Why and How Do Banks Lay off Credit Risk?

The Choice between Retention, Loan Sales and Credit Default Swaps*

Mehdi Beyhaghi
mehdi.beyhaghi@utsa.edu
College of Business
University of Texas at San Antonio
1 UTSA Circle
San Antonio, TX 78249, USA
T: +1 210 458 8291

Nadia Massoud
n.massoud@mbs.edu
Melbourne Business School
The University of Melbourne
200 Leicester Street
Carlton, Victoria 3053, Australia
T: +61 3 9349 8130

Anthony Saunders
asaunder@stern.nyu.edu
Stern School of Business
New York University
44 West 4th Street - Suite 9-190
New York, N.Y. 10012, USA
T: +1 212 998 0711

May 2016

* We would like to thank Markit for providing the CDS database. Massoud thanks Social Sciences and Humanities Research Council (SSHRC) of Canada for financial support. The authors also thank Peter DeMarzo, Christian Eufinger, Mark Flannery, Mark Kamstra, Lawrence Kryzanowski, Debarshi Nandy, Silvio Petriconi, Manju Puri, Gordon Roberts, Zhongyan Zhu and the seminar participants at 2015 EuroFit Conference on Syndicated Loans at London Business School, the 2015 Annual Conference of Financial Intermediation Research Society in Reykjavik, the Bank of Canada, the Brattle Group, Bocconi University, Queen's University, the U.S. Securities and Exchange Commission, the University of Cambridge, the University of Texas at San Antonio, the University of Melbourne, and York University for their helpful comments.

Why and How Do Banks Lay off Credit Risk?
The Choice between Retention, Loan Sales and Credit Default Swaps

Abstract

We find that banks with capital and liquidity constraints are more likely to use credit risk transfer (CRT) instruments, including the credit derivative and the secondary loan markets. Relationship lenders and lead syndicate lenders are more likely to hold loans on their balance-sheets regardless of borrowers' riskiness. Finally, we find a separating equilibrium in the CRT market: loans to ex-ante riskier borrowers are more likely to be sold and loans to safer borrowers are more likely to be hedged with CDS. We view credit derivatives and loan sales as joint choice variables in determining the hedging instrument to use.

Key Words: Credit Risk Transfer, Loan Sales, Credit Default Swaps, Financial and Regulatory Constraints.

JEL Classifications: G21, G32

I. Introduction

The recent explosive growth in the credit-derivative and the loan-sale markets, henceforth credit risk transfer mechanisms (CRT), have equipped the banking industry with a variety of instruments to lay off their credit risk. Figure 1 shows the dramatic growth and popularity of these markets over time. At its peak in 2007 the notional value of the CDS market was approximately $62.2 trillion, larger in size than the size of the world economy in 2007 (nominal world GDP was about $60 trillion). The use of CRT tools, although facilitating more efficient risk management by banks, has created concerns. This is because these tools themselves create potential moral hazard incentives under which lenders might issue low quality loans knowing that they may not need to retain the credit risk of the borrower on their balance sheets (Gorton and Pennacchi, 1995; Ashcraft and Santos, 2009; Purnanandam, 2011; Gande and Saunders, 2012; Martin and Roychowdhury, 2015; Kim, Shroff, Vyas and Wittenberg-Moerman, 2015).

To date, few empirical studies have investigated the choice of credit risk transfer (CRT) mechanisms that banks use to manage the credit risk of their loan portfolios.[1] One important

[1] An exception is Minton, Stulz, and Williamson (2009) who look at both choices of credit derivative use and loan sales and argue that they are complements within a regression framework in which the use of credit derivatives (whether the bank is the net buyer of credit risk protection) is the choice variable and dummy variables indicating whether or not the bank has ever securitized or sold loans as explanatory variables. The variables used by Minton et al. (2009) are at an aggregate bank level, that is, one observation per bank per year. Moreover, they do not distinguish between credit risk exposures to each individual borrowers separately. In this paper, observations are at the loan level. We focus on commercial loans, and by extracting detailed borrower, lender and loan data, we study how a borrowing firm's performance and risk, in addition to lender's capital and liquidity status, affect a lender's decision to manage a loan's credit risk exposure. Additionally, Minton et al. use the Federal Reserve reports (FR Y-9C) for data on aggregate levels of sold loans and credit derivative, we use the actual loan sales and CDS market data. Lastly, Minton et al. considers loan securitization as another CRT method. Our sample does not include any loan that is securitized at origination since we exclude loans with a presence of CLOs in their lending syndicate (Benmelech, Dlugosz and

question, so far unanswered, concerns the conditions under which a bank might use loan sales rather than credit default swaps (CDS) or even use both to lay off or hedge all or part of its credit risk exposure in a certain loan. Regardless of being a method for bank's transferring credit risk, purchasing credit derivatives or making loan sales have different implications for a bank in terms of (i) maintaining control rights, (ii) providing incentives to continue monitoring the borrower, (iii) its overall reputation, (iv) its future lending relationships, (v) its cost and revenue generation and (vi) the effects on its overall capital and liquidity, many of which have been overlooked. This paper seeks to analyze a bank's decision to use these markets based on carefully collected data on characteristics and constraints of both borrowers and lenders as well as specific contractual features of loans.[2]

The first contribution of this paper is to examine the joint choice and trade-off of CDS and loan sales as tools of hedging a loan's credit risk. As such our paper is more comprehensive than prior studies who have focused only on one of these CRT mechanism.

The second contribution of this paper is to show that bank lenders' risk characteristics matter as much if not more than borrower's risk characteristics. Prior studies have generally focussed on borrower rather than bank characteristics, mainly by distinguishing between

Ivashina, 2012). If a loan is securitized in the future, that is, if it is sold to a CLO, the loan will appear in our sold loan sub-sample.

[2] We focus on bank's CRT decision at the time of loan origination, that is, we examine the factors that explain a bank's originate-to-distribute (transaction-based) approach or origination-to-hold (relationship-based) approach with respect to a certain loan. While a bank gives up interest income when it sells a loan, or incurs cost of insurance when it purchases CDS, banks find many benefits in an originate-to-distribute approach through collecting origination and assignment fees (in case of sales), reducing the incidence of strategic default and maintaining their relationships with borrowers and right to cash flows (in case of CDS), strengthening their bargaining power and managing balance sheet risks more effectively (in case of both sales and CDS) (Taylor and Sansone, 2007; Bolton and Oehmke, 2011).

investment-grade and non-investment grade (junk) borrowers.[3] We show that while borrower characteristics matter, lender characteristics, such as their liquidity status and capital adequacy, also matter in a bank's decision as to which CRT mechanism to use. Thus, our paper provides a more comprehensive analysis of how banks manage the credit risk of their loans. Specifically we analyze why a bank chooses to sell, insure or retain a loan's risk, as well as combinations of the two CRT mechanisms. We also distinguish between term loans and revolvers. Evidence from the loan sale market indicates that banks often sell drawn parts of a revolver to third parties (see Taylor and Santose (2007)). Moreover, we distinguish between lead banks and other members of lending syndicate. Our results show that due to contractual restrictions on transferring participations and also due to higher reputational costs of transferring risk, lead banks are less likely to transfer risk, when compared to other banks in the lending syndicate of the same loan, even when they are capital and liquidity constrained.

The third major contribution of the paper is to use a nested logit approach, in addition to simple discrete choice models, that allows for the joint determination of CDS usage and loan sales by a given lender. As such we do not view them as separable choices a bank makes but rather as a joint or nested choice.

[3] One exception is the paper by Minton et al (2009) in which the authors do not consider borrower characteristics. Instead they focus on lender characteristics and find that liquidity is a constraint on bank's use of CDS to hedge. Another exception is the paper by Irani and Meisenzahl (2015) in which the authors use another bank level data (known as SNC or Shared National Credit Program) and relate banks' decision to change the level of their loan ownerships during the recent crisis to a banks' funding mix. SNC covers annual levels of material loans/loan commitments that are shared by three or more financial institutions supervised by the Federal Reserve System. SNC facilitates tracking loan ownership in general, however, it does not distinguish between lender-driven and borrower-driven decisions to reduce loan levels. Moreover, unlike our paper, SNC data does not contain information about loan's material contract terms including loan pricing, borrowers' information or lenders' activities in the credit derivative market.

Finally, the ideal way to test predictions of prior theoretical work is to identify who are the exact buyers and sellers of loans and CDSs along with the size of their position and the times of trade. As the buyers and sellers in the CDS and loan sale markets are not directly known because of the over-the-counter (OTC) nature of these markets, the other contribution in this paper is to examine alternative methodologies to circumvent the problems of trader anonymity in OTC CRT markets. Overall, our results are robust to various measures of bank activity in the CRT markets.

The remainder of the paper is as follows. Section II contains a literature review and regulatory background on CRT mechanisms. Section III discusses our data and sample selection. Section IV presents our test methodologies, empirical results and robustness checks. Section V concludes with certain policy implications.

II. Literature and Regulatory Background

Our paper is related to theoretical research focusing on the use of CRT instruments in the corporate loan market. Duffee and Zhou (2001) provide a novel theoretical model incorporating both loan sale and credit derivative markets. Their model predicts that when there is no credit derivative market, banks hedge ex-ante high-quality and ex-ante low-quality loans with loan sales, i.e. there is a pooling equilibrium. With the introduction of credit derivatives, banks that hold high-quality loans may choose to retain the loan and hedge part of their risk with credit derivatives, thereby eliminating the pooling equilibrium in the loan-sales market. If adverse selection costs are high the model predicts that banks will use the credit derivatives market for ex-ante high quality loans and the secondary loan market for ex-ante low quality loans. Parlour and Winton (2013) develop a model that has similar predictions. They argue that lenders are more likely to sell ex-ante low quality loans rather than use CDS.

However, the models in Parlour and Winton (2013) and Duffee and Zhou (2001) differ in the timing of the CRT decision by banks. Duffee and Zhou assume that banks have private information about the borrower at the time of loan initiation, and some of these (ex-ante) borrower characteristics are not observed by the market. Moreover, the bank does not convey the quality of a borrower through the interest rate charged on the loan. The decision to transfer risk is then made at the time of loan initiation. However, in Parlour and Winton it is assumed that borrower's quality is observable by the market at the time of loan initiation. The decision to transfer risk is made a period after loan initiation, during which the bank receives a private signal about a borrower's investment choice. While the timing of the CRT decision in our paper is generally consistent with Duffee and Zhou, our empirical set-up deviates in two ways: first, the bank's decision is made based on observable borrower characteristics that proxies for monitoring costs and information asymmetries between borrower and lender and between lender and market participants at the time of loan initiation. Second, unlike either theoretical paper, banks in our sample are not homogeneous and they do not necessarily have unconstrained capital and liquidity.

Our research is also motivated by the recent regulatory reforms concerning banks' risk taking behavior. Under Basel capital regulation, when a bank uses CDS as a hedging instrument either OTC (Basel I and II) or through a clearing house (Basel III), it decreases its regulatory capital.[4] Aside from freeing up regulatory capital, using CDS also enhances the liquidity of banks, as a result of which banks can increase borrowing more easily and obtain better rates in borrowing

[4] The credit risk weight on cleared CDS transactions is 2% and 20% on OTC CDS contracts under Basel III. The risk weight on retained unhedged loan is100% under Basel III. Any recognition of credit risk mitigation associated with cleared CDS should include the usual considerations of asset, maturity and currency mismatch, as required in the existing Basel requirements. Moreover, a CDS indirectly referencing counterparty (e.g. a related entity) is not considered an eligible hedge under Basel III. See http://www.bis.org/bcbs/basel3.htm.

from other banks and counterparties. Similarly, loan sales increase balance sheet liquidity and reduce regulatory capital by replacing risky assets (loans) with cash.[5] Hence, loan sales and CDS are expected to be used more when banks face liquidity and regulatory constraints. For example, Pennacchi (1988) and Allen and Carletti (2006) argue that liquidity and regulatory constraints on banks will affect a bank's decision to use CRT. Therefore, the more binding are these two constraints the more important role they should play in the decision to use CRT.

Theory also suggests that lenders treat repeat (or relationship) borrowers more favorably than transactional borrowers, after controlling for selection issues (Petersen and Rajan, 1994; Berger and Udell, 1995; Degryse and Van Cayseele, 2000; Dass and Massa, 2011; Bharath, Dahiya, Saunders and Srinivasan, 2009)[6]. Bharath et al. (2009) find that relationships are especially valuable when a borrower is relatively opaque. Specifically, the information frictions caused by adverse selection and moral hazard in the loan market (Diamond, 1984; Ramakrishnan and Thakor, 1984; and Fama, 1985), can be mitigated if the lending bank has a strong past relationship with a borrower through producing reusable borrower-specific information. Dass and Massa (2011) also show that better monitoring, improves a borrower's corporate governance. Thus the size and presence of bank monitoring costs are likely to impact a banks CRT choice. Consequently, while banks are more likely to use CRT for borrowers with high monitoring costs, they are less likely to use CRT if they have had a prior relationship with borrowers. Thus, the

[5] Loan sales are without recourse by the buyer to the seller should a loan default. Although Gorton and Pennacchi (1995) argue they may be implicit recourse (i.e. a buyback).

[6] Another stream of literature focuses on the role of banks and borrowers connections through interpersonal linkages, for example, when firm and bank executives attended the same college or previously worked together (Engelberg, Gao and Parsons, 2012) or when they belong to the same social club (Haselmann, Schoenherr, and Vig, 2015). Karolyi (2014) and Khan, Li, Williams, and Wittenberg-Moerman (2015) even find that the relationship a lender develops with a firm's manager can migrate with the manager when the manager leaves the firm and/or joins another firm.

existing literature suggests that bank lenders are more likely to use CRT and especially loan sales for transactional borrowers.

Finally, there are reputational effects in CRT markets. If bank monitoring has certification value for borrowers, borrowers will prefer to enter into a relationship with a bank that is more likely to monitor them. In world of repeat lenders, reputational concerns motivates a bank to commit to monitoring even though they may have transferred a borrower's credit risk in the CRT market. Moreover, loan buyers and the CDS sellers (insurers) are also concerned with the quality of bank monitoring. Therefore, we expect that reputation works as a device that mitigates moral hazard and the adverse selection issues and assists banks in engaging in efficient credit risk transfer.

III. Data and Sample Selection

We construct a sample to examine two questions: (1) a bank's choice as to whether or not to lay off the credit risk of a specific loan and (2) a bank's choice of which CRT mechanism to use if it chooses to lay off its credit risk, using data from seven different databases.

Our primary (origination) loan dataset comes from Reuters Loan Pricing Corporation's DealScan. DealScan provides comprehensive information about contract terms for the majority of U.S. syndicated loans at the deal (loan package) and facility (loan) levels. It also identifies the borrower and lenders.[7] Importantly, in choosing our sample period we consider the following four major limitations: (i) The CDS market has existed since the early 1990s, however, its use only increased in size rapidly after 2003, (ii) Following Lehman's failure and AIG's rescue in September 2008 the use of CDS declined dramatically and this continued through the crisis

[7] For a detailed description of Reuters' LPC DealScan see Sufi (2007) and Nini, Smith, and Sufi (2009).

period[8,9], (iii) In 2001 the Federal Financial Institutions Examination Council (FFIEC) announced modifications to the Bank Reports of Condition and Income (call reports). These modifications affected how banks reported their balance sheets and income statements, and (iv) after 2009 with the impending introduction of Basel III the capital cost of using CDS to hedge increased relative to the pre-crisis period.

With these limitations in mind our sample period runs from January 1, 2003, to December 31, 2007. We consider all U.S. dollar denominated facilities belonging to public borrowers with available financial and stock price data on Compustat and CRSP at the time of loan initiation. We also restrict our sample to borrowers with positive total assets and market-to-book ratios. To mitigate the effect of outliers, we exclude borrowers with stock prices below $1 and further restrict the sample to borrowers with a sufficient number of trading days (having been traded for at least 20 days within the year prior to loan initiation). The sample at the end of this first stage includes 5,113 loan facilities.[10]

We next omit facilities without lender information. We also exclude all loans with a non-U.S. bank lender in their lending syndicate. After these screens we are left with 1,059 loan facilities. Of this number, 323 loan facilities, belonging to 202 borrowers, have a long-term issuer

[8] This issue was also identified in the Senior Supervisors Group Report of 2008, "Observations on Risk Management Practices during the Recent Market Turbulence" available at www.newyorkfed.org. Moreover, according to the International Swaps and Derivatives Associations (ISDA), the CDS market had a notional value of $62.2 trillion at the beginning of 2008 and by the end of 2008 notional amount outstanding had fallen 38 percent to $38.6 trillion. The market has continued to fall to slightly over $25 trillion in early 2012.

[9] For more on how business environment and banks behaviour changed during the crisis see: Acharya, Schnabl and Suarez (2013) and Acharya and Mora (2015) on the role of government intervention and regulatory arbitrage, and Ivashina and Scharfstein (2010), Cornett, McNutt, Strahan and Tehranian. (2011), Acharya and Merrouche (2012), Bord and Santos (2014), Greenwood, Landier and Thesmar (2015) and Irani and Meisenzahl (2015) on bank's liquidity management, asset management, and fire sales and on the impact of the crisis on banks' supply of credit.

[10] Facilities are also called tranches.

debt rating who have a CDS trading in the market. Finally, as a robustness check, we exclude revolvers from the sample and find that our results do not qualitatively change.[11]

We construct borrower quality and control variables using data from Compustat and CRSP. To obtain information on lenders, we note that each facility can have one or more lender. We hand-match each lender to its Uniform Bank Performance Report (UBPR) provided by the FFIEC. The UBPR includes detailed data extracted from bank call reports along with various performance ratios and is created for bank supervisory, examination and evaluation purposes.[12] As the final step loans are carefully hand-matched to loan sale transactions (see Appendix A for more details on the matching process).

We perform our analysis at the facility (loan) level because our secondary market loan sales dataset is at the facility level (facilities, not deals, trade in the secondary markets). This approach is similar to Drucker and Puri (2009), Bushman, Smith, and Wittenberg-Moerman (2010), and Gande and Saunders (2012). Our key variables for loan characteristics include relative size of the loan, defined as the ratio of loan amount to market value of a borrower's equity, the maturity of the loan and the existence or not of a prior relationship with the lead syndicate lender. Table 1 provides a description of how the variables in this paper are constructed. Table 2 provides summary statistics at the facility level. Appendix A also provides detailed information on our borrower data, our loan sale data, our CDS data and our lender information data.

[TABLES 1 AND 2 HERE]

[11] It can be argued that the magnitude of the benefits from risk transfer are not clear for these types of loans. However, Taylor and Sansone (2007) report that the drawn part of revolvers can be traded on the secondary market.

[12] The UBPR for a given bank is usually published within a day of the underlying Call Report being filed at the Central Data Repository. If the Call Report for a given bank contains errors then the UBPR may not be published until those errors are corrected. Visit http://www.ffiec.gov/ubpr.htm for more information.

IV. Methodology and Results

In this section we provide descriptive statistics of the sample, and explain our univariate and multivariate methodologies. We use two-stage logistic regressions as well as nested logit models to explain banks' decision to lay-off a loan's credit risk. Also, we examine the robustness of our findings using different empirical set-ups. A discussion of our findings is also provided for each model.

A. Summary Statistics

Table 2 shows that on average the borrowers in our sample have a credit rating of BB+ under S&P's long-term debt issuer credit rating[13]. The lowest quality borrower in our sample has a rating of D and the best quality borrower has a rating of AAA. A rating of BB+ and lower is considered as below investment-grade, and BBB- and better is considered investment-grade. The average firm has an equity market value of $7.601 billion, quarterly return on assets (ROA) of 2.5%, leverage ratio (total liabilities to total assets) of 59.4%, and market to book ratio of 2.780 at the time of loan initiation. On average 3 to 5 percent of loans have lenders that are experiencing relatively binding capital and liquidity constraints based on different measures of bank capital adequacy and liquidity. An average lead lender has a 5.644% market share in the syndicated loan market, where market share is defined by the total number of loans initiated by the lender relative to total numerical size of the loan market in the DealScan universe. On average, 66.3% of borrowers have a prior relationship with their lead lenders. The average loan size to market value of borrower equity is 18.4%, and a typical loan has 45 months to maturity. Moreover, loans have

[13] Issuer Credit Rating (ICR) ranges from AAA (extremely strong capacity to meet financial obligations) to D (in default). In our analysis, we rank long-term ratings from 22 to 1, where AAA receives 22 and D receives 1. If a borrower does not have an S&P rating but has a Moody's rating, we would use the equivalent Moody's rating instead (this is the case for 2% of observations).

on average 3.33 lenders in their lending syndicate (Median = 3). The minimum size of a lending syndicate is 1, while the largest syndicate in our sample has 13 lenders. In terms of the primary purpose of the loan, 66.9% of the loans are issued for corporate purposes (equipment purchase, capital expenditure, etc.). 22% of loans are issued for acquisition purposes including LBOs, 9.3% for debt repayment and 1.5% for other purposes.

B. Univariate Analysis and Methodology

We use both univariate tests and discrete choice (logistic, nested logit) models to examine the effect of borrower and lender characteristics on the choice of CRT by lenders. Using the univariate analysis we first divide loans into two groups: loans for which the lender uses a CRT mechanism (CRT loans) and those loans retained on a bank's balance sheet (or no CRT loans). Then we divide CRT loans into three groups: loans for which the lender uses only loan sale, loans for which the lender uses only CDS, and loans for which the lender uses both loan sale and CDS. Table 3 shows that banks use at least one type of CRT for 30% of the loans. About 8% of sample loans are sold, 20% are hedged with CDS and 2% are in part sold and in part hedged with CDS.

[TABLE 3 HERE]

Next, we compare the lender, borrower and loan characteristics across CRT and no-CRT loan groups. Our univariate results in Table 4 Panel 1 suggest that borrowers of CRT loans, on average, have a slightly better ratings than no CRT loans (An average rating of BBB- for CRT borrowers which is one notch higher than an average rating of BB+ of no-CRT borrowers significant at the 1% level). They also have slightly higher quarterly ROA of 2.8% when compared to 2.3% ROA of their peers (significant at the 5% level). Borrowers with CRT status are larger $17.1 billion versus $3.6 billion (significant at the 1% level) and have a higher market-to-book ratio 3.3 versus 2.6 (significant at the 5% level). The results are all statistically and economically

significant. CRT loans and no-CRT loans respectively have mean loan sizes of 13.27% and 20.5% when compared to the borrower's (market value of) equity, and loan maturity of 50.4 and 42.8 months at the time of initiation (significant at the 1% and 5% levels respectively). Loans that are hedged are more likely to be issued for acquisition purposes than for corporate purposes. The difference across other characteristics are not statistically significant.

In Table 4 Panel 2 we compare the sub-sample of loans that are either sold or hedged with CDS, we find that on average sold loans belong to a borrower with ex-ante credit rating of BB-, a quarterly ROA of 1.6%, and a market-to-book ratio of 2.4, all significantly lower than CDS-hedged loans with an average ex-ante credit rating of BBB+, quarterly ROA of 3.3%, and market-to-book ratio of 3.7 (all differences are significant at the 1% level, except for the market-to-book ratio that is significant at the 5% level). On average 48% and 44.5% of loan sale and CDS borrowers had a prior relationship with the lead lender (significant at the 5% level) and a sold loan had a relative loan size (to borrower equity) of 22.6% and a loan maturity of 69 months when compared to 20.9% relative loan size and about 40 months loan maturity of CDS loans (All differences significant at the 1% level). Finally loans that are sold are more likely to be issued for acquisition purposes, while loans that are hedged with CDS are more likely to be issued for corporate purposes.

[TABLE 4 HERE]

C. Multivariate Approach 1. – Logistic Regressions

To answer the two questions posed in this paper we use logistic analysis. In the first step the choice is a binary variable that takes a value of 1 for a loan of a lender who decides to use CRT (either loan sale or CDS) and zero if chooses to retain the loan (unhedged) on its balance-sheet. In the second step, conditioning on choosing a CRT instrument by the lender, the choice is a binary variable which takes a value of 1 if the lender uses the loan sale market and a value of 0 if the

lender uses the CDS market to lay off credit risk. Our first group of control variables relate to borrower characteristics and include a measure of its credit risk (long-term issuer's debt rating), borrower profitability (ROA), market-to-book ratio, market equity value, and leverage. The second group of controls relate to lender characteristics, which includes measures of a bank lender's capital and liquidity constraints as well as reputation measured as lender's market share in the loan market (over the 5 years prior to a loan's initiation). The third group of control variables are related to loan characteristics themselves, including loan size, time-to-maturity, syndicate size, and existence of a prior relationship between the borrower and the lead lender.

Table 5 provides the results of estimating these logit models using different combinations of explanatory variables and choice sets.

[TABLE 5 HERE]

C.1. Multivariate Analysis – CRT versus no CRT

Our dataset creates the opportunity to examine competing views in the theoretical literature regarding the relative importance of a borrower's characteristics relative to a lender's characteristics (especially its capital and liquidity constraints) in determining a lender's decision to lay off or retain the credit risk of a particular loan.

In Table 5 Panel 1 Column (1) a borrower's credit quality and size are used as explanatory variables. In Column (2) we employ a measure of lender's capital and liquidity constraints in addition to the explanatory variables used in Column (1). In Column (3) in addition to the variables used in Column (2) we add borrower and lender controls including the lender's reputation and the

borrower's ROA, leverage and market-to-book ratio, in addition to other loan controls[14]. Column (4) has a complete set of control variables.

We use two additional specifications to examine the robustness of our results. In Column (5) we restrict the observations only to non-revolvers. In Columns (6), we use an alternative measure of capital and liquidity constraints for lenders.[15] Standard errors across all specifications are clustered for borrower and time (fiscal quarter) fixed effects.

Overall, the results in Panel 1 show that a bank's capital and liquidity constraints play a key role in the decision to use a CRT instrument, regardless of the credit quality of borrower. The coefficient for the capital and liquidity constraint variable is positive and significant across all variable specifications. Thus, banks with capital and liquidity constraints are more likely to use CRT rather than retain a loan unhedged on their balance-sheet[16]. With respect to borrower characteristics only borrower size is significant, i.e. banks are more likely to use a CRT instrument

[14] Additionally we control for other loan characteristics such as the size of lending syndicate and loan purpose fixed effects concerning acquisition purpose, debt repayment purpose, corporate purpose, and other. The results stay qualitatively the same if we include these controls. In order to prevent econometric problems due to small sample size, especially in Panel B tests, from now on and for robustness tests we only employ controls that have a significant impact in our main tests.

[15] The dummy for bank's liquidity and capital constraint equals 1 under the following conditions: We sort all banks with call reports in the observation year separately based on a measure of liquidity and a measure of capital adequacy. If a bank belongs to the bottom deciles of both sorts, then the dummy receives a value of 1, zero otherwise. In Columns (1) to (5), the measure of a bank's liquidity and capital constraint is constructed based on the capital ratio of *equity-capital to total long-term liabilities*, and the liquidity ratio of *net federal funds sold divided by total short-term noncore funding*. In model (6) we use an alternative measure for robustness checks: We use *total risk based capital to total risk weighted assets* as the capital ratio and *short-term assets to short-term liabilities* as the liquidity ratio.

[16] A study of bank's behavior in CRT markets can raise concerns in the sense that a bank with liquidity and capital constraints is more likely to extend loans that can be sold later or extend loans to borrowers with an active CDS market. However, our results are robust to such concerns as we control for various loan and borrower characteristics in our multivariate tests. Moreover, all the borrowers in our sample have an active CDS market. For more information on our selection criteria read Appendix A.

for larger borrowers. The coefficient for credit quality is insignificant across 4 specifications and significant at 10% across only two specifications. The accounting measures of borrower performance and risk such as ROA, leverage and market-to-book ratio are all insignificant. The results imply that a borrower's size and a bank's liquidity and capital constraints are both important factors in a bank's decision to use CRT. The results in Panel 1 also suggest that reputable lenders (measured by lender market share) are more likely to use CRT. The coefficients for lenders' reputation are all significant at the 1% level across all specifications. Also, lenders are less likely to use CRT markets for borrowers with whom they had a prior relationship (significant at 5% and 10% levels), implying that CRT instruments are more used for "transactional" borrowers. Finally, as must be expected a priori, the results suggest loans with longer maturities are more likely to be hedged with a CRT instrument than short maturity loans.

C.2. Multivariate Analysis – Loan Sales versus CDS

Next, we use a logistic regression to examine the factors contributing to a bank's decision to choose the loan sale market rather than the CDS market as the CRT mechanism, conditioning on bank's decision to use CRT. The dependent variable equals 1 if loan sale is chosen, and 0 if CDS is chosen. Panel 2 of Table 5 presents the results. Unlike the results in Panel 1, we find that in choosing the "type" of CRT instrument, a borrower's credit quality plays the key role. The coefficient for credit quality is negative and significant across all specifications, suggesting that as the credit quality of a borrower improves the likelihood of a loan sale decreases relative to use of the CDS market. i.e., banks use the market for loan sale for borrowers with ex-ante lower credit quality. Also, the coefficients for return on assets (ROA) supports the finding that loans provided to borrowers with higher ROA are less likely to be sold in the secondary market. The coefficient for a lender's capital and liquidity constraints are insignificant across all specifications. Additionally, the results show that loans with longer maturities are more likely to be sold in the

secondary market than be hedged with CDS as are loans that belong to borrowers with lower market-to-book and leverage ratios.

Overall, the results of our multivariate analysis indicate that in the first stage of a CRT decision (whether to choose a CRT or not), banks' liquidity and capital status play a critical role. In the second stage of the CRT decision, i.e. what CRT instrument to use: a loan sale or a CDS, borrower's credit quality is a key determining factor.

D. Multivariate Approach 2. – Nested Logit

In the above tests we assumed that a bank chooses a method of credit risk transfer in a two-stage process: first the bank decides whether to transfer risk or not. If it decides to transfer risk, the bank chooses among the loan sales and CDS markets to transfer risk. An alternative econometric approach is a discrete choice model, which allows for more than two choices as dependent variables. In our paper these choices would be retention, sale, CDS, or both sale and CDS. However, the basic Multinomial Logit Model imposes the restriction that the distribution of the random error terms is independent and identical over choices. This representation of choice behavior may produce biased estimates and incorrect predictions. Therefore, as a robustness check for our results in the previous section, we use a nested logit model that allows the error terms of groups of choices within the risk-transfer decision group (nest) to be correlated. The parameters of a nested model can be estimated by standard maximum likelihood techniques. Appendix 3 explains the details of how our nested logit model is constructed and estimated.

In a nested decision framework, each bank in managing the credit risk of a loan is faced with four alternatives: to retain the risk, to use loan sale, to use CDS and to use a combination of loan sale and CDS. The bank then selects one alternative and rejects the other three. There are 323 times 4 (number of facilities * 4 alternatives per facility), equal to 1,292, possible alternatives in

total. Out of these possible alternatives, 323 are selected by banks (as observed in the data). Banks choose the alternatives that maximize their utility function (see Appendix 3 for the details).

Figure 2 provides a schematic representation of the alternative structure in our two-level nested logit model. Level 1 is the choice level, and Level 2 is the nest level. Level 1 includes the choices of CDS, Loan Sale, Both, and Retention. Each of these choices belong to one of the two nests in Level 2, CRT and No-CRT. Within the CRT nest, there are 3 choices, CDS, Loan Sale and Both. Within No-CRT nest, there is only one choice, Retention. Table 6 presents the results at two levels, as defined in Figure 2. Note that the estimated coefficients in Table 6 are measures of marginal expected utility associated with one unit increase in the independent variable. If the estimated coefficient is positive, it means an increase in the independent variable is desirable (utility adding) for the bank. If it is negative it means an increase in the independent variable provides disutility for bank. The underlying assumption in the nested logit, as explained before, is that the decision-maker (bank) choses the alternative that maximizes its utility function.

[TABLE 6 HERE]

Table 6 reports two groups of models. Each model is different in the choice of lender's capital and liquidity constraint as defined in Table 5. Consistent with our prior findings, the results in Table 6 show that for different specifications, an improvement of one grade in a borrower's credit rating is associated with an expected disutility of between -0.333 and -0.348 for the choice of sale (all significant at the 10% level), whereas for the choice of CDS, the utility is between 0.420 and 0.428 (all significant at the 1% level). Moreover, for a one unit increase in the log(maturity) of a loan, a loan sale becomes more preferable than CDS. At level 2, the nest level, our results show that when the lender is capital and liquidity constrained the utility of using a CRT market (i.e. choosing the CRT nest) is increased as it is when the lender has a higher market share.

The expected utility of choosing CRT when capital and liquidity constrained in specification (1) is 1.273 and the expected utility of choosing CRT per 1 unit (percent) increase in market share is 0.107, statistically significant at the 5% (or 1%) levels. These results are consistent with our prior findings under the two-stage multinomial logit model. The estimates for borrower size and relative loan size are, however, not consistent with the two-stage model. For instance an increase in one unit log borrower size is associated with a disutility of -0.048 (significant at the 10%) level in model (1). For the same model, an increase in 1 unit relative loan size (loan size divided by borrower's book value of asset) is associated with -1.826 disutility of choosing CRT. The result for borrower and relative size were insignificant in our two-stage multinomial logit estimation in Table 5. These results indicate that banks prefer to retain a loan on their balance-sheet if the size of the loan is a large part of borrower's loan book structure (loan is material). The result for prior relationships is also insignificant in the nested model, although with the predicted sign. It was significant with a negative sign in Table 5 indicating that banks with prior relationship with borrowers are more likely to refrain transferring risk.

E. Lead Bank and Other Members of Lending Syndicate

As described earlier in the sample selection process, we only focus on loans whose members are banks. Restricting lenders to banks helps us better analyze lenders behavior in CRT markets, as all banks are subject to similar capital and liquidity constraints. In this section, we distinguish between lead banks and other syndicate members[17]. Prior work on hedging activities

[17] In general, a syndicated loan is a loan extended to a single customer by multiple financial institutions (banks or non-bank), which are formed into a "syndicate", for that purpose. The same terms and conditions apply to all of the lenders in the syndication, and there is only one loan agreement. However, the lead bank (arranger) might be subject to additional terms and conditions. The lead bank serves as contact point for all parties, negotiates lending terms, and arranges the syndicate. The lead bank often play the role of the "agent" as well. The agent's responsibility is to handle

of lenders, mostly ignore lender characteristics and focus on borrower characteristics. The implied assumption in these studies is that banks are capital and liquidity unconstrained and therefore only borrower's risk profile motivates banks to take part in CRT markets. Moreover, prior studies usually focus only on the lead lenders and lead bank characteristics and ignore other syndicate members. In terms of CRT decision, there are generally two main differences between lead lenders and other syndicate members. First, as Taylor and Sansone (2007) and Drucker and Puri (2009) discuss, there are usually provisions in loan contracts that restrict the sale of all or part of participations by lead banks without the consent of the borrower[18]. Second, a loan default has a higher reputational cost for lead lenders than other members of lending syndicate.

Because of reputational costs and contractual restrictions, we predict that a lead lender's capital and liquidity constraints play a less critical role in their decision to use a CRT market compared to other syndicate participants. To examine this, we create a dummy variable that represents lead lender's capital and liquidity constraint and add that to our main tests. The dummy variable is constructed similar to the lender capital and liquidity constraint dummy, i.e. the lender has to be within the bottom decile of a capital ratio and a liquidity ratio when we sort all banks with a call reports in the year of observation, with the exception that the bank has to be the lead bank for the loan. A lead bank is defined as a bank that receives a value of "Yes" for the field Lead Arranger Credit in the DealScan dataset. If the loan has only one lender, then that sole-lender is the lead bank, even if Lead Arranger Credit field is not equal to "Yes". In the few cases that a loan

various administrative tasks, such as processing loan applications, assigning loan portions, and disbursing principal and interest payments to the other syndicate members.

[18] However, the restriction of the power to sell is not completely effective unless the restriction is expressly and precisely stated in the contract. Essentially in many cases, this is an implicit contract.

has multiple lead arrangers, we take the largest lead arranger as the lead bank. Table 7 presents the results with the new explanatory variable.

[TABLE 7 HERE]

The results in Table 7 show that lead banks are in general different from other participants. We use two groups of specifications: The first group of specifications are similar to our previous logit setup, with the exception that instead of a dummy variable for Lender's Liquidity and Capital Constraint, we use a dummy variable for Lead Lender's Liquidity Capital Constraint. In the second group, we include both of these dummies together, that is the dummy variables for both Lender's and Lead Lender's Liquidity and Capital Constraint. To check the robustness of our results we use alternative measures of constraints as described before. Specifications (1), (2), (5) and (6) use Measure 1, and Specifications (3), (4), (7) and (8) use Measure 2. Specifications (1) to (4) examine the choice between CRT and No-CRT and Specifications (5) to (8) test the choice between Sale and CDS conditioning on CRT. Specifications with odd numbers include just the dummy for lead bank. Specifications with even numbers include both dummies for lead banks and all banks. To interpret the results in (2), (4), (6) and (8), note that the meaning of the dummy variable "Lender's Capital and Liquidity Constraint" changes with the inclusion of the new variable, "Lead Lender's Capital and Liquidity Constraint". The former receives a value of one if any bank in the lending syndicate has binding capital and liquidity constraint, zero otherwise. The latter becomes one only if the lead bank has binding capital and liquidity constraints. Therefore, in a model that we use both variables, the coefficient for the former variable, that is the more general variable, explains the effect of non-lead bank participants in CRT decisions. To that end the results indicate that while the non-leads' capital and liquidity constraints are still important, the coefficient for constraints of lead banks are not significantly different from zero. The results are robust to

alternative definitions of liquidity and capital. In unreported result we consider lead banks in the bottom quartile of liquidity and capital, instead of bottom decile, as those with binding constraints and find similar results.

The results in Table 7 confirm the finding that due to high reputational costs and also contractual restrictions, lead banks are usually less likely to be involved in CRT activities, even if they have binding capital and liquidity restrictions. The results for other explanatory variables in Table 7 stay qualitatively the same as the results in Table 5.

F. Robustness Test – Lenders with Evidence of Involvement in the Loan Sale and Credit Derivative Markets

While the identities of traders in the secondary loan market and the derivative market are not directly known due to the over-the-counter nature of these markets, in this section, we take one step further and restrict our bank lender sample to only those with clear evidence of activity in the loan sale and credit derivative markets.

To identify whether a bank is active in the loan sale market, we extract the related information about loans and leases held for sale (Federal Reserve Schedule HC-C Line Item 4(a)). This item reports the amount of loans and leases held for sale at the lower of cost or fair value. If a bank is the lender of loans held for sale during the time period that the loan is active, the bank reports a positive value for this item on its call report, then we identify the bank as a bank with potential involvement in the secondary loan market.

To identify whether a bank is active in the credit derivative market, from bank's call reports we extract information regarding credit derivative activities by banks (Federal Reserve Schedule HC-L Line Items 100-107). Credit derivative, as an off-balance sheet category, refers to the notional amount and fair value of all credit derivatives held by a bank, where credit derivatives are

defined as arrangements that allow one party (the "beneficiary") to transfer the credit risk of a "reference asset" to another party (the "guarantor"). However, credit derivative items on a bank financial statement are not limited to CDS, but also include total return swaps, credit options and other credit derivatives. Nevertheless, Hirtle (2009) find that around 97% of all credit derivatives held by U.S. commercial banks in 2006 were Credit Default Swaps.[19] If a bank is hedging loans for sale during the time period that the loan is initiated and the bank reports positive holdings of a credit derivative then we identify the bank as a bank with evidence of involvement in the loan sale and credit derivative markets. To that end, as a robustness check of our previous results, we repeat our main test, by only focusing on lenders that are actively involved in both the credit derivative and loan sale markets. Table 8 presents the results.

[TABLE 8 HERE]

While our sample size drops, the results in Table 8 confirm our main findings. In the first group of tests, that examines the choice between CRT and no-CRT, it can be seen that lender's capital and liquidity constraints play the key role in bank's CRT decision rather than borrower credit quality. Our results are robust for the two measures of constraints. The results in the second group of tests, examining the choice of sale relative to CDS conditioning on CRT, also support our prior findings. Loans belonging to borrowers with lower credit quality are more likely to be sold rather than be hedged with CDS.

G. Robustness Test – Abnormal Return Measure of CDS use

[19] The reporting requirements on credit derivative increased during the late decade. As of March 2006, banks were required to separate the type of credit derivative reported, including CDS, total return swaps, credit options, and other credit derivatives. However, they do not necessarily need to distinguish between single-name CDS exposures and index-based CDS exposures. As of March 2007, banks were required to report "Net gains (losses) on credit derivatives" separately for "held for trading" and for "purposes other than trading."

In Appendix 2 we explain how we infer a measure of a banks' decision to use CDS to hedge the credit risk of a loan by measuring abnormal increases in CDS prices around loan initiation. Specifically, our proxy for an increase in CDS demand is abnormal positive change in CDS spreads around loan initiations. We also discuss and rule out different possibilities that our proxy measures things other than an increase in CDS demand.

In this section, we consider the possibility that an abnormal change in CDS spreads might be due to factors other than an increase in demand as a result of new loan initiation (new exposures to a borrower's credit risk). We consider the possibility that an increase in CDS demand could be due to an unrelated change in firm-level fundamentals that happened around the same time.

As an instrument for change in firm-level fundamentals, we measure borrower's abnormal stock return around loan initiation by considering the same control and treatment periods that we use in our abnormal CDS spread calculations. The underlying assumption here is that a change in fundamentals is also reflected in the firm's stock price. A borrower has an abnormal stock return around loan initiation if the average return premium (return in addition to the return of the market, represented by the S&P 500 index) during this period is significantly different from the average return premium during the control period. We find that of the 25 loans in our only-CDS sample (the loans for which banks use CDS and not loan sale for hedging credit risk), 20 percent (5 observations) face an abnormal stock return around loan initiation. Also out of 6 observations in the Both CDS and Loan Sale category, 2 loans have such a characteristic. As a robustness test we exclude these observations from our only-CDS sample and "Both" samples (loans for which both CDS and Loan Sale are used). We re-run our main regressions (as in Table 5) with the new measure of CDS use. The results are reported in Table 9 and are qualitatively similar to the findings in Table 5.

[TABLE 9 HERE]

V. Conclusion

The existing theoretical literature suggests different factors that might impact a banks' choice of credit risk transfer (CRT) mechanism. A borrower's credit quality, bank capital requirements and liquidity constraints, the existence of a prior relationship and reputational concerns may all impact CRT choice. In this paper we have merged seven different datasets to build measures of borrower and lender characteristics along with CRT choice. Using alternative empirical methodologies, we show that banks are more likely to use a CRT instrument rather than hold (unhedged) loans on their balance sheets when they are facing capital and liquidity constraints. In addition, if they decide to use a CRT instrument, they are more likely to sell loans when loans have been made to ex-ante low-quality borrowers, and use CDS when loans have been made to ex-ante high-quality borrowers. Additionally, we show that banks are more likely to keep loans on their balance sheets if they have an ongoing relationship with a borrower, and to use CRT instrument for transactional borrowers.

Finally, our findings have a regulatory implication. Specifically, if a bank is viewed as an extensive seller of its loans it indicates that it is either capital and liquidity constrained and/or making high risk loans. Thus the volume of loan sales may be viewed as a signal of bank risk exposure for bank examiners and regulators.

Appendix A: Sample Construction

A.1. Borrower Data

We match the borrowers of the sample facilities with Compustat data using Wharton Research Data Services (WRDS) DealScan-Compustat Link Data (Chava and Roberts, 2008). Borrowers' financial information is from the Compustat-Fundamentals Quarterly dataset. To ensure that we use the most recent accounting information available at the time of loan initiation, we use the accounting data related to the last quarter end before the facility's activation date. In addition we extract our main measure of credit quality (S&P's long-term debt credit rating) from a separate dataset on WRDS. Also, we use return on assets (ROA), leverage and market value of equity along with market-to-book ratio as other borrower controls. To extract stock prices and returns, we carefully match borrowers with CRSP data. Table 1 provides the description of how each variable is constructed.

A.2. Loan Sale Data

Our next dataset is secondary loan pricing data from the Loan Syndication and Trading Association (LSTA) provided through Reuters. The dataset provides average bid and ask quotes on loans, the means of average bid and ask quotes, number of quotes, date, type of facility, loan identification numbers, and borrower names and IDs for loans offered for trade in the secondary market. More details about this dataset are available in Bushman et al. (2010). We follow Gande and Saunders (2012), Drucker and Puri (2009) and Wittenberg-Moerman (2008) in merging this dataset with the DealScan primary loan dataset via facility IDs and/or loan identification numbers (LINs). We obtain loan sale quotes for about 10% of facilities. Summary statistics for facilities with a secondary loan market is presented in Table 2.

To denote facilities that are available for sale, we create a dummy variable, loan sale. In general, if a loan appears in the loan sale dataset (LSTA), there is market interest in selling the loan. Accordingly, the loan sale dummy equals 1 when the loan facility has an LTSA record (a quote or multiple quotes) and 0 otherwise. This approach is similar to Drucker and Puri (2009).[20] According to the Reuters Loan Pricing Corporation, LSTA covers more than 80% of the trading volume of the secondary loan market in the United States (Bushman et al., 2011). There are two limitations to using this database, however, according to Drucker and Puri (2009). First, the LSTA database includes loan quotations, but does not indicate whether actual trades occurred. For this reason, we only use this information to identify whether a loan is available for sale. The second restriction with the LSTA database is that it does not include the identities of the loan sellers and loan buyers.

A.3. Credit Default Swaps Data

Credit default swap data, is from Markit CDS. Our key variable from this database is the *CDS spread*. In general, the higher the CDS spread, the greater a firm's perceived credit risk. Markit provides mark-to-market CDS spreads derived from market makers. CDS data are available by entity, term, currency, and restructuring clause. The contract-level information includes: CDS spread, credit ratings, credit event types, seniority, and currency.[21] We focus on CDS transactions

[20] LSTA is the sole source of the secondary loan data. See Gande and Saunders (2012) as the most recent example

[21] The quotes reported on Markit are subject to filtering that removes outliers and stale observations. Although, Markit is one of the most comprehensive and widely employed CDS dataset in financial research (Acharya and Johnson, 2007; Jorion and Zhang, 2009, Zhang, Zhou and Zhu, 2009; and Cao, Yu, and Zhong, 2010, Qiu and Yu, 2012, Kim et al., 2015), it is subject to two limitations. First, information about the identities of parties trading and posting quotes through the broker from whom data is collected is privileged, and our data source's agreements with the participating institutions do not allow them to reveal it. Second, the overall trading volume is not available. However, it provides a rich data on CDS spreads over a large number of underlying entities. The literature provides insight on how CDS supply and demand mechanisms affect CDS spreads.

for our borrowers denominated in U.S. dollars. We match US borrower names to CDS data using combinations of company names, Markit's unique identifier for firms (RED codes) and ticker symbols. After each round of matching, we manually check the accuracy of the match. Following Acharya and Johnson (2007), we consider the CDS spreads of five-year maturity contracts, which are usually the most liquid contracts, with the U.S. dollar as the underlying currency and debt restructuring as the event of default.[22] Our final sample includes 323 facilities belonging to borrowers with an active CDS market. This means that for these facilities, lenders have the possibility of using the CDS market to lay off credit risk.

We use the change in CDS spreads as a proxy for bank activity to hedge their credit-risk exposure. That is because in general, when lenders hedge their credit-risk exposure to a borrower by buying CDS contracts, the demand for CDS contracts increases around the facility initiation date increasing CDS spreads. Acharya and Johnson (2007) use the same measure as an indication that lenders trade on information related to borrower credit quality. To limit our measure to hedging at loan origination, we consider the cumulative abnormal change in the borrowers CDS spread over a [-5, +30] trading-day interval around the loan facility's initiation date. If the cumulative abnormal change in spreads during the event period is positive, we assume that lenders are using the CDS for hedging purposes. If the CDS cumulative abnormal change is negative or

[22] Achariya and Johnson (2007) mention CreditTrade as their data source. In our dataset, seniority level is reported under the variable name *Tier*. We choose *Tier*=SNRFOR, which stands for senior unsecured debt (corporate/financial), foreign currency sovereign debt (government). Markit CDS data is based on how a CDS contract covering restructuring events (reported as document clause types) provides different spreads. These clause types include CR, which is Cum (With) Restructuring or Old Restructuring; MR, which is Modified Restructuring; MM, which is Modified-Modified Restructuring; and XR, which is Ex-Restructuring or Without Restructuring. A contributor's spreads must follow the inequality XR < MR < MM < CR. We noticed that MR trades more frequently in North America, so we use MR as the main document clause type; we compare trades of each security at different trading dates and not with other securities. We used XR whenever MR is not available.

does not change, we assume that the lender is not using CDS to hedge against the loan. We then create a CDS hedging dummy that equals 1 if cumulative abnormal CDS spreads are positive and 0 otherwise. Our preliminary results show that 22% of loans are hedged with CDS contracts (all borrowers in our sample have a CDS market, but only the CDS for 22% of these borrowers are used by their lenders for hedging their loans). Summary statistics on these loans is provided in Table 2. More details on the construction of CDS spreads are also provided in the Appendix B. Alternative measures of CDS use are explained in the paper under robustness tests.

A.4. Lender Information

Our final dataset relates to bank's financial condition information. Most empirical work related to loan syndications focuses on borrower characteristics and/or a limited number of lender characteristics such as lending relationships, market share, reputation, and lender type (see, for example, Bharath et al., 2009; Sufi, 2007; Güner, 2006; Drucker and Puri, 2009; Massoud, Nandy, Saunders, and Song, 2011; and Kamstra, Roberts, and Shao, 2014). The limited scope in measuring lender characteristics is mainly due to the existence of multiple lenders in a loan syndicate and also the difficulty of matching lender names in DealScan Reuters with other databases that contain additional financial information about lenders. Moreover, the diversity of lenders in the syndicated loan market is another reason that the lending side has not been as explored as the borrowing side in studies related to corporate loans. Some lenders can come from regulated industries such as commercial banking; while others, such as hedge funds, belong to less regulated industries. Hence lender data availability and comparability remains an issue.

DealScan data provides no unique, common, numerical identifier for each lender. Therefore, matching to other datasets, e.g., call reports, has to be based on name, address, and ticker, if available, and thus has to be done manually. In this paper we focus on loan deals extended

purely by banks. We manually check the identity of each bank in different databases. We then collect the accounting data for banks from UBPR, which is provided by the US regulatory authorities (FFIEC) based on the Reports of Condition and Income forms (Call Reports) that banks must file quarterly with the Federal Deposit Insurance Corporation (FDIC) under Section 1817(a)(1) of the Federal Deposit Insurance Act. Moreover, bank names are quoted differently in different datasets; to that end, first, we find unique identifiers such as the Federal Reserve's Research Statistics Supervision Discount (RSSD) IDs for each bank to extract data from different datasets. We manually extract lenders' RSSD IDs from the National Information Center.[23] If we cannot match banks from the loan dataset to the bank regulatory dataset directly, we use the information of the first parent that can be matched.

Our major key financial risk variables at the bank lender level include two measures of capital adequacy and two measures of liquidity. The former group include bank's ratios of total risk-based capital to total risk-based assets, and total equity capital to total long-term liabilities. Our measures of liquidity include ratios of net federal funds sold divided by total short-term non-core funding, and short-term assets to short-term liabilities. The construction of each variable is described in Table 1. The capital measures reflect in part minimum capital restrictions imposed upon banks by regulatory authorities. For example, there is a minimum requirement on the amount of total (tier 1 and tier 2) capital a bank has relative to risk weighted assets. Deviation below minimum capital requirements might induce banks to sell loans to a third party. Alternatively, under Basel II as our sample period, CDS hedged loans had a 20% risk weight while non-hedged loans had a 100% risk weight. Liquidity measures reflect lenders' ability to manage short-term

[23] Available on http://www.ffiec.gov/nicpubweb/nicweb/NicHome.aspx. "The National Information Center (NIC) provides comprehensive information on banks and other institutions for which the Federal Reserve has a supervisory, regulatory, or research interest including both domestic and foreign banking organizations operating in the U.S."

liquidity shocks. We use two measures, net federal funds sold divided by total short-term non-core funding indicting a bank has excess liquidity, and short-term assets to short-term liabilities, indicating the bank has excess short-term assets relative to liabilities.

To identify the degree to which a bank's capital and liquidity constraints impact its CRT decision we sort all US banks (whose call reports are provided by FFIEC), based on each capital and liquidity measure for each fiscal quarter. If a bank belongs to both the bottom decile of a liquidity measure and the bottom decile of a capital measure, then the bank is identified as a bank whose capital and liquidity constraints are likely more binding. In the next step, we identify all loan facilities, whose lender syndicate includes at least one member with these capital and liquidity constraints. Then, we assign a value of one to a binary variable that we call "measure of capital and liquidity constraints" zero otherwise. To test the robustness of our results we define three alternative measures of capital and liquidity.

Moreover, we assume lenders with a higher market share in the loan market are more reputable. We calculate the market share of a specific lender for a specific loan as the ratio of the total number of loans issued by the lender over 5 years prior to loan initiation to total number of loans issued in the primary market over the same time period. As an alternative measure we also use amount of loans. To examine if a bank had a prior relationship with a borrower we examine the 5 year prior to loan initiation to see if the lead lender has any other lending relationship with the borrower, following Bharath et al. (2009). All details of these variables construction are provided in Table 1.

Appendix B: CDS Spread

We use the change in CDS spreads as a proxy for lender trading activities to hedge credit risk. In general, when lenders issue new loans, they might hedge their credit risk exposure to a borrower by buying CDS contracts. Accordingly, the market demand for CDS contracts increases around the facility initiation date. As a result, one would expect CDS spreads to increase. To limit our measure to hedging at loan origination, we consider the cumulative abnormal change in the CDS spread in a [-5,+30] trading-day interval around the facility's initiation date. If the cumulative abnormal change in the spread during the event period is positive, there is a possibility that the lender used CDS for hedging purposes.[24] We choose a +30 trading day as the end of the event period to allow lenders enough time to hedge against a new contract with a borrower and to limit potential changes in borrower quality (i.e., credit quality) that might impact CDS spreads. Also, our choice of -5 trading days of the event period accounts for early hedging. We measure the abnormal change in CDS spread for each facility as the difference between the change in the five-year spread from one trading date to the next and the average change in five-year spreads in the control period, which is 120 trading days around the event date—excluding the event period and 20 trading days around the event period (i.e., [-60, -15] U [+40,+60]). The change in five-year spreads is calculated as (spread on trading date t less spread on the previous trading date) divided by (spread on last trading date times the number of trading days between two dates). The cumulative abnormal change is the sum of the abnormal changes during the event period.[25]

[24] Staleness in reported spreads does not affect our results. If there is no change in reported prices, we would not capture any movement in abnormal cumulative spreads.

[25] If a CDS is not traded on all trading days during the event period, we normalize the cumulative abnormal change to create consistent comparisons. For example, a firm might have CDS spread data for only 14 out of 30 trading days. In those cases, we multiply the 14 days cumulative abnormal changes in the CDS spread by 30/14 to make it comparable to a 30-day window.

Subsequently, we create a CDS hedging dummy that equals 1 when the cumulative abnormal CDS spread is positive, and equals 0 otherwise. This binary variable is our proxy for using CDS as a hedging instrument by lenders.

It might be argued that a spread change can be related to other market participants' increase in demand as a result of loan initiation, but this argument cannot be reasonable for the following reason: an increase in demand from other participants indicates that negative news has affected their perceptions about default probabilities and they, as a result, demand more insurance. However, prior studies (see for example, James, 1987; Lummer and McConnell, 1989; Best and Zhang, 1993; and Billett, Flannery, and Garfinkel, 1995) find positive impact of loan-origination announcements on borrowers' stock returns at the time of loan origination.

Alternatively, one might argue that market participants increase their demand for CDS in anticipation of lenders' potential hedging activities. In other words, traders are front-running the bank lenders. This potential trading pattern may not have an impact on the CDS spread, because those investors are most likely small or buy small exposures. Additionally, this view is consistent with our argument because those banks are more likely to hedge their loans.

A lender might enter the CDS market long before the event period. In that case, we consider this behavior speculative rather than hedging because the lender as an informed trader could predict future changes in borrowers' credit quality. Therefore, it trades CDS before it really experiences any relevant change in its loan portfolio that requires hedging.

One might argue that a bank's CDS trades are related to a prior loan to the same borrower. The probability that a lender will make two loans to the same borrower near the specified event periods is very low because lenders generally try to satisfy all of a borrower's needs at once in one loan package. (Our sample rules out this possibility).

Another concern is related to cases in which the lender has fully or partially hedged against the new renegotiated loan in the CDS market before the initiation date. If these cases exist in our sample, they make our results weaker because we focus abnormal increases in CDS spreads around loan origination (-5, 30 day window). In addition, in the multivariate analysis we control for renegotiated deals. Accordingly, this concern should not change our conclusions.

Another concern is that since banks can use both loan sales and CDS to hedge the credit risk of a loan, it might be loan sales that trigger the widening of CDS spread and not lenders' usage of CDS as a hedge instrument. The reason is that a loan sale might be considered as bad news by market participants (Dahiya, Puri and Saunders, 2003). Three reasons exist to refute this concern: (1) the study by Dahiya et al. (2003) in which the authors find that the reaction of equity investors to loan sales was negative is based on a sample of 29 borrowers during 1995 to 1998. A more recent study by Gande and Saunders (2012) shows that the secondary market trading in loans in fact elicits a significant positive stock price response by a borrowing firm's equity investors. They find the major reason for this response is the alleviation of borrowing firms' financial constraints. (2) Our results show that less than 2% of the loans in our sample experience a loan sale and CDS spread increase concurrently. (3) The way we measure CDS activity (abnormal change in CDS spread around loan initiation) rules out this possibility. This means that a loan needs to be initiated, sold, and hedged with CDS on the same day in order for this concern to be valid. Although we cannot completely rule out the possibility that this might have happened to some of the loans with both sale and CDS activities (less than 2% of the sample) we find it very unlikely.

Moreover, if multiple loans exist in the same window, our measure of abnormal change in spreads would be a noisy measure of lenders' hedging activities. The common practice in the syndicated loan market is to structure loan deals consisting of multiple loan facilities issued on the

same day with a common lead bank and set of participant lenders. The syndicate participants provide different loan facilities including term loans and credit lines to address all funding needs of a borrower. It is not likely/allowed by existing lenders that the borrower enters into a parallel syndicated loan contract with another group of lenders at the same time the borrower is in a relationship with the existing lenders, unless the new syndicate refinances the old contract. Therefore, parallel loans can exist only within the same loan syndicate structure. Our proxy from the CDS market does not distinguish between different loan facilities within the same loan package. This can create bias as the composition of lenders can vary across different facilities, although most lenders, specifically administrative lenders, are repeated across all facilities. We conjecture that this issue affects less than 10% of our loans with lenders' hedging activities.

Finally we consider the possibility that an abnormal change in CDS spreads is due to an unrelated change in firm-level fundamentals that is happened to be around the same time as the time of loan initiation. We consider this possibility in Section V.5 in detail.

Appendix C: Nested Logit

Nested logit model is a utility-based model, meaning that the choice is represented by a random utility model (RUM) estimated by the conditional logit technique. The utility equations for our alternatives are

$$U_{Ret} = V_{Ret} + \varepsilon_{Ret} \quad (1)$$

$$U_{CDS} = V_{CDS} + V_{CRT} + \varepsilon_{CDS} + \varepsilon_{CRT} \quad (2)$$

$$U_{Sale} = V_{Sale} + V_{CRT} + \varepsilon_{Sale} + \varepsilon_{CRT} \quad (3)$$

$$U_{Both} = V_{Both} + V_{CRT} + \varepsilon_{Both} + \varepsilon_{CRT} \quad (4)$$

Where U_i is the random utility function of choice i for a facility.[26] U_i has a deterministic portion (V_i) estimated by the model and an error term (ε_i). For CDS, Sale or both decisions, the utility term includes a distinct observed component, V_{CDS}, V_{Sale}, and V_{Both} and a common observed component, V_{CRT} for the choice of CRT, they also include distinct and common random components, respectively ε_{CDS}, ε_{Sale}, ε_{Both}, and ε_{CRT}.

The model assumes for facility j, a method of CRT is chosen so that a utility function V (for the lender) is maximized. The utility of method i for the facility j can be expressed as:

$$V_{j,i} = \beta\, Z_{j,i} \quad (5)$$

[26] Defining a utility function for a facility might seem unusual. However, in this model by facility we mean a bundle of bank-firm-contract characteristics that are represented by a facility. To that end, the utility function can be perceived as the utility that the bank obtains from choosing an alternative, considering the characteristics of the bank, the borrower and the contract that are associated with the facility. The nested logit is consistent with bank's utility maximizing behavior. The underlying assumption is that what we observe from banks' choices of CRT alternatives are the result of this maximization behavior with some noise.

Where $Z_{J,i}$ is a vector of characteristics of the choice and the facility. Note that the subscript for the facility was suppressed in equations (1) to (4). The conditional probability of choice i given that this choice is in the nest method k is equal to:

$$P[j\ chooses\ i] = \frac{exp(V_{j,i}/\theta_k)}{\sum_{all\ i\ in\ nest\ k} exp(V_{j,i}/\theta_k)} \quad (6)$$

Where θ_k is the scale parameter for nest k (Train, 2009).

The derivation of nested logit is based on the assumption that the alternatives including sale, CDS and both share common components in their random errors (all are CRT methods, or to put differently, all belong to the CRT "Nest")[27]. Similar to Brownstone and Small (1989) we analyze a two-level nested logit model (Figure 2). Level 1 is at the choice level. It includes choices of Retention, CDS, Loan Sale, and Both. Level 2 is at the nest level. It includes two nests, CRT and No-CRT). Each of the choices in Level 1 belong to one nest in Level 2. The first nest of choices in our study, No CRT, has only one alternative (retention)[28], and the second nest, CRT, has three alternatives (CDS, Sale, Both). The chosen alternative is explained by bank characteristics, borrower characteristics and contract characteristics as in the previous section.

[FIGURE 2 HERE]

C.1. Defining the Choice Set

The nested logit estimates the coefficients of the RUM by comparing characteristics of the chosen alternative with those of the rejected alternatives. We build a new sample, where there are

[27] This approach is similar to the classic commuter problem in Brownstone and Small (1989) in which commuter's choice of arrival time at work consists of alternatives (between 42.5 minutes early and 17.5 minutes late indexed by 12 alternatives using 5-minutes interval groups) based on their preference for arriving at work early, on-time or late. The chosen alternative is then explained by commuter's travel time, the choice of car or carpooling, allowable delay by the work place, etc.

[28] Therefore it is a degenerate branch as in Brownstone and Small (1989).

a total of 4 records per facility corresponding to possible CRT methods, for a total of 323*4 = 1,292 records. If a certain facility-bank-borrower characteristic is systematically more prevalent in the chosen CRT decision than in the rejected ones, it is judged to positively affect the choice of a CRT. Important to this process, naturally, is identification of the rejected alternatives, which are known in our study.

The following table shows an example of how the observations for our nested logit analysis look like. The table includes 8 observations belonging to two facilities (fictional). Each facility has one selected alternative and three rejected alternatives. The selected alternative for facility 1 is CDS and for facility 2 is Retention. Each alternative has a vector of alternative-specific characteristics as demonstrated in the table. Although nested logit permits some flexibility in covariate specifications, having too many alternative-specific covariates builds a model that is not able to fit properly due to convergence problems. To that end, we restrict the choice of independent variables to the important characteristics based on our previous findings and the prediction from the theory.

A Schematic Representation of How the Data for Nested Logit Analysis Looks Like

Each row in the table represents a facility-choice observation. Each facility is associated with four alternatives with respect to how banks manage its credit risk. These alternatives include retention (the bank keeps the loan and associated risk on the balance sheet), CDS (the bank use CDS to hedge the credit risk of loan), sale (the bank sells all or part of the loan), and both (the bank use a combination of loan sale and CDS to hedge against the loan's credit risk). Exactly one alternative for each loan is selected and three are rejected. This is shown by the binary variable Choice in the table. We create a set of alternative specific characteristics by multiplying the loan, lender and borrower characteristics by a binary variable that equals one for the alternative and zero for other alternatives. # denotes a non-zero vector including Loan characteristics, lender characteristics or borrower characteristics that are associated with the loan observation. 0 means a zero vector, the size of which equals a # vector that is in the same column of the table.

Obs	Facility ID	Alternative	**Choice**	Alternative specific characteristics											
				Retention*(loan-lender-borrower characteristics)			CDS*(loan-lender-borrower characteristics)			Sale*(loan-lender-borrower characteristics)			Both*(loan-lender-borrower characteristics)		
				Loan Char	Lender Char	Borrower Char	Loan Char	Lender Char	Borrower Char	Loan Char	Lender Char	Borrower Char	Loan Char	Lender Char	Borrower Char
1	1	Retention	**0**	#	#	#	0	0	0	0	0	0	0	0	0
2	1	CDS	**1**	0	0	0	#	#	#	0	0	0	0	0	0
3	1	Sale	**0**	0	0	0	0	0	0	#	#	#	0	0	0
4	1	Both Sale and CDS	**0**	0	0	0	0	0	0	0	0	0	#	#	#
5	2	Retention	**1**	#	#	#	0	0	0	0	0	0	0	0	0
6	2	CDS	**0**	0	0	0	#	#	#	0	0	0	0	0	0
7	2	Sale	**0**	0	0	0	0	0	0	#	#	#	0	0	0
8	2	Both Sale and CDS	**0**	0	0	0	0	0	0	0	0	0	#	#	#

References

Acharya, Viral V., and Timothy C. Johnson. "Insider trading in credit derivatives." *Journal of Financial Economics* 84, no. 1 (2007): 110-141.

Acharya, Viral V., and Ouarda Merrouche. "Precautionary hoarding of liquidity and interbank markets: Evidence from the subprime crisis." *Review of Finance* 17 (2012): 107-160.

Acharya, Viral V., and Nada Mora. "A crisis of banks as liquidity providers." *The Journal of Finance* 70, no. 1 (2015): 1-43.

Acharya, Viral V., Philipp Schnabl, and Gustavo Suarez. "Securitization without risk transfer." *Journal of Financial economics* 107, no. 3 (2013): 515-536.

Ashcraft, Adam B., and Joao AC Santos. "Has the CDS market lowered the cost of corporate debt?." *Journal of Monetary Economics* 56, no. 4 (2009): 514-523.

Allen, Franklin, and Elena Carletti. "Credit risk transfer and contagion." *Journal of Monetary Economics* 53, no. 1 (2006): 89-111.

Benmelech, Efraim, Jennifer Dlugosz, and Victoria Ivashina. "Securitization without adverse selection: The case of CLOs." *Journal of Financial Economics* 106, no. 1 (2012): 91-113.

Berger, Allen N., and Gregory F. Udell. "Relationship lending and lines of credit in small firm finance." *Journal of business* (1995): 351-381.

Berndt, Antje, and Anurag Gupta. "Moral hazard and adverse selection in the originate-to-distribute model of bank credit." *Journal of Monetary Economics* 56, no. 5 (2009): 725-743.

Best, Ronald, and Hang Zhang. "Alternative information sources and the information content of bank loans." *The Journal of Finance* 48, no. 4 (1993): 1507-1522.

Bharath, Sreedhar T., Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan. "Lending Relationships and Loan Contract Terms." *Review of Financial Studies* 24, no. 4 (2011): 1141-1203.

Billett, Matthew T., Mark J. Flannery, and Jon A. Garfinkel. "The effect of lender identity on a borrowing firm's equity return." *The Journal of Finance* 50, no. 2 (1995): 699-718.

Bolton, Patrick, and Martin Oehmke. "Credit default swaps and the empty creditor problem." *Review of Financial Studies* 24, no. 8 (2011): 2617-2655.

Bord, Vitaly M., and João AC Santos. "Banks' Liquidity and the Cost of Liquidity to Corporations." *Journal of Money, Credit and Banking* 46, no. s1 (2014): 13-45.

Brownstone, David, and Kenneth A. Small. "Efficient estimation of nested logit models." *Journal of Business & Economic Statistics* 7, no. 1 (1989): 67-74.

Bushman, Robert M., Abbie J. Smith, and Regina Wittenberg-Moerman. "Price discovery and dissemination of private information by loan syndicate participants." *Journal of Accounting Research* 48, no. 5 (2010): 921-972.

Cao, Charles, Fan Yu, and Zhaodong Zhong. "The information content of option-implied volatility for credit default swap valuation." *Journal of Financial Markets* 13, no. 3 (2010): 321-343.

Chava, Sudheer, and Michael R. Roberts. "How does financing impact investment? The role of debt covenants." *The Journal of Finance* 63, no. 5 (2008): 2085-2121.

Cornett, Marcia Millon, Jamie John McNutt, Philip E. Strahan, and Hassan Tehranian. "Liquidity risk management and credit supply in the financial crisis." *Journal of Financial Economics* 101, no. 2 (2011): 297-312.

Dahiya, Sandeep, Manju Puri, and Anthony Saunders. "Bank Borrowers and Loan Sales: New Evidence on the Uniqueness of Bank Loans." *The Journal of Business* 76, no. 4 (2003): 563-582.

Dass, Nishant, and Massimo Massa. "The impact of a strong bank-firm relationship on the borrowing firm." *Review of Financial Studies* 24, no. 4 (2011): 1204-1260.

Degryse, Hans, and Patrick Van Cayseele. "Relationship lending within a bank-based system: Evidence from European small business data." *Journal of Financial Intermediation* 9, no. 1 (2000): 90-109.

Diamond, Douglas W. "Financial intermediation and delegated monitoring." *The Review of Economic Studies* 51, no. 3 (1984): 393-414.

Drucker, Steven, and Manju Puri. "On loan sales, loan contracting, and lending relationships." *Review of Financial Studies* 22, no. 7 (2009): 2835-2872.

Duffee, Gregory R., and Chunsheng Zhou. "Credit derivatives in banking: Useful tools for managing risk?." *Journal of Monetary Economics* 48, no. 1 (2001): 25-54.

Engelberg, Joseph, Pengjie Gao, and Christopher A. Parsons. "Friends with money." *Journal of Financial Economics* 103, no. 1 (2012): 169-188.

Fama, Eugene F. "What's different about banks?" *Journal of Monetary Economics* 15, no. 1 (1985): 29-39.

Gande, Amar, and Anthony Saunders. "Are banks still special when there is a secondary market for loans?." *The Journal of Finance* 67, no. 5 (2012): 1649-1684.

Gorton, Gary B., and George G. Pennacchi. "Banks and loan sales marketing nonmarketable assets." *Journal of Monetary Economics* 35, no. 3 (1995): 389-411.

Greenwood, Robin, Augustin Landier, and David Thesmar. "Vulnerable banks." *Journal of Financial Economics* 115, no. 3 (2015): 471-485.

Güner, A. Burak. "Loan sales and the cost of corporate borrowing." *Review of Financial Studies* 19, no. 2 (2006): 687-716.

Haselmann, Rainer, David Schoenherr, and Vikrant Vig. "Rent-seeking in elite networks." (2015) Working Paper.

Hirtle, Beverly. "Credit derivatives and bank credit supply." *Journal of Financial Intermediation* 18.2 (2009): 125-150.

Irani, Rustom M., and Ralf R. Meisenzahl. "Loan Sales and Bank Liquidity Risk Management: Evidence from a US Credit Register." (2015).

Ivashina, Victoria, and David Scharfstein. "Bank lending during the financial crisis of 2008." *Journal of Financial economics* 97, no. 3 (2010): 319-338.

James, Christopher. "Some evidence on the uniqueness of bank loans." *Journal of Financial Economics* 19, no. 2 (1987): 217-235.

Jorion, Philippe, and Gaiyan Zhang. "Credit contagion from counterparty risk." *The Journal of Finance* 64, no. 5 (2009): 2053-2087.

Kamstra, Mark J., Gordon S. Roberts, and Pei Shao. "Does the Secondary Loan Market Reduce Borrowing Costs?" *Review of Finance* 18, no. 3 (2014): 1139-1181.

Karolyi, Stephen A. "Personal Lending Relationships." (2014) Working Paper.

Khan, Urooj, Xinlei Li, Chris Williams, and Regina Wittenberg-Moerman. "Co-migration and the benefits of relationships in bank lending." (2015) Working Paper.

Kim, Jae B., Pervin K. Shroff, Dushyantkumar Vyas, and Regina Wittenberg-Moerman. "Active CDS trading and managers' voluntary disclosure." *Singapore Management University School of Accountancy Research Paper* (2015) No. 2015-27.

Lummer, Scott L., and John J. McConnell. "Further evidence on the bank lending process and the capital-market response to bank loan agreements." *Journal of Financial Economics* 25, no. 1 (1989): 99-122.

Martin, Xiumin, and Sugata Roychowdhury. "Do financial market developments influence accounting practices? Credit default swaps and borrowers ′reporting conservatism." *Journal of Accounting and Economics* 59, no. 1 (2015): 80-104.

Massoud, Nadia, Debarshi Nandy, Anthony Saunders, and Keke Song. "Do hedge funds trade on private information? Evidence from syndicated lending and short-selling." *Journal of Financial Economics* 99, no. 3 (2011): 477-499.

Minton, Bernadette A., René Stulz, and Rohan Williamson. "How much do banks use credit derivatives to hedge loans?." *Journal of Financial Services Research* 35.1 (2009): 1-31.

Nini, Greg, David C. Smith, and Amir Sufi. "Creditor control rights and firm investment policy." *Journal of Financial Economics* 92, no. 3 (2009): 400-420.

Parlour, Christine A., and Andrew Winton. "Laying off credit risk: Loan sales versus credit default swaps." *Journal of Financial Economics* 107, no. 1 (2013): 25-45.

Pennacchi, George G. "Loan sales and the cost of bank capital." *The Journal of Finance* 43, no. 2 (1988): 375-396.

Petersen, Mitchell A., and Raghuram G. Rajan. "The benefits of lending relationships: Evidence from small business data." *The Journal of Finance* 49, no. 1 (1994): 3-37.

Purnanandam, Amiyatosh. "Originate-to-distribute model and the subprime mortgage crisis." *Review of Financial Studies* 24, no. 6 (2011): 1881-1915.

Qiu, Jiaping, and Fan Yu. "Endogenous liquidity in credit derivatives." *Journal of Financial Economics* 103, no. 3 (2012): 611-631.

Ramakrishnan, Ram TS, and Anjan V. Thakor. "Information reliability and a theory of financial intermediation." *The Review of Economic Studies* 51, no. 3 (1984): 415-432.

Sufi, Amir. "Information asymmetry and financing arrangements: Evidence from syndicated loans." *The Journal of Finance* 62, no. 2 (2007): 629-668.

Taylor, Allison and Alicia Sansone. *The handbook of loan syndications and trading*. McGraw-Hill, New York, New York (2007).

Train, Kenneth E. *Discrete choice methods with simulation*. Cambridge university press, 2009.

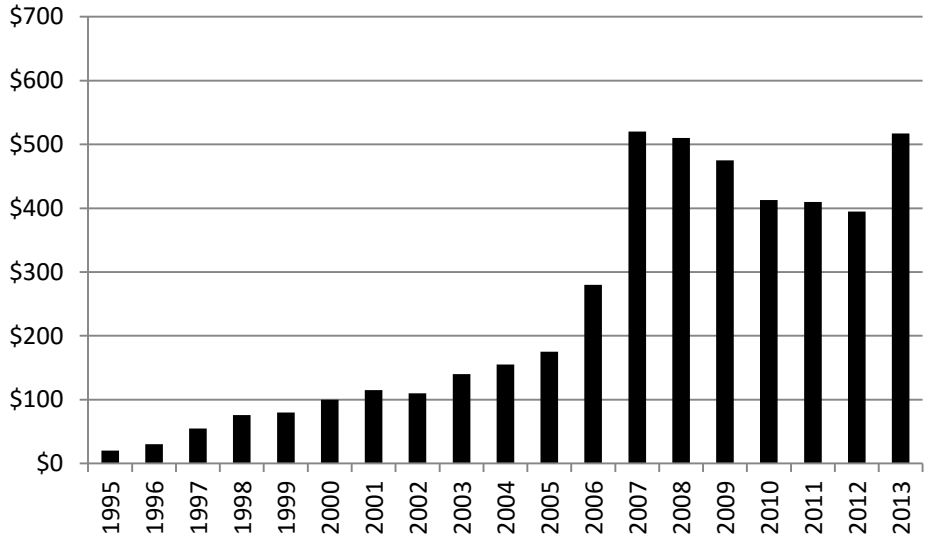
Wittenberg-Moerman, Regina. "The role of information asymmetry and financial reporting quality in debt trading: Evidence from the secondary loan market." *Journal of Accounting and Economics* 46, no. 2 (2008): 240-260.

Zhang, Benjamin Yibin, Hao Zhou, and Haibin Zhu. "Explaining credit default swap spreads with the equity volatility and jump risks of individual firms." *Review of Financial Studies* 22, no. 12 (2009): 5099-5131.

Figure 1 – Aggregate Market Size of Two Credit Risk Transfer Markets: Loan Sale Market and CDS Market

The top and the bottom figures respectively show the growth and size of loan sale market (source: Loan Pricing and Trading Corporation) and the CDS market (source: International Swaps and Derivatives Association's Market Survey, complement with 2011-2013 data from the Bank of International Settlement). Numbers are in billions of U.S. dollars.

Loan Sale Market



CDS Market

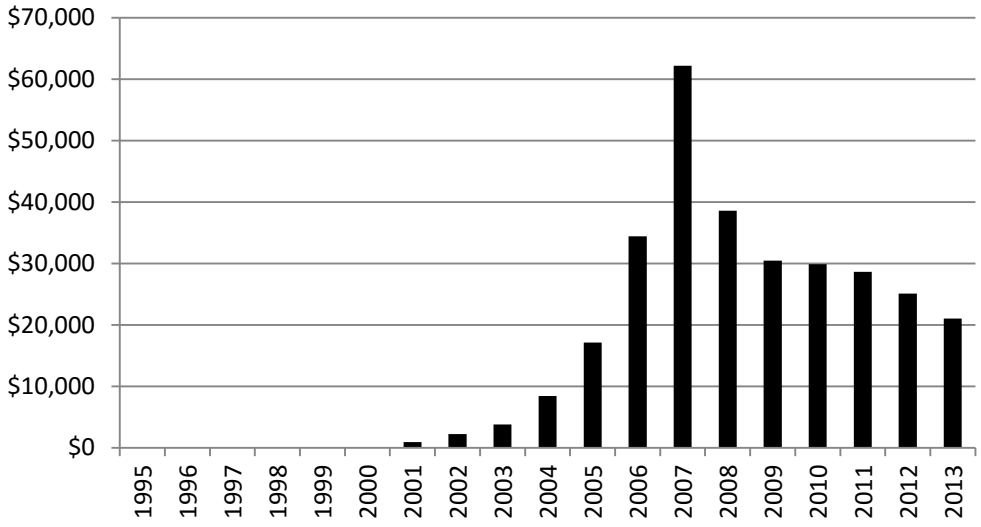


Figure 2- Structure of the Decision Model (Nested Logit)

Bank's decision to manage the credit risk of a loan is divided into two categories: Credit Risk Transfer (CRT) and No CRT. Within the CRT category, bank choses among markets for Credit Default Swaps (CDS), Loan Sale and Both (a combination of the CDS market and the Sale Market).

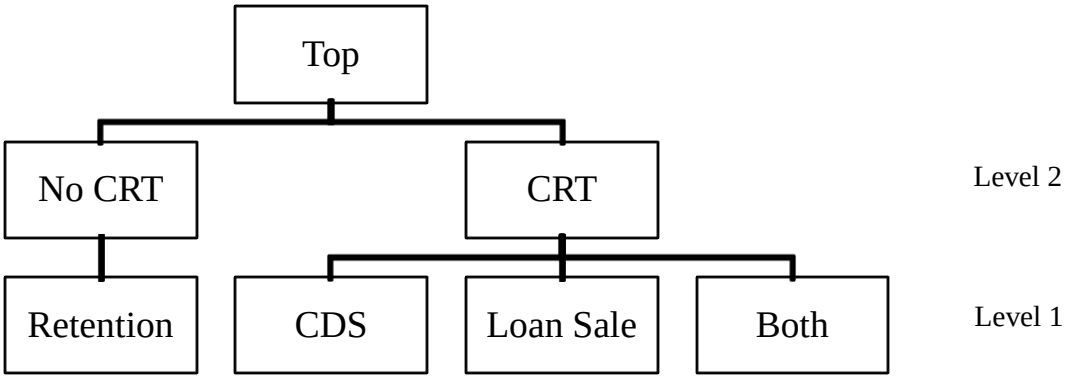


Table 1 - Variable Descriptions

This table provides information and discussion related to variable construction.

Panel 1A: Borrower Characteristics

Market Size	Market value of equity at the last quarter end prior to loan initiation: [(CRSP PRC (Share Price-Closing) × CRSP SHROUT (Number of Shares Outstanding))*1,000].
Log (Market Size)	Natural Logarithm of Market Size
ROA	Compustat OIADPQ (Operating Income After Depreciation Quarterly) / Compustat ATQ (Assets-Total Quarterly)
Leverage	Compustat LTQ (Liabilities-Total Quarterly) / Compustat ATQ (Assets-Total Quarterly)
Market to Book	[(CRSP PRC (Share Price-Closing) × CRSP SHROUT (Number of Shares Outstanding))/1,000] / [Compustat ATQ (Assets-Total Quarterly) – Compustat LTQ (Liabilities-Total Quarterly)]
Credit Rating (Long-Term Issuer Debt Rating)	S&P Long-Term Issuer Credit Rating (ICR) ranges from AAA (extremely strong capacity to meet financial obligations) to CC (highly vulnerable) and D (In default). In our analysis, we rank long-term ratings from 22 to 1, where AAA receives 22 and D receives 1. (SPLTICRM). S&P in its data guide: "The Standard & Poor's Issuer Credit Rating (ICR) is a current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations. This opinion focuses on the obligor's capacity and willingness to meet its long-term (short-term) financial commitments as they come due." If a borrower does not have an S&P rating but has a Moody's rating, we would use the equivalent Moody's instead (this is the case for 2% of observations).

Panel 1B: Lender Characteristics

Sub-Panel 1B-1: Capital Measures

Equity Capital to Total Long-term Liabilities	Total Bank Equity Capital from Schedule RC divided by the sum of Subordinated Notes and Debentures from Schedule RC Federal Home Loan Bank Advances with a maturity of more than one year + other borrowings with a remaining maturity of more than one year from Schedule RC-M . Equivalent to 100/UBPRE628 extracted from Bank's Uniform Bank Performance Report.
Total Risk Based Capital to Total Risk Weighted Assets	Total Risk-Based Capital Ratio (RCFD7205) from Schedule RC-R * 100. Equivalent to UBPRD488 from Bank's Uniform Bank Performance Report.

Sub-Panel 1B-2: Liquidity Measures

Net Federal Funds Sold divided by total short term noncore funding	Federal funds sold and securities purchased under agreements to resell (RCONB987 + RCFDB989) - Federal Funds Purchased & Re-sales (RCONB993 + RCFDB995) divided by short term non-core funding, which equals the sum of time deposits of more than $100,000 with a remaining maturity of one year or less + brokered deposits issued in denominations of $100,000 and less with a remaining maturity or one year

	or less + other borrowed money with a remaining maturity one year or less + time deposits with a remaining maturity of one year or less in foreign offices + securities sold under agreements to repurchase and federal funds purchased (equivalent to UBPRE584). Using data from the Uniform Bank Performance Report, the ratio equals to (UBPR0081 + UBPRD493 – UBPRF858) / UBPRE584.
Short-term Assets to Short-term Liabilities	Short term assets divided by short term liabilities. Short term assets equals the sum of interest-bearing bank balances + federal funds sold + securities purchased under agreements to resell + debt securities with a remaining maturity of one year or less + loans and leases with a remaining maturity of one year or less. Short term liabilities equals the sum of time deposits less than $100,000 with a remaining maturity of one year or less + time deposits of $100M or more with a remaining maturity of one year or less + other borrowed money with remaining maturity 1 year or less + deposits in foreign offices with remaining maturity 1 year or less + securities sold under agreements to repurchase and federal funds purchased. The ratio is also equal to UBPRE598 from Bank's Uniform Bank Performance Report.

Sub-Panel 1B-3: Capital and Liquidity Constraints

Measure 1	All US banks that file call reports are sorted separately based on a capital ratio and a liquidity ratio at each calendar quarter. The measure is a binary variable that equals 1 If at least one of the banks in the lending syndicate falls within both the lowest decile (10%) of the capital ratio and the lowest decile of the liquidity ratio. The measure is zero otherwise. For measure 1 the choice of capital ratio is Equity Capital to Total Long-term Liabilities, and the choice of liquidity ratio is Net Federal Funds Sold divided by total short term noncore funding.
Measure 2	All US banks that file call reports are sorted separately based on a capital ratio and a liquidity ratio at each calendar quarter. The measure is a binary variable that equals 1 If at least one of the banks in the lending syndicate falls within both the lowest decile (10%) of the capital ratio and the lowest decile of the liquidity ratio. The measure is zero otherwise. For measure 2 the choice of capital ratio is Total Risk Based Capital to Total Risk Weighted Assets, and the choice of liquidity ratio is Short-term Assets to Short-term Liabilities.

Panel 1C: Loan Characteristics

Loan Size	The facility size (US$).
Relative Loan Size	Loan Size divided by the market value of equity of the borrower at the time of loan initiation
Loan Maturity (Month)	Months to Maturity
Log(Maturity)	Natural Logarithm of Loan Maturity
Relationship	An indicator that equals unity when a past Relationship between the borrower and the lead lender is present in the DealScan data and zero otherwise.

Lender's Market Share (%)	Market share is the ratio of total number of all loans initiated by the lender over the last 5 year to the total number of all loans issued over the last 5 year. The ratio is expressed in a percentage format.
Size of Lending Syndicate	Number of lenders in the lending syndicate
Loan Purpose – Acquisition	A binary variable that equals 1 if the primary purpose of the loan facility is for acquisition related activities, zero otherwise.
Loan Purpose – Repayment	A binary variable that equals 1 if the primary purpose of the loan is to repay prior debt, zero otherwise.
Loan Purpose – Corporate	A binary variable that equals 1 if the primary purpose of the loan is for corporate purposes, such as equipment purchase, capital expenditure, etc., zero otherwise.
Loan Purpose – Other	A binary variable that equals 1. If the primary purpose of the loan is something other than the above purposes, zero otherwise.

Table 2 – Summary Statistics

This table presents descriptive statistics for all loan facilities related to US borrowers with available accounting and stock price information for which all lending syndicate participants are US banks and the borrower has a long-term debt issuer credit rating and a credit derivative market (323 loan facilities belonging to 202 borrowers). Data covers loans initiated between January 1, 2003 and December 31, 2007. Two measures of lender's capital and liquidity constraint are used in this table. If a bank's both capital ratio and liquidity ratio fall within the lowest deciles when we sort all US banks in a year based on a capital ratio and a liquidity ratio then we assume the bank has more binding capital and liquidity constraints. The measure then will be assigned a value of 1 if the lending syndicate has at least a member with such constraints, and 0 otherwise. Variable definitions are provided in Table 1.

Variable	Mean	Std Dev	Minimum	Median	Maximum
Borrower:					
Credit Rating	12.183 (BB+)	3.491	2.000 (D)	11.000 (BB)	22.000 (AAA)
Market Size ($ Billion)	7.601	21.275	0.058	1.871b	192.682
Log (Market Size)	21.461	1.528	17.885	21.350	25.984
ROA (Quarterly)	0.025	0.016	-0.017	0.024	0.099
Leverage	0.594	0.158	0.139	0.609	0.967
Market to Book	2.780	2.382	0.397	2.021	18.921
Lender:					
Capital and Liquidity Constraint (Measure 1)	0.034	0.182	0.000	0.000	1.000
Capital and Liquidity Constraint (Measure 2)	0.046	0.211	0.000	0.000	1.000
Lender's Market Share (%)	5.644	5.079	0.000	4.185	22.804
Loan:					
Relationship	0.663	0.474	0.000	1.000	1.000
Relative Loan Size	0.184	0.256	0.003	0.098	1.564
Loan Maturity	45.035	24.705	3.000	55.000	180.000
Log (Loan Maturity)	3.576	0.757	1.099	3.951	5.193
Size of Lending Syndicate	3.334	2.447	1.000	3.000	13.000
Loan Purpose – Acquisition	0.223	0.417			
Loan Purpose – Repayment	0.093	0.291			
Loan Purpose – Corporate	0.669	0.471			
Loan Purpose – Other	0.015	0.124			

Table 3 – Credit Risk Transfer (CRT) Decision

This table presents the choice of CRT by lenders of loan facilities related to US borrowers with available accounting and stock price information for which all lending syndicate participants are US banks and the borrower has a long-term issuer debt rating and a credit derivative market (323 loan facilities belonging to 202 borrowers). Data covers loans initiated between January 1, 2003 and December 31, 2007.

	Number	%		Number	%		Number	%
All Loans	323	100%	The lender has used a CRT mechanism	95	29.4%	CRT Choice: Only Sale	25	7.7%
						CRT Choice: Only CDS	64	19.8%
						CRT Choice: Both Sale and CDS	6	1.9%
			The lender has not used a CRT mechanism	228	70.6%			

Table 4 – Univariate Analysis

In this table we provide two groups of univariate analyses. In the first group we compare loans for which banks use a CRT instrument (sale, CDS or both) with other loans (unhedged loans retained on banks' balance-sheets). In the second group we compare loans that are sold to loans that are hedged by CDS. Panels A and B present the following statistics for mean differences: number of observations, mean, standard deviation, mean difference, t-statistic and its degree of significance. The sample includes all loan facilities related to US borrowers with available accounting and stock price information for which all lending syndicate participants are US banks and the borrower has a long-term debt rating and a credit derivative market. It covers loans initiated between January 1, 2003 and December 31, 2007. Two measures of lender's capital and liquidity constraint are used in this table. If a bank's both capital ratio and liquidity ratio fall within the lowest deciles when we sort all US banks in a year based on a capital ratio and a liquidity ratio then we assume the bank has more binding capital and liquidity constraints. The measure then will be assigned a value of 1 if the lending syndicate has at least a member with such constraints, and 0 otherwise. Variable definitions are provided in Table 1. *, **, and *** respectively shows significance at the 10%, 5% and 1% levels.

Panel 1- CRT Loans versus No CRT Loans

	CRT (N=95)		No-CRT (N=228)			
Variable	Mean	Std Dev	Mean	Std Dev	Diff	T-Stat
Borrower:						
Credit Rating	13.337 (BBB-)	3.645	11.702 (BB+)	3.316	1.635	3.77***
Market Size ($B)	17.101	35.76	3.642	7.689	13.458	3.634***
Log (Market Size)	22.481	1.475	21.0356	1.339	1.445	8.240***
ROA (Quarterly)	0.028	0.016	0.023	0.016	0.005	2.472**
Leverage	0.590	0.144	0.596	0.164	-0.006	-0.305
Market to Book	3.306	2.525	2.561	2.291	0.745	2.482**
Lender:						
Capital and Liquidity Constraint (Measure 1)	0.0526	0.224	0.026	0.160	0.026	1.038
Capital and Liquidity Constraint (Measure 2)	0.0737	0.263	0.035	0.184	0.039	1.305
Lender's Market Share (%)	7.1007	6.095	5.037	4.466	2.064	2.984***
Loan:						
Relationship	0.6632	0.475	0.662	0.474	0.001	0.015
Relative Loan Size	0.1327	0.205	0.205	0.272	-0.072	-2.600***
Loan Maturity	50.3804	28.768	42.780	22.467	7.601	2.260**
Log (Loan Maturity)	3.6760	0.777	3.534	0.746	0.142	1.511
Size of Lending Syndicate	3.242	2.314	3.373	2.504	-1.130	-0.442
Loan Purpose – Acquisition	0.305	0.463	0.189	0.392	0.117	2.314**
Loan Purpose – Repayment	0.116	0.414	0.083	0.277	0.033	0.915
Loan Purpose – Corporate	0.579	0.496	0.706	0.456	-0.127	-2.221**
Loan Purpose – Other	0.000	0.000	0.022	0.147	-0.022	-1.454

Panel 2- Sold Loans versus Loans Hedged by CDS

	Sale (N=25)		CDS (N=64)			
Variable	Mean	Std Dev	Mean	Std Dev	Diff	T-Stat
Borrower:						
Credit Rating	9.920 (BB-)	1.320	14.797 (BBB+)	3.447	-4.877	-9.651***
Market Size ($B)	2.490	2.701	23.576	41.931	-21.086	-4.002***
Log (Market Size)	21.069	1.106	23.048	1.251	-1.980	-7.308***
ROA (Quarterly)	0.016	0.010	0.033	0.015	-0.016	-5.752***
Leverage	0.563	0.176	0.599	0.133	-0.036	-0.923
Market to Book	2.445	1.612	3.667	2.783	-1.222	-2.577**
Lender:						
Capital and Liquidity Constraint (Measure 1)	0.120	0.332	0.031	0.175	0.089	1.27
Capital and Liquidity Constraint (Measure 2)	0.040	0.200	0.078	0.270	-0.038	-0.728
Lender's Market Share (%)	8.018	9.233	6.595	4.077	1.423	0.743
Loan:						
Relationship	0.480	0.510	0.734	0.445	-0.254	-2.19**
Relative Loan Size	0.226	0.185	0.095	0.209	0.131	2.882***
Loan Maturity	69.200	15.785	39.770	23.437	29.430	6.757***
Log (Loan Maturity)	4.207	0.261	3.427	0.785	0.780	7.018***
Size of Lending Syndicate	2.960	1.695	3.391	2.536	-0.431	-0.781
Loan Purpose – Acquisition	0.600	0.500	0.172	0.380	0.428	4.364***
Loan Purpose – Repayment	0.200	0.408	0.094	0.294	0.106	1.373
Loan Purpose – Corporate	0.200	0.408	0.734	0.445	-0.534	-5.213***
Loan Purpose – Other	0.000	0.000	0.000	0.000	0.000	NA

Table 5 – The Effect of Borrower and Lender Characteristics on Bank's Credit Risk Transfer Decision

The sample includes all loan facilities related to US borrowers with available accounting and stock price information for which all lending syndicate participants are US banks and the borrower has a long-term debt rating and a credit derivative market. It covers loans initiated between January 1, 2003 and December 31, 2007. In Panel 1, we use a logistic framework to test bank's decision to use CRT for a loan by considering borrower's credit quality, measured by long-term issuer debt rating, and bank's capital and liquidity constraint. If a bank's both capital ratio and liquidity ratio fall within the lowest deciles when we sort all US banks in a year based on a capital ratio and a liquidity ratio then we assume the bank has more binding capital and liquidity constraints. The measure then will be assigned a value of 1 if the lending syndicate has at least a member with such constraints, and 0 otherwise. In models (1) to (5), the measure is constructed based on the capital ratio of Equity Capital to Total Long-term Liabilities, and the liquidity ratio of Net Federal Funds Sold divided by total short term noncore funding. In model (6) we use an alternative measure as robustness check: Total Risk Based Capital to Total Risk Weighted Assets as the capital ratio and Short-term Assets to Short-term Liabilities as the liquidity ratio. In Panel 2, we use a logistic framework to test bank's decision to use Sale versus CDS conditioning on the bank decides to use a CRT instrument. Models (1) to (4) use the first measures and Model (5) uses an alternative measure of capital and liquidity constraint. The results for non-revolvers are not presented in Panel 2 due to sample size issues. Standard errors are clustered for borrower and time effects in all models. Variable definitions are provided in Table 1. *, **, and *** respectively shows significance at the 10%, 5% and 1% levels.

Panel 1: CRT versus no CRT, all loans

	Measure 1 of Capital and Liquidity Constraint					Measure 2
	All Observations				Non-revolvers	All Observations
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Borrower's Credit Rating	-0.079 (0.050)	-0.093* (0.051)	-0.092* (0.054)	0.012 (0.063)	-0.040 (0.098)	0.020 (0.063)
Log (Borrower's Market Size)	0.844*** (0.130)	0.921*** (0.137)	0.936*** (0.143)	0.094*** (0.160)	0.750*** (0.223)	0.904*** (0.159)
Lender's Capital and liquidity constraint		1.976*** (0.696)	2.175*** (0.721)	2.346*** (0.809)	1.949* (1.164)	1.700** (0.674)
Lender's Market Share (%)			0.085*** (0.027)	0.108*** (0.032)	0.109** (0.044)	0.103*** (0.033)
Borrower and Contract Controls:						
ROA			-3.765 (11.789)	-5.410 (12.482)	-11.703 (16.454)	-4.327 (12.893)
Leverage			-0.052 (1.046)	0.198 (1.132)	-0.647 (1.599)	-0.055 (1.126)
Market to Book			-0.006 (0.070)	0.022 (0.071)	0.110 (0.112)	0.005 (0.072)
Relationship				-0.630* (0.352)	-0.826** (0.497)	-0.620* (0.349)
Relative Loan Size				0.471 (0.743)	0.496 (0.895)	0.470 (0.733)
Log (Loan Maturity)				0.560*** (0.214)	0.672** (0.276)	0.577*** (0.214)
Clustered for Borrower Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Clustered for Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	Yes$^{\alpha}$	Yes$^{\alpha}$	Yes$^{\alpha}$
N Of Obs	323	323	323	323	150	323
Wald	50.49***	53.639***	59.317***	66.028***	27.795**	65.185***
R-Square	0.186	0.205	0.229	0.283	0.257	0.279

Panel 2: Sale versus CDS, Hedged (CRT) loans

	Measure 1 of Capital and Liquidity Constraint				Measure 2
Variable	(1)	(2)	(3)	(4)	(5)
Borrower's Credit Rating	-0.443**	-0.477**	-0.657**	-1.111*	-0.119*
	(0.189)	(0.202)	(0.289)	(0.591)	(0.620)
Log (Borrower's Market Size)	-0.682*	-0.585	-0.393	-0.233	-1.451
	(0.383)	(0.419)	(0.561)	(1.093)	(1.567)
Lender's Capital and Liquidity Constraint		0.799	0.330	-1.981	-5.981
		(1.424)	(1.788)	(2.287)	(3.897)
Lender's Market Share (%)			0.110*	0.049	-0.086
			(0.064)	(0.127)	(0.158)
Borrower and Contract Controls:					
ROA			-118.081**	-189.014**	-251.020**
			(51.322)	(97.407)	(112.411)
Leverage			-13.176***	-16.320*	-14.800*
			(4.936)	(8.998)	(8.140)
Market to Book			0.668**	1.323**	1.531**
			(0.276)	(0.609)	(0.661)
Relationship				0.739	1.233
				(1.508)	(1.641)
Relative Loan Size				-1.049	-1.407
				(1.482)	(4.592)
Log (Loan Maturity)				2.606*	3.965*
				(1.581)	(2.112)
Clustered for Borrower Fixed Effect	Yes	Yes	Yes	Yes	Yes
Clustered for Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	No	Yes[α]	Yes[α]
N Of Obs	89	89	89	89	89
Wald	20.761***	20.567***	19.589***	11.748	11.322
R-Square	0.400	0.403	0.501	0.584	0.599

[α] The results are qualitatively the same when we remove other loan controls including the size of lending syndicate and fixed effects for loan purpose (acquisition, debt repayment, corporate, other). We exclude the controls that do not have a significant effect from reported robustness regressions (next tables) due to the small sample size in the regressions and to avoid potential econometric problems.

Table 6 – Utility Maximized Nest Logit Models

Table reports random utility models of the choice of CRT instrument for each facility. Two models are presented. Each model is different with respect to the choice of lender's capital and liquidity constraint measures. The sample includes all the loan facilities in this study and their set of possible CRT alternatives. The set of possible CRT alternatives include retention (the bank keeps the loan and associated risk on the balance sheet), CDS (the bank use CDS to hedge the credit risk of loan), sale (the bank sells all or part of the loan), and both (the bank use a combination of loan sale and CDS to hedge against the loan's credit risk). Each facility has one selected alternative and three rejected alternatives. The nested logit in this table has two levels. Level 1 is the choice of CRT instrument (Retention, CDS, Loan Sale, Both). Level 2 is the nest level, representing the decision of CRT versus No-CRT. Of the choices in Level 1, CDS, Loan Sale and Both belong to the nest CRT in Level 2, and Retention belongs to the nest No-CRT. Figure 2 provides a schematic presentation of the choice structure. *, **, and *** respectively shows significance at the 10%, 5% and 1% levels.

	Measure of Capital and Liquidity Constraint	
Parameters	Measure 1	Measure 2
Level 1 (Choice Level) Attributes		
Borrower's Credit Rating * Sale	-0.333* (0.185)	-0.342* (0.190)
Borrower's Credit Rating * CDS	0.428*** (0.128)	0.426*** (0.129)
Log (maturity) * Sale	1.193** (0.481)	1.216** (0.493)
Log (maturity) * CDS	-0.820** (0.385)	-0.817** (0.387)
Level 2 (Nest Level) Attributes		
Lender's Capital and Liquidity Constraint * CRT	1.273** (0.598)	1.504** (0.714)
Lender's Market Share (%) * CRT	0.107*** (0.028)	0.107*** (0.208)
Relationship * CRT	-0.408 (0.292)	-0.379 (0.291)
Borrower's Log (Market Size) * CRT	-0.048** (0.023)	-0.046** (0.023)
Relative Loan Size * CRT	-1.826** (0.736)	-1.977*** (0.757)
Inclusive Value Parameter 1	1.273 (.)	1.439 (.)
Inclusive Value Parameter 2	0.196 (0.139)	0.178 (0.134)
- Log Likelihood	230.302	230.361
Number of Observations	1,292	1,292
Number of Cases	323	323

Table 7 – The Effect of Borrower and Lender Characteristics on Bank's Credit Risk Transfer Decision – Distinguishing between Lead Banks and Other Syndicate Participants

The sample includes all loan facilities related to US borrowers with available accounting and stock price information for which all lending syndicate participants are US banks and the borrower has a long-term debt rating and a credit derivative market. It covers loans initiated between January 1, 2003 and December 31, 2007. In the first four models, we use a logistic framework to test bank's decision to use CRT for a loan by considering borrower's credit quality, measured by long-term issuer debt rating, and bank's capital and liquidity constraint. If a bank's both capital ratio and liquidity ratio fall within the lowest deciles when we sort all US banks in a year based on a capital ratio and a liquidity ratio then we assume the bank has more binding capital and liquidity constraints. The measure then will be assigned a value of 1 if the lending syndicate has at least a member with such constraints, and 0 otherwise. A similar variable constructed with the exception that the lender has to be the lead lender in the loan facility. In models (1), (2), (5) and (6), the measure of lender's capital and liquidity constraint is constructed based on the capital ratio of Equity Capital to Total Long-term Liabilities, and the liquidity ratio of Net Federal Funds Sold divided by total short term noncore funding. In models (3), (4), (7) and (8) we use Total Risk Based Capital to Total Risk Weighted Assets (capital ratio), and Short-term Assets to Short-term Liabilities (liquidity ratio). Standard errors are clustered for borrower and time effects in all models. Variable definitions are provided in Table 1. *, **, and *** respectively shows significance at the 10%, 5% and 1% levels.

	CRT versus No-CRT				Sale versus CDS conditioning on CRT			
	Measure 1		Measure 2		Measure 1		Measure 2	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Borrower's Credit Rating	-0.027 (0.058)	-0.038 (0.059)	-0.026 (0.058)	-0.023 (0.059)	-0.999** (0.445)	-0.986** (0.483)	-1.176** (0.570)	-0.822* (0.429)
Log (Borrower's Market Size)	0.933*** (0.150)	1.013*** (0.155)	0.927*** (0.147)	0.966*** (0.151)	0.780 (0.764)	0.332 (0.798)	0.692 (0.778)	-0.567 (0.944)
Lender's Capital and Liquidity Constraint		1.383* (0.802)		2.278* (0.705)		-0.976 (2.417)		-14.894 (287.9)
Lead Lender's Capital and Liquidity Constraint	0.092 (0.561)	16.420 (105.59	-0.167 (0.457)	0.744 (1.593)	12.599 (359.6)	12.685 (601.5)	2.423 (2.129)	24.516 (1001.3)
Lender's Market Share (%)	0.095*** (0.027)	0.110*** (0.031)	0.098*** (0.031)	0.099*** (0.030)	0.069 (0.086)	0.104 (0.094)	0.056 (0.082)	0.062 (0.097)
Borrower and Contract Controls:								
ROA	-3.082 (12.210)	-0.543 (12.363)	-3.209 (12.229)	-2.918 (12.386)	-199.9** (84.656)	-177.5** (80.620)	-178.3** (83.127)	-193.5** (81.601)
Leverage	-0.161 (1.080)	0.001 (1.109)	-0.174 (1.080)	-0.202 (1.095)	-12.692* (7.709)	-15.071* (8.414)	-15.814* (8.781)	-11.520 (7.244)
Market to Book	0.001 (0.067)	-0.025 (0.071)	-0.001 (0.068)	-0.015 (12.386)	1.058*** (0.404)	1.058*** (0.422)	1.124** (0.447)	1.014*** (0.379)
Relationship	-0.685** (0.335)	-0.839** (0.346)	-0.687** (0.335)	-0.739** (0.336)	1.303 (1.563)	0.635 (1.522)	0.874 (1.469)	0.504 (1.597)
Relative Loan Size	0.782 (0.694)	0.649 (0.734)	0.776 (0.264)	0.895 (0.700)	1.071 (4.248)	0.516 (4.443)	1.974 (3.940)	-0.932 (5.134)
Log (Loan Maturity)	0.490** (0.207)	0.432** (0.209)	0.479** (0.209)	0.502** (0.210)	4.225** (2.076)	3.678** (1.775)	4.396** (2.066)	4.174** (2.070)
Clustered for Borrower Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered for Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Of Obs	323	323	323	323	84	84	84	84
Wald	60.450***	64.095***	60.498***	61.490***	11.770	12.400	11.572	12.664
R-Square	0.239	0.270	0.239	0.250	0.566	0.560	0.564	0.590

Table 8 – The Effect of Borrower and Lender Characteristics on Bank's Credit Risk Transfer Decision – Restricting to Bank Lenders with Clear Evidence of Involvement in the Loan Sale and Credit Derivative Markets

Banks might report items on their call reports regarding their activities in the loan sale and credit derivative markets. In this table we only consider bank lenders who report a positive amount of loans held for sale a positive amount for credit derivative holdings during the period in which they extend a loan. These items are extracted from balance-sheet (loans held for sale) or off-balance sheet (credit derivatives) sections of banks' call reports. The sample includes all loans with at least one bank with clear involvement in both CRT markets. In the first two columns, we use a logistic framework to test bank's decision to use CRT for a loan by considering borrower's credit quality, measured by long-term issuer debt rating, and bank's capital and liquidity constraint. In the next two columns, we use a logistic framework to test bank's decision to use Sale versus CDS conditioning on the bank decides to use a CRT instrument. In models (1) and (3), the measure of lender's capital and liquidity constraint is constructed based on the capital ratio of Equity Capital to Total Long-term Liabilities, and the liquidity ratio of Net Federal Funds Sold divided by total short term noncore funding. In models (2) and (4) we use Total Risk Based Capital to Total Risk Weighted Assets (capital ratio), and Short-term Assets to Short-term Liabilities (liquidity ratio). Standard errors are clustered for borrower and time effects in all models. Variable definitions are provided in Table 1. *, **, and *** respectively shows significance at the 10%, 5% and 1% levels.

	CRT versus No-CRT		Sale versus CDS conditioning on CRT	
Variable	(1)	(2)	(3)	(4)
Borrower's Credit Rating	-0.104 (0.068)	-0.094 (0.068)	-2.957* (1.608)	-4.125 (5.622)
Log (Borrower's Market Size)	1.067*** (0.176)	1.008*** (0.172)	-0.153 (1.837)	-5.302 (12.510)
Lender's Capital and Liquidity Constraint	2.673*** (0.829)	1.657** (0.705)	-1.600 (3.654)	-23.742 (34.376)
Lender's Market Share (%)	0.111*** (0.034)	0.100*** (0.034)	0.244 (0.236)	0.235 (0.682)
Borrower and Contract Controls:				
ROA	-3.205 (13.708)	-0.514 (14.272)	-329.5* (198.3)	-1090.2 (1350.8)
Leverage	-0.355 (1.276)	-0.839 (1.265)	-37.121 (24.735)	-71.474 (77.327)
Market to Book	0.032 (0.078)	0.028 (0.078)	2.777** (1.318)	5.560 (4.148)
Relationship	-0.319 (0.411)	-0.328 (0.400)	4.240 (3.101)	4.624 (11.549)
Relative Loan Size	-0.084 (0.997)	0.134 (0.964)	9.168 (8.039)	-1.225 (32.702)
Log (Loan Maturity)	0.322 (0.239)	0.374* (0.208)	3.421 (5.544)	13.964 (21.428)
Clustered for Borrower Fixed Effect	Yes	Yes	Yes	Yes
Clustered for Time Fixed Effect	Yes	Yes	Yes	Yes
N Of Obs	253	253	55	55
Wald	54.964***	52.597***	6.334	2.492
R-Square	0.286	0.274	0.622	0.679

Table 9 – The Effect of Borrower and Lender Characteristics on Bank's Credit Risk Transfer Decision – Robustness definition for CDS hedge

CDS spreads around loan initiation can rise because of an increase in demand by the parties that face more exposure to firm's credit risk as a result of the new loan, or because of an unrelated change in firm-level fundamentals around loan initiation. In this table, we use an alternative measure of CDS use. We do not consider an increase in a firm's CDS demand that is accompanied with an abnormal stock return (as a measure of change in firm fundamentals) around loan initiation, an indication that lenders have used CRT, and specifically CDS to hedge loans. The sample includes all loans in this study. In the first two columns, we use a logistic framework to test bank's decision to use CRT for a loan by considering borrower's credit quality, measured by long-term issuer debt rating, and bank's capital and liquidity constraint. In the next two columns, we use a logistic framework to test bank's decision to use Sale versus CDS conditioning on the bank decides to use a CRT instrument. In models (1) and (3), the measure of lender's capital and liquidity constraint is constructed based on the capital ratio of Equity Capital to Total Long-term Liabilities, and the liquidity ratio of Net Federal Funds Sold divided by total short term noncore funding. In models (2) and (4) we use Total Risk Based Capital to Total Risk Weighted Assets (capital ratio), and Short-term Assets to Short-term Liabilities (liquidity ratio). Standard errors are clustered for borrower and time effects in all models. Variable definitions are provided in Table 1. *, **, and *** respectively shows significance at the 10%, 5% and 1% levels.

	CRT versus No-CRT		Sale versus CDS conditioning on CRT	
Variable	(1)	(2)	(3)	(4)
Borrower's Credit Rating	-0.027 (0.058)	-0.035 (0.059)	-0.869* (0.469)	-0.983*** (0.500)
Log (Borrower's Market Size)	0.968*** (0.151)	1.016*** (0.154)	-0.566 (0.972)	0.405 (0.789)
Lender's Capital and Liquidity Constraint	1.408* (0.645)	2.271*** (0.760)	-4.103 (2.421)	-0.428 (2.237)
Lender's Market Share (%)	0.098*** (0.030)	0.102*** (0.030)	0.068 (0.094)	0.083 (0.083)
Borrower and Contract Controls:				
ROA	-2.792 (12.364)	-4.130 (11.972)	-193.679** (82.688)	-182.691** (80.474)
Leverage	-0.238 (1.090)	0.009 (1.100)	-13.735* (7.765)	-16.428* (9.045)
Market to Book	-0.014 (0.069)	-0.009 (0.069)	1.048*** (0.396)	1.056** (0.433)
Relationship	-0.741** (0.336)	-0.742** (0.341)	0.405 (1.480)	1.055 (1.406)
Relative Loan Size	0.885 (0.700)	0.841 (0.714)	-0.625 (4.580)	1.534 (3.912)
Log (Loan Maturity)	0.494** (0.209)	0.474** (0.209)	4.035** (2.006)	3.779** (1.779)
Clustered for Borrower Fixed Effect	Yes	Yes	Yes	Yes
Clustered for Lender Fixed Effect	Yes	Yes	Yes	Yes
N Of Obs	323	323	84	84
Wald	61.235***	63.356***	11.877	11.745
R-Square	0.249	0.257	0.585	0.563