3.222	-3.082	-3.337
	(2.426)	(2.526)	(2.423)	(2.271)	(2.424)	(2.522)	(2.421)	(2.266)
Loan growth$_{06}$	-0.998***	-0.907**	-1.094***	-0.838**	-0.996***	-0.904**	-1.090***	-0.835**
	(0.348)	(0.356)	(0.381)	(0.331)	(0.348)	(0.356)	(0.381)	(0.330)
ROA$_{06}$	31.49***	31.55***	29.45***	31.33***	31.33***	31.39***	29.24***	31.16***
	(9.499)	(9.367)	(9.555)	(9.133)	(9.490)	(9.361)	(9.541)	(9.121)
Interest from	-7.709***	-7.774***	-9.034***	-7.355***	-7.727***	-7.793***	-9.039***	-7.372***
loans/Loans$_{06}$	(2.655)	(2.665)	(2.711)	(2.601)	(2.643)	(2.654)	(2.704)	(2.588)
MBS held	1.712	1.388	1.656	1.574	1.724	1.400	1.668	1.586
to maturity/Assets$_{06}$	(1.087)	(1.061)	(1.066)	(1.107)	(1.088)	(1.063)	(1.068)	(1.106)
Securitization/Assets$_{06}$	0.270	0.226	0.258	0.263	0.271	0.228	0.259	0.265
	(0.212)	(0.205)	(0.225)	(0.232)	(0.218)	(0.208)	(0.227)	(0.242)
Derivatives	0.772*	0.760*	0.898**	0.760*	0.767*	0.755*	0.891**	0.755*
not for trade/Assets$_{06}$	(0.398)	(0.414)	(0.407)	(0.402)	(0.398)	(0.413)	(0.406)	(0.401)
Gross position	-7.786	-8.057	-6.816	-11.59	-8.255	-8.547	-7.326	-12.05
CD/Assets$_{06}$	(10.69)	(10.80)	(10.98)	(10.59)	(10.63)	(10.76)	(10.92)	(10.54)
Net position	-1.907	-1.671	-1.533	-1.122	-1.842	-1.605	-1.452	-1.054
CD/Assets$_{06}$	(4.702)	(4.890)	(4.647)	(4.672)	(4.709)	(4.896)	(4.651)	(4.677)
TARP		-0.0891**				-0.0890**		
		(0.0395)				(0.0395)		
Betas$_{06}$			-0.0354				-0.0360	
			(0.0483)				(0.0482)	
Zscore$_{06}$				0.00479***				0.00480***
				(0.00106)				(0.00106)
Observations	195	195	193	195	195	195	193	195
R-squared	0.419	0.436	0.429	0.470	0.418	0.436	0.429	0.469

The dependent variable is the bank's share price performance over the period 2 January 2007 until 31 December 2009. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

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