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BY

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Consuelo Silva Buston†

Abstract

This paper analyzes 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 insolvency. 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 become insolvent 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.

Keywords: Financial innovation, credit derivatives, financial stability, financial crisis

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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), within the banking sector the use of credit default swaps (CDS)[1], one of the main financial innovations, increased from an outstanding gross notional amount near $3.5 trillion at the end of 2005 to its peak level of around $14 trillion in the second half of 2007. In the aftermath of the crisis, the outstanding gross notional amount slightly declined, reaching $6 trillion in the first 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[2]. 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[3]. On the one hand, financial innovations 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 fi-

[1]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.

[2]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).

[3]See Duffie (2008) for an overview of credit risk transfer with financial innovations and its potential effects on financial stability.

nancial 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[4].

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[5]. However, access to CDS allows

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

[5]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.

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 Federal Reserve Y-9C data 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[6]. 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[7]. These results hold 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

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

[7]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-correlation sample.

for a reduction in procyclicality for large banks[8].

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 insolvency. 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 becoming insolvent than do other banks. Specifically, active risk management reduces the probability of insolvency over six years by 1.2 percentage points[9].

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 becoming insolvent 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 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,

[8]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.

[9]The average probability of insolvency in this sample for this period is 2%.

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.

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 (2012) 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 insolvency.

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[10]. We first introduce in Section 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 3.2, we allow the bank to rebalance its portfolio using credit derivatives once a shock to the risk of the portfolio is realized.

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.

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 $E(\epsilon) = 0$. The bank holds a continuum of measure one of loans with *iid* returns. If the borrower defaults, the bank

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

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[11].

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, risk-weights and 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 can hold at $t = 0$ consistent with these requirements is

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

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

$$L_{max} = (1-d) - \theta(\bar{p} + \epsilon) - \tau. \tag{2}$$

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

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

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

$$\begin{aligned}\Pi &= [(1-p_\epsilon)(1+r(L)) + p_\epsilon(1-\lambda)]\,L + (1-L) - c\,[max(e(L,\epsilon),0)] - (1+i)d \\ &= [r(L) - (\bar{p}+\epsilon)(\lambda + r(L))]\,L + (1-d) - c\,[max(e(L,\epsilon),0)] - id. \end{aligned} \quad (3)$$

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 $c\,[max(e(L,\epsilon),0)]$. 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

$$\Pi(L, \epsilon_c^B, i(L, \epsilon_c^B)) = 0, \quad (4)$$

which is given by

$$\epsilon_c^B = \epsilon_c^B(L). \quad (5)$$

Using (5), we can write the expected return on equity at $t = 0$ as

$$E(\Pi) = \int_{\underline{\epsilon}}^{\epsilon_c^B} [(r(L) - (\bar{p}+\epsilon)(\lambda + r(L)))\,L + (1-d) - c[max(e(L,\epsilon),0)] - id]\,\phi(\epsilon)\,d\epsilon. \quad (6)$$

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) 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

$$\begin{aligned}&\int_{\underline{\epsilon}}^{\epsilon_c^B} (i+1)d\phi(\epsilon)\,d\epsilon \\ &\quad + \textstyle\int_{\epsilon_c^B}^{\bar{\epsilon}} \left[(1+i)d - (\epsilon - \epsilon_c^B)(\lambda + r(L))L - ca(\epsilon - \epsilon_c^B)\right]\phi(\epsilon)\,d\epsilon = d. \end{aligned} \quad (7)$$

Thus, the interest payment to the depositors is given by

$$id = \int_{\epsilon_c^B}^{\bar{\epsilon}} \left((\epsilon - \epsilon_c^B)(\lambda + r(L))L + ca(\epsilon - \epsilon_c^B)\right)\phi(\epsilon)\,d\epsilon. \quad (8)$$

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 (6) and (7). Hence, at $t = 0$ the bank solves

$$MaxE(\Pi) = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \left[(r(L) - (\bar{p} + \epsilon)(\lambda + r(L)))\, L + 1 - c\,(max(e(L, \epsilon), 0)) - d \right] \phi(\epsilon)\, d\epsilon \quad (9)$$

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 $\theta(p_\epsilon)$,

$$\begin{aligned} q(L) &= p(L_{max} < L) \\ &= p(f(L) < \epsilon) \\ &= \int_{f(L)}^{\bar{\epsilon}} \phi(\epsilon)\, d\epsilon \end{aligned} \quad (10)$$

where $f(L) = \frac{(\hat{L} - L)}{a}$. Thus, we can write the FOC for L as[12]

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

Then, the optimal L^* solves

$$r(L^*) - \bar{p}(r(L^*) + \lambda) + (r_L - \bar{p} r_L) L^* = c\,(-f_L e(L^*, f(L^*)) + q(L^*))\,. \quad (11)$$

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

$$L^B = min[L^*, \hat{L}] \quad (12)$$

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

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

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[13]. 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[14]. Therefore, the price of protection is equal to the expected payment of losses $(\bar{p} + \epsilon)(r(L) + \lambda)$, plus a

[13]This can be understood as outside agents such as insurance companies being the major traders of protection.

[14]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)).

compensation γ that reflects these transaction costs. Then, at $t = 1$ the price of one unit of protection is

$$w = (\bar{p} + \epsilon)(r(L) + \lambda) + \gamma. \tag{13}$$

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

$$L_{max} \geq (L + LS(L, \epsilon)). \tag{14}$$

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 (14) is binding. Thus, the optimal protection sold will be

$$\begin{aligned} S^*(L, \epsilon)_s &= \frac{(L_{max} - L)}{L} \\ S^*(L, \epsilon)_s &= \frac{-e(L, \epsilon)}{L} \end{aligned} \tag{15}$$

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 (14). Thus,

$$
\begin{aligned}
ce(L,\epsilon) &= -wS(L,\epsilon)L + (\bar{p}+\epsilon)(r(L)+\lambda)S(L,\epsilon)L \\
S(L,\epsilon)_b &= -\frac{c}{\gamma}\frac{e(L,\epsilon)}{L}
\end{aligned}
\tag{16}
$$

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 (14), the optimal protection bought by the bank is

$$
S(L,\epsilon)_b^* = -min\left[\left|\frac{c}{\gamma}\frac{(L_{max}-L)}{L}\right|, \left|\frac{(L_{max}-L)}{L}\right|\right] \tag{17}
$$

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 (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

$$
S^*(L,\epsilon) = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \frac{-e(L,\epsilon)}{L}\phi(\epsilon)\,d\epsilon, \tag{18}
$$

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

$$\begin{aligned}\Pi &= \left[(1-p_\epsilon)(1+r(L)) + p_\epsilon(1-\lambda)\right] L + S^*(L,\epsilon)L\gamma + (1-L) - (1+i)d \\ &= \left[r(L) - (\bar{p}+\epsilon)(\lambda + r(L)) + S^*(L,\epsilon)\gamma\right] L + (1-d) - id. \qquad (19)\end{aligned}$$

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

$$\Pi(L, \epsilon_c^{RM}, i(L, \epsilon_c^{RM})) = 0 \qquad (20)$$

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

$$E(\Pi) = \int_{\underline{\epsilon}}^{\epsilon_c^{RM}} \left[(r(L) - (\bar{p}+\epsilon)(\lambda + r(L)) + S^*(L,\epsilon)\gamma) L + (1-d) - id\right] \phi(\epsilon)\, d\epsilon. \qquad (21)$$

Using (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

$$\int_{\underline{\epsilon}}^{\epsilon_c^{RM}} (i+1)d\phi(\epsilon)\, d\epsilon + \int_{\epsilon_c^{RM}}^{\bar{\epsilon}} \left[(1+i)d + (\epsilon_c^{RM} - \epsilon)(\lambda + r(L) + \gamma a)L\right] \phi(\epsilon)\, d\epsilon = d. \qquad (22)$$

Therefore, the interest payments are

$$id = \int_{\epsilon_c^{RM}}^{\bar{\epsilon}} (\epsilon - \epsilon_c^{RM})(\lambda + r(L) + \gamma a)L\phi(\epsilon)\, d\epsilon. \qquad (23)$$

Using (21) and (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

$$Max E(\Pi) = \int_{\underline{\epsilon}}^{\bar{\epsilon}} \left[(r(L) - (\bar{p}+\epsilon)(\lambda + r(L)) + S^*(L,\epsilon)\gamma) L + 1 - d\right] \phi(\epsilon)\, d\epsilon \qquad (24)$$

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

$$r(L^*) - \bar{p}(r(L^*)+\lambda) + (r_L - \bar{p}r_L)L^* = \gamma. \tag{25}$$

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:*

$$L^{*B} < L^{*RM}. \tag{26}$$

Proof. See the Appendix. ■

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. (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.

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:*

$$\left|\frac{dL^{*RM}}{dE(\epsilon)}\right| < \left|\frac{dL^{*B}}{dE(\epsilon)}\right|. \tag{27}$$

Proof. See the Appendix. ■

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.

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

$$p(\epsilon_c < \epsilon) = \int_{\epsilon_c}^{\bar{\epsilon}} \phi(\epsilon)\, d\epsilon. \tag{28}$$

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:*

$$\epsilon_c^B < \epsilon_c^{RM}. \tag{29}$$

Proof. See the Appendix. ■

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.

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 becoming insolvent one year ahead.

6.1 Data

The analysis is based on bank-level data from the Federal Reserve Y-9C 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. 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 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 fell into insolvency in a given year. To identify the insolvent 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 insolvent 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 insolvent banks. A first look at the means of the insolvency dummy shows that banks using CDS to manage risk may fall into insolvency less than other banks: the mean of the insolvency 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.

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:

$$C\&I/TA_{b,t} = \alpha + \sum_{b=1}^{B} \beta_{1b} bank_b + \sum_{t=1}^{T} \beta_{2t} year_t + \beta_3 CD_{b,t} + \sum_{i=1}^{K} \phi_i B_{i,b,t} + \epsilon_{b,t} \quad (30)$$

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%, 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 [15].

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[16].

[15] 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 dealers 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. Using this proxy for market makers, our sample of small banks does not contain this type of banks. Therefore, our results are not driven by market makers transactions.

[16] 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,

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[17] [18]. 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 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.

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.

[17]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.

[18]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 for these type of banks that the bank and the borrower are located in the same state.

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.

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 fall into insolvency one year ahead. We expect a negative relationship between CDS use and the probability of insolvency, lending support to the hypothesis of greater stability for these banks. The model for bank insolvency 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:

$$Insolvency_{b,t} \quad = \quad p(CD_{b,t-1}, \sum_{i=1}^{K} \phi_i B_{i,b,t-1}) \tag{31}$$

where $Insolvency_{b,t}$ is a dummy variable that is equal to one if the BHC became insolvent 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 insolvency-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 insolvency 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 becoming insolvent one year ahead that is 0.2 percentage points lower. Thus, over the entire period (six years), the decrease in the probability of insolvency is 1.2 percentage points. This effect is considerable since the average probability of insolvency 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 insolvency 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 falling into insolvency 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 insolvency 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[19]. Less-diversified banks will display a lower 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 insolvency. We do not split the sample in this case to maximize the variability of the dependent variable, the dummy $Insolvency$. 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

[19] Univariate analysis shows that large banks are significantly more correlated with the market ROA than small banks are. They are therefore more diversified.

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 insolvency as a result of CDS use. In contrast, low-correlation banks using CDS have a lower probability of insolvency 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.

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 insolvency 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.

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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

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

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 (11) we have

$$L^{*B} = \frac{x(1-\bar{p}) - \bar{p}\lambda - c(1/2 - \hat{L}/2a\bar{\epsilon})}{2z(1-\bar{p}) + c/2a\bar{\epsilon}}. \tag{32}$$

Then,

$$\begin{aligned} \frac{x(1-\bar{p}) - \bar{p}\lambda - c(1/2 - \hat{L}/2a\bar{\epsilon})}{2z(1-\bar{p}) + c/2a\bar{\epsilon}} &> -\bar{\epsilon} + \frac{2\gamma}{c}\bar{\epsilon}a + \hat{L} \\ \frac{x(1-\bar{p}) - \bar{p}\lambda - \gamma}{2(\hat{L} - \bar{\epsilon}a + 2\frac{\gamma}{c}\bar{\epsilon}a)(1-\bar{p})} &> \tilde{z}. \end{aligned} \tag{33}$$

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

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, $|\frac{dL^{*RM}}{dE(\epsilon)}| < |\frac{dL^{*B}}{dE(\epsilon)}|$. ■

Numerical Proof of Prediction 1. For $c > \gamma$, solving Eq. (20) shows that the critical shock for the RM case is

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

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. (4):

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

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 $z < \tilde{z}$. For the example we use the following parameter values: $x = 1, \lambda = 0.25, d = 0.5, \bar{p} = 0.3, \bar{\epsilon} = 0.10, a = 0.15, \tau = 0.08, z = 0, c = 0.9$, and $\gamma \in [0, c/2)$.

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[20]. 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 $L^{*B} = \hat{L} - a\bar{\epsilon} + \frac{x(1-\bar{p})-\bar{p}\lambda}{c/2a\bar{\epsilon}} < \hat{L}$[21].

[20]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.

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

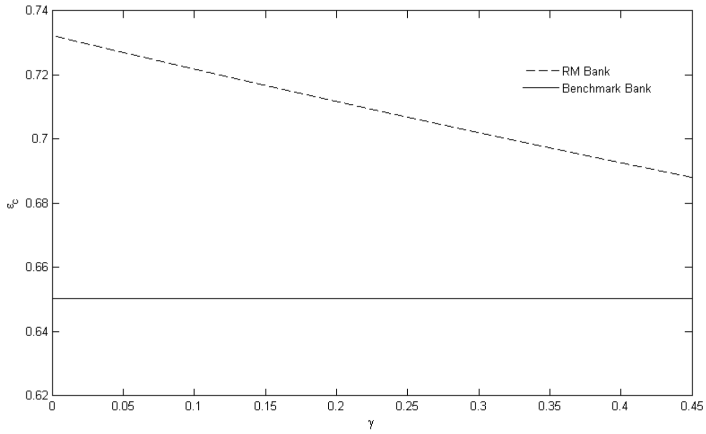

Figure 1: ϵ_c as a function of γ.

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, $\epsilon_c^B > \tilde{\epsilon}$.

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., $z < \tilde{z}$.

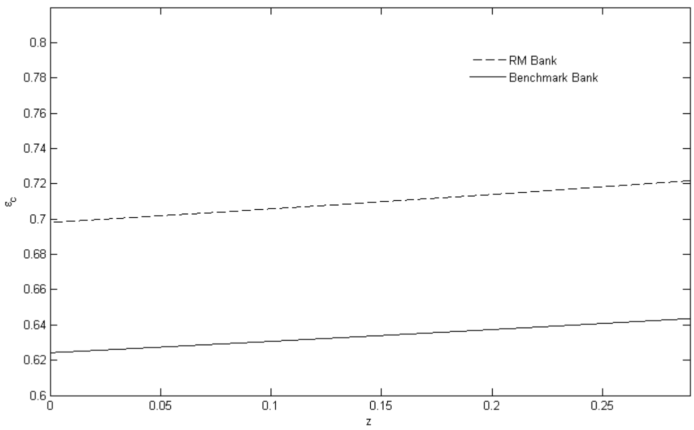

Figure 2: ϵ_c as a function of the level of competition, z.

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. ■

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

Variables	(1) C&I/TA	(2) C&I/TA	(3) C&I/TA	(4) C&I/TA	(5) C&I/TA	(6) C&I/TA	(7) C&I/TA	(8) C&I/TA	(9) C&I/TA
		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

Variables	(1) C&I/TA All Banks	(2) C&I/TA Small Banks	(3) C&I/TA 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

Variables	(1) C&I/TA All Banks	(2) C&I/TA Small Banks	(3) C&I/TA 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)
Variables	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency	Insolvency
		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 insolvency 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) Insolvency
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 insolvency 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.