US Banks Participation in Credit Derivatives and the Financial Crisis

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This paper was a study of US bank participation in credit derivatives around the financial crisis of 2008 by using data between 1997 and 2017. The results from a more detailed analysis showed that the financial crisis represented a transitional period for US banks' holdings of credit derivatives. The results indicate that US banks increased their hedging and their appetite for risk. The financial crisis also represented a structural change in type of loans held by participating US banks. The results show that US banks converged towards hedging around the financial crisis in credit derivatives.

Keywords: credit derivatives, hedge, banks, financial crisis

INTRODUCTION

As hedging instruments, credit derivatives were viewed as stabilizing instruments on the financial markets prior to the financial crisis because they provided banks with the flexibility to manage the credit risk of their assets independently of their holdings. Greenspan (2004) argued that banks were able to increase their interest income from assets while transferring the default risk to other less leveraged institutions.

To state that credit derivatives were used for hedging the banking system's credit risk may be an overstatement. As Figure 1 shows, the volume of outstanding credit derivatives exceeded total banking system assets beginning in 2005 and continued to rapidly increase through 2007. The use of credit derivatives continued to increase until the financial crisis. The literature provides varying motivations for utilizing credit derivatives by American banks. Minton, Stulz, and Williamson (2009) found that banks mainly used credit derivatives for speculation purposes rather than hedging. However, newer literature, post the financial crisis of 2007 and 2008, argued that banks used credit derivatives for hedging (Li and Marinč, 2014; Bliss, Clark, and DeLisle, 2018).

In this paper, we attempt to address the following questions using observations that encompass the financial crisis of 2007 and 2008:

(1) What are the characteristics of banks that participate in the credit derivatives market?

(2) What are the changes in the determinants of a bank's gross holdings of credit derivatives around the financial crisis?
(3) What are the changes in the determinants of a bank's net position as a guarantor or beneficiary in the credit derivatives market around the financial crisis?

The remainder of this paper is organized as follows. Section II presents a review of the disseminated literature and a discussion on the banks' holdings of credit derivatives. Section III presents a description of the sample and data sources. Section IV presents the empirical tests? and the regression results. Finally, section V presents the summary and conclusion of the paper.

LITERATURE REVIEW AND DISCUSSION

Origins of Credit Derivatives

Credit derivatives in various forms existed since the early 1990s (Smithson & Mengle 2006). Guill (2016) reported that Bankers Trust was active in developing risk management tools in the 1970s and 1980s. The Economist (2013, February 02) and Philips (2008) credits JP Morgan with creating the modern version of credit derivatives when JP Morgan sold a credit default swap to the European Bank of Reconstruction and Development to transfer the risk JP Morgan took on when it extended a $4.8 billion line of credit to Exxon to cover its potential $5 billion in punitive damages after the Exxon Valdez oil spill. According to Lanchester (2009), JP Morgan sold the credit default swap to improve its balance sheet.

Literature Survey

Since the financial crisis was a critical economic and political event in the US and the world, we review the credit derivatives literature in two sections. In the first section, we review the pre-financial crisis literature while the post-financial crisis is reviewed in the second section.

Pre-Financial Crisis Literature

Although the publication dates for some of the papers reviewed were after 2008, the sample data in these papers were observed before the financial analysis. The early part of the literature concentrated on the benefits and costs of credit derivatives and their use for transferring credit risk to third parties. Smith and Stulz (1985) showed that firms are more likely to hedge higher financial distress costs they face than other risks. The literature shows that banks use credit derivatives to hedge credit risk (Batten and Hogan, 2002; Cebenoyan and Strahan, 2004; Duffie, 2008). Brewer, Jackson, and Moser (1996) argued that hedging allows banks to increase diversification of their sources of income. Rule (2001) argued that credit derivatives are beneficial to banks because the separation of credit risk from the asset origination would provide stability to lending institutions and facilitate increased resource allocation efficiency. Duffie and Zhou (2001) showed that the source of the asymmetric information in the credit market determines the value of credit derivatives. In cases of adverse selection, banks would be better off while in the case of moral hazard, they would be worse off. The use of credit derivatives may also impact the economy in other ways.

The ability of the banks to separate the risk of the asset from holding it causes shifts in banks' behavior. In the past, investors viewed a bank's extension of credit to a corporation as a type of certification regarding the financial health of the borrower. Morrison (2005) argued that bank debt has a certification value to the financial markets. The existence of credit derivatives may cause banks to reduce the quality of their assets to sub-investment quality. Credit derivatives could reduce welfare by disintermediation in the credit market due to decreased quality and lack of certification of bank loans. In addition, the reduction of the signaling effect due to credit derivatives may lead to changes in financing decisions. Therefore, the lack of transparency would prevent banks from committing to holding the newly originated assets which leads to suboptimal investment and reduced welfare. The certification argument may no longer hold if banks are able to transfer the credit risk of corporate borrowers to third parties.

Instefjord (2005) showed that the use of credit derivatives to transfer risk depends on credit prices and the price elasticity of the underlying credit market. If the price elasticity is high, the stability of banks would be threatened. If the price is inelastic, banks would be stabilized by credit derivatives. Instefjord (2005) also used cost of financial distress analysis and found that credit derivatives increase the benefit of risk sharing and transfer. Therefore, if banks use credit derivatives only to hedge their credit risk exposure in an elastic market, their risk increases, and they would destabilize.

The literature also studied the impact of credit derivatives on the banking sector and the economy by evaluating how innovation affects the credit market. Wagner (2007) showed that the value of innovation such as credit derivatives would depend on the state of the economy. In normal states of the economy, innovation in risk transfer would increase stability in the financial sector because banks are incentivized to reduce their risk. However, in recessions, such innovations would destabilize the financial markets because banks are incentivized to increase their risk. Rajan (2006) suggested that the world is better off due to the innovation of risk transfer and sharing because it expanded the credit market. Expanding the economy's credit capacity and, therefore, the credit market made companies and households better off.

The motivation behind the use of credit derivatives by banks was also investigated in the literature. Ashraf, Altunbas, and Goddard (2007) found that bank size was the main factor that determined the institution's participation in the credit derivatives market. They also found evidence that banks use credit derivatives to manage their credit risk exposure. Nicolò and Pelizzon (2008) studied the optimal credit derivative contract design under asymmetry of information. They proved that binary credit derivative contracts are optimal when banks are under strict capital loss requirements. Hirtle (2009) found only a limited relationship between the use of credit derivatives and increases in corporate loans and suggested that the benefits may be narrow. Minton, et al (2009) evaluated the motivation for banks to participate in the credit derivatives market. Their analysis questioned whether banks use the credit derivatives market for hedging. Using a detailed analysis of participating banks, they found evidence of speculation.

In summary, pre-financial crisis literature while arguing that credit derivatives were not always used for hedging or risk transfer, they generally were beneficial to banks and contributed to the stability of the credit markets. In addition, some argued that credit derivatives increased intermediation and helped expand the economy.

Post Financial Crisis Literature

We now turn our attention to the post financial crisis literature on credit derivatives. The newer literature mainly concentrated on the impact of the credit derivatives on the credit markets. Norden, Buston, and Wagner (2014) found that the banks' gross holdings of credit derivatives led to lower corporate credit spreads while net positions were not related to corporate loan pricing. They argued that the pricing reaction to holdings of credit derivatives was consistent with passing on the benefits of credit derivatives to their borrowers. They also did not observe a change in risk management due to the financial crisis. The literature also showed that credit derivatives were used for hedging financial risk. For example, Li and Marinč (2014) analyzed bank holding companies using observations between 1997 and 2012 and found that the use of credit derivatives was positively and significantly related to the institution's exposure to systematic risk. Their findings were consistent with Bliss, et al, (2018) who found that banks use credit derivatives in addition to other instruments to hedge financial stress risk exposure.

Luis, Rodriguez Gil, Sara, and Santomil (2015) argued that the view of credit derivatives has changed around the financial crisis from making banks sounder to taking the blame for the crisis. However, their empirical evidence showed that credit derivatives did not cause the financial crisis.

SAMPLE SELECTION AND VARIABLE DEFINITION

Sample

In this section we present the variables used in the regression analysis and their definition. We also describe the sample selection process and the data source.

To answer the three questions posed in the Introduction section of this paper, we evaluate the determinants of three dependent variables. The first dependent variable is *PARTICIPATE*. For the first regression set, we used logistic regression to determine the characteristics of banks that participated in the credit derivatives market. Hence, *PARTICIPATE* is a dummy variable equal to 1 if the bank participated in the credit derivatives market and 0 otherwise. The second variable is *GROSS_HOLD*. We used the second regression set to analyze the determinants of a bank's gross holdings of credit derivatives. Since the analysis was performed on only a subset of banks that participated in credit derivatives, we used the 2-stage Heckman regression to account for any selection bias in the observations (Heckman, 1979). The third variable is *NETGRNTR*. We analyzed the determinants of a bank acting as a net guarantor or beneficiary in the credit derivatives market. Hence *NETGRNTR* is a dummy variable equal to 1 if the bank was a net guarantor and 0 otherwise. Since this analysis was also performed on a subset of banks, we used simultaneous logit regressions to account for any selection bias. We did not use 2-stage Heckman because the second stage would have to be OLS and we used logistic regression.

We obtained our data from the FDIC website statistics on depository institutions. The data can be accessed at https://www5.fdic.gov/sdi/download_large_list_outside.asp. The sample included all banks that reported $5 billion in total assets for any quarter between 1997 and 2017.

Table 1 shows the summary statistics. Although the number of US banks steadily declined by more than 50% between 1997 and 2017, the number of banks that reported $5 billion in total assets in any quarter for the same period decreased by about 44%. However, the number of participating banks increased by more than fivefold during the same period. Table 1 also shows that the size of the credit derivatives market exhibited rapid growth before 2008 and declined steadily afterwards. The average holdings exhibited a similar trend. Average holdings increased steadily through 2008 and started to decline afterwards. The summary statistics also show that the holding averages are much greater than the medians which indicates a concentration on credit derivatives in larger banks. The information presented in Table 1 indicates that the financial crisis years represented a structural change in the CD market.

Variables

We look to published literature to gauge the influence of the bank's portfolio on its participation in credit derivatives. Minton, Stulz, and Williamson (2009), Broccardo, Mazzuca, Yaldiz (2014), and Mattana, Petroni, & Rossi (2015) argued that the composition of the loan portfolio would impact its desire to hedge. Li, et al. (2013) found that agricultural loan (AGRILOANS) default rates are not higher or are lower than those of other bank assets. Therefore, increases in agricultural loans would require less hedging than other assets. Minton, Stulz, and Williamson (2009) argued that banks are more likely to hedge with increases in their holdings of commercial and industrial loans (COMM_IND). Ghosh, A. (2016) found that Commercial real estate loans (COMM_RE) and Construction loans (CONSTRCT) are cyclical in nature with the local economy and the overall GDP. The cyclical nature of these loans would present increased risk for the lending bank and, hence, increase the need for hedging. Rajaratnam, Beling, and Overstreet (2017) showed that banks would increase consumer loans beyond the ideal which would increase their risk. Therefore, banks with higher consumer loans would increase their participation in the credit derivatives market. Doukas and Melhem (1987) showed that the default rate in foreign loans is lower than that for domestic assets. Therefore, an increase in originating foreign loans would reduce the need for hedging. However, Minton, Stulz, and Williamson (2009) found that banks who originate foreign loans are more likely to hedge.

TABLE 1
SUMMARY STATISTICS OF BANKS PARTICIPATING IN THE CREDIT DERIVATIVE (CD) MARKET

Year	*Number of Participating Banks*	*Number of banks $5 billion total assets*	*Number of Banks on FDIC Website*	*Minimum CD holdings ,000s*	*Maximum CD holdings ,000s*	*Average CD holdings ,000s*
1997	11	373	10,946	10,000	7,526,000	1,778,741
1998	15	364	10,484	10,000	25,878,000	5,263,880
1999	20	358	10,240	10,000	41,911,000	5,705,154
2000	22	351	9,920	9,000	68,247,000	7,007,346
2001	26	352	9,630	6,793	271,673,000	16,171,481
2002	21	344	9,369	3,805	366,050,000	30,531,217
2003	25	335	9,194	1,345	577,693,000	40,023,429
2004	26	327	8,988	1,075	1,066,160,000	90,255,075
2005	29	322	8,845	65	2,301,064,000	200,748,428
2006	35	307	8,691	38	4,654,282,000	257,704,262
2007	36	294	8,544	175	7,900,570,000	440,617,651
2008	37	282	8,314	175	8,391,629,000	433,219,318
2009	35	265	8,021	301	6,079,453,000	403,203,371
2010	34	257	7,667	301	5,474,978,000	416,192,931
2011	35	249	7,366	3,097	5,775,740,000	421,683,305
2012	40	241	7,092	2,022	5,982,888,000	329,751,820
2013	43	236	6,821	47	5,334,563,000	260,233,625
2014	48	233	6,518	125	4,247,239,000	196,843,807
2015	52	223	6,191	240	2,893,039,000	134,344,765
2016	52	217	5,922	153	2,007,083,000	99,858,615
2017	58	209	5,679	85	1,664,568,000	72,151,615

The sample banks reported $5 billion in total assets for any quarter between 1997 and 2017. The data was obtained from the FDIC website, www.FDID.gov

To capture a bank's attitude towards risk, we use the bank's risk weighted assets (LN_RISK). A positive coefficient of risk assets indicates that the bank is using credit derivatives to hedge its risk. However, a negative sign indicates that the bank is using credit derivatives to speculate (Rajan, 2006; Ashraf, Altunbas, and Goddard, 2007). We also use gross loans and leases (LOAN_AST) and nonperforming loans (BAD_LOANS) to proxy the quality of the bank's portfolio. The sign of the coefficients would be similar to LN_RISK. Banks are highly regulated. Therefore, they have to maintain certain capital levels. We capture the impact of regulation on banks by using the bank's capital as a variable, Tier 1 capital (TIER_1). A positive coefficient for TIER_1 suggests that the bank is using credit derivatives when they have sufficient capital, while a negative sign indicates that the bank is attempting to hedge the possibility of default or financial distress (Ashraf, Altunbas, and Goddard, 2007).

Minton, Stulz, Williamson (2009) argued that banks would use all available instruments to manage risk. We capture the bank's use of hedging instruments using three variables, derivatives holdings including CD (DRVTVS), whether the bank holds interest rate contracts (HAS_RT), and whether the bank sells its loans (LOANSALE).

Other control variables. A more profitable bank is less likely to experience financial distress than a less profitable one. Therefore, we expect a negative coefficient for profitability (Minton, Stulz, Williamson, 2009; Broccardo, Mazzuca, Yaldiz, 2014). Following Minton, Stulz, Williamson (2009), we proxy profitability as net interest margin as a proxy for profitability (NIM). In addition, a bank's holding of liquid assets enables the bank to take on more risk or increase its appetite for risk. We also consider the bank's investments. We use the bank's securities holdings (SC_AST) as proxy for investments. Securities are more liquid than other assets and, therefore, holding them reduces the bank's exposure to financial distress. We hypothesize that increased security holdings increase the probability the bank would act as a guarantor in the credit derivatives market.

We also control for the bank size using the natural log of the bank's total assets (LN_ASSET). According to the literature, the larger the bank the more likely it will participate in the credit derivatives market (Ashraf, Altunbas, and Goddard, 2007; Minton, Stulz, Williamson, 2009; Broccardo, Mazzuca, Yaldiz, 2014; Mattana, Petroni, & Rossi, 2015).

The variable definitions and calculations used in this paper are presented in Appendix A. To analyze the three questions posed in the introduction section of this paper, we base our hypotheses on the disseminated literature. We hypothesize that larger banks are more likely to participate in credit derivatives. We also expect hedging instruments to complement rather than substitute for each other. The type of loans banks hold is also a factor in determining a bank's holding of credit derivatives. Therefore, the paper will evaluate the impact of different types of loans on banks' participation in credit derivatives. We expect banks' holdings of credit derivatives to converge towards hedging because of the financial crisis. Finally, we also hypothesize that banks which act as net guarantors have an increased appetite for risk.

The change in the credit derivatives market around the financial crisis is also evident in Figure 1. As the figure shows, the sample banks' holdings of credit derivatives exceeded the entire banking system's loans before the financial crisis. The volume of credit derivatives holdings suggests that banks were speculating rather than hedging. This is consistent with the findings of Minton, Stulz, and Williamson (2009). Figure 1 also shows that the total assets and loans for banks with more than $5 billion in assets, while both greater than those of the participating banks, were smaller than their holdings of credit derivatives. The volumes of assets and loans appeared to be rather steady for the banks in this study as well as all the banks in the US during the 1997 through 2017 period. During the same period, the US banks holdings of credit derivatives exhibited an entirely different pattern. Figure 1 shows that there are three distinct holding patterns of credit derivatives. Bank holdings of credit derivatives steadily increased between 1997 through 2007, stayed roughly steady between 2007 and 2011, and declined after 2011. According to the Business Cycle Dating Committee, the National Bureau of Economic Research dating cycle, the Great Recession in the US started in June 2007 and ended in June, 2009. However, for the purposes of our paper, based on the banking industry's holdings of credit derivatives, we define the period 1997 through 2006 as pre-financial crisis, the period 2007 through 2011 as a transitional period, and the period 2012 through 2017 as post financial crisis.

EMPIRICAL RESULTS

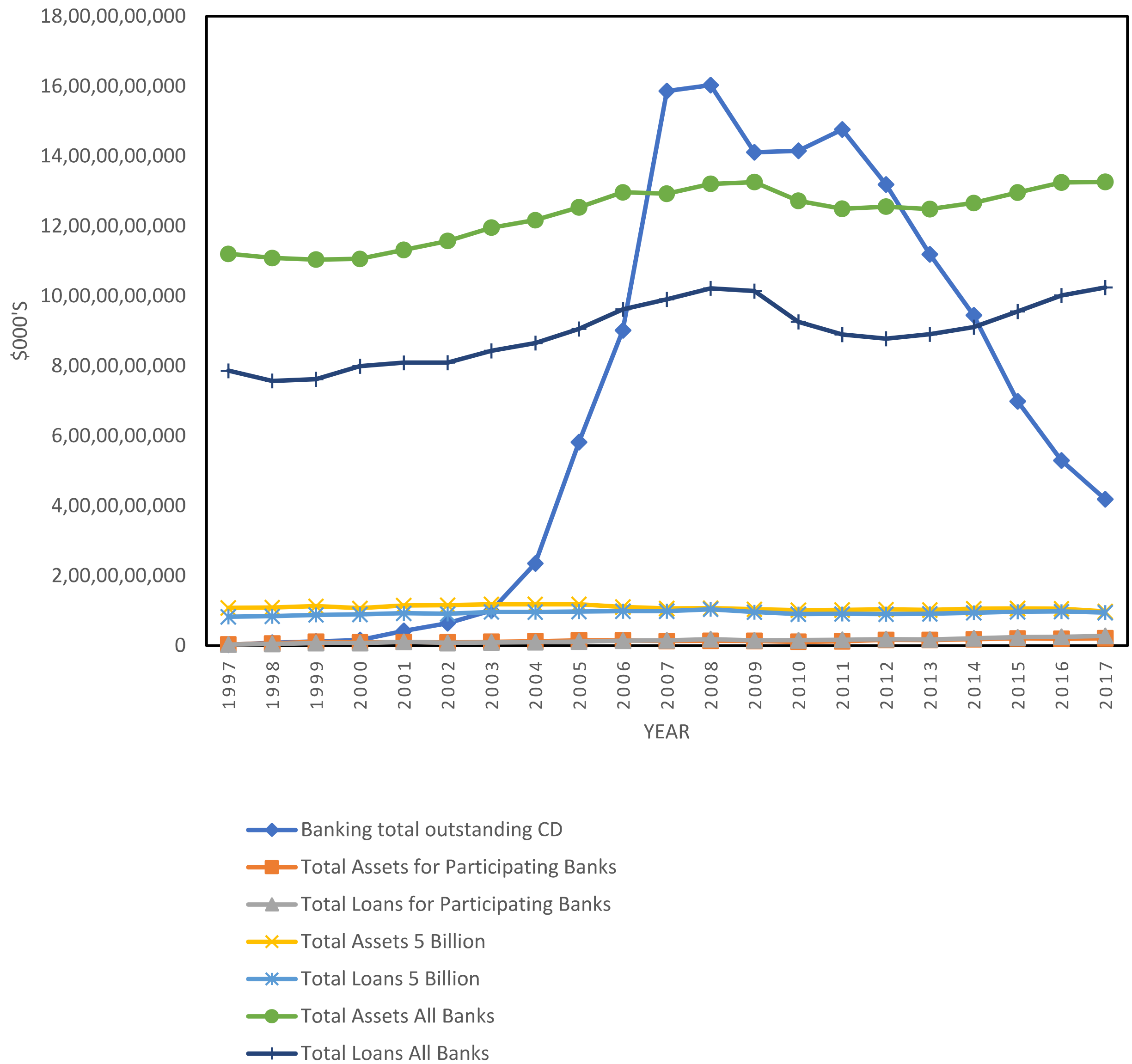
In this section, we present the results of our analysis of the banks involvement in credit derivatives to answer the three questions posed by this paper in the introduction section.

Determinants of Bank Participation in Credit Derivatives

To determine the characteristics of banks that participate in the credit derivatives market, we ran a logistic regression where the dependent variable, *PARTICIPATE*, is equal to one if the bank holds credit derivatives and zero otherwise. We used a synthesized matched pair technique. For each bank in the sample, we synthesized a matched bank by calculating the average value of the variables for nonparticipating banks with total assets equal to +/- 10% of the total assets of the sample bank. The number of banks used to create the synthesized matching bank varied for each bank.

We ran the regression as four models defined below to avoid correlation values of 0.3 or higher between the independent variables. Tier 1 capital, commercial and industrial loans, and agricultural loans were common to all four models. The additional independent variables are as follows. In model one, we used the natural logarithm of assets, liquidity, net interest margin, and derivatives holdings divided by assets. In model two, we used the natural logarithm of risk assets, securities holdings divided by assets, loans to individuals, derivatives holdings, and construction loans. In model three, we used total loans divided by assets, securities holdings divided by assets, loans to individuals, liquidity, originates foreign loans, and construction loans. In model four, we used has-interest-rate contracts, nonperforming loans, total loans divided by assets, net interest margin, originates foreign loans, and construction loans.

FIGURE 1
SHOWS CREDIT DERIVATIVE HOLDINGS, ASSETS, AND LOANS FOR US BANKS FOR THE ANALYSIS PERIOD 1997 THROUGH 2017



The data was downloaded from the FDIC statistical data on depository institutions website https://www5.fdic.gov/sdi/download_large_list_outside.asp

Table 2 shows the results of the logistic regression. The results generally agree with the predictions of the theoretical part of the paper presented earlier. We found that banks are more likely to participate in the credit derivatives market if they utilize other hedging instruments. The coefficients for holding interest rate contracts and other derivatives were positive and significant at the 0.01 level. We also found that the size of the bank as measured in this paper, risk assets, and total assets were a positive and a significant contributor to the probability of participating in the credit derivatives market. Larger banks were more likely to participate in the credit derivatives market than smaller ones. The coefficient of Tier 1 capital was negative and significant indicating that banks were less likely to participate in the credit derivatives market with increases in their core capital. Increasing Tier 1 capital reduces the bank's risk. The results for the bank size and core capital variables indicate that larger banks are either more skilled in managing their risk which reduced their dependence on core capital or that they relied on credit derivatives to manage the risk of their assets. The results also indicate the sample banks were more likely to participate in the credit derivatives market with increases in their nonperforming loans and the size of their loan portfolios.

As hypothesized, we also found that the types of loans the bank held in its loan portfolio contributed to the likelihood of participating in credit derivatives. The results show that banks were more likely to participate in credit derivatives if they increased their holdings of wholesale loans. The coefficients for foreign and commercial and industrial loans were positive and significant. However, banks were less likely to participate in credit derivatives with increases in retail lending. The coefficients for loans to individuals, agricultural, and construction loans were negative and significant. Wholesale loans are less costly for the bank to originate but are usually larger than retail loans. We also report that banks were more likely to participate in this market if their liquidity increased and their profitability decreased. The coefficient for liquidity is positive and significant while that for profitability is negative and significant. Increases in liquidity enable a bank to fulfill credit derivatives claims from others in cases where it has acted as a guarantor. We test for which class of bank acted as a guarantor later in this paper.

Determinants of US Banks Gross Holdings

For the second step in our analysis of credit derivatives in US banks, we analyze the determinants of the gross holdings of credit derivatives. For the first stage of the Heckman regression, we used model 2 from the previous regression since it had the highest goodness-of-fit measure. The results are presented in Tables 3 through 6. Table 3 represents the regression results for the entire analysis period. Tables 4, 5, and 6 show the results for the three subperiods.

As in the case with other regressions in this paper, we ran the regression as three models to avoid correlation values of 0.3 or higher between the independent variables. Nonperforming loans, commercial and industrial loans, originated foreign loans, agricultural loans, sells loans, and liquidity were common to all models. The additional independent variables are as follows. In model one, we used commercial real estate loans and net interest margin. In model two, we used construction loans and net interest margin. In model three, we used loans to individuals.

Results for the Entire Period

As Table 3 shows, the sample banks increased their gross holdings of credit derivatives with increases in loans to consumers and to foreign entities. The coefficients of loans to consumers and foreign loans were positive and significant at the 1% level. In addition, selling loans, liquidity, and bad loans positively and significantly contributed to bank holdings of credit derivatives. The coefficient for agricultural loans was negative. However, the coefficient for agricultural loans was significant at the 10% level in only one model. Commercial real estate loans, construction loans, commercial and industrial loans, and profitability were not significant. We did not report the first stage Hickman results because they are a reproduction of model two in the first set of regressions in this paper.

Results for the Three Subperiods

We then drilled deeper into the data by analyzing banks' gross holdings of credit derivatives during the three subperiods described above. The results for the subperiods show that banks changed their credit derivatives holdings around the financial crisis. This paper posits that the financial crisis represented a transition period for banks.

TABLE 2
LOGISTIC REGRESSION RESULTS FOR THE DETERMINANTS OF PARTICIPATION IN THE CREDIT DERIVATIVES MARKET

	Model 1	Model 2	Model 3	Model 4
INTERCEPT	-4.9696*** <.0001	-13.5053*** <.0001	-1.6063*** <.0001	-2.1594*** <.0001
HAS_RT				1.7006*** <.0001
LN_RISK	--	0.7524*** <.0001	--	--
LN_ASSET	0.2746*** <.0001	--	--	--
BAD_LOANS	--	--	--	1.9722*** 0.0076
LOAN_AST	--	--	0.1109*** <.0001	0.0897*** <.0001
SC_AST	--	0.3768 0.1193	-0.0085 0.9657	--
INDVIDUAL	--	-1.6077*** <.0001	-0.6057*** <.0001	--
LIQUID	0.3369** 0.0431	--	0.5520*** 0.0005	--
NIM	-0.2562*** <.0001	--	--	-0.2204*** <.0001
DRVTVS	3.1041*** <.0001	1.8478*** <.0001	--	--
HAS_FORN	--	--	1.1034*** <.0001	0.8803*** <.0001
CONSTRCT	--	-2.7621*** <.0001	-3.0277*** <.0001	-3.0122*** <.0001
TIER1	-0.0266*** <.0001	-0.0012 0.8471	-0.0150*** 0.0020	-0.0086 0.1842
COMM_IND	2.1192*** <.0001	1.7897*** <.0001	1.6443*** <.0001	1.2895*** <.0001
AGRILOANS	-6.4116*** 0.0024	-5.6904** 0.0193	-5.8956*** 0.0025	-5.6930*** 0.0077
McFadden's Pseudo R^2	0.2295	0.4176	0.2206	0.3268
Observations	6139	6139	6139	6139
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively				

TABLE 3
SHOWS THE SECOND STAGE OF THE 2-STAGE HECKMAN REGRESSION USED TO ESTIMATE THE DETERMINANTS OF A BANK'S GROSS HOLDINGS OF CREDIT DERIVATIVES FOR THE ENTIRE ANALYSIS PERIOD, 1997 THROUGH 2017

Heckman second stage	**Model 1**	**Model 2**	**Model 3**
INTERCEPT	-51.8102	-41.5741	-160.4866**
	0.6594	0.7146	0.0393
COMM_RE	56.6797	--	--
	0.8041		
CONSTRCT	--	-308.4908	--
		0.4688	
INDVIDUAL	--	--	446.0161**
			0.0246
NIM	-17.7367	-14.2482	--
	0.4249	0.5257	
BAD_LOANS	4042.0177***	4038.3914***	4091.7636***
	<.0001	<.0001	<.0001
COMM_IND	-208.6217	-205.564	-150.12
	0.1192	0.1247	0.2689
HAS_FORN	119.7501***	112.8377***	107.5206***
	0.0071	0.0069	0.0096
AGRILOANS	-3368.8605	-3315.5406	-3778.0887*
	0.1403	0.1433	0.0901
LOANSALE	4.2492E-5***	4.2281E-5***	4.1382E-5***
	<.0001	<.0001	<.0001
LIQUID	373.3637***	356.0227**	432.7728***
	0.0098	0.0134	0.0002
lambda	-34.9398	-27.8554	-42.4658
	0.3263	0.4288	0.2152
Adjusted R^2	0.3236	0.3241	0.3288
Observations, Stage 1	6139	6139	6139
Observations, Stage 2	701	701	701
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively			

As Tables 4, 5, and 6 show, the impact on profitability changes from negative and significant to positive and significant from before to after the crisis. The coefficient was not significant during the transition period. In addition, the coefficient on bad loans changed from not significant to positive and significant.

TABLE 4
REPORTS THE RESULTS FOR THE ANALYSIS REPORTED IN TABLE 3 BUT LIMITED TO PRE-FINANCIAL CRISIS

Heckman second stage	Model 1	Model 2	Model 3
INTERCEPT	125.566	126.028	-63.820367
	0.3051	0.3048	0.4638
COMM_RE	375.3705	--	--
	0.2741		
CONSTRCT	--	319.7199	--
		0.4594	
INDVIDUAL	--	--	441.0564**
			0.0365
NIM	-41.4552*	-35.2327	--
	0.0748	0.1135	
BAD_LOANS	-693.272	-713.753	-857.8228
	0.5676	0.5571	0.4778
COMM_IND	-40.3524	-7.3519	88.6765
	0.7791	0.9589	0.5514
HAS_FORN	23.4179	20.1405	4.2046
	0.5788	0.6321	0.9199
AGRILOANS	-8074.3793**	-8179.6909**	-9234.4700***
	0.0255	0.0242	0.008
LOANSALE	2.9336E-5***	2.9322E-5***	2.9650E-5***
	<.0001	<.0001	<.0001
LIQUID	111.4581	78.4373	212.5887
	0.4925	0.6201	0.1129
lambda	-69.3792**	-68.7923*	-84.2059**
	0.0455	0.0502	0.0155
Adjusted R2	0.3476	0.3458	0.353
Observations, Stage 1	3433	3433	3433
Observations, Stage 2	230	230	230
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively			

TABLE 5
REPORTS THE RESULTS FOR THE ANALYSIS REPORTED IN TABLE 3 BUT LIMITED TO THE FINANCIAL CRISIS

Heckman second stage	Model 1	Model 2	Model 3
INTERCEPT	-107.1455	-186.7337	-340.3328
	0.7401	0.5611	0.14
COMM_RE	-992.0266	--	--
	0.1479		
CONSTRCT	--	-778.1723	--
		0.4619	
INDVIDUAL	--	--	556.0186
			0.3767
NIM	1.4163	-0.8962	--
	0.9785	0.9865	
BAD_LOANS	6809.6355**	6496.4563**	6514.2878**
	0.0143	0.0197	0.0179
COMM_IND	-188.7571	-143.4996	-97.8816
	0.6265	0.7123	0.7983
HAS_FORN	192.4037	255.3888*	256.4912*
	0.1827	0.0622	0.0581
AGRILOANS	-11768	-13040	-13832
	0.1947	0.159	0.139
LOANSALE	5.4256E-5***	5.5038E-5***	5.4746E-5***
	<.0001	<.0001	<.0001
LIQUID	370.687	340.0817	497.2757
	0.3157	0.3979	0.1185
lambda	31.9992	13.1104	-5.5871
	0.7473	0.8943	0.9535
Adjusted R2	0.4009	0.3956	0.4
Observations, Stage 1	1347	1347	1347
Observations, Stage 2	177	177	177
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively			

TABLE 6
REPORTS THE RESULTS FOR THE ANALYSIS REPORTED IN TABLE 3 BUT LIMITED TO POST-FINANCIAL CRISIS

Heckman second stage	Model 1	Model 2	Model 3
INTERCEPT	-443.1540***	-476.0594***	-119.1197
	0.0094	0.0049	0.2209
COMM_RE	-285.1254	--	--
	0.2816		
CONSTRCT	--	-1288.1382	--
		0.1682	
INDVIDUAL	--	--	707.5014***
			0.0026
NIM	129.0527***	135.2479***	--
	0.0014	0.001	
BAD_LOANS	1696.0039	1688.1112	2409.3521**
	0.1056	0.1046	0.0212
COMM_IND	-47.2663	-14.6575	64.7188
	0.7992	0.9377	0.731
HAS_FORN	353.4062***	369.7283***	340.9970***
	<.0001	<.0001	<.0001
AGRILOANS	-902.908	-1004.53	-27.2719
	0.6534	0.6146	0.9889
LOANSALE	2.7974E-5***	2.7699E-5***	2.7263E-5***
	0.0002	0.0002	0.0003
LIQUID	551.8049***	550.0227***	156.1398
	0.0059	0.006	0.3279
lambda	-59.460805	-63.325086	-43.0509
	0.2387	0.1913	0.3531
Adjusted R2	0.3214	0.3231	0.3204
Observations, Stage 1	1359	1359	1359
Observations, Stage 2	294	294	294
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively			

While originating foreign loans and liquidity increased in significance, the significance of agricultural loans decreased around the financial crisis. However, the signs of the coefficients did not change. The results show that banks' use of credit derivatives converged towards hedging and increased their appetite for risk assets. We did not report the results for the first stage Heckman for the three subperiods since they are qualitatively similar to the ones for the entire period.

Determinants of US Banks Acting as Guarantor in Credit Derivatives

Finally, we analyze which banks act as net guarantors in the credit derivatives market. Again, we used model 2 from the first part of the analysis as one of the two simultaneous logistic regressions since it had the best-goodness-of-fit.

We ran the regression as four models to avoid correlation values of 0.3 or higher between the independent variables. Commercial and industrial loans, agricultural loans, and tier 1 capital were common to all models. The additional independent variables are as follows. In model one, we used total loans divided by assets, securities holdings divided by assets, loans to individuals, construction loans, originates foreign loans, and liquidity. In model two, we use the natural logarithm of assets, liquidity, derivatives, and net interest margin. In model three, we used total loans divided by assets, has-interest-rate contracts, construction loans, originates foreign loans, nonperforming loans, and net interest margin. In model four, we used commercial real estate loans, construction loans, originates foreign loans, liquidity, derivatives, nonperforming loans, and net interest margin.

The results for the entire period are presented in Table 7 while the results for the three subperiods are presented in Tables 8 through 10.

Results for the Entire Period

As Table 7 shows, the coefficients for all types of domestic of loans investigated in this section of the paper were positive and significant. However, the coefficient for originating foreign loans was negative and significant. The coefficients for derivatives holdings and profitability were positive and significant, while Tier 1 capital and liquidity were negative and significant. The coefficients obtained in the regression indicate that the participating banks exhibited increases in their appetite for risk.

Results for the Three Subperiods

As Tables 8, 9, and 10 show, construction loans underwent a structural change. Construction loans changed from negative and significant during the pre-crisis period to positive and significant during the post crisis period. Liquidity increased in significance gradually from pre-crisis to post crisis while commercial and industrial loans lost significance over the three subperiods. The other variables did not exhibit significant changes during the three subperiods. The results confirm the findings of the previous section. US banks converged towards hedging and away from speculation in credit derivatives around the financial crisis. The increase in hedging may be a factor in US banks increasing their appetite for risk assets.

TABLE 7
REPORTS THE RESULTS OF THE LOGISTIC REGRESSION WHERE *NETGRNTR*, SET EQUAL TO 1 IF THE BANK WAS A NET GUARANTOR IN CREDIT DERIVATIVES AND 0 OTHERWISE

	Model 1	Model 2	Model 3	Model 4
Intercept	0.1836 0.5255	0.303 0.8443	-1.4341** 0.0234	-0.5227 0.1764
Loan_Ast	0.0643*** 0.0095	--	0.0858*** 0.0002	--
LN_Asset	--	-0.0622 0.519	--	--
HAS_RT	--	--	0.539 0.2791	--
COMM_RE	--	--	--	1.3818** 0.0344
Sc_Ast	0.7285 0.1006	--	--	--
INDVIDUAL	1.0635* 0.0667	--	--	--
LIQUID	-2.0579*** <.0001	-1.8279*** <.0001	--	-1.2141*** 0.0069

Drvtvs	--	0.8674** 0.0345	--	1.1099*** 0.0006
CONSTRCT	0.2097 0.8699	--	-0.4861 0.6941	-0.9170*** 0.454
HAS_FORN	-0.6202*** <.0001	--	-0.7083*** <.0001	-0.4893*** 0.0002
BAD_LOANS	--	--	-4.1505 0.1494	-3.7257 0.1794
NIM	--	0.1563** 0.0115	0.2971*** <.0001	0.1834*** 0.0053
COMM_IND	2.5644*** <.0001	2.2109*** <.0001	2.1353*** <.0001	2.2458*** <.0001
AGRILOANS	-17.3518** 0.0166	-12.7500* 0.063	-22.3679*** 0.0034	-21.2125*** 0.005
Tier1	-0.0832*** <.0001	-0.0567*** 0.0011	-0.0765*** 0.0002	-0.0770*** 0.0002
Rho	0.1760* 0.0787	0.2681*** 0.0048	0.1329 0.1895	0.1455 0.1839
Observations, Stage 1	6139	6139	6139	6139
Observations, Stage 2	701	701	701	701
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively				

TABLE 8
REPORTS THE RESULTS FOR THE ANALYSIS REPORTED IN TABLE 7 BUT LIMITED TO PRE-FINANCIAL CRISIS

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	-0.4432 0.3716	0.3888 0.9016	-0.752 0.5488	-1.4871** 0.0369
Loan_Ast	0.0888* 0.0873	--	0.0889* 0.0732	--
LN_Asset	--	-0.1339 0.4894	--	--
HAS_RT	--	--	-0.8018 0.4142	--
COMM_RE	--	--	--	0.6921 0.7387
Sc_Ast	-1.1384 0.2294	--	--	--
INDVIDUAL	1.2719 0.234	--	--	--
LIQUID	-1.3287* 0.0704	-0.3468 0.6882	--	-0.0653 0.9444
Drvtvs	--	-0.4563 0.6151	--	0.2224 0.7495
CONSTRCT	-3.8562* 0.0963	--	-5.3920** 0.0156	-5.0801** 0.0452

HAS_FORN	-0.4245** 0.04	--	-0.3833* 0.0686	-0.3326 0.1105
BAD_LOANS	--	--	-36.2614** 0.0147	-33.3563** 0.0241
NIM	--	0.2090* 0.0752	0.3158*** 0.002	0.2734** 0.0338
COMM_IND	3.3179*** <.0001	2.8028*** <.0001	3.1423*** <.0001	2.9670*** <.0001
AGRILOANS	22.4363 0.1988	15.7406 0.3403	5.633 0.737	11.9703 0.4741
Tier1	-0.0775** 0.011	-0.0502* 0.0916	-0.0501* 0.0937	-0.048 0.1044
Rho	0.2127 0.201	0.1725 0.3121	0.1652 0.4078	0.2634* 0.0959
Observations, Stage 1	3433	3433	3433	3433
Observations, Stage 2	230	230	230	230
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively				

TABLE 9
REPORTS THE RESULTS FOR THE ANALYSIS REPORTED IN TABLE 7 BUT LIMITED TO THE FINANCIAL CRISIS

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	-0.1029 0.8707	6.4781** 0.0392	-0.7507 0.5294	-1.0411 0.169
Loan_Ast	0.1904*** 0.0003	--	0.2040*** <.0001	--
LN_Asset	--	-0.4722** 0.0209	--	--
HAS_RT	--	--	-0.2663 0.7858	--
COMM_RE	--	--	--	3.7901** 0.0187
Sc_Ast	0.1605 0.8545	--	--	--
INDVIDUAL	1.2994 0.3618	--	--	--
LIQUID	-1.4994* 0.0914	-1.9597** 0.0113	--	-1.5135* 0.0945
Drvtvs	--	0.5316 0.5543	--	2.1773*** 0.0063
CONSTRCT	1.4157 0.583	--	1.2152 0.5801	-0.0738 0.9735
HAS_FORN	-0.8109*** 0.0025	--	-0.8945*** 0.0021	-0.3045 0.3241
BAD_LOANS	--	--	4.9271 0.3915	1.1602 0.8402
NIM	--	0.1920* 0.0521	0.1785* 0.0766	0.139 0.186

COMM_IND	2.5897*** 0.0039	3.5304*** 0.0002	2.8766*** 0.002	3.1904*** 0.0011
AGRILOANS	5.567 0.7599	18.1457 0.2942	10.3913 0.5654	8.547 0.6397
Tier1	-0.0880** 0.0323	-0.0809** 0.0419	-0.1005** 0.0253	-0.0807* 0.0677
Rho	0.0697 0.7422	0.037 0.8596	0.0065 0.9753	-0.0653 0.7775
Observations, Stage 1	1347	1347	1347	1347
Observations, Stage 2	177	177	177	177
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively				

TABLE 10
REPORTS THE RESULTS FOR THE ANALYSIS REPORTED IN TABLE 7 BUT LIMITED TO POST FINANCIAL CRISIS

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept	0.3583	-3.443	-13.3555***	0.3332
	0.5524	0.1736	<.0001	0.6868
Loan_Ast	-0.0255	--	0.0072	--
	0.5316		0.847	
LN_Asset	--	0.2148	--	--
		0.166		
HAS_RT	--	--	12.3773***	--
			<.0001	
COMM_RE	--	--	--	-0.8559
				0.4274
Sc_Ast	1.6981**	--	--	--
	0.0282			
INDVIDUAL	2.5425**	--	--	--
	0.0101			
LIQUID	-2.7648***	-1.9091*	--	-1.6882**
	0.0003	0.0136		0.0463
Drvtvs	--	1.3310**	--	0.7132
		0.0264		0.1531
CONSTRCT	13.0948***	--	6.7659*	7.3962*
	0.0006		0.0665	0.0553
HAS_FORN	-0.3722	--	-0.3652	-0.324
	0.1322		0.1396	0.2197
BAD_LOANS	--	--	-13.9133**	-13.9285**
			0.0288	0.016
NIM	--	0.3751**	0.5533***	0.3199*
		0.0219	0.0001	0.0642
COMM_IND	2.0546**	2.6613***	1.5281*	1.5458*
	0.0181	0.0004	0.0856	0.0647
AGRILOANS	-33.2743***	-30.1298**	-45.6530***	-36.5506***
	0.0059	0.0125	0.0015	0.006
Tier1	-0.1077*	-0.1716***	-0.0980*	-0.1408***
	0.0515	0.0005	0.0604	0.0071

Rho	0.1024	0.3694*	-0.026	0.2045
	0.6376	0.0691	0.9034	0.4011
Observations, Stage 1	1359	1359	1359	1359
Observations, Stage 2	294	294	294	294
***, **, * Represent significance at the 0.01, 0.05, and 0.10 level respectively				

SUMMARY AND CONCLUSION

This paper was a study of US bank participation in credit derivatives. After their development, credit derivatives' popularity with US banks increased rapidly between 1997 and 2007, stayed stable between 2007 and 2011, and declined steadily after 2011.

The results for the first regression show that banks are more likely to participate in the credit derivatives market if they have interest rate contracts, are larger, have more risk assets, hold more nonperforming loans, have larger loan portfolios, hold other derivatives, originate foreign loans, have commercial and industrial loans, and have higher liquidity. We also find that banks are less likely to participate in the credit derivative market if they have higher Tier 1 capital.

The paper used 2-stage Heckman regression to investigate the determinants of gross holdings of credit derivatives by US banks. The regression was run as three models to avoid having variables with correlation coefficients of 0.3 or more in the regression. The results show that loans to consumers, foreign loans, loan sale, liquidity, and bad loans were significant contributors to gross holdings of credit derivatives. The coefficients of these variables were positive and significant at the 1% level. However, construction and commercial loans were not significant. The results for more detailed analysis of the three subperiods showed that the financial crisis represented a transitional period for US banks' holdings of credit derivatives. The results indicate that US banks increased their hedging and increased their appetite for risk assets.

Finally, we used simultaneous logistic regressions to determine which banks acted as guarantors in credit derivatives. The regression was run as four models to avoid having variables with correlation coefficients of 0.3 or more in the regression. The results show that banks with increases in all types of domestic loans, other derivatives holdings, and profitability were more likely to act as net guarantor. However, banks with increases in foreign loans, tier 1 capital, and liquidity were less likely to act as net guarantors. The results generally indicate that US banks converged towards hedging during and after the great financial crisis. Hedging may cause US banks to increase their appetite for risk assets and therefore returns.

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APPENDIX A

Variable definitions. The first column shows the name of the variable as used in the paper, the second column shows the definition of the variable and how it is calculated, and the third column shows the name and calculations of the variable as listed on the FDIC statistics on depository institutions website.

Variable	Definition	Calculation
PARTICIPATE	Participated in the credit derivatives (CD) market. Dummy variable = 1 if the bank participated, 0 otherwise	idctder > 0
NETGRNTR	Net Guarantor indicates that the bank's holdings of CD as a guarantor exceed its holdings as a beneficiary. Dummy variable =1 if the bank acted as net guarantor, 0 otherwise.	(ctdergty – ctderben) > 0
GROSS_HOLD	Gross CD holdings divided by total assets	ctdergty + ctderben
AGRILOANS	Farm loans divided by gross loans and leases.	lnag/lnlsgr
BAD_LOANS	Nonperforming loans divided by gross loans and leases.	nclnls/lnlsgr
COMM_IND	Commercial and industrial loans divided by gross loans and leases.	lnci/lnlsgr
COMM_RE	Commercial real estate loans divided by gross loans and leases.	lnrenres/lnlsgr
CONSTRCT	Construction loans divided by gross loans and leases.	lnrecons/lnlsgr
DRVTVS	Total derivatives including CD divided by assets	obsdir/asset
HAS_FORN	Originates foreign loans. Dummy variable = 1 if the bank originated foreign loans, 0 otherwise	lnfg > 0
HAS_RT	Has interest rate contracts. Dummy variable = 1 if the bank held interest rate contracts, 0 otherwise	rt > 0
INDVIDUAL	Loans to individuals divided by gross loans and leases.	lncon/lnlsgr
LIQUID	Liquid assets = (Cash and Balances due from depository institutions + Trading account assets + Available-for-sale securities (fair market value)) divided by total assets	(chbal+trade+scaf)/asset
LN_ASSET	Bank assets. Natural log of the bank's total assets	LN(asset)
LN_RISK	Bank risk assets. Natural log of the Bank's risk weighted assets	LN(rwajt)
LOAN_AST	Gross loans and leases divided by total assets	lnlsnet/asset
LOANSALE	Selling of bank's loans. Dummy variable = 1 if the bank sold part of its loan portfolio, 0 otherwise	Lnlssale > 0
NIM	Net interest margin as a proxy for profitability	nimy
SC_AST	Securities holdings divided by total assets	sc/asset
TIER1	Tier 1 capital divided by risk assets	rbc1aaj