Why and How Do Banks Lay Off Credit Risk?

The Choice between Loan Sales versus Credit Default Swaps

Mehdi Beyhaghi

PhD candidate in Finance, Schulich School of Business, York University

Nadia Massoud*

Associate Professor of Finance, Schulich School of Business, York University

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Please address all correspondence to Mehdi Beyhaghi, Finance Department, Schulich School of Business, York University, 4700 Keele St., Toronto, Ontario M3J 1P3, Canada Tel: (416) 736-2100 ext. 77911, e-mail: mbeyhaghi06@schulich.yorku.ca

Abstract

This paper investigates why banks use different credit risk transfer (CRT) instruments to hedge the credit risk of syndicated loans. We examine banks' decision to insure, sell or continue to hold a loan by considering the specific characteristics of both lenders and borrowers. We find that loans to borrowers with low credit quality are more likely to be sold in the secondary loan markets while loans to those with high credit quality are more likely to be hedged using credit default swaps, which are consistent with the predictions of theoretical literature. Interestingly, we find that bank lenders are more likely to use loan sales for low credit quality borrowers regardless of their binding financial or regulatory constraints. Additionally, we find that bank lenders are more likely to use CDS as a hedge instrument for relatively good quality borrowers especially if monitoring costs are relatively high. Finally, when we investigate reputable lenders with no financial and regulatory constraints, we find that these lenders are not significantly different from other lenders in choosing CRT instruments, which is inconsistent with the predictions of the theoretical literature.

Key Words: Credit Risk, Loan Sales, Credit Default Swaps, Syndicate Loans, Hedging

JEL Classifications: G21, G32

I. Introduction

As the banking industry has come under increasing scrutiny during the recent financial crisis, one of the most heated public debates has been about the deterioration in the quality of bank loans. This issue is addressed in an article in the New York Times in May 2009: "[The] overall loan quality at American banks is the worst in at least a quarter century, and the quality of loans is deteriorating at the fastest pace ever, according to statistics released this week by the Federal Deposit Insurance Corporation"[1]. Concerns have been particularly raised about how banks perceive and manage the credit risks associated with their loan portfolios. These concerns are further frustrated by discerning the recent explosive growth in the credit derivative and the loan sale markets which has equipped the banking industry with a variety of tools to lay off their credit risk.[2]

Despite the severe concerns about how banks manage their credit risks, very few theoretical studies and empirical work have investigated this issue. One important relevant question that is still unanswered by empirical research is that under what circumstances a bank would lay off its credit risk using loan sales versus Credit Default Swaps (CDS)? This paper aims to fill this gap by taking in consideration the special characteristics and constraints of borrowers as well as their lenders.

The theoretical literature addresses this issue by investigating (i) why do banks use credit risk transfer (CRT) for some of the loans?, and (ii) if banks choose to use CRT, why do they

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[1] "Troubled Bank Loans Hit a Record High", Floyd Noriss, Off the Charts, The New York Times, May 29, 2009

[2] The Loan Syndications and Trading Association (LSTA) (2007) reports that since the 1990s the secondary loan market has grown at an exponential rate in both the par and the distressed areas. In the fourth quarter of their 2009 report, Thomson Reuters LPC states that leverage loan lending issuance reached over $400 billion in 2007. The market size of Credit Default Swaps, the other main venue for trading credit risk, has grown even more rapidly. This market had a notional value of $45 trillion in 2007 (ISDA Market Survey year-end 2008)

choose loan sales versus CDS? A handful of seminal papers provide different and even conflicting explanations/predictions for these two questions. On one hand, Duffee and Zhou (2001); and Parlour and Winton (2008) state that the quality of the loans, the costs of monitoring, and the status of the borrower are the main factors influencing banks' decision to lay off credit risk. On the other hand, Pennacchi (1988); Allen and Carletti (2006); and Thomson (2008) believe that binding financial and regulatory restrictions of the banks, specifically regulatory capital ratio or liquidity, might induce banks to use CRT. The latter view is justified by the fact that banks must act within certain restrictions imposed by regulatory bodies and/or liquidity needs of depositors. Berndt and Gupta (2009); and Purnanandam (forthcoming) provide another explanation. They show that banks use the CRT markets, especially the secondary market, to play a new role as a dealer that originates loans, earns origination fees and transfers them to new owners. In summary, the existing theoretical literature cannot reach a consensus over whether it is either the characteristics of the lenders, or the characteristics of the borrower, or a combination of these characteristics that determines the bank's choice of CRT instruments.

This is the first paper to empirically investigate this question by using a unique dataset that incorporates both the lenders' characteristics (for example, capital constraint, cost of capital, liquidity, reputation, and etc.) and the borrowers' characteristics (for example, their credit quality, profitability, and etc). Unlike previous empirical studies that mainly focus on the benefits/losses of CRT for borrowers (see for example Drucker and Puri, 2009), one of the main foci of this paper is to investigate the aforementioned issues from the lenders' perspective.[3] To

[3] Most of previous studies in the field of CRT, especially the secondary market, focus on the benefits/losses of CRT for borrowers. Some of their results are controversial however. Dahiya, Puri and Saunders (2003) find significant negative stock returns for the borrower on the loan sale announcement. Berndt and Gupta (2009) show borrowers whose loans are sold underperform their peers significantly over three years after first loan sale. Duffee (2009) however blames the peer selection process in this paper. Drucker and Puri (2009) show that borrowers whose loans are sold are more likely to receive loans in the future from the original lead lenders. Gande and Saunders (2009)

incorporate the borrowers' and the lenders' characteristics in the banks' decision making process, we merge five different datasets including Loan Pricing Corporation's primary loan market, loan sales, credit default swaps transactions, COMPUSTAT (financial accounting data for borrowers), and quarterly financial statement (call reports) filled with Federal Depository Insurance Corporation (financial accounting data for banks).

Investigating why and how banks lay off the credit risk associated with their loan portfolios has important implications for regulatory bodies. In particular, it provides explanations to what extent banks are responsible for the deteriorating quality of loans and for the financial crisis, and whether the usage of CRT instruments is appropriate. An arising important question from the regulatory bodies' perspective is: do lending banks participate in CRT for hedging purposes or for exploiting their private information about the borrowers?[4] The focus of this paper is to investigate the reasons of banks' choices of CRT rather than its consequences. Since banks are repeated players in private debt markets, we also examine the impact of the bank's reputation on CRT choices.

In light of the predictions of the theoretical literature we propose four hypotheses. To examine each hypothesis we consider at least three possible CRT choices banks have to manage credit risk associated with syndicate loans originated by them: loan sale, loan insurance (CDS), or none. In our investigation we consider a variety of methodologies including: univariate tests, logistic regressions, and multinomial logit models.

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argue that a benefit of trade in the secondary market to the borrower firm is that it could alleviate the borrower's financial constraint. Aligned with their findings, Kamstra, Roberts and Shao (2010) provide evidence that for low quality borrowers, the benefits of access to cheap funding, overweight the costs of reduced monitoring efforts following the loan sale.

[4] Another related question from regulatory perspective is; what are the negative consequences of banks' participations in the CRT markets? This question is about the severity and magnitude of moral hazard and adverse selection problems that arise from lenders' lack of incentive to further monitor the borrowers after transferring their credit risk which is investigating by Berndt and Gupta (2009) and Purnanandam (forthcoming).

Supporting some of the theoretical predictions, our results show that loans to low credit quality borrowers are more likely to be hedged using loan sales rather than CDS. Interestingly, we find that bank lenders sell the loan of the low credit quality borrowers regardless of their binding financial or regulatory constrains. These results are also consistent with the view that banks play a new role as intermediaries between highly leveraged borrowers and investors with high appetite for risk.[5] Moreover, we find that bank lenders are more likely to use CDS as a hedge instrument for relatively good quality borrowers especially if monitoring costs are relatively high which is consistent with Parlour and Winton (2008)'s model predictions. Finally, inconsistent with the Parlour and Winton's (2008) model prediction, we find partial support to their theoretical prediction; reputable bank lenders are less likely to use CRT instruments for high quality borrowers especially if their financial or regulatory constraints are not binding. In particular, our results show that CRT instruments are less likely to be used for high quality borrowers, however, our results are not supported for reputable lenders with no binding financial or regulatory constraints.

The remainder of the paper is organized as follows: Predictions from the related Theoretical Literature and the Associated Hypotheses are discussed in Section II, Data Description and Sample Selection are presented are discussed in section III, and Methodology and Results are presented in section IV, and Section V provides the Conclusion.

II. Predictions from the related Theoretical Literature and the Associated Hypotheses

In this section, we discuss some of the related predictions of the theory models and outline the associated testable hypotheses. In a seminal paper Duffee and Zhou (2001) provide a

[5] Gande and Saunders (2009) also point out to the alleviation of financial constraints as a benefit to borrowers.

novel theoretical model incorporating both loan sale and credit derivative markets. Their model predicts that when there is no credit derivative market, high-quality and low-quality loans are hedged by loan sale. In the existence of adverse selection, loan buyers treat good and bad loans alike; therefore it is costly for the holders of good loans to enter the sale market. With the introduction of credit derivatives, banks that hold high-quality loans may choose to hedge part of their risk with credit derivatives, destroying the pooling equilibrium in the loan-sale market. If adverse selection cost is severe, their model predicts that banks use the credit derivative markets for good loans and the secondary loan market for bad loans. As a result, the secondary loan sale market may cease to exist. On the other hand, Parlour and Winton's (2008) predicts that when the credit quality of a borrower is low, loan sales are more likely to be used than insurance, because monitoring is particularly important for the low quality borrower. This model assumes that new loan owners have an ability to monitor the borrower; although less perfectly than the original lenders, but in the derivative markets the risk buyers do not have that ability. Therefore lenders prefer loan sale over insurance for low credit quality borrowers (monitoring equilibrium). As you can see, given the credit quality of the borrower, the two theoretical models predict similar hedge instruments but they disagree on the lenders' motives of hedging. In addition, all models predict that the secondary loan market may only exist if the information asymmetry cost is very minimal. Observing the coexistence of the two markets, the empirical regulatory support this views as well, implies that the information asymmetry cost is very minimal. Accordingly, our first hypothesis states that:

H1: Bank lenders are more likely to use loan sales versus CDS as a hedge instrument for low quality borrowers.

Next, we further investigate the importance of binding financial and regulatory constraints in the banks' choice of loan sales as a hedging instrument for low credit quality borrowers. Although the theoretical literature pays special attention to these constraints the empirical evidence does not support these predictions. Drucker and Puri (2009) show that sold loans are more likely to be traded shortly after initiation and those borrowers are more likely to receive loans in the future from the original lead lenders. Accordingly, an unexpected change in capitalization or liquidity between initiation and sale is less likely. In addition, empirical regulatory shows that the level of regulatory capital for the banking industry is on average significantly higher than minimum requirements (see for example Allen, Carletti and Marquez, forthcoming). Moreover, the majority of banks active in the primary market are very large banks, and they act as an intermediary between lenders and investors with huge appetite for credit risk for the highly leveraged loans. These loans are mostly originated-to-distribute, see also Gupta, Singh and Zebedee (2008).[6] Therefore, we hypothesis that binding financial or regulatory constraints play less important role in the decision of the lender to sell these loans. Accordingly, our second hypothesis states that:

H2: Bank lenders are more likely to use loan sales for low credit quality borrowers regardless of their binding financial or regulatory constraints.

With respect to monitoring costs, in general, banks prefer not to use CRT for high credit quality loans and instead they monitor the borrowers themselves. However, if monitoring costs are high they might use CRT instruments. Parlour and Winton (2008)'s model predicts that CDS is more likely to be used for cases in which monitoring cost is high for relatively high credit quality borrower. In their model loan sale does not have any advantage in the existence of high

[6] Ross (forthcoming RFS) shows three large banks control over half of the US commercial loan market.

monitoring costs, because the new loan buyers also will not have an incentive to monitor after they perceive costs are high, i.e. there is no monitoring equilibrium in the secondary market. Additionally, hedging using CDS allows the transaction to remain anonymous to the borrower so lender-borrower relationship is not affected directly.[7] Accordingly, we hypothesis that CDS is more likely to be used as a hedging instrument especially for loans with high monitoring costs and relatively good credit quality. Our third hypothesis states that:

H3: Bank lenders are more likely to use CDS as a hedge instrument for relatively good quality borrowers especially if monitoring costs are relatively high.

Parlour and Winton's (2008) provide more thorough analysis for the usage of CDS for good credit quality borrowers. In particular, they argue that when the quality of the borrower is relatively high, banks prefer not to use CRT. The reason is that a history of defaults on loans to a bad borrower is not a clear signal that banks did not perform good monitoring. However, a history of defaults on good borrower loans would be perceived by the market as a signal of banks' low ability to monitor, or the lack of incentive to monitor due to the hedging of the credit risk. This perception by the market has a negative reputation effect for banks. Therefore, banks choose not to use the credit risk transfer markets when their loan belongs to a good borrower. They prefer to monitor the borrower themselves. They suggest that only when the cost of capital, or the cost of monitoring the borrower is sufficiently high the lender might use CDS for a loan to a borrower with high credit quality. Accordingly, our fourth hypothesis states that:

[7] Minton, Stulz and Williamson (2009) by looking at the use of credit derivatives by US bank holdings, ask a relevant question: "How much do banks use credit derivatives to hedge loans?" They find that lemons problem has made the CDS market not a very popular tool for risk hedging of low quality loans as the protection seller is always concerned that lenders want credit protection because they have adverse information about the borrower on which they want to buy protection. Therefore banks try CDS market when its borrower is of a high credit quality with a credit rating since adverse selection problems is minimal.

H4: Reputable Bank lenders are less likely to use CRT instruments for high quality borrowers especially if their financial or regulatory constraints are not binding.

III. Data and Sample Selection

In this section we provide a detailed discussion about how we construct our sample from combining five different databases including: primary loan data from Reuters Loan Pricing Corporation's Dealscan, the borrower financial reporting from compustat, lender financial reporting from call reports, loan sale data from secondary loan pricing data and Credit Default Swap data from Markit CDS dataset. In addition, we explain the construction of our key variables.

III.1. Primary Loan Data

Our primary dataset for this study comes from Reuters Loan Pricing Corporation's Dealscan (Henceforth LPC). LPC provides comprehensive information on the majority of US syndicated loan contract terms at deal and facility (loan) levels. It also provides the identities of the borrower and lenders. Our sample period is from January1, 2005 to December 31, 2008, in order to be consistent with the availability of our CDS sample (2006-2008). LPC Sample includes 64,221 facilities (loans)[8]. This number of facilities belongs to 41,883 deals (packages). Each deal consists of one or more facilities with different terms and lender structures packaged as one deal. After eliminating all non-North American issuers (borrowers) and those facilities for which the facility amount is not in $US currency, the sample size drops to 24,643 facilities related to 16,132 deals. We omit facilities without lender information then match borrowers of the remaining facilities with COMPUSTAT through a combination of different matching criteria

[8] Also called tranches

including company name, location (state, city, and postal code), ticker, and fiscal year. As a result, we have 2,818 issuers with unique gvkeys and 7,919 facilities related to 5,679 deals remained. Each facility can have one or more lenders. Our final sample includes 61,263 facility-lender relationships and the total number of lenders in our sample is 2,052.

Our analysis is performed at the facility (loan) level not deals as the secondary loan dataset is at the facility levels (facilities are actually traded in the secondary markets not deals) following the approach of Drucker and Puri (2009), Bushman, Smith and Wittenberg-Moerman (2009) and Wittenberg-Moerman (2008). We found that 3,940 deals (about 69% of all deals) are refinancing deals.[9] Our key variables for loan Characteristics include loan amount (we have used natural log of loan amount), being secured/unsecured, number of lenders, number of relationship banks and other characteristics. Table 1, Panels A and B provides some summary statistics at the deal (package) level. Descriptive statistics at the facility (loan) level can be found in Table 2. Variable definitions are presented in the Appendix A.

II.2. Borrower Data

The borrowers' financial information is obtained from Compustat-Fundamentals Quarterly dataset. To ensure that we use most recent accounting information available at the time of loan initiation, we use the accounting data related to the last quarter before facility activation date. Our key variable for borrower characteristic is credit quality. For credit quality we consider two alternative measures S&P's long term and short term issuer credit ratings (ICR). These ratings are provided in a monthly frequency showing credibility of the underlying firm in

[9] Refinancing deals is hand checked from the borrowers filing with SEC forms 10K, 10Q or 8Ks (768 deals). This variable is important in controlling previous relationships between borrower and lenders.

fulfilling its long term or short term obligations.[10] Long-term refers to those loans with maturities of more than one year and short-term refers to maturities of one year or less. Long term ICRs range from AAA (extremely strong capacity to meet financial obligations) to CC (highly vulnerable). In our analysis we rank long term ratings from 22 to 1, where AAA receives 22 and CC receives 1. Short-term ICRs range from A-1 (strong capacity to meet financial obligations) to C (currently vulnerable). Likewise, we rank short-term credits from 10 (assigned to A-1) to 1 (assigned to C). Table 1, Panel C, provides our key variables of borrower characteristics and other control variables such as total assets, Asset Book Equity, and Market Equity.

III.3. Loan Sale Data

Our third dataset includes secondary loan pricing data and it is obtained from the Loan Syndications and Trading Association (LSTA). The dataset provides average bid and ask quotes, mean of average bid and ask quotes, number of quotes, date, type of facility, loan identification number and borrower name and ID. More details about this dataset are available in Bushman, Smith, and Wittenberg-Moerman (2009). We followed Drucker and Puri (2009) and Wittenberg-Moerman (2008) approach in merging the Loan Sale dataset with LPC primary loan dataset through using facility IDs and/or Loan Identification IDs (LINs). As shown in Table 2, Panel B, out of 7,919 facilities, we obtained the quotes of the 1,426 (18%) facilities that have been traded in the secondary loan market.

To keep record of the facilities that were potentially sold we create an indicator variable equals one for the loans that are potentially sold during the life of the loan contract (we call it

[10] As mentioned 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".

loan sale dummy). In general, if a loan has a record in the loan sale dataset (LSTA) then this is an indicator that there are some interests in trading these loans. Accordingly, our loan sale dummy is equal one when the loan facility has a record (a quote or multiple quotes) the LSTA dataset and zero otherwise. Our approach is similar to Drucker and Puri (2009).

II.4. Credit Default Swaps Data

Our forth dataset, including Credit Default Swap data, is obtained from Markit CDS dataset. Markit provides mark-to-market data for firms with sufficiently liquid CDS markets obtained from different market makers. CDS data are available by entity, term structure, currency and restructuring clause. The information provided at the contract level includes: CDS spread, credit ratings, and CDS across different credit event types, different seniority levels and in different currencies. It is important to note that the CDS trading volume is not provided by the database. CDS spread, quoted in basis points for the notional value of the contract, is the premium paid by the insurance buyer to the insurance seller. Its value depends on the contract's notional value, the recovery rate, the time to maturity, the nature of the credit event under which insurance is provided, the underlying firm's credit quality and lastly, the market microstructure factors. Spreads in the Markit dataset are composite. Sufficient number of price contributors must provide data per instrument to calculate a composite.[11] For the period from January 2, 2006 to November 17, 2008 there are 20,568,845 observations of which 7,059,689 observations are US dollar based. 3,840 single firms are identified in the sample[12]. These firms belong to 101 countries across the globe. Out of 3,840 borrowers in the whole CDS sample, 1,597 are US

[11] Field 'CompositeDepth5y' in the Markit dataset represents "The number of distinct contributors at the composite fallback level."

[12] By comparing to Hull, Predescu and White (2004)'s sample that covers the period from January 5, 1998 to May 24, 2002 with 233,620 observations and 1,599 named entities one can see how CDS market has grown exponentially over time.

borrowers[13]. Our main sample has 2,818 borrowers. Borrowers in both datasets are matched using combination of company names/first 8 letters of company names, with tickers. After each round of matching, the accuracy of match is rechecked manually. In total, 779 common borrowers were identified. Following Acharia and Johnson (2007) CDS transactions of five-year maturity, which are usually the most liquid across all maturities, with the underlying reference credit being senior unsecured is considered to be used in later analyses[14]. Moreover, the credit event under which the CDS contracts under this study are written is bankruptcy and with modified or without restructuring.[15] Our final sample includes 1,399 facilities with the relevant CDS transactions data.

We use the change in CDS spreads as a proxy for the lender trading activities to hedge its credit risk exposure. In general, when lenders issue new loans they might decide to 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 and as a result one would expect to observe an increase in the CDS spreads. Acharya and Johnson (2007) have also used this measure in their paper as an indication of lender banks trading on information related to a borrower credit quality.

To limit our measure to hedging in relation to the event of the loan origination, we consider the cumulative abnormal change in the CDS spread in a [-5, +30] trading day interval

[13] 332 are Japanese, 275 are from the United Kingdom, and the rest belong to Germany, Canada, France, and others.
[14] Achariya and Johnson (2007) mention CreditTrade as their data source. In our dataset seniority level is reported under the variable name ‘Tier’. We have chosen Tier=’SNRFOR’ which represents ‘Senior Unsecured Debt (Corporate/Financial), Foreign Currency Sovereign Debt (Government)’
[15] Markit CDS data based on how a CDS contract cover 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 is more frequently traded and used than others in North America, So we used MR as the main document clause type, and since we compare trades of each security by itself among different trading dates and not with other securities we used XR whenever MR was not available.

around the facility's initiation date. If cumulative abnormal change in spread during the event period is positive there is a possibility that the CDS has been used for hedging purposes. If the CDS cumulative abnormal change is negative we can be sure that the CDS is not used to hedge against the loan. The reason is that if banks want to hedge against a loan, the increase in the demand for the related CDS contracts will lead to positive cumulative spread change. We are using this proxy since the buyers and sellers of the CDS contracts and trade volumes are *not* available from this database.

One might argue that an observed positive cumulative abnormal spread change can be related to other market participants' increase in demand around loan initiation. This argument cannot be reasonable for the following reason; an increase in the demand by other participants is an indication that their perception about default probabilities has been affected by negative news and as a result they demand more insurance. However, there is no support in the literature that bank loan initiations are treated as bad news by the market participants. Alternatively, one might argue that market participants increase their demand of the CDS in anticipation of lender's potential hedging activities. In other words, those 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 exposure. Additionally, this view is consistent with our argument since those banks are more likely to hedge their loans.

A lender might enter the CDS market much before the event period. In that case, we consider this behaviour as speculation rather than hedging because the lender as an informed trader could predict future changes in borrower's credit quality therefore it has traded CDS before it really has experienced any relevant change in its loan portfolio that requires hedging. One might argue what if trading CDS contracts by a bank is related to another loan that the same borrower has issued with the lender right before the new loan. The probability of two consequent loan issuances with the same lender around specified event periods is very low as the lender tries to satisfy all the borrower's needs all at once in one loan package. (Our sample rules out this possibility). Another concern is related to cases in which the lender has hedged partly or fully against the new renegotiated loan in the CDS market much before the initiation date. If these cases exist in our sample they will make our results much weaker. In addition, in the multivariate analysis we control for renegotiated deals. Accordingly, this concern should not change our conclusions.

Our choice of +30 trading day as the end of the event period is to allow the lender enough time to hedge against its new contract with the borrower and to limit potential changes in borrower's quality (i.e. credit quality of borrower) that might have an impact on CDS spreads. Also, our choice of -5 trading days of the event period is to account for early hedging by lenders. We measure the abnormal change in CDS spread for each facility as the difference between change in 5 year spread from one trading date to next and the average change in 5 year spreads in the control period, where the control period is a 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]. Change is 5 year spread is calculated as follows:

$$\frac{\text{(spread on the trading date t – spread on the last trading date)}}{\text{(spread on the last trading date)} \times \text{(number of trading days between two dates)}}$$

As a result, the cumulative abnormal change is derived as sum of abnormal change during the event period.[16] After that, we create CDS hedging dummy which is a binary variable equals one

[16] If CDS is not traded in all trading days during event period, the cumulative abnormal change is normalized to create consistent comparisons. For example, for 30 trading days event period, a firm might have CDS spread data for

when cumulative abnormal CDS spread is positive and 0 otherwise. This binary variable would be our proxy for using CDS as a hedging instrument by lenders.

III.5. Lender Information

Most of the previous empirical work related to loan syndication has focused mainly on borrower characteristics. A handful of studies, however, have investigated only few features of the lead lender characteristics available from LPC Reuters database such as lending relationships, lenders' market share, reputation and type of lenders (see for example Bharath, Dahia, Saunders and Srinivasan 2009A, and B; Sufi, 2007; Güner, 2006; Drucker and Puri; 2009, Massoud, Nandy, Saunders and Song (forthcoming), and Kamstra, Roberts and Shao, 2010). The limited interest in the lender side characteristics in the empirical research is mainly due to the difficulty in matching the lenders names from LPC Reuters with other databases of lenders. The first challenge is related to the diversity of lenders in a syndicated loan. It varies from regulated industries such as commercial banking to less-regulated lenders such as hedge funds. This makes the comparison between lenders more difficult. Also having access to all private lenders is not possible. Secondly, there is no unique common numerical identifier for each lender in the different data bases. The matching is based on name, address and ticker if it was available. Accordingly, this matching has to be done manually. Thirdly, there is more than one participant lender for each loan facility.

This paper deals with these issues by focusing on loan deals extended *purely by banks*. We manually checked the identity of each bank from different databases. Secondly, to deal with the cases in which the facility has more than one lender we construct indices for the variable of

only 14 days out of 30 days. In cases similar to this, we multiply the 14 days cumulative abnormal changes in the CDS spread by 30/14 to make it comparable for 30 day window.

interest for each facility. For example, because this study focuses on financial and regulatory constraints of the lenders we construct a capital ratio index for each facility.

We collect the accounting data for banks from the Reports of Condition and Income forms that banks must file quarterly with the Federal Deposit Insurance Corporation (FDIC) under Section 1817(a)(1) of the Federal Deposit Insurance Act. This data are available from Bank Regulatory dataset on Wharton Research Data Services (WRDS).[17] As bank names are quoted differently on different datasets, we need to use bank unique identifications such as RSSD IDs to match different datasets. The RSSD ID is a unique identifier assigned to institutions by the Federal Reserve. Available information about Lenders' RSSD identification numbers were extracted from the National Information Center manually.[18] If we cannot match banks from our loan dataset to Bank Regulatory dataset directly we move upward in the hierarchy of bank's parents and use the information of the first parent that can be matched. Thereafter we look up each RSSD in WRDS' Bank Regulatory Dataset either in the commercial bank section or Bank Holding Section to extract the most recent Quarterly Accounting Data before each loan initiation.

Our major key financial variables at the lender level include financial risk and capitalization and measures of liquidity. Our accounting data refers to the latest quarter preceding the facility activation date. In general, if the facility has more than one lender we construct indices for the variable of interest for each facility where we multiply the key variable

[17] The original formats of reports are provided by the Board of Governors of the Federal Reserve Systems. The reports that are used in this paper are either "Consolidated Reports of condition and Income for A Bank with Domestic and Foreign Offices" or "Consolidated Financial Statements for Bank Holding Companies".

[18] 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."

by the lender's share in the loan. For the financial risk and capitalization measures, we consider two alternative measures including *"Lender Capitalization (Tier1)"* and *"Lender Capitalization (Tier1and 2)"*. *Lender Capitalization (Tier1)* is measures as a weighted Average Lenders' Tier1 in a loan facility, where weights are shares of lenders in the facility if stated by LPC, otherwise each lender receives equal weights. *Lender Capitalization (Tier1and2)* is measured as a weighted Average Lenders' Tier1and 2 in a loan facility. For financial constraints measures we consider two alternative measures "*Lender Illiquidity"* and "Lender Liquidity". *Lender Illiquidity* is measured as the ratio of net loans to deposits times 100. *Lender Liquidity* equals the ratio of liquid Assets to deposits. Appendix A provides detailed description of these variables and Panel B of Table 3 provides summary Statistics of lenders' key accounting variables.

There are 21,507 lender-borrower pairs across 2,595 facilities. Out of 21,507 lender-borrower relationships, 3,732 and 5,105 are lead arranger-borrower relationships based on lead arranger credit and lender role definitions, respectively. We construct different variables to characterize lenders relationship with the borrowers, lenders role, and reputation. Panel A of Table 3 provides summary Statistics of these variables and other related ones.

One of the important variables for our tests is to identify the lead loan arrangers on a syndicated loan. Bharath , Dahia, Saunders and Srinivasan (forthcoming) have suggested two separate methods to identify the lead lenders.[19] The first method, henceforth called lead credit method, is to use lead-arranger-credit variable in the LPC dataset. If this variable is equal to 'Yes' for a lender-facility pair then the lender is a lead arranger. The second method, which is called lead role method, utilizes the lender role that is assigned in the LPC dataset. In Bharath et al's (forthcoming) sample period there were only 21 lender roles in LPC database and they

[19] More information about what the responsibilities of lead loan arrangers are in Sufi (2007)

identifies four lender roles as equivalent to lead arranger role. For a comparison, in our sample period there are 97 lender roles, following Bharath et al's (forthcoming) approach in identifying lead lender we are able to identify 24 roles.[20] If a lender is the sole lender of a facility, that lender is defined as the lead arranger no matter what lender role is assigned by the LPC. These two methods, i.e. lead credit method or lead role method are used for robustness checks.

To measure a lender's reputation and strength of its relationship with a borrower, we follow Bharath's (2007) approach. Reputation is measured based on the size of the market share of the lender in the primary loan market in the past 5 years. With respect to relationship lending, we first identify the lead arranger for each facility as explained above then we identify the history of relationships of borrowers and lenders in the past five years. Then we used number of previous relationships (loans) as the measure for the strength of lending relationship. Also in a part of tests we used a dummy variable indicating whether or not a previous relationship exist between lenders and the borrower as another measure.

IV. Methodology and Results

In this section we present our methodology and results for each hypothesis. We consider three different methodologies including: univariate tests, logistic regressions and multinomial use dichotomous choice multinomial logit models. In the Univariate tests, for each loan facility, we construct four categories of potential usages of CRT: (i) loans that are only sold, (ii) loans that are only hedged with CDS, (iii) loans that are both sold and hedged with CDS, and (iv) loans that are neither sold nor hedged with CDS. Borrowers are ranked into two groups of bad and

[20] These roles include: Agent, Admin agent, Arranger, Co-agent, Co-arranger, Co-manager, Coordinating arranger, Coordinator, Lead arranger, Lead bank, Lead manager, Manager, Managing agent, Mandated Lead arranger, Mandated arrange, Senior arranger, Senior co-arranger, Senior co-lead manager, Senior co-manager, Senior lead manager, Senior manager, Senior managing agent, Syndications Agent, and Bookrunner.

good borrowers while lenders are ranked into two groups based on financial or regulatory constraints across the different four categories of potential usages of CRT.

To test our different hypotheses using the multivariate approach we consider this general model:

$$\begin{aligned} &\textit{Choice Variable} = A_0 + A_1(\textit{borrower characteristics}) + A_2(\textit{Lender characteristics}) + \\ &A_3(\textit{Loan characteristics}) + A_4(\textit{Other control Variables}) + \textit{Error Term}, \end{aligned} \quad (1)$$

where A_i's are model coefficients and the dependent variable is a choice variable of using two or three possible choices of CRT (loan sale, CDS or none). Our key variables that are related to the borrower characteristics include credit quality (Long-term and Short-term) and a control of the borrower size, Log (Borrower Market Equity). The second group of key variables that is related to the lenders characteristics includes financial constraints as measured by capital ratio and liquidity (Lender Capitalization: tier1 or tier1 plus tier2), Lender Illiquidity (loan to deposit), and lender liquidity (liquid assets to total assets). The third group of explanatory variables that are related to the loan characteristics includes loan size measured through log(facility amount), number of lenders, and whether the loan is refinanced or renegotiated. In our discussion we will only focus on the key variable(s) and the significant results in all specifications. In Table 4 we discussed the key variables for each hypothesis, the multivariate methodology, and the expected results.

IV.1 Testing Hypothesis 1 (H1)

To test H1, "Bank lenders are more likely to use loan sales versus CDS as a hedge instrument for low quality borrowers", we employ univariate and multilogit tests.

A. Univariate Tests

We consider the two alternative variables to measure the credit quality of borrower at the time of loan origination Standard & Poor's short- and long-term issuer credit ratings. Based on these measures, borrowers are ranked into two groups of bad and good borrowers across the four categories of CRT instruments. In Table 5, for each rank of borrower across the CRT categories, we report, the number of deals and the percentage of total number of deals within the sample period. Panel A reports the Standard & Poor's long-term issuer credit ratings while Panel B reports Standard & Poor's short-term issuer credit ratings. The *p* scores are related to a one-tailed 2-sample binomial test of equal proportions.[21]

To test hypothesis 1, our key variables are the CRT choice of loan sale versus CDS for good versus bad borrowers. In the percentage of loan sale column 'sale', one can observe that proportion of loan sales in the bad borrower category is significantly higher than those in the good borrower category while it is the opposite in the CDS column --proportion of CDS in the bad borrower category is significantly lower than those in the good borrower category. These results are robust to using alternative measures of the borrowers' credit quality. For example, in Panel A, loan sale is 24.3% for low quality borrowers while it is 0.9% for high quality ones and the difference is significant at 1%. Therefore the univariate test provides support to the first hypothesis that Bank lenders are more likely to use loan sales versus CDS as a hedging instrument for low quality borrowers.

B. Multivariate Tests

In order to test H1 we use dichotomous choice multinomial logit models. The dependent variable is CRT_instrument which is a categorical variable. It equals one if the lenders have

[21] Binomial test is used when data in each category is dichotomous and we want to know if the proportion of observations falling in each category differs from each other.

chosen no CRT, equals two if they have chosen CDS, and three if they have chosen loan sales.[22] Since our hypothesis compares the usage of CDS versus loan sale, the base for comparison in these multinomial logit regressions is usage of CDS, that is CRT_instrument equal to 2. In equation 1 our choice variable is log of the ratio of the two probabilities, it is either *P(NO CRT=1)/P(CDS=2)* or *P(Loan sale=3)/P(CDS=2)*.

Our multinomial logit results are presented in Table 6. The results for the choice variable of loan sale versus CDS are reported in panels A while those for No CRT versus CDS are reported in Panel B. We report the raw regression coefficients of the multinomial logit analysis together with the elasticity (economic importance) for each of the explanatory variables described above. Following Petersen (2006), we adjust the robust standard errors for the impact of firm-level clustering. In Table 6, we examine three models, starting with a set of variables for which observations are available for most of the sample (i.e., 1,007 observations).

To test hypothesis 1, our key binary choice variable is Sale versus CDS and our key explanatory variable is the credit quality of the borrower (long- and short-term). As you can see from Panel A the Credit Quality coefficient is negative and significant at 1% in all three models. These result is also economically significant, for example, using the elasticity, in Model 1 of Panel A, a 1% increases in long-term Credit quality decreases the probability of using loan sales (versus CDS) by 0.0275%.[23] Interestingly in Panel B, the banks (as lenders) are more likely to choose no CRT (versus CDS) for borrowers with lower credit quality and lenders with higher liquidity of the lender.

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[22] Facilities that are both sold and hedged through CDs are dropped from the regression.

[23] Using the raw coefficients in Model 1 of Panel A, we can say that for one unit change in the variable credit quality of the borrower, the log of the ratio of the two probabilities, P(Loan sale=2)/P(CDS=1), will be decreased by -0.505. Therefore, we can say that, in general, the lower the credit quality the more likely a lender prefers loan sale.

In summary, our main results (using univariate and multivariate tests) provide strong support for hypothesis 1, loan sales are more likely to be used by bank lenders to lay off risk when a loan belongs to borrowers with higher credit risk.

IV.2 Testing Hypothesis 2 (H2)

To test H2, "Bank lenders are more likely to use loan sales for low credit quality borrowers regardless of their binding financial or regulatory constraints." we employ univariate and multilogit tests.

A. Univariate Tests

To test hypothesis 2, we double sorted the four CRT choices based on borrower's as well as lender's characteristics. We investigate the lender's choice of CRT conditional on the credit quality of borrowers (low/high) and the financial and capital constraint of lender -- capitalization/Liquidity of the lenders (low/high). Borrowers are sorted into two groups (above and below median) based on their long-term issuer credit rating provided by S&P. Lenders are sorted into two types (high and low) based on two alternative capital adequacy measures: tier1 ratio, cumulative tier1 and tier2 ratios; or two alternative liquidity measured: loans to deposits ratio and liquid assets to deposits ratio. For robustness test, we also sort the lenders into two groups based on the combination of liquidity and capital adequacy, i.e. high liquidity and high capital ration versus low liquidity and low capital. The results are presented in Table 7 where the percentages are based on the total number of facilities in each borrower group i.e. sum of number of facilities in CDS, Loan Sale, both and none categories for each ranking group.

To test H2, we compare the percentage of loan sale for low credit quality borrowers across the borrower characteristics such as low versus high lender capitalization ratio. In general, the difference in the loan sale ratio is insignificant across all the different measures except that it is slightly significant when we use a measure of liquidity based on loan to deposit (Panel C). For example when we use tier1 capital ratio as a lender constraint, in Panel A, the loan sale for the low credit quality borrowers is 23.8% for low capital group and 24.2% for high capital group while the difference is insignificant. These results imply that the financial constraints of lenders do not play a significant role in their choice of loan sale for low credit quality borrowers which support hypothesis 2.

B. Multivariate Tests

In order to test H2 we use dichotomous choice multinomial logit models similar to that in Section 3.1. Since our hypothesis compares the usage of loan sale versus CDS, the base for comparison in these multinomial logit regressions is usage of CDS. Our multinomial logit results are presented in Table 8. The results for the choice variable of loan sale versus CDS are reported in panels A while those for No CRT versus CDS are reported in Panel B. Our key binary choice variable is loan sale versus CDS and our key explanatory variables are the credit quality of the borrower (measured by S&P long term issuer credit ranking), lenders' capitalization (tier1), loans to deposits ratio as a measure of lender's illiquidity, lender's liquid assets to deposits as a measure of liquidity, and an interactive variable *"Binding Financial and Regulatory Const"* that is equal one if lenders' tier1 and liquidity (based on loans to deposits in definition 1 and liquid assets to deposits in definition 2) are both less than sample median tier1 and liquidity measures.

For the tests of the loan sale versus CDS (Panel A), H2 predicts that the coefficient of borrower's credit quality to be negative while the coefficient on the other key variables related to regulatory constraints and liquidity to be statistically insignificant, see Table 4. As you can see from Panel A of Table 8, our results support these predictions. In particular, a 1% increases in the credit quality of the borrowers the usage of CDS versus loan sale decreases by -0.0247% and the result is significant at the 1% level. The coefficients on Lender Capitalization (tier1), Lender Illiquidity (loan to deposit), lender Liquidity (liquid Assets to deposit), Binding Financial and Regulatory Const are insignificant.

IV.3 Testing Hypothesis 3 (H3)

In this section, we also employ the univariate and multilogit tests to test H3, “Bank lenders are more likely to use CDS as a hedge instrument for relatively good quality borrowers especially if monitoring costs are relatively high”.

A. Univariate Tests

Table 9 presents the results for H3. We present the lender’s choice of Credit Risk Transfer conditional on the credit quality of borrowers (low/high) and the borrower’s monitoring costs for lenders (low/high). Borrowers are assigned to two groups based on their long-term issuer credit rating provided by S&P while lenders are grouped into two types based on how costly is monitoring the borrower for them on each facility (high and low). Our proxy for monitoring cost is relationship lending. We argue the monitoring cost is lower for lenders if a lender has issued previous loans to the same borrowers since the lender is familiar with lenders operation and performance. Accordingly, we consider the borrower’s monitoring cost is low when there is at least one previous relationship between lead syndicate arranges before the initiation of the current loan, and it is high otherwise. The numbers and percentages are provided based on four possible credit risk transfer methods applied by banks and the percentages are based on the total number of facilities in each borrower group i.e. sum of number of facilities in

CDS, Loan Sale, both and none categories for each ranking group. The table also shows the difference and difference in difference results and their significance. To test H3 we compare the variation in the bank's usage of CDS for good borrowers across the two different levels of monitoring cost. We expect to observe that for good quality borrowers the usage of CDS by banks is higher for high monitoring cost relative to low monitoring cost group.

As you can see from Table 9, our univariate tests show that there is no significant difference between the usage of CDS by lenders for high quality borrowers for high monitoring costs group versus the low ones. It is 32.20% for high monitoring cost group while it is 30.58% for the low monitoring group but the difference is not economically or statistically insignificant. Accordingly, our univariate test results do not provide support to H3.

B. Multivariate Tests

In this section, we also use the dichotomous choice multinomial logit models explained in H1. Our multinomial logit results are presented in Table 10. The results for the choice variable for CDS versus No CRT are reported in panels A while those for CDS versus loan sale are reported in Panel B. In Table III, we examine three models, starting with a set of variables for which observations are available for most of the sample (i.e., 1,094 observations).

To test hypothesis 3, we create a binary variable (First relationship with a good borrower) equals one for high credit quality borrowers that previous relationship with lenders (low monitoring cost) while it is zero for high credit quality borrowers that has no previous relationship with lenders (high monitoring cost). Our key binary choice variable is CDS versus sales. As you can see from Table 10 Panel B, the first relationship with a good borrower variable is negative and significant at 1% in all specifications. For example, the coefficient on the first relationship with a good borrower dummy is -32.557.

In summary, our results provide some support to the argument that bank lenders are more likely to use CDS as a hedge instrument for relatively good quality borrowers especially if monitoring costs are relatively high.

IV.4 Testing Hypothesis 4 (H4)

To test H4 we employ the univariate and logit tests, "*Reputable Bank lenders are less likely to use CRT instruments for high quality borrowers especially if their financial or regulatory constraints are not binding*".

A. Univariate Tests

Table 11 presents the results for H4. We present the lender's choice of CRT conditional on the credit quality of borrowers (low/high); and the borrower's reputation or a combination of borrower's reputation and tier 1 capital ratio (low/high). Lenders are sorted into two groups based on reputation in Panel A, and a combination of reputation and tier1 capital ratio in Panel B. Lenders in the Low category column in Panel B are those lenders whose both tier1 ratios and reputation are less than median tier1 and reputation. To test H4 we compare for the high credit quality borrowers the difference in the percentage of no CRT choice by banks based on either the lender reputations in low versus high group or the combination of reputation and tier1 capital ratio in the low versus high group. We expect to observe that for good quality borrowers the percentage of no CRT is higher for reputable banks or for lenders whose both tier1 ratios and reputation in the high group.

As you can see from Table 11 Panel A, for the high credit quality borrowers, the percentage of no CRT for the reputable banks is 68.10% while it is 66.84% for the less reputable banks but the difference is not statically significant. In Panel B, we obtain similar results. The percentage of no CRT for the high group using the combination bank's reputation and tier 1 capital ratio is 64.12% while it is 61.86% for the low group but the difference is not statically significant.

B. Multivariate Tests

To test H4 we use logit models in which the dependent variable is a binary variable (using a CRT instrument) equals one if the lenders have chosen at least one CRT instrument (CDS or loan sale) and equals 0 they have not chosen to use any CRT instrument. The key explanatory variables to test hypothesis 4 are borrower's credit quality, Lender's reputation, lender's capital adequacy (tier1 ratio) and lender's illiquidity (loans to deposits ratio). In addition, we create and interactive variable (reputable lender with good liquidity and Capitalization dealing with a good quality borrower) equals one for combination of good quality borrowers, reputable lenders, lenders with high capital ratio, and high liquidity (above median) and zero otherwise.

The results are presented in Table 12 in two models. In model 2 we incorporate more control variables. There are 953 observations. We report the logit model coefficients as well as its elasticity and the robust standard error. Following Peterson we cluster our tests at the bank level. The coefficient on the credit quality of borrowers is negative and significant at 5% in the two models. The results show that for 1% increase in the credit quality of borrowers the usage of CRT instruments decreases by 0.0213%. In addition, the coefficient on the lender illiquidity

(Loan-to-Deposit) is positive and significant at 1% in the two models. This result confirms the tendency of banks to use CRT instruments the higher is their illiquidity. Our interactive variable (reputable lender with good liquidity and capitalization dealing with a good quality borrower), tier 1 capital ratio, and lender reputation have the expected sign but is insignificant.

In summary, our results provide partial support to H4. In particular, we find that CRT instruments are more likely to be used for low credit quality borrowers and when banks have lower liquidity.

V. Conclusion

The recent financial crisis once again put a spotlight on banks. In the media, it seems that Thomas Jefferson cries from the grave every now and then and calls banks 'more dangerous than standing armies'[24] once again. Individuals are increasing questioning the behaviour of banks, which are widely believed as the most important and sophisticated players in financial markets. Specifically, how banks manage the risks associated with their loan portfolios has raised concerns in academia, the financial industry, among regulators, and also in the public media. This study relates to a recent literature that explains how banks layoff the credit risk of their loan portfolio.

The literature suggests different factors that might have an impact on banks' method of loan portfolio management. These factors are not only limited to borrowers' credit quality, but they also include costs of raising capital, monitoring costs, reputational concerns and liquidity. In this study, we consider two popular instruments that are specifically designed for credit risk management: credit default swaps and loan sales agreements. We are the first to empirically show under which conditions a bank prefers to transfer control rights to a new owner through a loan sale agreement, to use insurance through CDS, or not to use risk transfer instruments at all.

We merge five different datasets including LPC primary loan market, loan sales, credit default swaps transactions, COMPUSTAT for borrowers accounting information, and bank regulatory dataset for lenders' accounting information. We then build measures for borrowers' quality and lenders' characteristics, including indices for the capital adequacy, financial liquidity, strength of relationship, and reputation of all lenders in a syndicated loan. Using different

[24] Thomas Jefferson in a letter to John Taylor, Monticello, 28 May 1816

methodologies we show that loan sales are more likely to be used by banks to lay off risk when the loan belongs to a poor borrower than when it belongs to a good borrower. Risk transfer instruments are less likely to be used to lay off risk by banks when credit quality of a loan is high; and finally, regardless of how well capitalized the lenders are, it is more likely to shed risk by good borrowers through CDS. Additionally, we show that CDS is more likely to be used with good borrowers when they impose higher monitoring costs to lenders. Aligned with the argument that banks, ex-ante, originate loans with low quality borrowers to trade later. We also show that sold loans are more likely to be larger. Dealing with larger borrowers encourages lenders to use both CDS and loan sale instruments as the benefits of hedging are higher. In sum, we provide conclusive explanations about a bank's mindset in managing portfolio credit risk, and also the benefits of modern risk transfer markets to lenders and borrowers.

Panel A: Borrowers' Characteristics from Compustat's Quarterly Fundamentals and Ratings

Asset	Total Assets (ATQ)
Book Equity	Total Assets- [Total Liabilities + Preferred Stock] + Deferred Taxes (ATQ - [LTQ + PSTKQ] + TXDITQ)
Credit Quality (Long-term)	S&P Long-Term Issuer Credit Rating (ICR) refers to loans with maturities of more than one year and ranges from AAA (extremely strong capacity to meet financial obligations) to CC (highly vulnerable). In our analysis we rank long term ratings from 22 to 1, where AAA receives 22 and CC receives 1. (SPLTICRM)
Credit Quality (Short-term)	S&P Short-Term Issuer Credit Rating (ICR) refers to loans with maturities of less than one year and ranges from 10 (assigned to A-1) to 1 (assigned to C). (SPSTICRM)
Market Equity	Common Shares Outstanding * Price (CSHOQ*PRCCQ)

Panel B: Lenders' Characteristics from the banks filings of Report of Conditions and Income (Call Reports) with FDIC

Tier1	Tier 1 Ratio is the ratio of bank's core (or most reliable) equity capital (showing bank's financial strength from regulator's perspective) to bank's total risk weighted assets (RCFD8274/RCFDA223, if not available: BHCK8274/ BHCKA223)
Tier1and2	The sum of Tier1 and Tier2 capital over bank's total risk weighted assets. Tier 2 capital is the ratio of bank's second most reliable equity capital (after Tier 1 capital) from regulator's perspective to bank's total assets ((RCFD8274+RCFD5311)/RCFDA223, if not available: (BHCK8274+BHCK5311)/ BHCKA223)
Lender Capitalization (Tier1)	Weighted Average Lenders' Tier1 in a loan facility. Weights are shares of lenders in the facility if stated by LPC, otherwise each lender receives equal weights.
Lender Capitalization (Tier1and2)	Weighted Average Lenders' Tier1and2 in a loan facility. Weights are shares of lenders in the facility if stated by LPC, otherwise each lender receives equal weights.
Lender Illiquidity (loan to deposit)	The ratio of Net Loans to Deposits times 100. Net Loans are calculated as loans and leases, net of unearned income and allowance (RCFDB529/BHCK529) Deposits are cash and balances due from depository institutions including non-interest bearing balances and currency and coin, domestic and foreign sources (RCON6631+RCFN6631/BHDM6631+BHFN6631). If there is more than one lender ina loan facility, the weighted average across all lenders are used. Weight for each lender then equals to a lender's share in the loan.
Lender Liquidity (Liquid Assets to Deposit)	The ratio of Liquid Assets to Deposits times 100. Liquid Assets include cash and balances due from depository institutions (RCFD0081+RCFD0071/BHCK0081+BHCK0395+BHCK0397), securities available for sale (RCFD1773/BHCK1773), Federal funds sold and securities purchased under agreement to resell (RCONB987+RCFDB989/BHDMB987+BHCKB989), total trading assets (RCFD3545/BHCK3545) and loans to depository institutions and acceptance of other banks (RCFDB532+RCFDB533+RCFDB534+RCFDB537/BHCK1292+BHCK1296). Deposits are cash and balances due from depository institutions including non-interest bearing balances and currency and coin, domestic and foreign sources (RCON6631+RCFN6631/BHDM6631+BHFN6631). If there is more than one lender ina loan facility, the weighted average across all lenders are used. Weight for each lender then

	equals to a lender's share in the loan.
Lender Reputation	Lender's market share in the primary loan market in 5 years before loan initiation. In case of multiple lenders the highest market share is used.

Panel C: Syndicate Loan Contracts' Characteristics from LPC data base

AISD	All in Spread Drawn; Describes the Amount the Borrower Pays in Basis Points over LIBOR for each Dollar Drawn Down. It Adds the Spread of the Loan with any Annual (of Facility) Fee Paid to the Bank Group (LPC Definition)
AISU	All in Spread Undrawn; Measures the Amount a Borrower Pays for each Dollar Available under a Commitment. It Adds the Commitment and Annual Fee (LPC definition)
Binding Financial and Regulatory Constraints	A binary variable that equals 1 when lenders tier1 capital is at the lowest quintile and lenders loan to deposit ratio is at the highest quintile among all lenders in the sample, and zero otherwise. This variable is an indication that the lender has capitalization (regulatory) and liquidity (financial) constraints.
Binding Financial and Regulatory Const (1)	A binary variable that equals 1 if lenders tier1 capital is at the lowest quintile, lender's loan to deposit is at the highest quintile across all lenders in the sample (low capitalization, high illiquidity) and the borrower's credit quality is less than median borrower credit quality in the sample
Binding Financial and Regulatory Const (1)	A binary variable that equals 1 if lenders tier1 capital is at the lowest quintile, lender's liquid assets to deposit is at the lowest quintile across all lenders in the sample (low capitalization, high illiquidity) and the borrower's credit quality is less than median borrower credit quality in the sample
CDS Transactions	Whether or Not CDS has been used to Hedge Against a Facility (equals 1 if CDS has been used, and 0 otherwise)
Corporate Purposes	Type of Purpose the Deal was Issued for (LPC definition)
Deal Amount	Total Amount that the Deal has received commitments for (LPC definition)
First Relationship with a Good Borrower	A binary variable showing that the lead lender did not have a previous loan with the borrower and the borrower is of a good credit quality, zero otherwise.
Loan Size	The Actual Amount of the Loan Facility Committed by the Facility's Lender Pool (LPC Definition)
Lead Lender	Lead Lender Arranger in a Facility based on LPC's definition. If the lead_arranger_credit flag in LPC is 'yes' for a lender then the lender is a lead lender.
Lender's Reputation	Market Share of Lender in last 5 years
Maturity	A Calculation of how Long (in months) the Facility will be Active from Signing Date to Expiration Date (LPC definition)
No of Facilities	Total Number of Facilities in the Package (Deal)

Number of Lenders	Total Number of Participating Lenders in the Facility
Number of Lead Lenders	Number of Lead Lenders in a Facility. See Lead Lender Definitions.
Previous Relationship	Number of times borrower and lead lender have previous relationships. See Lead Lender Definitions.
Refinanced Loan	A binary flag indicating whether or not the current Deal refinances a prior Deal. Equals 1 when it does and 0 otherwise.
Relationship Lending	A binary variable showing that the lead lender has had previous loans with the borrower before loan initiation and zero otherwise
Reputable Lender with Good Liquidity and Capitalization Dealing with a Good Quality Borrower	A binary variable showing that the lender reputation is over sample's median, Borrower's long term credit quality is higher than sample's median, the lender has over median tier1 capital and under median loans to deposits ratio. Zero otherwise.
Secured	A Binary Variable indicating whether or not the Facility is Secured (1 for Secured, 0 otherwise)
Senior	A Binary Variable that indicates whether the facility has seniority in the company's over debt structure (1 for senior, 0 otherwise)
Share in Loan	Lender Share in a facility wherever it is available

References

Acharya, V.V., and T.C. Johnson, Insider Trading in Credit Derivatives, Journal of Financial Economics 84 (2007) 110-141

Allen, F. And E. Carletti, Credit Risk Transfer and Contagion, Journal of Monetary Economics, (2006), 53, 89-111

Allen, F., E. Carletti and R. Marquez, Credit Market Competition and Capital Regulation, Review of Financial Studies, forthcoming

Ashcraft, A.B. and J.A.C. Santos, Has the CDS Market Lowered the Cost of Corporate Debt?, Journal of Monetary Economics 56 (2009) 514-523

Allen L, H. Guo, and J. Weintrop, 2009, The information content of quarterly earnings in syndicated bank loan prices, Asia-pacific Journal of Accounting and Economics, Forthcoming

Berndt, A. and A. Gupta, Moral Hazard and Adverse Selection in the Originate-to-Distribute Model of Bank Credit, Journal of Monetary Economics 56 (2009) 725-743

Bharath, S., S. Dahia, A. Saunders and A. Srinivasan (Forthcoming), Lending Relationships and Loan Contract Terms, RFS

Bharath, S., S. Dahia, A. Saunders and A. Srinivasan, So what do I get? The bank's view of lending relationships, Journal of Financial Economics 85 (2007) 368-419

Bushman, R.M., A.J. Smith, and R. Wittenberg Moerman, Price Discovery and Dissemination of Private Information by Loan Syndicate Participation (July 3, 2009). Chicago Booth Research Paper no. 09-24.

Bushman, R.M., and R. Wittenberg Moerman, Does Secondary Loan market Trading Destroy Lenders' Incentives? (Nov 2, 2009). Chicago Booth Research Paper no. 09-45.

Cebenoyan, A.S., and P.E. Strahan, Risk Management, Capital Structure and Lending at Banks, Journal of Banking & Finance 28 (2004), 19-43

Coleman A.D.F., E. Neil, and I.G. Sharpe, Does bank monitoring influence loan contract terms?, Journal of Financial Services Research, 2006

Dahiya, S., M. Puri and A. Saunders, Bank Borrowers and Loan Sales; new Evidence on the Uniqueness of Bank Loans, Journal of Business, Vol 76, No 4, 2003

Dass, N. and M. Massa, The Impact of a Strong Bank-Firm Relationship on the Borrowing Firm, Forthcoming, Review of Financial Studies

Dimond, D., Financial Intermediation and Delegated Monitoring, Review of Economic Studies 51, 1984, 393-414

Drucker, S. And M. Puri, On Loan Sales, Loan Contracting, and Lending Relationships, Review of Financial Studies, v 22 n 7 2009

Duffee, G.R., and C. Zhou, Credit Derivatives in Banking: Useful Tools for Managing Risk?, Journal of Monetary Economics 48 (2001) 25-54

Dufee, G. Discussion on *Moral Hazard and Adverse Selection in the Originate-to-distribute Model of Bank Credit*, Journal of Monetary Economics 56, 2009, 744-747

Fama, E., What's Different about Banks, Journal of Monetary Economics 10, 1985, 10-9

Güner, A.B., Loan Sales and the Cost of Corporate Borrowing, Review of Financial Studies, v 19 n 2 2006

Gande, A., and A. Saunders, Are Banks Still Special When There is a Secondary Market for Loans?, 2009, Working Paper

Gupta, A., A.K. Singh, and A.A. Zebedee, Liquidity in the Pricing of Syndicated Loans, Journal of Financial Markets 11 (2008) 339-376

Hull, J., M. Predescu and A. White, The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements, Journal of Banking and Finance 28, 2004, 2789-2811

Kamstra, M., G.S. Roberts, and P. Shao, Does the Secondary loan Market Reduce Borrowing Costs?, April 2010, Working Paper

LSTA, 2007, The Handbook of Loan Syndications and Trading, A. Taylorand A. Sansose

Massoud, N., D. Nandy, A. Saunders and K. Song, Do Hedge Funds Trade on Private Information? Evidence from Syndicated Lending, 2009, Forthcoming Journal of Financial Economics

Minton, B.A., R. Stulz, and R. Williamson, How Much Do Banks Use Credit Derivatives to Hedge Loans?, Journal of Financial Services Research (2009) 35:1-31

Morrison, A.D., Credit Derivatives, Disintermediation, and Investment Decisions, Journal of Business, 2005, vol 78 no 2

Nordan, L. And M. Weber, Informational Efficiency of Credit Default Swap and Stock Markets: the Impact of Credit Rating Announcements, Journal of Banking & Finance 28 (2004) 2813-2843

Panyagometh K., and G.S. Roberts, Do Lead Banks Exploit Syndicate Participants? Evidence from Ex Post Risk, Financial Management, Spring 2010, pp 273-299

Parlour, C., and G. Plantin, Loan Sales and Relationship Banking, Journal of Finance, Vol. LXIII. No. 3, June 2008

Parlour, C., and A. Winton, Laying off Credit Risk: Loan Sales versus Credit Default Swaps, working paper Aug 29. 2008

Pennacchi, G., Loan Sales and the Cost of Bank Capital, Journal of Finance 1988, 43, 37596.

Purnanandam, A., Originate-to-Distribute model and the Subprime Mortgage Crisis, Review of Financial Studies, Forthcoming

Roberts, M.R., and A. Sufi, Renegotiation of Financial Contracts: Evidence from Private Credit Agreements, Journal of Financial Economics 93 (2009) 159-184

Standard & Poor's, 2007, A Guide to the Loan Market

Sufi, A., Information asymmetry and financing arrangements: Evidence from syndicated loans, The Journal of Finance, 2007

Ross, D.G., The "Dominant Bank Effect:" How High Lender Reputation Affects the Information Conent and Terms of Bank Loans, forthcoming , Review of Financial Studies

Thomson, J.R., Credit Risk Transfer: to Sell or to Insure, 2008, Working Paper

Wittenberg-Moerman, R., The Role of Asymmetry and Financial Reporting Quality in Debt Trading: Evidence from the Secondary Loan Market, Journal of Accounting and Economics 46 (2008) 240-260.

Table 1 – Descriptive Statistics of Deals (Packages)

This Table presents descriptive statistics for the sample of 5,679 deals related to 2,818 American borrowers (matched with COMPUSTAT) from January 1, 2005 to December 31, 2008. Panel A presents the descriptive statistics for deal purpose, Panel B presents the descriptive statistics for deal level. Panel C presents accounting data for borrowers of these deals. It includes Total Assets, Leverage as the ratio of long term and current debt to total assets, earnings (Income Before Extraordinary Items+ Depreciation and Amortization) to assets, Profitability which is the ratio of EBITDA on Sales, Tangibility which is the ratio of property, plant, and equipment to total assets, Current Ratio which is the ratio of Current Assets to Current Liabilities, Market to Book that equals to [Total Assets-[Total Liabilities + Preferred Stock]+ Deferred Taxes]/[Common Shares Outstanding × Price]. Also LT rating and ST rating are based on S&P's Issuer Credit Ratings, where the best long term rate (AAA) receives 22 and the worst rate (CC) receives 1. Also the best short term rate (A-1) receives 10 whereas the worst rate (C) receives 1.

Panel A : Deal Purpose

Deal Purpose	No of Deals	Deal Purpose	No of Deals
Corporate Purposes	2,686	*CP[*] backup LBO*	120
Working Capital	1,476	*Real Estate*	77
Takeover	393	*Stock Buyback*	49
Acquisition Line	327	*Dividend Recap*	47
LBO	164	*Debtor in Possession*	41
Debt Repayment	156	*Other[**]*	77

Panel B : Deal Characteristics

	Number	Mean	Std. dev.	1st Percentile	Median	99th Percentile
No of Facilities	5,679	1.4	0.7	1.0	1.0	2.0
Deal Amount ($ millions)	5,679	724.3	1,629.9	0.4	250.0	600.0
Refinancing Indicator	4,781	0.8	0.4	0	1	1

Panel C : Borrower Characteristics at Firm Level

	Number	Mean	Std. dev.	1st Percentile	Median	99th Percentile
Assets ($millions)	5,448	14,048.8	68,186.6	26.12	1,654.8	350,432.6
Leverage	4,994	0.30	0.26	0.0	0.26	1.11
Earnings to Assets	4,882	0.02	0.05	-1.16	0.02	0.11
Profitability	4,934	0.02	5.97	-0.69	0.15	0.80
Tangibility	5,062	0.32	0.26	0.00	0.24	0.91
Current Ratio	4,561	2.01	7.03	0.29	1.50	7.79
Market to Book	4,168	3.91	22.39	0.45	1.99	22.88
LT Rating	3,113	12.39 (BB+)	3.48	2 (C)	13 (BBB-)	20 (AA)
ST Rating	1,086	7.97 (A-2)	1.68	3 (B-3)	8 (A-2)	10 (A-1+)

[*] CP stands for Commercial Papers
[**] Other includes Spinoff, Exit Financing, Capital Expenditure, Project Finance, IPO Related Financing, Equipment Purchase, Lease finance, and Other

Table 2 – Summary Statistics of Loans (Facilities)

This Table presents descriptive statistics for the sample of 7,919 loans with American borrowers (matched with COMPUSTAT) from January 1, 2005 to December 31, 2008. Panel A provides information about loan characteristics. Facility Amounts are in million dollars. Maturity measures the duration of the loan in a number of months between facility active date and maturity date. AISD or All in Spread Drawn describes the amount the borrower pays in basis points over LIBOR for each dollar drawn down. AISD or All in Spread Not Drawn al measures the amount a borrower pays for each dollar available under a commitment. Senior equals one if the facility has seniority in company's overall debt structure, it equals zero otherwise. Secured equals one when facility is secured, 0 otherwise. Panel B reports the lender relationship highlights of the 2,595 facilities. Number of Lenders shows how many lenders a facility has. Number of Lead Lenders (Lead Arrangers) is based on LPC's definition. If the lead_arranger_credit flag in LPC is 'yes' for a lender then the lender is counted as a lead lender. Previous relationships with lead arrangers are also provided. This can be equal to 0 if there is no previous relationship with lead arrangers or 1 otherwise. If Credit Default Swaps of the underlying borrower is traded then CDS transactions equals 1, otherwise it equals zero. Our CDS data starts from January 2006 to November 2008. If a specific loan is traded on the secondary loan market then its secondary market transactions equals 1 and 0 otherwise. All Lenders Bank is a dummy that is assigned 1 if all the lenders involving in a facility are domestic or foreign banks. If the facility has at least one non-bank lenders e.g. a hedge fund then this dummy equals 0.

	No of Loans	Mean	Std. dev.	1st Percentile	Median	99th Percentile
Panel A: Loan Characteristics						
Facility Amount ($ millions)	7,919	512.6	1,151.3	4.3	200.0	5,000.0
Maturity (months)	7,672	51.15	22.05	4.0	60	96
AISD (basis points)	7,162	187.87	156.32	15.00	150.00	780.00
AISU (basis points)	7,919	27.33	27.73	4.00	25.00	100.00
Senior	7,919	0.49	0.50	0	0	1
Secured	7,919	0.99	0.06	1	1	1
Panel B: Lender Relationships						
Number of Lenders	7,919	7.7	8.1	1	6	34
Number of Lead Lenders	7,919	1.45	0.55	1	1	2
Previous Relationship	7,919	0.56	0.49	0	1	1
CDS Transactions	7,919	0.37	0.47	0	0	1
Secondary Market Transactions	7,919	0.18	0.38	0	0	1
All Lenders Bank	7,919	0.45	0.50	0	0	1

Table 3 – Lenders Reputation/Relationship Characteristics and Financial Status

The Table presents descriptive statistics for the Lenders of 50,927 lender-loan pairs in which lenders are all banks and their borrowers are matched with COMPUSTAT. The sample is from January 1, 2005 to December 31, 2008. Table reports Lenders reputation and relationship characteristics together with their capitalization and liquidity status at the time of loan initiation. Lender's Reputation provides lender's share in the US primary loan market over the five years preceding loan activation date. Previous Relationship is the number of previous loans both the lender and the borrower were involved over previous 5 years. Lead Lender is a dummy variable that equals one if the lender is a lead arranger in a loan contract (see appendix). Tier1 is Tier1 ratio calculated as Tier1 capital over total risk-weighted assets. Tier1and2 is the summation of Tier1 and Tier2 capital divided by total risk-weighted assets. Lender's illiquidity is measured as its loan to deposit ratio; finally lender's illiquidity is measured as its ratio of liquid assets to deposits at the last quarter before loan initiation (for more information see appendix)

	Number of Facility-Loans	Mean	Std. dev.	1st Percentile	Median	99th Percentile
Lender's Reputation	50,341	0.146	0.149	0.000	0.095	0.592
Previous Relationship	50,927	1.678	2.764	0	0	13
Lead Lender	50,927	0.197	0.397	0	0	1
Tier1	28,246	0.090	0.080	0.065	0.083	0.273
Tier1and2	28,246	0.120	0.078	0.102	0.112	0.276
Lender Illiquidity (Loan to Deposit)	27,905	444,736	7,746,304	107.0	386.5	56,444.3
Lender Liquidity (Liquid Assets to Deposits)	27,905	164,216	2,905,358	51.6	253.4	25,431.2

Table 4: Key Variables for Each Hypothesis, its Multivariate Methodologies, and the Expected Results

	H1	H2	H3	H4
	Bank lenders are more likely to use loan **sales versus CDS** as a hedge instrument for **low borrower quality**	Bank lenders are more likely to use loan **sales** for **low credit quality** borrowers **regardless of their binding financial or regulatory constraints**	Bank lenders are more likely to use **CDS** as a hedge instrument for relatively **good quality** borrowers **especially if monitoring costs are relatively high**	**Reputable** bank lenders are **less likely to use CRT instruments** for **high quality** borrowers **especially if their financial and regulatory constraints are not binding**
Model	Multinomial Logit	Multinomial Logit	Multinomial Logit	Logit
Dependent Base/Key Variable	Base = CDS Key= Sale	Base = CDS Key = Sale	Base = None Key = CDS	CRT
Featured Independent Variables:	**Credit Quality**	**Binding Financial and Regulatory Const.** (binding capital and liquidity constraints, i.e. liquidity and capital at the lowest quintiles + the credit quality of the borrower is below median)	**First Relationship with a Good Borrower** (no previous relationship between lead arrangers and the borrower before loan initiation + the credit quality of the borrower is over median)	**Reputable Lender with Good Liquidity and Capitalization dealing with Good Quality Borrower** (over median lenders reputation + over median long term credit quality + over median tier 1 capital and liquidity
Expected sign for the featured independent variable	Negative	Insignificant	Positive	Negative

Table 5– Hypothesis1- The Effect of Borrower's Credit Quality on Lenders' CRT Decision (Univariate Tests)

This Table presents univariate tests for hypothesis 1. Borrowers are ranked based on their credit quality into two groups of high and low. Two measures of credit quality have been used: in Panel A we use long-term issuer's credit rating (ICR) while in Panel B we use short-term ICR. Both measures are provided by Standard and Poor's. The former refers to borrower's capacity to meet long-term (over one year) financial obligations and the latter refers to borrower's capacity to meet short-term (less or equal to one year) financial obligations. Number and Percentages of loans are provided based on four possible credit risk transfer methods applied by banks: using loan sale, using CDS, using both CDS and Loan Sale and none (not to use any risk transfer instrument). Percentages are based on the proportion of each category to the total number of facilities in each ranking group. We report the significance signs based on one-way binomial test, where the null hypothesis is that the proportion of low (high) quality borrowers in a credit risk transfer category is more than those of high (low) quality borrowers.

Credit Risk Transfer (CRT) Choice

		Sale		CDS		Both Sale and CDS		No CRT Instrument		Total
		Number of Loans	Percentage of Loans	Number of Loans	Percentage of Loans	Number of Loans	Percentage of Loans	Number of Loans	Percentage of Loans	
Panel A: Long-Term Credit Quality										
Borrower's Credit Quality (Long-term)	**Low**	137	**24.3%**	43	**7.6%**	33	**5.9%**	351	**62.2%**	564
	High	5	**0.9%**	165	**30.3%**	3	**0.6%**	372	**68.3%**	545
	Low minus High		***23.4%****		***-22.7%***		***5.3%****		***-6.0%***	
	High minus Low		***-23.4%***		***22.7%****		***-5.3%***		***6.0%***	
Panel B: Short-Term Credit Quality										
Borrower's Credit Quality (Short-term)	**Low**	16	**7.4%**	48	**22.3%**	14	**6.5%**	137	**63.7%**	215
	High	0	**0.0%**	74	**45.4%**	1	**0.6%**	88	**54.0%**	163
	Low minus High		***7.4%****		***-23.1%***		***5.9%****		***9.7%****	
	High minus Low		***-7.4%***		***23.1%****		***-5.9%***		***-9.7%***	

*** significant at 1% level ** significant at 5% level * significant at 10% level

Table 6– Hypothesis1- The Effect of Borrower's Credit Quality on Lenders' CRT Decision (Multivariate Tests)

This Table presents multivariate tests for hypothesis 1. Three Multinomial Logit models have been used to show the impact of different factors on lender banks risk transfer decision. The dependent variable is CRT_instrument which is a categorical variable. It equals 1 if the lenders have chosen no CRT, equals 2 if they have chosen CDS, and 3 if they have chosen loan sales. Facilities that are both sold and hedged through CDs are dropped from the regression. The base for multinomial logit regressions is CRT_instrument equal to 2, i.e. using CDS. The results for sale and none are reported in panels A and B, respectively. Therefore the coefficients in panel A (B) shows what the effect of one additional unit change in the independent variable is on the odds of being sold (using no CRT instrument) rather than using CDS as a CRT instrument. We also report *"Elasticity"* which is calculated as d(lnF)/d(lnx), where d is the first derivative, ln(F) is the natural logarithm of the density function and ln(x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. The main independent variable to test hypothesis 1 is borrower's credit quality (two measures are used here). We have used some lender and contract characteristics for controls. The descriptions for all variables can be found in Appendix A.

CRT Instrument	Model 1			Model 2			Model 3		
	Coefficient	**Std. Error**	**Elasticity**	**Coefficient**	**Std. Error**	**Marginal Effect**	**Coefficient**	**Std. Error**	**Elasticity**
Panel A – Choosing Sale vs. CDS									
Credit Quality (Long-term)	**-0.5050*****	*(0.052)*	-0.0275				**-0.5211*****	*(0.077)*	-0.0297
Credit Quality (Short-term)				**-1.4345*****	*(0.208)*	-3.3e-10			
Lender Capitalization (tier1)	**2.2640**	*(2.018)*	0.3469	**-9.2503**	*(21.77)*	1.2e-11	**1.5490**	*(3.152)*	0.2520
Lender Illiquidity (loan to deposit)	**9.3e-8**	*(7e-08)*	2.0e-8	**-0.0002**	*(2e-04)*	-5.3e-14	**1e-07**	*(7e-08)*	1.8e-08
Log (loan size)	**0.2864****	*(0.123)*	0.0280	**-0.2046**	*(0.399)*	-2.8e-11	**0.3390****	*(0.154)*	0.0224
Log (Borrower Market Equity)							**-0.8774**	*(0.174)*	0.0066
Number of Lenders							**0.0028**	*(0.040)*	-0.0006
Refinanced Loan							**-0.0897**	*(0.375)*	0.0030
_cons	**-0.1254**	*(2.284)*		**12.7933**	*(8.584)*		**-0.2190**	*(2.530)*	
Panel A – Choosing no CRT vs. CDS									
Credit Quality (Long-term)	**-0.1790*****	*(0.034)*					**-0.1110****	*(0.044)*	
				-0.3185**	*(0.131)*				
Lender Capitalization (tier1)	**-2.8319**	*(2.481)*		**-14.0077**	*(11.91)*		**-2.6374**	*(2.357)*	
Lender Illiquidity (loan to deposit)	**-2.1e-7****	*(9e0-8)*		**-3.1e-7*****	*(1e-07)*		**-2.0e-7****	*(9e-08)*	
Log (loan size)	**-0.0994**	*(0.095)*		**-0.1493**	*(0.103)*		**0.01632**	*(0.127)*	
Log (Borrower Market Equity)							**-0.2295***	*(0.122)*	
Number of Lenders							**-0.0071**	*(0.024)*	
Refinanced Loan							**-0.0568**	*(0.220)*	
_cons	**5.8877*****	*(1.760)*		**7.5467**	*(2.404)*		**4.6800****	*(1.990)*	
Number of Observations	**1007**			**337**			**928**		
Wald Chi Square	**188.79*****			**64.40*****			**183.32*****		
Pseudo R Square	**0.1178**			**0.1669**			**0.1211**		

*** significant at 1% level ** significant at 5% level * significant at 10% level

Table 7– Hypothesis2- The Effect of Borrower's Credit Quality and Lenders' Regulatory and Financial Constraints on Lenders' CRT Decision (Double Sorting Technique)

This Table presents results related to testing hypotheses 2 based on a double sorting technique. We present the lender's choice of Credit Risk Transfer conditional on the credit quality of borrowers (low/high) and the capitalization/Liquidity of the lenders (low/high). Borrowers are assigned to two groups based on their median value of long-term issuer credit rating provided by S&P. Lenders are grouped into two types (high and low) based on the median values of two alternative capital adequacy measures, i.e. their tier1 ratio (Panel A), cumulative tier1 and tier2 ratios (Panel B) or their liquidity measured based on their loans to deposits ratio (Panel C) or liquid assets to deposits ratio (Panel D). Also a combination of liquidity and capital adequacy is used (Panel E). Lenders in the Low category are those lenders whose financial ratios are less than median values. Measures for lenders are weighted based on each lender's share in a syndicate. Number and Percentages are provided based on four possible credit risk transfer methods applied by banks: loan sale, CDS, both CDS and Loan Sale and none. Percentages are based on the total number of facilities in each borrower group i.e. sum of number of facilities in CDS, Loan Sale, both and none categories for each ranking group. The table also shows the difference and difference in difference results and their significance using one-tail binomial tests. The descriptions for all variables can be found in Appendix A. We report the significance signs based on one-way binomial tests.

Panel A: Lender Capital

(Tier 1 Ratio)

		CRT	Low		High		Diff (Low - High Capital)	Diff (High - Low Capital)
			Number	Percentage	Number	Percentage		
Borrower Quality (Long-Term)	Low	Both	16	**7.00%**	16	**5.80%**	1.20%	-1.20%
		CDS	13	**5.70%**	25	**9.00%**	-3.30%	3.30%
		None	144	**63.40%**	169	**61.00%**	2.40%	-2.40%
		Sale	54	**23.80%**	67	**24.20%**	**-0.40%**	**0.40%**
	High	Both	3	**1.00%**	0	**0.00%**	1.00%*	-1.00%
		CDS	85	**29.50%**	68	**29.70%**	-0.20%	0.20%
		None	197	**68.40%**	159	**69.40%**	-1.00%	1.00%
		Sale	3	**1.00%**	2	**0.90%**	0.10%	-0.10%

		Low	High
Diff (Low - High credit)	Both	6.00%***	5.80%***
	CDS	-23.80%	-20.70%
	None	-5.00%	-8.40%
	Sale	**22.80%*** **	**23.30%*** **
Diff (High - Low credit)	Both	-6.00%	-5.80%
	CDS	23.80%***	20.70%***
	None	5.00%	8.40%**
	Sale	-22.80%	-23.30%

Diff in Diff (Low - High)

Both	0.20%
CDS	-3.10%
None	3.40%
Sale	**-0.50%**

*** significant at 1% level   ** significant at 5% level   * significant at 10% level

Panel B: Lender Capital

(Tier 1 and 2 Ratio)

		CRT	Low		High		Diff (Low - High Capital)	Diff (High - Low Capital)
			Number	Percentage	Number	Percentage		
Borrower Quality (Long-Term)	Low	Both	13	**5.60%**	19	**6.99%**	-1.38%	1.38%
		CDS	9	**3.88%**	29	**10.66%**	-6.78%	6.78%***
		None	161	**69.40%**	152	**55.88%**	13.51%***	-13.51%
		Sale	49	**21.12%**	72	**26.47%**	**-5.35%**	**5.35%***
	High	Both	1	**0.43%**	2	**0.71%**	-0.28%	0.28%
		CDS	68	**29.06%**	85	**30.04%**	-0.98%	0.98%
		None	162	**69.23%**	194	**68.55%**	0.68%	-0.68%
		Sale	3	**1.28%**	2	**0.71%**	0.58%	-0.58%

		Low	High
Diff (Low - High credit)	Both	5.18%***	6.28%***
	CDS	-25.18%	-19.37%
	None	0.17%	-12.67%
	Sale	**19.84%*** **	**25.76%*** **
Diff (High - Low credit)	Both	-5.18%	-6.28%
	CDS	25.18%***	19.37%***
	None	-0.17%	12.67%***
	Sale	-19.84%	-25.76%

Diff in Diff (Low - High)

Both	-1.10%
CDS	-5.81%
None	12.83%
Sale	**-5.93%**

*** significant at 1% level ** significant at 5% level * significant at 10% level

Panel C: Lender Liquidity

(Based on Loans to Deposits)

		CRT	Low		High		Diff (Low - High Capital)	Diff (High - Low Capital)
			Number	Percentage	Number	Percentage		
Borrower Quality (Long-Term)	Low	Both	18	**7.06%**	14	**5.62%**	1.44%	-1.44%
		CDS	18	**7.06%**	20	**8.03%**	-0.97%	0.97%
		None	150	**58.82%**	163	**65.46%**	-6.64%	6.64%*
		Sale	69	**27.06%**	52	**20.88%**	**6.18%****	**-6.18%**
	High	Both	3	**1.00%**	0	**0.00%**	1.00%*	-1.00%
		CDS	102	**34.11%**	61	**25.52%**	8.59%	-8.59%
		None	191	**63.88%**	176	**73.64%**	-9.76%	9.76%***
		Sale	3	**1.00%**	2	**0.84%**	0.17%	-0.17%

Diff (Low - High credit)	Both	6.06%***	5.62%***
	CDS	-27.05%	-17.49%
	None	-5.06%	-8.18%
	Sale	**26.06%*****	**20.05%*****
Diff (High - Low credit)	Both	-6.06%	-5.62%
	CDS	27.05%***	17.49%***
	None	5.06%	8.18%**
	Sale	-26.06%	-20.05%

Diff in Diff (Low - High)

Both	0.42%
CDS	-9.56%**
None	3.12%
Sale	**6.01%**

*** significant at 1% level ** significant at 5% level * significant at 10% level

Panel D: Lender Liquidity

(Based on Liquid Assets to Deposits)

		CRT	Low Number	Low Percentage	High Number	High Percentage	Diff (Low - High Capital)	Diff (High - Low Capital)
Borrower Quality (Long-Term)	Low	Both	6	**2.78%**	26	**9.03%**	-6.25%	6.25%***
		CDS	11	**5.09%**	27	**9.38%**	-4.28%	4.28%**
		None	150	**69.44%**	163	**56.60%**	12.85%***	-12.85%
		Sale	49	**22.69%**	72	**25.00%**	**-2.31%**	**2.31%**
	High	Both	0	**0.00%**	3	**0.79%**	-0.79%	0.79%
		CDS	39	**24.38%**	124	**32.80%**	-8.43%	8.43%**
		None	119	**74.38%**	248	**65.61%**	8.77%**	-8.77%
		Sale	2	**1.25%**	3	**0.79%**	0.46%	-0.46%

	CRT	Low Percentage	High Percentage
Diff (Low - High credit)	Both	2.78%**	8.23%***
	CDS	-19.28%	-23.43%
	None	-4.93%	-9.01%
	Sale	**21.44%*** **	**24.21%*** **
Diff (High - Low credit)	Both	-2.78%	-8.23%
	CDS	19.28%***	23.43%***
	None	4.93%	9.01%***
	Sale	-21.44%	-24.21%

Diff in Diff (Low - High)

Both	-5.46%**
CDS	4.15%
None	4.08%
Sale	**-2.77%**

*** significant at 1% level ** significant at 5% level * significant at 10% level

Panel E: Lender Liquidity and Capitalization

(Tier1 and Loans to Deposits)

		CRT	Low		High			Diff (Low - High Capital)	Diff (High - Low Capital)
			Number	Percentage	Number	Percentage			
Borrower Quality (Long-Term)	Low	Both	12	**8.89%**	10	**6.37%**		2.52%	-2.52%
		CDS	8	**5.93%**	15	**9.55%**		-3.63%	3.63%
		None	82	**60.74%**	101	**64.33%**		-3.59%	3.59%
		Sale	33	**24.44%**	31	**19.75%**		**4.70%**	**-4.70%**
	High	Both	3	**1.57%**	0	**0.00%**		1.57%*	-1.57%
		CDS	68	**35.60%**	42	**30.88%**		4.72%	-4.72%
		None	118	**61.78%**	93	**68.38%**		-6.60%	6.60%
		Sale	2	**1.05%**	1	**0.74%**		0.31%	-0.31%

		Low	High
Diff (Low - High credit)	Both	7.32%***	6.37%***
	CDS	-29.68%	-21.33%
	None	-1.04%	-4.05%
	Sale	**23.40%*** **	**19.01%*** **
Diff (High - Low credit)	Both	-7.32%	-6.37%
	CDS	29.68%***	21.33%***
	None	1.04%	4.05%
	Sale	-23.40%	-19.01%

Diff in Diff (Low - High)

Both	9.49%
CDS	-8.35%
None	3.01%
Sale	**4.39%**

*** significant at 1% level   ** significant at 5% level   * significant at 10% level

Table 8– Hypothesis2- The Effect of Borrower's Credit Quality and Lenders' Regulatory and Financial Constraints on Lenders' CRT Decision (Multivariate Tests)

This Table presents multivariate tests for hypothesis 2. Three Multinomial Logit models have been used to show the impact of different factors on lender banks risk transfer decision. The dependent variable is CRT_instrument which is a categorical variable. It equals 1 if the lenders have chosen no CRT, equals 2 if they have chosen CDS, and 3 if they have chosen loan sales. Facilities that are both sold and hedged through CDs are dropped from the regression. The base for multinomial logit regressions is CRT_instrument equal to 2, i.e. using CDS. The results for sale and no CRT are reported in panels A and B, respectively. The coefficients in panel A (B) shows what the effect of one additional unit change in the independent variable is on the odds of being sold (using no CRT instrument) rather than using CDS as a CRT instrument. We also report *"Elasticity"* which is calculated as *d(lnF)/d(lnx)*, where *d* is the first derivative, *ln(F)* is the natural logarithm of the density function and *ln(x)* is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. The main independent variables to test hypothesis 2 are borrower's credit quality (measured by S&P long term issuer credit ranking) and lenders' capitalization (tier1), illiquidity/liquidity and their binding financial and regulatory constraints. Loans to deposits ratio is used as a measure of illiquidity and liquid assets to deposits is used as a measure of liquidity. Binding financial and regulatory constraints are binary variables that equals one if lenders' tier1 and liquidity (based on loans to deposits in definition 1 and liquid assets to deposits in definition 2) are both less than sample median tier1 and liquidity measures. The descriptions for all variables can be found in Appendix A.

CRT Instrument	Model 1 Coefficient	Model 1 Std. Error	Model 1 Elasticity	Model 2 Coefficient	Model 2 Std. Error	Model 2 Marginal Effect	Model 3 Coefficient	Model 3 Std. Error	Model 3 Elasticity
Panel A – Choosing Sale vs. CDS									
Credit Quality (Long-term)	**-0.4630*** **	*(0.052)*	-0.0247	**-0.5223*** **	*(0.079)*	-0.0289	**-0.5231*** **	*(0.077)*	-0.0297
Lender Capitalization (tier1)	**1.7846**	*(1.682)*	0.3218	**0.9913**	*(3.854)*	0.1962	**1.6854**	*(3.043)*	0.2647
Lender Illiquidity (loan to deposit)	**1.0e-07**	*(7e-08)*	-2.3e-8	**1.1e-07**	*(7e-08)*	1.8e-08			
Lender Liquidity (liquid Assets to deposit)							**2.8e-07**	*(2e-07)*	4.5e-08
Binding Financial and Regulatory Const (1)				**-1.6896**	*(1.489)*	-0.0661			
Binding Financial and Regulatory Const (2)							**0.1504**	*(1.239)*	0.0341
Log (Loan Size)				**0.3702** **	*(0.156)*	0.0240	**0.3425** **	*(0.154)*	0.0225
Log (Borrower Market Equity)				**-0.1406**	*(0.175)*	0.0025	**-0.0844**	*(0.174)*	0.0070
Number of Lenders				**-0.0001**	*(0.041)*	0.0003	**0.0031**	*(0.041)*	0.0006
Refinanced Loan				**-0.0806**	*(0.376)*	-0.0021	**-0.0831**	*(0.376)*	-0.0024
_cons	**5.0288*** **	*(0.627)*		**-0.3226**	*(2.575)*		**-0.3154**	*(2.533)*	
Panel B – Choosing no CRT vs. CDS									
Credit Quality (Long-term)	**-0.1946*** **	*(0.308)*		**-1.1093** **	*(0.044)*		**-0.1116** **	*(0.044)*	
Lender Capitalization (tier1)	**-2.7302**	*(0.527)*		**-2.0754**	*(2.075)*		**-2.7238**	*(2.462)*	
Lender Illiquidity (loan to deposit)	**-2.2e-07** **	*(9e-08)*		**-2.0e-07** **	*(9e-08)*				
Lender Liquidity (liquid Assets to deposit)							**-4.8e-07***	*(2e-07)*	
Binding Financial and Regulatory Const (1)				**0.6255**	*(1.049)*				
Binding Financial and Regulatory Const (2)							**--0.3488**	*(1.094)*	
Log (Loan Size)				**0.0121**	*(0.128)*		**0.0166**	*(0.128)*	
Log (Borrower Market Equity)				**-0.2230***	*(0.122)*		**-0.2324***	*(0.122)*	
Number of Lenders				**-0.0059**	*(0.024)*		**-0.0075**	*(0.024)*	
Refinanced Loan				**-0.0606**	*(0.221)*		**-0.0594**	*(0.221)*	
_cons	**4.1458*** **	*(0.502)*		**4.6554** **	*(1.989)*		**4.7229** **	*(1.990)*	
Number of Observations	**1007**			**928**			**928**		
Wald Chi Square	**174.83*** **			**179.70*** **			**216.78*** **		
Pseudo R Square	**0.1062**			**0.1263**			**0.1216**		

*** significant at 1% level ** significant at 5% level * significant at 10% level

Table 9– Hypothesis3- The Effect of The Effect of Borrower's Credit Quality and Borrower's Monitoring Costs for Lenders on Lenders' CRT Decision (Double Sorting Technique)

This Table presents results related to testing hypotheses 3 based on a double sorting technique. We present the lender's choice of Credit Risk Transfer conditional on the credit quality of borrowers (low/high) and the borrower's monitoring costs for lenders (low/high). Borrowers are assigned to two equally sized groups based on their long-term issuer credit rating provided by S&P. Lenders are grouped into two types based on how costly is monitoring the borrower for them on each facility (high and low). Borrower's monitoring cost for lender is low when there is at least one previous relationship between Lead Syndicate Arranges before the initiation of the current loan, and it is high otherwise. Numbers and Percentages are provided based on four possible credit risk transfer methods applied by banks: loan sale, CDS, both CDS and Loan Sale and none. Percentages are based on the total number of facilities in each borrower group i.e. sum of number of facilities in CDS, Loan Sale, both and none categories for each ranking group. The table also shows the difference and difference in difference results and their significance. The descriptions for all variables can be found in Appendix A.

		CRT	Monitoring Cost (Relationship Lending) Low		High		Diff (Low - High Capital)	Diff (High - Low Capital)
			Number	Percentage	Number	Percentage		
Borrower Quality (Long-Term)	Low	Both	25	**7.51%**	8	**3.46%**	4.04%**	-4.04%
		CDS	32	**9.61%**	11	**4.76%**	4.85%**	-4.85%
		None	202	**60.66%**	149	**64.50%**	-3.84%	3.84%
		Sale	74	**22.22%**	63	**27.27%**	-5.05%	5.05%*
	High	Both	3	**0.67%**	0	**0.00%**	0.67%	-0.67%
		CDS	137	**30.58%**	38	**32.20%**	**-1.62%**	**1.62%**
		None	303	**67.63%**	80	**67.80%**	-0.16%	0.16%
		Sale	5	**1.12%**	0	**0.00%**	1.12%	-1.12%

		Low	High
Diff (Low - High credit)	Both	6.84%***	3.46%**
	CDS	-20.97%	-27.44%
	None	-6.97%	-3.29%
	Sale	21.11%***	27.27%***
Diff (High - Low credit)	Both	-6.84%	-3.46%
	CDS	**20.97%*** **	**27.44%*** **
	None	6.97%**	3.29%
	Sale	-21.11%	-27.27%

Diff in Diff (Low - High)

Both	3.37%
CDS	**6.47%**
None	-3.68%
Sale	-6.17%

*** significant at 1% level   ** significant at 5% level   * significant at 10% level

Table 10– Hypothesis3- The Effect of The Effect of Borrower's Credit Quality and Borrower's Monitoring Costs for Lenders on Lenders' CRT Decision (Multivariate Tests)

This Table presents multivariate tests for hypothesis 3. Three Multinomial Logit models have been used to show the impact of different factors on lender banks risk transfer decision. The dependent variable is CRT_instrument which is a categorical variable. It equals 1 if the lenders have chosen no CRT, equals 2 if they have chosen CDS, and 3 if they have chosen loan sales. Facilities that are both sold and hedged through CDs are dropped from the regression. The base for multinomial logit regressions is CRT_instrument equal to 1, i.e. no CRT instrument is used. The results for sale and none are reported in panels A and B. Therefore the coefficients in panel A (B) shows what the effect of one additional unit change in the independent variable is on the odds of being hedged through CDS (being sold) rather than using CDS as a CRT instrument. We also report *"Elasticity"* which is calculated as *d(lnF)/d(lnx)*, where d is the first derivative, *ln(F)* is the natural logarithm of the density function and *ln(x)* is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. The main independent variables to test hypothesis 3 are borrower's credit quality (measured by S&P long term issuer credit ranking), whether or not it is the first time that a good borrower enters into a loan agreement with the lead arranger lenders, and existence of a previous relationship independent of the quality of the borrower (relationship lending). The descriptions for all variables can be found in Appendix A.

CRT Instrument	Model 1			Model 2			Model 3		
	Coefficient	Std. Error	Elasticity	Coefficient	Std. Error	Elasticity	Coefficient	Std. Error	Elasticity
Panel A – Choosing CDS vs. no CRT									
Credit Quality (Long-term)	**0.1702*** **	*(0.031)*	0.0257	**0.0741**	*(0.046)*	0.0115	**0.0499**	*(0.047)*	0.0075
First relationship with a good borrower	**0.9016** **	*(0.457)*	0.1839	**1.1645** **	*(0.551)*	0.2418	**1.0041** **	*(0.567)*	0.1986
Relationship Lending	**0.7804** **	*(0.398)*	0.1072	**0.9206***	*(0.494)*	0.1252	**0.7227**	*(0.506)*	0.0971
Lender Capitalization (tier1)				**2.5196**	*(2.388)*	0.3842	**2.6513**	*(2.207)*	0.3912
Lender Illiquidity (Loan-to-Deposit)				**2.1e-07** **	*(9e-08)*	3.1e-8	**2.2e-07** **	*(10e-8)*	3.3e-08
Log (loan size)				**-0.0200**	*(0.124)*	-0.0032	**-0.0286**	*(0.131)*	0.3912
Log (Borrower Market Equity)				**0.2477** **	*(0.124)*	0.0379	**0.2310***	*(0.122)*	3.3e-08
Number of Lenders							**0.0027**	*(0.024)*	-0.0004
Refinanced Loan							**0.1198**	*(0.227)*	0.0177
Secured Loan							**-0.7737** **	*(0.352)*	-0.1043
cons	**-4.2574*** **	*(0.507)*		**-5.0382*** **	*(1.934)*		**-4.1928** **	*(2.061)*	
Panel A – Choosing CDS versus Sale									
Credit Quality (Long-term)	**-0.2252*** **	*(0.042)*		**-0.3559*** **	*(0.073)*		**-0.3016*** **	*(0.082)*	
First relationship with a good borrower	**-32.557*** **	*(0.343)*		**-34.477*** **	*(0.403)*		**-32.223*** **	*(0.453)*	
Relationship Lending	**-0.3780**	*(0.274)*		**-0.2860**	*(0.324)*		**-0.1060**	*(0.327)*	
Lender Capitalization (tier1)				**4.6406**	*(3.804)*		**2.3067**	*(5.061)*	
Lender Illiquidity (Loan-to-Deposit)				**3.1e-07*** **	*(5e-08)*		**2.4e-07*** **	*(6e-08)*	
Log (loan size)				**0.3507*** **	*(0.111)*		**0.3805*** **	*(0.108)*	
Log (Borrower Market Equity)				**0.1217**	*(0.145)*		**0.1853**	*(0.154)*	
Number of Lenders							**-0.0035**	*(0.041)*	
Refinanced Loan							**-0.2631**	*(0.311)*	
Secured Loan							**1.2285*** **	*(0.395)*	
cons	**1.1508*** **	*(0.422)*		**-5.6212*** **	*(1.989)*		**-7.6906*** **	*(2.129)*	
Number of Observations	**1094**			**928**			**928**		
Wald Chi Square	**36008.08*** **			**48057.30*** **			**31398.28*** **		
Pseudo R Square	**0.1190**			**0.1346**			**0.1545**		

*** significant at 1% level   ** significant at 5% level   * significant at 10% level

Table 11– Hypothesis4- The Effect of Borrower's Credit Quality and Lenders' Reputation on Lenders' CRT Decision (Double Sorting Technique)

This Table presents results related to testing hypotheses 4 based on a double sorting technique. We present the lender's choice of Credit Risk Transfer conditional on the credit quality of borrowers (low/high) and the reputation of the lenders (low/high). Borrowers are assigned to two equally sized groups based on their long-term issuer credit rating provided by S&P. Lenders are grouped into two types (high and low) based on their reputation measured as market share in the primary loan market. If there is more than one lender in a loan facility the maximum market share is used as a measure for reputation. Also a combined measure of reputation and capital adequacy is used in panel B. Number and Percentages are provided based on four possible credit risk transfer methods applied by banks: loan sale, CDS, both CDS and Loan Sale and none. Percentages are based on the total number of facilities in each borrower group i.e. sum of number of facilities in CDS, Loan Sale, both and none categories for each ranking group. The table also shows the difference and difference in difference results and their significance.

Lenders are divided into two groups correspondingly based on reputation in Panel A, and a combination of reputation and tier1 ratio in Panel B. Lenders in the Low category in Panel B are those lenders whose both tier1 ratios and reputation are less than median tier1 and reputation. The descriptions for all variables can be found in Appendix A.

No stands for Number and % stands for Percentage

		CRT	Lender Reputation (Market Share in the Primary Market) Low Number	Low Percentage	High Number	High Percentage	Diff (Low - High Capital)	Diff (High - Low Capital)
Borrower Quality (Long-Term)	Low	Both	15	**5.62%**	18	**6.06%**	-0.44%	0.44%
		CDS	24	**8.99%**	19	**6.40%**	2.59%	-2.59%
		None	161	**60.30%**	190	**63.97%**	-3.67%	3.67%
		Sale	67	**25.09%**	70	**23.57%**	1.52%	-1.52%
	High	Both	1	**0.52%**	2	**0.54%**	-0.02%	0.02%
		CDS	62	**32.12%**	113	**30.29%**	1.83%	-1.83%
		None	129	**66.84%**	254	**68.10%**	**-1.26%**	**1.26%**
		Sale	1	**0.52%**	4	**1.07%**	-0.55%	0.55%

		Low	High
Diff (Low - High credit)	Both	5.10%***	5.25%***
	CDS	-23.14%	-23.90%
	None	-6.54%	-4.12%
	Sale	24.58%***	22.50%***
Diff (High - Low credit)	Both	-5.10%	-5.25%
	CDS	23.14%***	23.90%***
	None	6.54%*	4.12%
	Sale	-24.58%	-22.50%

Diff in Diff (Low - High)	
Both	-0.42%
CDS	0.76%
None	-2.42%
Sale	2.08%

*** significant at 1% level ** significant at 5% level * significant at 10% level

		CRT	Lender Reputation and Capitalization (Tier1 and Market Share)				Diff (Low - High Capital)	Diff (High - Low Capital)
			Low		High			
			Number	Percentage	Number	Percentage		
Borrower Quality (Long-Term)	Low	Both	9	**7.20%**	11	**5.85%**	1.35%	-1.35%
		CDS	7	**5.60%**	13	**6.91%**	-1.31%	1.31%
		None	78	**62.40%**	119	**63.30%**	-0.90%	0.90%
		Sale	31	**24.80%**	45	**23.94%**	0.86%	-0.86%
	High	Both	1	**1.03%**	0	**0.00%**	1.03%*	-1.03%
		CDS	36	**37.11%**	60	**35.29%**	1.82%	-1.82%
		None	60	**61.86%**	109	**64.12%**	**-2.26%**	**2.26%**
		Sale	0	**0.00%**	1	**0.59%**	-0.59%	0.59%

		Low	High
Diff (Low - High credit)	Both	6.17%***	5.85%***
	CDS	-31.51%	-28.38%
	None	0.54%	-0.82%
	Sale	24.80%***	23.35%***
Diff (High - Low credit)	Both	-6.17%	-5.85%
	CDS	31.51%***	28.38%***
	None	-0.54%	0.82%
	Sale	-24.80%	-23.35%

Diff in Diff (Low - High)	
Both	0.32%
CDS	-3.13%
None	1.36%
Sale	1.45%

*** significant at 1% level   ** significant at 5% level   * significant at 10% level

Table 12– Hypothesis4- The Effect of Borrower's Credit Quality and Lenders' Reputation and Regulatory and Financial Constraints on Lenders' CRT Decision (Multivariate Tests)

This Table presents multivariate tests for hypothesis 3. Two Logit models have been used to show the impact of different factors on lender banks risk transfer decision. The dependent variable is using a CRT instrument which is a binary variable. It equals 1 if the lenders have chosen at least one CRT instrument (CDS or loan sale) and equals 0 otherwise. Each coefficient shows what the effect of one additional unit change in the independent variable is on the odds of being hedged through CDS or sale. We also report *"Elasticity"* which is calculated as *d(lnF)/d(lnx)*, where d is the first derivative, *ln(F)* is the natural logarithm of the density function and *ln(x)* is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. The main independent variables to test hypothesis 4 are borrower's credit quality (measured by S&P long term issuer credit ranking), Lender's reputation, lender's capital adequacy (tier1 ratio), lender's illiquidity (loans to deposits ratio), lender's reputation, lender's binding financial and regulatory constraints, and whether or not the loan is related to a reputable lender with good liquidity and capitalization dealing with a good quality borrower. The descriptions for all variables can be found in Appendix A.

Using a CRT Instrument (CDS/Sale)	Model 1			Model 2		
	Coefficient	**Std. Error**	**Elasticity**	**Coefficient**	**Std. Error**	**Elasticity**
Panel A – Choosing at least one CRT instrument vs. no CRT						
Credit Quality (Long-term)	**-0.0958****	*(0.039)*	-0.0213	**-0.0947****	*(0.040)*	-0.0211
Lender Capitalization (tier1)	**3.1509**	*(2.323)*	0.7020	**3.1408**	*(2.353)*	0.6993
Lender Illiquidity (Loan-to-Deposit)	**2.1e-07*****	*(6e-08)*	4.7e-08	**2.3e-07*****	*(6e-08)*	5.0e-08
Lender Reputation	**-1.0869**	*(1.050)*	-0.2422	**-1.3873**	*(1.180)*	-0.3089
Binding Financial and Regulatory Constraints	**-0.0777**	*(0.329)*	-0.0171	**-0.1104**	*(0.339)*	-0.0242
Reputable lender with good liquidity and Capitalization dealing with a good quality borrower	**-0.0986**	*(0.293)*	-0.0217	**-0.1084**	*(0.290)*	-0.0238
Log (loan size)	**0.1391**	*(0.093)*	0.0310	**0.1333**	*(0.097)*	0.0297
Log (Borrower Market Equity)	**0.2182****	*(0.989)*	0.0486	**0.2204****	*(0.098)*	0.0491
Relationship Lending				**0.1501**	*(0.211)*	0.0330
Number of Lenders				**-0.0162**	*(0.021)*	-0.0036
Refinanced Loan				**0.1737**	*(0.185)*	0.0384
cons	**-4.1167*****	*(1.544)*		**-4.1297*****	*(1.607)*	
Number of Observations	**953**			**953**		
Wald Chi Square	**31.44*****			**34.29*****		
Pseudo R Square	**0.0303**			**0.0324**		

*** significant at 1% level   ** significant at 5% level   * significant at 10% level