The Effect of Credit Derivatives on Financial Stability

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Due to the recent financial turmoil, questions have been raised about the impact of complex financial products, like credit derivatives, on financial stability. The academic literature however does not provide a clear answer to this question. This paper empirically links the stability of the financial sector to the use of credit derivatives for the main constituents of the European financial sector. We find that the use of credit derivatives increases the probability of default and thus reduces the overall financial sector stability. In addition, we find evidence that this relationship is progressive and economically meaningful.

Keywords: Credit derivatives, credit risk transfer, financial sector stability, probability of default.

1. Introduction

The debate regarding the impact of financial derivatives on financial sector stability is a long-standing one, but became more relevant as a result of the global financial crisis. There is no unambiguous answer to this question in the literature. The IMF Global Financial Stability Report explains that the increase in credit transfers has helped to make the banking and overall financial system more resilient and increases financial stability. With a broader and more diverse investor base, credit markets may deepen and liquidity should improve. At the same time, the transition from bank-dominated to a more market-based financial system presents new challenges and vulnerabilities.

Rule (2001) explains that the development of the credit derivative market has clear potential benefits for financial stability. Credit derivatives allow the origination and funding of credit to be separated from the allocation of the resulting credit risk. A more efficient allocation of credit risk allows banks to expand granting loans and taking deposits, which enhances portfolio diversification even more and reinforces risk reducing effects of credit risk transfer.

Rule (2001) also acknowledges, however, that credit risk transfer markets present some challenges and may carry potential costs. Separating the exposure to credit risk from the direct relationship with the borrower might lessen capacity to monitor creditworthiness. Sellers of protection in a CDS contract have no contractual rights, thus reducing their ability to influence the decision making of the reference company. It might also make it more difficult for creditors, regulators and the monetary authorities to assess the actual credit exposures of banks and of the banking system as a whole. Although credit derivatives are in Rules' (2001) view more likely to disperse credit risk, there is also the possibility that they could deliberately or inadvertently concentrate it.

In the recent years regulators have been largely welcoming the development of credit derivatives, not only because of the more efficient allocation of credit risk or diversification effects but also because credit derivatives increase the relative liquidity of loans. In the past, illiquidity of bank loans has been a main source of banking fragility. An improved ability to sell assets will make banks less vulnerable to liquidity shocks. Instefjord (2003) states, however, that this ignores that banks may change their behaviour as a result of the increased liquidity of their assets. They may take on new risks following a reduction in the risks on their balance sheet through credit risk transfer.

Instefjod (2003) notes that banks that have access to a richer set of derivatives to manage risk, will also play the risk acquisition game more aggressively. Risk exposures become more attractive, knowing that they can be offloaded through a more active derivatives trading policy. These views are consistent with the empirical work of Cebenoyan and Strahan (2004), who provide evidence that banks who manage their risks in a loan sale market hold a larger share of their portfolio in risky assets than banks inactive in loan sale.

The question that naturally arises is how much of the extra risk will be transferred to outside parties and how much remains within the bank. Instefjod (2001) claims this is conditional on the price of credit and the price elasticity of the underlying credit markets. If too elastic, banks operate too aggressively in the underlying credit markets following a derivatives innovation which threaten bank stability. If too inelastic there is an opposite effect and the banking sector is stabilized by the development of the credit derivatives market.

Clearly, the literature shows no conclusive answer to the question whether credit derivatives raise or lower financial stability. Some authors believe that the introduction of credit derivatives increases the stability, while others claim that banks will change their behaviour now that they have access to credit derivatives. In the current study, we empirically investigate the relation between credit derivatives and financial stability, measured by the probability of default of the 20 largest European financial institutions. We find a negative relationship between the financial stability and the increased use of credit derivatives. Also, credit rating agency Standard & Poor's is found to incorporate CDS positively, but insignificant. In addition, we find evidence that this relationship is progressive and economically meaningful.

2. Methodology and data characteristics

We will use three different methods of calculating the probability of default: bond spread, CDS spread, and Merton (1974) distance to default model. In addition, we will use the credit rating of Standard and Poor (S&P) to see to what extent they incorporate the use of CDS. In the model, we use the probabilities of default as dependent variable and the amounts outstanding on credit derivatives as independent variables. We use Altman's (1968) bankruptcy prediction model as a source for control variables: working capital to total asset, the retained earnings to total asset, pre-tax income (earnings before tax) to total assets, the market value of equity to book value of total debt, and the sales to total asset. Greatrex (2008) finds that market data, like implied volatility, can explain deviations in credit spreads. We therefore add the implied volatility of the stock prices into the model as a sixth control variable. The seventh explanatory variable is the variable of interest, the amount outstanding on credit derivative contracts to total assets.

Our sample consists of 20 main players in the European financial sector. We obtain the 20 largest banks in Europe, measured by total assets, using Bureau van Dijk's Bankscope. In this sample, we include only publicly traded banks. Even though the sample consists of only 20 banks, because of the relative size it provides a fair coverage of the European banking sector. Moreover, the largest banks are obviously of particular interest due to their relatively large impact in the stability, and the fact that they make up the majority of the credit derivative market. Table 1 lists the sample of financial institutions.

Table 1: Sample banks

Royal Bank of Scotland Group Plc	UniCredit SpA
Barclays Plc	Banco Santander SA
Deutsche Bank AG	Fortis
BNP Paribas	Credit Suisse
HSBC Holdings Plc	HBOS Plc
Crédit Agricole SA	Dexia
UBS AG	Commerzbank AG
ING Groep NV	Lloyds Banking Group Plc
Société Générale	Danske Bank Group
ABN Amro Holding NV	Nordea Bank AB

The outstanding amount of credit derivatives will be obtained by examining the annual reports of each of these financial institutions. We use data from 2001-2008. Since the market for credit derivatives before 2001 was small, only a limited number of financial institutions released information about their holdings. After the implementation of IFRS in 2004, almost all banks provide sufficient information on their derivative positions. The market based information that is used in this study is gathered using Thomson One Banker, Reuters, and Datastream. We use the CDS premium on senior secured debt; for bonds we use the variable rate over the swap curve.[1]

The probability of default as calculated with bond spreads shows a pattern that is comparable with that of the overall economy. The probability of default increases during economic downturns (2001 – 2002 and 2007 – 2008), and decreases in prosperous times. Especially during the recent financial crisis the probabilities of default increased drastically. At the end of 2008 several banks had a probability of default of over 12% (HBOS and Nordea) while others remained around 2% (Santander).

There is no CDS spread data available for 2001; for 2002 this data is only available for two companies (ING and Nordea). Especially during the years 2003 – 2006 the CDS spread is extremely low and so is the default probability. Only in 2007 and 2008 the probability of default increases. In 2008 however the average probability of default using CDS spreads is 2.7%, which is remarkably lower than that of the bond spread. The highest default probability is that of Dexia with 6.7%. Both methods use market data so that one would expect the results to be more or less comparable.

The probability of default from the Merton model shows the most extreme results. During the economic downturn of 2001 the probabilities of default are considerably higher than those during the next years. However, starting in 2007 and maturing in 2008, the Merton DD model provides its extreme results when comparing with the previous two methods. In 2008 the average probability of default was 10.6% while Fortis had a 36.3% probability to default on its obligations.

The probability of default using S&P's credit rating shows the smoothest pattern. Only small adjustments in the credit rating are made by S&P. A few companies have the same rating throughout the entire sample and most other companies have only one adjustment during these eight years. Even in 2008 the average probability of default is 0.055% and the maximum 0.08% which is rather low considering the problems in the financial sector.

Figure 1a: Average probability of default using bond spreads

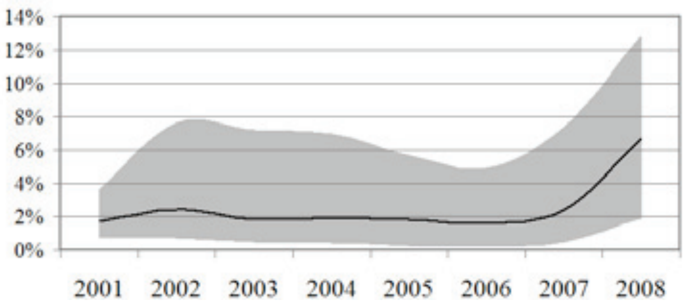

Figure 1b: Average probability of default using CDS spreads

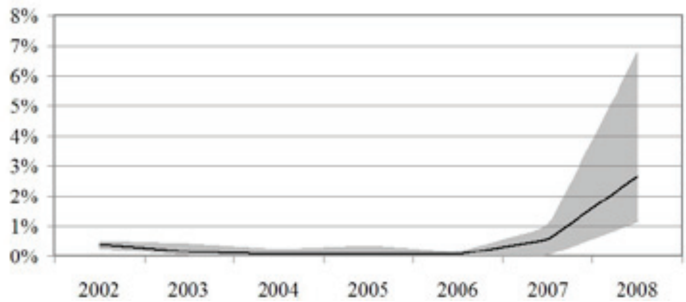

Figure 1c: Average probability of default using Merton DD model

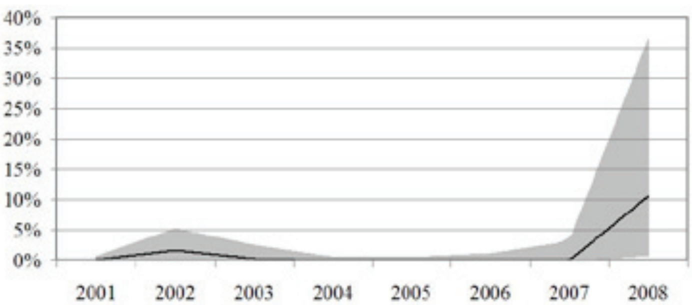

Figure 1d: Average probability of default using Standard and Poor's credit rating

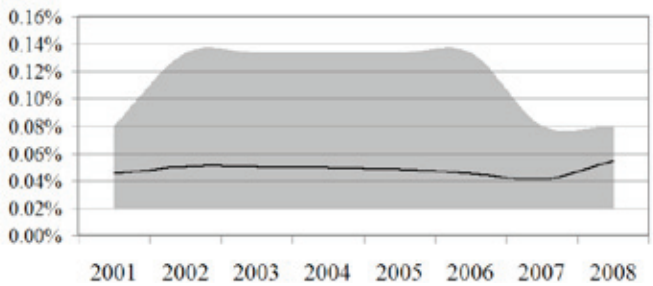

Table 2 presents the descriptive statistics of both the probabilities of default (a) and the control variables (b). A noticeable thing is the relatively high standard deviation of X7, which is the credit derivative variable. The mean is much higher than the median, indicating that a small number of banks uses a large amount of credit derivatives.

Table 2a: Descriptive statistics of the probabilities of default

	Bond spread	CDS spread	Merton DD	S&P
Mean	0.02537	0.00600	0.05861	0.00048
Median	0.01755	0.00121	0.00192	0.00047
Maximum	0.12811	0.06735	0.48875	0.00133
Minimum	0.00262	0.00013	0.00000	0.00020
Std. Dev.	0.02433	0.01071	0.10972	0.00022
Skewness	1.82	2.91	2.23	1.92
Kurtosis	6.75	13.10	7.55	8.12
Observations	160	115	156	156

Notes: Table displays the descriptive statistics of our three measures of default, plus the credit rating.

Table 2a: Descriptive statistics of the probabilities of default

	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Mean	0.03690	0.01763	0.00607	0.05982	0.06145	0.31301	0.45446
Median	0.03138	0.01699	0.00696	0.05551	0.05483	0.22236	0.18153
Maximum	0.16162	0.04395	0.01725	0.18487	0.17425	1.00193	2.81736
Minimum	0.00648	-0.01126	-0.02321	0.00629	0.00189	0.11205	0.00000
Std. Dev.	0.01841	0.00997	0.00574	0.03084	0.02779	0.20255	0.67281
Skewness	2.90	-0.22	-2.14	0.75	1.34	1.42	2.02
Kurtosis	18.20	3.73	9.94	4.05	5.19	4.20	6.36
Observations	126	155	158	157	157	132	130

Notes: X_1 = working capital to total assets; X_2 = retained earnings to total asset; X_3 = pre-tax income to total asset; X_4 = market value of equity to book value of total debt; X_5 = sales to total asset; X_6 = implied volatility using at-the-money options; X_7 = notional amount of credit derivative contracts to total assets.

Table 3 shows the correlations between the probabilities of default and the explanatory variables. Between the probabilities, the correlation is the highest between the CDS spreads and Merton DD with 78%. The correlation between the bond spreads and CDS spreads is 67%. The correlation of the default probabilities with X7, the notional amount of credit derivatives to total assets, provides a first answer to our research question. For the bond spread, CDS spread, and Merton DD model, the correlation is highly comparable and positive. This indicates that the probability of default increases with an increased use of credit derivatives. The credit rating, on the other hand, depicts a negative correlation. As such, S&P views the use of credit derivatives as increasing the creditworthiness of a financial institution.

Table 3: Correlation matrix of the probabilities of default and the variables

	Bond spread	CDS spread	Merton DD	S&P	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Bond spread											
CDS spread	0.67302										
Merton DD	0.70205	0.77675									
S&P	0.09530	0.21300	0.06511								
X_1	-0.21041	-0.20864	-0.19280	0.01052							
X_2	-0.33039	-0.26846	-0.22941	-0.14501	0.29261						
X_3	-0.69611	-0.69254	-0.61629	-0.33067	0.49749	0.41794					
X_4	-0.52361	-0.55462	-0.60109	-0.25363	0.63972	0.31786	0.72644				
X_5	-0.01837	0.10420	-0.14118	-0.11069	-0.02780	-0.38205	0.10512	0.02730			
X_6	0.79103	0.87358	0.86052	0.14154	-0.21524	-0.22834	-0.73496	-0.64466	-0.05313		
X_7	0.26390	0.25212	0.28177	-0.10191	-0.38802	0.13979	-0.33986	-0.37703	-0.27246	0.27602	

Notes: X_1 = working capital to total assets; X_2 = retained earnings to total asset; X_3 = pre-tax income to total asset; X_4 = market value of equity to book value of total debt; X_5 = sales to total asset; X_6 = implied volatility using at-the-money options; X_7 = notional amount of credit derivative contracts to total assets.

Table 4: Regression using Bond spreads, CDS spreads, Merton DD and Standard & Poor

Variable	Bond Spread	CDS Spread	Merton DD	S&P
C	22.583*** (0.211)	3.456*** (0.218)	5.477*** (0.712)	3.295*** (0.060)
X_1	0.690 (26.085)	-2.420 (3.984)	-13.054 (25.813)	-0.281 (1.224)
X_2	-33.413 (49.584)	-2.693 (6.929)	-6.718 (26.722)	2.459 (2.499)
X_3	125.341 (111.507)	-9.631 (12.222)	11.421 (48.464)	8.907** (3.806)
X_4	10.484 (12.438)	6.448*** (2.234)	-0.112 (14.369)	-0.688 (0.644)
X_5	25.044* (14.539)	-2.978*** (0.955)	5.492* (3.108)	-0.272 (0.448)
X_6	-0.937*** (0.145)	-1.835*** (0.299)	-6.429*** (1.461)	0.002 (0.059)
X_7	-0.061* (0.038)	-0.104*** (0.036)	-0.145 (0.142)	0.011 (0.521)
Adjusted R^2	0.6633	0.831	0.613	0.781
AIC	0.0696	-0.0330	3.1218	-2.4891
Observations	93	79	89	93

Notes: X_1 = working capital to total assets; X_2 = retained earnings to total asset; X_3 = pre-tax income to total asset; X_4 = market value of equity to book value of total debt; X_5 = sales to total asset; X_6 = implied volatility using at-the-money options; X_7 = notional amount of credit derivative contracts to total assets. The numbers in parenthesis are standard errors; *, **, and *** denotes significance at the 1, 5, and 10% level, respectively.

3. Empirical results

The estimation results are presented in Table 4. In this regression the Z-score of the probability of default is the dependent variable[2].

Overall, we observe in Table 4 that the use of credit derivatives is detrimental to the stability of the financial institutions. This relation is significant in two cases. The probability of default given by the credit rating agency S&P actually decreases with the use of CDS, although not significantly.

Using the bond spreads, sales to total assets, implied volatility, and our variable of interest credit derivatives to total sales, are significant. In increase in sales to total assets decreases the probability of default. An increase in implied volatility increases the probability of default. The coefficient for X7 is negative, so that an increase in credit derivative positions increases default risk and thus decrease stability.

When focusing on the CDS spreads, there are four significant variables: market value to total debt, sales to total assets, implied volatility, and credit derivatives to total assets. The sign of the coefficient for the sales to total assets is minus, though, which implies that a rise in this ratio increases risk, which is in contradiction with the result from the model using bond spreads. The credit derivative coefficient is again negative.

For the Merton model, only two variables are significant: sales to total assets and the implied volatility. The signs of these variables are consistent with those from the model using bond spreads. The coefficient of the implied volatility, however, is much higher than with the other models.
In this model using the S&P rating, only pre-tax income to total assets is significant; all other variables have high p-values. The credit derivative variable has a positive sign, in contrast to the previous models[3].

To determine the economic impact of the credit derivative variable on the probability of default, we use our estimated models and calculate the probability of default when the companies would have held one standard deviation more credit derivative contracts and compare them to the probabilities from the original model. An increase in the holdings of credit derivatives with one standard deviation would increase the probability of default of a company with 9.5, 18.2, and 8.5 percent for the bond spread, CDS spread, and Merton model, respectively. These numbers can be considered economically meaningful. S&P reduces the probability of default by 2.5%.

So far we have introduced the credit derivative variable as a linear variable in our model. However, it could be possible that the relationship between the outstanding amount of credit derivatives and the probability of default is non-linear. The probability of default could increase more than proportional due to the leverage embedded in the credit derivatives.

The squared value becomes negative and significant for all three measures. For CDS and Merton, the AIC value decreases, indicating a better fit. This progressive effect of CDS on the probability of default could indicate the initial stabilizing effect, and the subsequent destabilizing effect. In addition, a possible explanation is the counter party risk. For S&P the coefficient remains positive, and insignificant; the fit of the model also deteriorates.

4. Conclusion

Our results indicate that an increase in the use of credit derivatives increases the probability of default. Therefore, we conclude that an increase in the credit derivatives held by financial institutions reduces the stability of the financial sector. This is even more pressing considering the fact that credit risk instruments are typically only used by large, systemic financial institutions. The magnitude of the impact of credit derivatives on the probability of default of the financial institutions is economically relevant. Results further suggest that the relation between credit derivatives held by financial institutions and the probability of default is not linear, but quadratic.

Table 5: Substituting the credit derivative variable with its squared value

	Coefficient	Std. Error	Prob.	AIC	+ / -
Bond spread	-0.0178	0.0106	0.0974	0.0756	(+)
CDS spread	-0.0363	0.0138	0.0112	-0.0364	(-)
Merton DD	-0.0752	0.0424	0.0797	3.1150	(-)
Credit rating (S&P)	0.0036	0.0051	0.4884	-2.4881	(+)

Notes: Table displays the effect of introducing a progressive measure for CDS usage.

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1 For calculating the probability of default, we apply a recovery rate of 51.9%.

2 The sign of the coefficient indicates whether the variable increases or decreases default risk. A minus sign implies that it increases risk.

3 Since Standard & Poor's credit rating is ordinal data, an OLS-regression can lead to biased results. We also used the Ordered Probit methodology to estimate the model. This method provides qualitatively similar results.

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