Syndicated loans and CDS positioning☆

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Abstract

This paper analyzes banks' usage of CDS by matching syndicated loan data with a unique EU-wide dataset on bilateral CDS positions. Stronger banks in terms of capital, funding and profitability tend to hedge more. We find no evidence of banks using the CDS market for capital relief. Banks are more likely to hedge exposures to relatively riskier borrowers and less likely to sell CDS protection on domestic firms. Lead arrangers tend to buy more protection, potentially exacerbating asymmetric information problems. Dealer banks seem insensitive to firm risk. These results allow for a better understanding of banks' credit risk management.

Keywords: syndicated loans, CDS, speculation, capital regulation, EMIR, cross-border lending, asymmetric information
JEL: G21, G28

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1. Introduction

Credit Default Swaps (CDS) are one of the main financial innovations of the past decades. Due to their superior liquidity conditions relative to the markets of their underlying assets, CDS have emerged as a key benchmark for price discovery in the corporate debt market, and CDS quotes have become the most direct price-based measure of corporate default risk (see Raunig and Scheicher (2008)) as well as sovereign default risk (Longstaff et al. (2011)). The most important feature of CDS contracts is that they enable investors to flexibly establish long or short positions in the credit risk of the relevant references entities. Such credit risk transfer, in turn, can be used to either reduce (i.e. hedge) or increase (i.e. "double-up") already existing exposures to the same entity. The implications of these two practices can differ substantially (due to, for example, the CDS network being centered around only a few players). Understanding how CDS are used in practice, particularly among banks, is a key research area that this paper seeks to inform.

We combine loan-level data from the syndicated loan market, balance sheet data for banks and a unique dataset on bilateral CDS positions for all EU counterparties available at the European Systemic Risk Board (ESRB) following the EMIR regulation.[3] We zoom in on the credit relationship existing between banks and non-financial corporations via the syndicated loan market, and analyze the behavior of lenders in terms of credit risk hedging, or lack thereof.

We construct a measure of the share of any given loan that remains unhedged ("uninsured") by banks at a given point in time. In particular, for all bank-firm pairs in any given period, we compute the ratio of the loan exposure minus the net protection bought (gross protection bought minus gross protection sold) over the loan exposure. We document that, on average, the share of uninsured loans is slightly larger than 1. In other words, at least to some extent, banks use the CDS market for position taking purposes (i.e. to "double up" on their credit risk exposures from the syndicated loan market). This is in line with recent evidence provided for U.S. Bank Holding Companies (see Caglio et al. (2016)). Our sample, however, is cross-country and very large relative to the datasets typically used in the literature: Our broadest sample of European banks (*S1*) contains 1022 banks from 28 countries that lend to 14660 different firms from 144 countries, whereas our narrowest sample features both CDS active banks and CDS traded firms (*S4*), with 142 banks from 16 countries lending to 652 firms from 51 different countries.[4] We use the variable capturing the share of uninsured loans in a panel setting to evaluate a series of hypotheses.

We first investigate the relationship between firm risk and the share of uninsured loans by banks. In line with expectations, we find that banks tend to hedge a larger share of the loans to relatively riskier firms. This effect, however, is moderated if we control for banks' activity in the index market (i.e. CDS written on pools of reference entities as opposed to individual issuers, see Fender and Scheicher (2009)).

We then investigate the relationship between bank health and hedging behavior. While always controlling for bank size and index market activity, we focus on the ability to explain the share of uninsured loans afforded by different measures of bank risk characteristics (leverage as a measure of banks' broad asset risk, and wholesale funding to assets ratio as a measure of banks' funding risk) and performance (return on average assets). We find evidence supporting the

[3]Following the commitment by G20 leaders in the 2009 Pittsburgh summit to make the OTC derivatives market more transparent, the EU enacted the European Markets Infrastructure Regulation (EMIR). This regulation requires that all European counterparties engaging in derivatives transactions report them to trade repositories, which are themselves regulated by the European Securities Market Authority (ESMA). The regulation grants access to the EU-wide dataset to both ESMA and ESRB (see Abad et al. (2016)).

[4]The two other samples we consider focus separately on CDS active banks (*S2*) and CDS traded firms (*S3*).

hypothesis that weaker banks (higher leverage, larger share of wholesale funding, lower return on assets) tend to insure a smaller share of their exposures. This is consistent with explanations based on charter value, as in Keeley (1990): lower charter values (which we associate with weaker banks) decrease the incentives for a bank to insure its credit risk exposures. Our finding remains robust to controlling for observed and unobserved, time-varying, firm heterogeneity through $time \cdot firm$ fixed effects.

Contrary to the evidence presented in Hasan and Wu (2016), we find no evidence supporting the hypothesis that banks use the CDS market for capital relief purposes.[5] Under such a hypothesis, we would expect banks with lower risk-based regulatory capital ratios to insure a larger share of their loans, as for such banks the incentives to hedge, in terms of capital relief, are stronger. Indeed, we find the opposite effect: banks with higher regulatory capital tend to insure more. This result is also in line with our previous hypothesis on bank health and hedging behavior. Taken together, these findings speak to the literature on bank capital and risk aversion, by pointing towards better capitalized banks being more risk averse.

We find that the idiosyncratic risk of domestic loans is less likely to be "doubled up" by selling protection on the borrower. By controlling for bank and time fixed effects, and for borrower specific characteristics (either time-invariant or time-varying), we compare two loans by the same type of bank to two firms which only differ in their location: while one firm is in the same country as the headquarters of the bank, the other is in a different country. We find that the credit risk of the latter loan is more likely to be doubled up, as banks try to offset the home bias in their lending portfolios. The results are robust to simultaneously controlling for $bank \cdot time$ and $firm \cdot time$ fixed effects.

We also present evidence suggesting that the CDS market may exert negative externalities on the syndicated loan market. In particular, we find that, controlling for a series of factors, lead arrangers are more likely to hedge their credit risk exposures than other syndicate members. One interpretation of this finding is that it may exacerbate issues of asymmetric information in the syndicated loan market, by undermining the *skin in the game* provided by lead arrangers' loan retentions in order to alleviate adverse selection and moral hazard concerns.[6] The OTC nature of the market provides for an incentive to anonymously shed the credit risk exposure, using the informational advantages already obtained from the lending relationship. As with other results in the paper, the finding that lead arrangers hedge more of their credit risk exposures is robust across the different datasets considered and to specifications in which we control for time-varying bank and firm-specific characteristics.

We re-evaluate the different hypotheses after distinguishing between, first, the behavior of banks that double-up on risk (i.e. "speculators" or "position-takers", with a share of uninsured loans larger than 1) and those that do not, and second, between dealers and non-dealers. Banks that use the market for position taking increase more their uninsured loan ratio for riskier exposures. Such banks also show signs of acting for purposes of capital relief and are less sensitive to the cross-border nature of loans. More profitable banks hedge more often, regardless of whether they use the market for hedging or doubling-up risks. Dealer banks seem insensitive to firm risk, and hedge more (less) than non-dealers when they are more (less) profitable. Similarly, they also hedge more when they have a larger wholesale funding ratio.

The remainder of the paper is organized as follows. Section 2 reviews the literature on credit default swaps and syndicated lending. In Section 3, we introduce the data, describe the main variables used in the empirical analysis, and state our main hypotheses and empirical strategy.

[5]Under certain conditions, credit risk mitigation tools, such as CDS, can be used to lower the risk weight applied to credit risk exposures; see Section 3.2 for details.

[6]See, among others, Amiram et al. (2017), Sufi (2007), Ivashina (2009) and Mora (2015).

The results, including both summary statistics for the different subsamples as well as regression tables, are shown in Section 4. Section 5 concludes.

2. Related literature

The driving purpose behind credit default swaps, when originally developed by JP Morgan in the early 1990s, was the possibility of managing and transferring credit risk. Soon thereafter, such instruments proved useful in serving other, related, purposes.[7] CDS have been found to be used by banks to exploit insider information gained from lending relationships (Acharya and Johnson (2007))[8], to (potentially) increase the likelihood of borrower default instead of reducing it (Subrahmanyam et al. (2014))[9], to lead to more aggressive behavior in terms of risk-taking (Shan et al. (2014)) and to capital regulation arbitrage (Shan et al. (2016)). Other papers have addressed the relationship between credit derivatives and bank credit supply, without conclusive evidence (Hirtle (2009), Saretto and Tookes (2013)).

Closer to our work, some papers have tackled the issue of whether banks use the CDS market for hedging or position taking/speculating. Using data for US Bank Holding Companies (BHC), Minton et al. (2008) find very limited support for the proposition that banks use the CDS market to hedge. More recently, and using much more granular data for a similar group of banks, Caglio et al. (2016) document that banks use the CDS market to take on additional risk instead of merely for hedging purposes. For a sample of the 6 largest US BHC, Hasan and Wu (2016) find mixed evidence for the hypothesis that banks use the CDS market to hedge corporate loans.

Our paper contributes to this literature not by pinpointing a specific mechanism that rationalizes banks' use of the market, but instead by evaluating if and how banks act upon specific credit risk exposures using the CDS market. We do so using the broadest dataset to date in terms of number of banks, firms and countries, as well as regional coverage (with the focus being on Europe instead of the US). We explore the characteristics that define those actors that hedge versus those that do not, as well as the loan characteristics that make such decisions more or less likely. In doing this, we make use of syndicated loan data, which allows for a granular, detailed view of lending relationships (while admittedly covering only a part of banks' lending portfolio). This connects our paper to the growing literature using syndicated loan data, and provides a link between this and the literature on CDS, which has remained largely unexplored.[10] In the syndicated loan market, two or more financial institutions agree, under the leadership of one of them (the "lead arranger"), to jointly lend funds to a borrower.[11] Companies borrowing through the syndicated loan market tend to be large (see Altunbas et al. (2009)), a feature which also identifies those companies on which credit default swaps are written.

Streitz (2016) studies the effect of CDS trading on bank loan syndication activity and finds that, once CDS are actively traded on the debt of a given borrower, banks are less likely to

[7]The story of the CDS market and its inception, as well as the many opposing views regarding its potential risks and benefits, are very well covered in the review article by Augustin et al. (2014), who also present an extensive literature review.

[8]Using a theoretical model, Hakenes and Schnabel (2010) argue that, with private information on loan quality, banks have an incentive to give more bad loans, provided they can then perform credit risk transfer via, for instance, CDS. As a means of credit risk transfer, the model of Parlour and Winton (2013) finds that CDS are more likely to undermine monitoring.

[9]They provide supporting evidence for the implications derived from the theoretical model of Bolton and Oehmke (2011), who argue that firms with more CDS trading are more likely to file for bankruptcy (the so-called "empty creditor problem").

[10]The most notable exception being the recent contribution by Hasan and Wu (2016).

[11]For an early overview of the syndicated loan market, see Dennis and Mullineaux (2000). See also Altunbas et al. (2006) for a book-long treatment of the subject.

syndicate loans and retain a larger loan fraction. Following Saretto and Tookes (2013) and Subrahmanyam et al. (2014), Streitz (2016) proxies CDS activity by using banks' foreign exchange derivatives holdings. Recent papers are starting to exploit the more widespread availability of transaction-level data on credit derivatives to refine the analysis of the CDS market and its relationship to related markets. Gündüz (2016) and Du et al. (2016) use transaction-level data, similar to what is used here (but for Germany and the US respectively), to study related aspects of counterparty risk in the CDS market. Gündüz (2016) finds that, after buying protection from a counterparty, trading-intensive dealer banks engage in hedging activities over both short and long horizons, whereas non-dealer banks hedge over longer intervals. Du et al. (2016) find that counterparty risk has little effect on CDS pricing, substantially affecting instead the choice of counterparty. Gündüz et al. (2016) address similar questions as Hirtle (2009), Saretto and Tookes (2013) and Minton et al. (2008), but using much more granular data and with a focus around the so-called "small bang" in the CDS market.[12] Using data for Germany, they find that the small bang increased CDS trading and that banks use CDS to manage risks. Interestingly, they find that banks do not abuse the CDS market to take more risks: if they hold more CDS of safer firms, they supply more credit to them.

Our paper relates most closely to a recent contribution by Hasan and Wu (2016), who also use syndicated loan data and granular CDS data. The authors focus on the 6 largest US bank holding companies in order to study whether these banks use the CDS market to hedge their corporate loans, provide credit enhancements, obtain regulatory capital relief, and exploit banking relationships and private information. Finally, our paper relates to the recent contribution by Amiram et al. (2017), who suggest that CDS trading initiation reduces the skin in the game of lead arrangers in the syndicated loan market. Results from one of our hypotheses complement their findings.

The papers using granular transaction-level data on derivatives all make use of the Depository Trust and Clearing Corporation (DTCC) data, a trade repository that collects the lion's share of reported transactions in the CDS market.[13] As discussed below in more detail, we also make use of DTCC data in our analysis.

3. Data, hypotheses and methods

3.1. Data

We use granular data from different sources and match them by a combination of bank and company identifiers, whenever possible, or otherwise by hand. The three main datasets we use are: Thomson Reuters DealScan for the syndicated loan data, the DTCC data on transaction-level CDS derivatives positions obtained under the reporting obligation of the EMIR regulation in Europe,[14] and bank-level balance sheet data from S&P Global SNL Financial. Figure 1 summarizes the datasets and how they fit together in the context of our project. We go over each dataset in detail below.

[12]This event, which followed the "big bang" of 2009, was characterised by a series of contract reforms related to restructuring and standardization to facilitate trading on European corporate CDS and western European sovereign CDS (see Markit (2009)).

[13]Recently, these data have been used to provide a series of stylized facts on the CDS market, see Peltonen et al. (2014), Abad et al. (2016) and D'Errico et al. (2017) among others.

[14]The European Market Infrastructure Regulation (EMIR), which became effective in 2014, requires that all EU counterparties engaging in derivatives transactions report them to trade repositories authorized by the European Securities Markets Authority (ESMA). The trade repositories are then obliged to report to the relevant national authorities, with ESMA and the ESRB having access to the full EU-wide data. For details on the regulation see the dedicated website of the European Commission. For a first look at the data see Abad et al. (2016), who show that DTCC accounts for close to 80% of the CDS market.

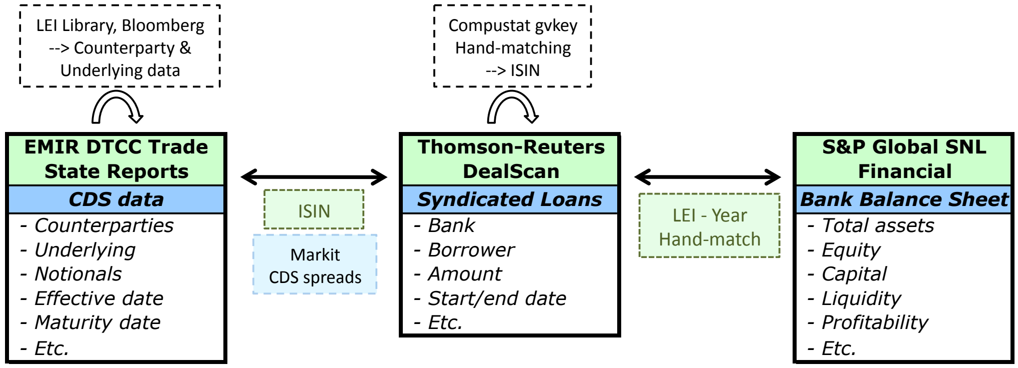

Figure 1: Overview of datasets and merging

Lending data. We obtain loan-level data from Thomson Reuters DealScan, which provides information on the terms and conditions of deals in the global commercial loan market. In the syndicated loan market, two or more banks (the "syndicate") agree to grant loans to other companies, under the leadership of one of the banks (the "lead arranger", who is responsible for most of the pre- and post-loan duties associated with bank lending). Lending in this market is organized in packages and facilities: a package is a loan agreement between a borrower and a group of lenders, and each package can contain one or more facilities. Our basic unit of observation is the facility. An appealing feature of these data is that it is possible to identify the identity of both borrower and lenders, as well as a rich set of loan characteristics. We focus on borrowers that are non-financial corporations, as well as on loan agreements with facility end date after October 2014.[15] We convert all non-euro loan amounts into euro at the exchange rate prevailing at loan origination. Using the Chava-Roberts Dealscan-Compustat Linking Database (see Chava and Roberts (2008)) plus additional hand-matching, we retrieve information on the International Security Identification Numbers (ISINs) belonging to the non-financial corporations (NFCs) we find as borrowers in the syndicated loan data from Compustat. We use this information to merge the loan data with the derivatives data. We also use the ISIN information to retrieve CDS spreads from Markit, for as many companies as possible.

Derivatives data. We obtain transaction-level derivatives data from DTCC, via the ESRB, which in turn has access to these data following the EMIR regulation. In particular, we use end-of-month "Trade State Reports" (TSR) ranging from October 2014 to December 2016.[16] Trade State Reports present the stock of all transactions as of a given date, thereby providing a snapshot of the entire market.

The data, as reported, is not readily usable for research purposes. For this reason, we perform an extensive cleaning procedure to take the data from its raw form to a state in which it can be used for analysis. Details of the cleaning procedure, which follows the one presented

[15] One reason for this restriction comes from the data we have available for CDS transactions. More details are provided below.

[16] There are Trade State Reports under the EMIR framework since April 2014, but due to poor data quality for some items, we leave them out of the analysis.

in Abad et al. (2016), are presented in Appendix A.[17] One feature of the data, as related to the regulation that underpins it, is worth noting here. The regulation requires that all EU counterparties engaging in a derivative transaction report it to an authorized trade repository. There is therefore a double reporting obligation, i.e. if the two counterparties are EU-based, then this should be reflected in a duplicated observation featuring reversed counterparties. The fact that each trade has a unique trade ID allows us to eliminate these duplicates, and provides for a sensible quality check of the data. Importantly, because the reporting obligation falls on EU counterparties, we are sure to see the entire market for them, but we cannot say the same about non-EU counterparties. We only see the latter to the extent that they are *reported* (as opposed to *reporting*). The focus of our analysis is therefore on EU-based banks, as in this case we are certain that, were there to be CDS activity, we should see it in the data.

In its raw form, the data present information on a trade-by-trade basis, with dozens of variables for each trade. The main variables of interest in our case are, besides the identity of reporting and reported counterparties: the identity of the underlying reference entity, the notional amount, and the effective and maturity dates. To identify counterparties, we use the Legal Entity Identifiers (LEIs) and complement them with a self-constructed LEI library.[18] We use this library to identify the sector of all counterparties, using information from the ORBIS dataset, which allows for this mapping between LEIs and sectors. Using the ISIN information to identify the underlying reference entities, we use Bloomberg to retrieve company and sector information. Importantly, since the focus is on NFCs, we exclude all trades on an ISIN not associated with a NFC.

As in most of the studies of the CDS market, we focus on the single-name market. Because of how the data is reported under the EMIR regulation, CDS contracts written on indices or bespoke baskets are since the fourth quarter of 2015 only identified with an "I" or a "B". This does not allow for a decomposition of the index into single-name equivalents. Nonetheless, we use the index market data to construct a bank-specific measure of index market activity that we include as control in our main regressions. More concretely, we build a summary measure of the overall activity of banks in the index market as follows: we compute the net-to-gross ratio and multiply it by the logarithm of total (index) market activity (see below for more details). We merge this indicator with our main dataset based on the LEIs.

As with the loan data, we convert all non-euro notional amounts to euro using the appropriate exchange rates. Beyond the focus on NFCs and the single-name market, we only consider transactions in which at least one counterparty is a financial institution. In order to combine the EMIR data with syndicated loan data, we hand-matched the counterparties of CDS transactions with lender names in Dealscan as well as the ISIN identifiers of the reference underlying (EMIR) and borrower (Dealscan).

Bank balance sheet data. We retrieve balance sheet information for banks from S&P Global SNL Financial. We match these data with syndicated loan data mostly by hand, using LEIs whenever possible. We retrieve information on size (total assets), performance (return on average assets), funding structure (wholesale funding-to-asset ratio) and risk (leverage, core equity capital to total risk-weighted assets - TIER1 ratio).

[17]The cleaning procedure involves getting rid of outliers, dropping duplicates, eliminating inconsistent/erroneous observations, dropping intragroup transactions, etc. The data we finally use for NFCs as reference entities represents around 50% of the cleaned data in terms of observations, and around 20% in terms of notional (see Appendix A).

[18]We thank several colleagues who contributed to the LEI library, especially Jorge Abad.

Construction of the sample. We start the construction of our sample by taking all syndicated loans that mature after October 2014 and calculate for each bank-firm relation the end of month stock of outstanding loans for the period October 2014 - December 2016. From the EMIR CDS data, we likewise calculate for each bank-reference underlying (firm) relation the aggregate end of month stock of notional amount of CDS outstanding both for the bank as a protection seller as well as for the bank as a protection buyer in a given month between October 2014 and December 2016. This allows us to observe the stock of net protection for bank i with respect to firm j in month t. We then merge the CDS information to the loan data on the bank i – firm j – time t level so that we observe, for each outstanding loan volume on the bank-firm level, the corresponding net notional stock of CDS bank i holds on firm j as the reference underlying of the CDS at time t. We drop all CDS information that did not match with the loan data, so our sample comprises all outstanding syndicated loans between October 2014 and December 2016. We merge banks' balance sheet information to the data, as well as market CDS quotes derived from Markit for the firms that have a CDS written on them.

Alternative sample specifications. Given the richness of our data, we can work with different subsamples. As in the EMIR data we observe only CDS transactions where at least one counterparty of the OTC trade is located in Europe, we cannot observe transactions of trades between two non-European entities. But of course our raw data includes a good amount of observations for non-European counterparties, whenever they are counterparty to a transaction reported by a EU counterparty. Therefore, the first, and more general, set of regressions involve the full sample of European banks, for which we would observe a CDS transaction if one took place. We refer to this sample as *Sample 1 (S1)*.

Many European banks that provide loans in a syndicate are in fact not active in the CDS market. This can be either out of choice, or because they do not have access to it due to, say, high fixed costs of entry. Hence, in a second sample we restrict observations to banks that are CDS active. We define CDS active banks as those that had at least one active CDS trade in the period between May 2014 and December 2016, and thus appeared at least once in the EMIR database.[19] We refer to this sample of CDS active European banks as *Sample 2 (S2)*.

An additional constraint might come from the firm's perspective: it can happen that a bank lends to a firm and wants to hedge (or double-up) the exposure, but there is just no market for CDS on that firm. For this reason, a third sample we consider is that of CDS traded firms: those firms for which there is a CDS available during May 2014 and December 2016. We refer to this sample as *Sample 3 (S3)*.

Finally, we combine the restrictions at the bank and firm level to construct a fourth sample that includes the overlap between the sets of CDS active banks and CDS traded firms. This is our more restrictive sample, and in it we can be confident that the lack of CDS activity is not due to either the bank not having access to the market or the firm not having a CDS written on it. While at first sight it might seem that this sample provides the strongest results, this need not be the case. For instance, it might occur that a bank does not participate in the CDS market because it does not wish to do so, or that it does not trade on a certain NFC because it is not part of its broader financial strategy. This sample leaves out many such observations, which have informational value.

[19] In this way, we assuage concerns that any lack of hedging we observe is simply due to lack of access to the market instead of a deliberate decision not to hedge a specific credit exposure. Note again that EMIR data is available since April 2014, but due to poor data quality and only very few observations in the early months, the sample we use for regressions starts in October 2014.

Due to space considerations, the regression analysis in the main text will focus on the broadest (*S1*) and the narrowest (*S4*) samples. Results for *Samples 2 & 3* are presented in Appendix B.

3.2. Hypotheses

With the structure of the data in mind, we now formulate the main hypotheses that we test in the empirical analysis. In our first hypothesis (Hypothesis 1), we argue that, other things being equal, banks are more likely to hedge their credit exposures to riskier firms. We proxy the riskiness of firms by means of their 5 year CDS market spreads. The idea that exposures to riskier firms are more likely to be hedged seems intuitive. Yet, one can argue that banks also want to be exposed to high return/high risk firms, and/or manage credit risk from a portfolio perspective (which would include exposures not captured by our syndicated loan data). In a refinement of our analysis, we will also zoom into the behavior of those banks that use the CDS market for position taking/speculation versus those that use it for hedging purposes.

Hypothesis 1 (Firm risk) *Ceteris paribus, banks insure a larger share of their syndicated loans to relatively riskier firms.*

Our second hypothesis explores the most basic dimension relating to banks' health and their hedging behavior. In particular, we posit that weaker banks will on average insure a smaller share of their exposures. In our analysis, weaker banks will be those scoring relatively poorly on risk (highly leveraged banks), profitability (low return on assets) and funding (a high share of wholesale funding, typically associated with more fragility). Cast in this way, the hypothesis can also be linked to a charter value argument, as put forward by Keeley (1990), even though we do not actually compute charter values for the banks in our sample. More precisely, lower charter values (associated to weaker banks) decrease the incentives for a bank to insure its lending business, i. e. , the circumstance that the threat of losing future rents is less severe might act as a deterrent to insure loan activities. Hypothesis 2 summarizes this conjecture.

Hypothesis 2 (Bank health and hedging behavior) *Ceteris paribus, weaker (stronger) banks tend to insure less (more).*

Under certain conditions, bank capital regulation allows banks to reduce the risk weights attached to some of their credit risk exposures by buying protection from a counterparty that has a better credit rating than the entity to which the bank is originally exposed to.[20] That is, CDS can be used for capital relief purposes (see for instance Shan et al. (2016) or Hasan and Wu (2016)). Under this "capital relief hypothesis", it is to be expected that banks that are in a weaker position in terms of their risk-weighted regulatory capital ratios have a greater incentive than their better capitalized peers to buy CDS protection on their credit risk exposures in order to lower the capital requirement implied by their lending portfolios. As in Hasan and Wu (2016), this hypothesis requires a negative correlation between net CDS positions and regulatory capital. This hypothesis also speaks to the vast literature on the relationship between bank capital and risk aversion.[21]

[20]For details on the treatment of risk mitigation in the credit risk framework, see for instance paragraph 167 and subsequent paragraphs in http://www.bis.org/bcbs/publ/d347.pdf.

[21]See for instance Flannery (1989), Gennotte and Pyle (1991), Kim and Santomero (1988) and Rochet (1992) among others. In their calibrated model, Calem and Rob (1999) find a U-shaped relationship between capital and bank risk-taking. While we do not explore the non-linear relationship, our findings are broadly in line with their model.

Hypothesis 3 (Capital relief) *Ceteris paribus, banks with lower risk-weighted capital ratios have stronger incentives to hedge their credit risk exposures for capital relief purposes.*

An interesting dimension afforded by the richness of our dataset relates to the cross-border nature of both lending and CDS data. It is sensible to expect that, after controlling for borrower-specific time-invariant and/or time-varying characteristics, cross-border (domestic) loans are more (less) likely to be insured. Consider the situation of a bank granting a loan to two firms of identical characteristics, but with one firm located in the same country of the bank and the second firm located in another country. We expect that the first loan is less likely to be insured than the second one. This can be due for instance to more uncertainties related to cross-border lending, less knowledge/proximity to the operations of the firm abroad, less ability to monitor, less strength of relationship lending, etc. Hypothesis 4 formalizes this conjecture.

Hypothesis 4 (Cross-border hedging) *Ceteris paribus, domestic (cross-border) loans are less (more) likely to be hedged.*

Syndicated loans are characterised by problems of asymmetric information. The structure of syndicated loans, where a lead arranger bank is in charge of establishing the relation with the borrower, negotiating and setting up the loan contract, monitoring/screening, etc., naturally leads to such problems. Lead arrangers have informational advantages over other lenders participating in the syndicate, and thereby have incentives to misrepresent the quality of the loan, i.e. an adverse selection problem. Furthermore, when retaining smaller shares of the loan, lead arrangers also have an incentive to underperform in the monitoring of the loan, i.e. a moral hazard concern (see Mora (2015)). Sufi (2007) explores issues of asymmetric information between lenders and borrowers in the syndicated loan market, and finds that, consistent with moral hazard concerns, lead arrangers retain a larger share of the loan. This can be a way to mitigate asymmetric information concerns by providing direct evidence of a commitment to monitor via *skin in the game*.[22] However, as noted by Parlour and Winton (2013), banks can shed credit risks via the credit default swap market, an option which allows the originating bank to retain the loan's control rights (as opposed to the alternative of loan sales). CDS can therefore undermine the *skin in the game* of lead arrangers and thereby exacerbate information asymmetry problems (see Amiram et al. (2017)). Given the OTC nature of the market, lead arrangers may thus have an incentive to tap this market, anonymously shed the credit risk arising from their loan share and thereby void the informational value of their loan share commitment. Furthermore, lead arrangers might find themselves with larger-than-expected shares when investors are willing to pay less than expected, leading to what Bruche et al. (2017) term "pipeline risk". This can provide an additional motivation to buy CDS protection. In any case, such OTC protection buying would tend to exacerbate information asymmetry problems. Hypothesis 5 summarises this idea.

Hypothesis 5 (CDS and asymmetric information externalities) *Ceteris paribus, lead arrangers tend to buy more protection, which can aggravate problems of asymmetric information in the syndicated loan market.*

3.3. Empirical approach

Dependent variable. Our empirical analysis attempts to explain the share of uninsured loans of bank i to firm j at time t (henceforth ULR_{ijt}, for Uninsured Loan Ratio). In order to calculate this share, we first derive the net notional amount of CDS protection on reference entity j by

[22] See also Ivashina (2009).

bank i at time t as the difference between the sum of bank i's CDS protection bought on reference entity j from any protection seller k and the aggregate amount of bank i's CDS protection sold on reference entity j to any protection buyer k,

$$\begin{aligned} &\mathit{NET\ NOTIONAL\ CDS\ HOLDINGS}_{ijt} \\ &\qquad = \sum_k \mathit{NOTIONAL\ CDS\ BUYING}_{ijt,k} - \sum_k \mathit{NOTIONAL\ CDS\ SELLING}_{ijt,k}. \end{aligned} \tag{1}$$

Next, we take the difference between the stock of loans from bank i to firm j that are in the loan portfolio of bank i at time t and the net notional holdings of CDS protection of bank i on reference entity j at time t as a ratio to the loan amount of bank i to firm j at time t:[23]

$$ULR_{ijt} = \frac{\mathit{LOAN\ HOLDING}_{ijt} - \mathit{NET\ NOTIONAL\ CDS\ HOLDINGS}_{ijt}}{\mathit{LOAN\ HOLDING}_{ijt}}. \tag{2}$$

We winsorise ULR_{ijt} at the 0.05%/99.95% level in order to eliminate the influence of extreme outliers. If $ULR_{ijt} = 1$, then bank i does not buy or sell (on net) protection on firm j at time t. Values of ULR_{ijt} larger than 1 indicate that the bank is doubling-up on its credit risk exposure, whereas value of ULR_{ijt} smaller than 1 indicate the bank is (at least partly) hedging the loan exposure. ULR_{ijt} can in fact take negative values, which would imply over-insurance on the part of the bank (i.e. buy net protection on firm j over and above the loan exposure from syndicated loans). In a refinement of the different hypotheses we explore, we will also distinguish between banks that double-up risk and the rest. Figure 2 presents the relative frequency of our uninsured loan ratio measure for the sample of CDS active banks and CDS traded firms (*S4*). The figure shows that the measure is centered around 1 and there is slightly more mass above than below this number, as well as larger numbers in the right tail.[24]

[23] In order to assign facility amounts to the different banks participating in the syndicates, we use the lender share variable whenever available, which gives an exact break-up of the contribution of each bank to the facility. Using the lender share data available, we construct average shares by "lender role type", distinguishing between the different top-tiers of arrangers versus plain "Participants" (for a similar approach see Bräuning and Ivashina (2017)), and use these average shares to distribute the lending in the syndicates for which we do not observe the lender shares. As a robustness test, we exclude all observations without lender share information and focus only on loans where bank shares within the syndicate are reported. The results remain broadly unchanged, see Appendix C.

[24] For confidentiality reasons, the buckets for the relative frequencies are the following: $[min, 0); [0, 0.5); [0.5, 1); 1; (1, 1.5); [1.5, 2); [2, max]$.

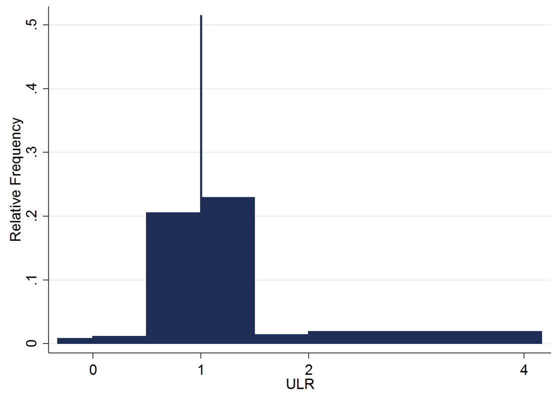

Figure 2: Relative frequency of the uninsured loan ratio (ULR) for *Sample 4*

Empirical model. The aim of our paper is to obtain insights regarding the correlation between several bank, firm and loan characteristics and the motivation to hedge or speculate. In order to clear off this correlation from third factors, we apply panel regressions and a series of fixed effects that allow us to control for bank- and firm-specific characteristics, either time-varying or time-invariant.

We start by testing for Hypothesis 1 in a regression where we model the uninsured loan ratio relating bank i to firm j at time t as a function of bank characteristics and a proxy for borrower risk. At the same time, we control for bank-specific (e.g. management style) and borrower-specific (e.g. industry) characteristics, as well as time fixed effects which absorb all variation that is time-specific and common to all banks (e.g. changes in regulation, global activity, etc.). In this way, we virtually compare the motivation to hedge a loan of two banks that are identical with regard to any time-constant factors and that lend to virtually identical firms (firms that are identical with respect to any time-constant factors), but differ in their risk characteristics. Using market CDS quotes restricts the sample size quite substantially. Furthermore, we can only run regressions using this variable for samples *3* and *4*. For this reason we present the results for this hypothesis separately.

For Hypotheses 2 and 3 we also run a stronger specification that fully controls for demand by including firm-time fixed effects, which capture all the variation that is both firm- and time-varying. Since this includes, but is not limited to, firm riskiness, in such specifications we cannot include the proxy for firm risk. By not including firm risk, however, we are able to test the hypotheses using samples other than *S3* and *S4*.

The baseline specification is thus given by:

$$ULR_{ijt} = \alpha_i + \alpha_t + \alpha_j + \alpha_{jt} + \kappa \cdot CDS_{j,t-1} + \boldsymbol{\beta'} \cdot \boldsymbol{BC}_{it-1} + \epsilon_{ijt} \tag{3}$$

where CDS_{jt} captures the firm riskiness and is represented by the market CDS spread of firm j in period t, and $\boldsymbol{BC}_{it} = (LEV_{it}, WF_{it}, ROA_{it}, TIER1_{it}, SIZE_{it}, IMA_{it+1})'$ is a vector containing different bank-specific characteristics such as different types of risk measures (LEV_{it} = leverage and WF_{it} = wholesale funding-to-assets ratio) and bank performance (ROA_{it} = return on average assets), as well as the regulatory TIER1 capital ratio, bank size, and a proxy measure for index market activity (IMA_{it}). $SIZE_{it}$ is measured as the bank's total assets in natural logarithm, and we use it as a control variable throughout all of our regressions. We construct IMA_{it} by computing, by bank, the overall net-to-gross ratio in the index market, and interact this with a measure of total index market activity of bank i. In particular, if we define gross buying and selling of protection by bank i in the index market in period t as b^I_{it} and s^I_{it} respectively, then $IMA_{it} = \frac{b^I_{it} - s^I_{it}}{b^I_{it} + s^I_{it}} log\left(b^I_{it} + s^I_{it}\right)$. Taking the net-to-gross ratio alone would not distinguish between dealers, who have small net to gross positions but are generally very active in the market, and other intermediaries who might have both small net to gross positions and reduced market activity. By controlling for index market activity, we aim to capture the portfolio hedging and general market positioning that different banks make. At the same time, it is a proxy way for capturing the nature of different players (say, banks that are more intensely involved in dealing). We lag the bank-specific variables by one period to avoid endogeneity. The only exception is IMA, which is used contemporaneously in order to capture contemporaneous substitution effects between single name and index CDS hedging. We further control for time-invariant bank characteristics by bank fixed effects (α_i), for time-varying common unobservables by means of time fixed effects (α_t), and for time-invariant borrower-specific characteristics via firm fixed effects (α_j). In the most saturated specification (highlighted in red), we further control for time-varying observed and unobserved firm heterogeneity with firm-time fixed effects α_{jt} (i. e., we include a dummy for every firm-month-year combination).

The corresponding parameters are collected in the vector $\boldsymbol{\beta'} = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6)$. According to Hypothesis 1, we expect $\kappa < 0$, that is, higher firm risk as captured by firms' market CDS spreads should be associated with a smaller share of the loan being uninsured. Based on Hypothesis 2, we expect the coefficients to be positive when looking at bank risk measures ($\beta_1, \beta_2 > 0$) and negative when considering profitability $\beta_3 < 0$. Under Hypothesis 3, we expect β_4 to be positive, i.e. lower regulatory capital values should be associated to a larger share of the credit exposure being insured.

In order to investigate Hypothesis 4, we expand the model in Equation 3 by incorporating a dummy ($DOM_{i,j}$) that captures whether the loan from bank i to firm j is domestic ($DOM_{i,j} = 1$) or cross-border ($DOM_{i,j} = 0$):

$$ULR_{ijt} = \alpha_i + \alpha_t + \alpha_j + \alpha_{jt} + \alpha_{it} + \kappa \cdot CDS_{jt-1} + \boldsymbol{\beta'} \cdot \boldsymbol{BC}_{it-1} + \gamma \cdot DOM_{i,j} + \epsilon_{ijt} \tag{4}$$

For Equation 4, our most saturated specification includes $bank \cdot time$ fixed effects, which control for all time-varying bank-specific characteristics, and $firm \cdot time$ fixed effects, that control for all observed and unobserved time-varying borrower-specific characteristics (these are highlighted in red in the equation above).[25] The reason behind this is that we aim to compare two loans by the same bank to two firms with identical characteristics other than their location, in order to evaluate whether the loan being domestic versus cross-border makes a difference, above and beyond pure bank- and firm-specific characteristics. We therefore exploit the within-bank, within-firm variation. Under Hypotheses 4 we expect $\gamma > 0$.

Finally, in order to test Hypothesis 5 we further expand the regression equation by incorporating a dummy, LA_{ijt}, which captures whether bank i is a lead arranger in loans granted to firm j during period t ($LA_{ijt} = 1$).[26]

[25] Note that when including $bank \cdot time$ fixed effects we cannot control for bank-specific time-varying characteristics such as size or the other bank characteristics used to address Hypotheses 2 and 3. We also of course drop bank, firm and time fixed effects.

[26] If bank i is involved in more than one loan to firm j in period t, the dummy takes the value of 1 if in at least one of these loans bank i is the lead arranger, as this would already capture the incentives underlying the hypothesis we want to explore.

$$ULR_{ijt} = \alpha_i + \alpha_t + \alpha_j + \alpha_{jt} + \alpha_{it} + \kappa \cdot CDS_{jt} + \boldsymbol{\beta'} \cdot \boldsymbol{BC}_{it-1} + \gamma \cdot DOM_{i,j} + \delta \cdot LA_{ijt} + \epsilon_{ijt} \tag{5}$$

As with the test for Hypothesis 4, our benchmark model in this case includes controls for firm characteristics, either time-invariant (α_j) or time-varying (α_{jt}). The goal is to compare loans by two banks to the same type of firm, with the difference stemming only from one bank being lead arranger. Again, we also explore the within-bank variation and compare, for the same bank, a loan where it acts as a lead arranger with a loan where it is not the lead arranger. Under Hypothesis 5 we expect δ to be negative. In all specifications, we cluster standard errors on the time level.[27]

4. Results

4.1. Descriptive statistics

Our broadest sample (*S1*) contains 1022 banks from 28 countries lending to 14660 different firms from 144 countries. Of the 1022 banks in the broadest sample, 280 (from 22 different countries) are CDS active and lend to a total of 13472 firms from 138 countries (*S2*). When we look at CDS traded firms (*S3*), the sample reduces substantially since a relatively small number of the firms on the broadest samples have a CDS traded on them: in this sample, 275 banks from 17 countries lend to 655 firms from 52 countries. Finally, in our most stringent sample containing both CDS active banks and CDS traded firms (*S4*), we observe 142 banks from 16 countries lending to 652 firms from 51 different countries. Even in this last sample, the number of different lenders and borrowers is substantial, and significantly larger than in the previous literature.

Table 1 provides descriptive statistics for the four different samples.[28]

[27] We cluster only on the time dimension following the argumentation in Abadie et al. (2017). We observe the population of bank-firm syndicated loan relations and CDS positions, but only for a subset of time periods. Thus, clustering errors on the bank and/or firm dimension would be correct only for an estimand based on the the presumption that there are bank / firm clusters in the population beyond the clusters that are in the sample.

[28] Note that we do not provide balance sheet characteristics for samples other than *S1* for confidentiality reasons.

Table 1: Summary statistics - Four samples

Variable	Obs	Mean	Std. Dev.	Min	Max
European Banks (S1)					
ULR	1207555	1.003	.107	-.326	4.164
$Size$	1207555	19.786	1.902	10.535	21.520
$Tier1$	1148339	15.396	14.558	-.700	261.370
LEV	1207555	19.158	16.105	1.002	425.020
WF	1151534	32.172	15.746	0	122.092
ROA	1207179	.248	.718	-52.536	21.910
IMA	1207555	.152	6.032	-22.774	20.028
DOM	1207555	.319	.466	0	1
LA	1207555	.696	.460	0	1
CDS active European Banks (S2)					
ULR	895061	1.004	.124	-.326	4.164
IMA	895061	.206	7.005	-22.774	20.028
DOM	895061	.268	.443	0	1
LA	895061	.713	.452	0	1
CDS traded Firms (S3)					
ULR	120360	1.030	.338	-.326	4.164
IMA	120360	.127	6.939	-22.774	20.028
DOM	120360	.153	.360	0	1
LA	120360	.580	.494	0	1
CDS active European Banks & CDS traded firms (S4)					
ULR	101906	1.035	.367	-.326	4.164
IMA	101906	.15	7.541	-22.774	20.028
DOM	101906	.140	.347	0	1
LA	101906	.586	.493	0	1

Notes: ULR is the uninsured loan ratio defined in (2). $Size$ stands for the logarithm of total assets, $Tier1$ for the TIER1 regulatory capital ratio, WF for the wholesale funding to assets ratio, LEV for total assets over equity, ROA for the return on average assets, IMA stands for the index market activity indicator, DOM is a dummy denoting the whether the loan is domestic or cross-border. LA stands for lead arranger.

For banks in the broadest sample, we observe an average share of uninsured loans of 100.3%, i. e., on average, banks use CDS not as an instrument for protection against credit events but rather seem to mildly double-up their credit risks. However, in *Sample 1*, a large number of banks does neither insure nor double-up risks (i.e. display a share of uninsured loans of 1).[29] We do observe, across all samples, a high maximum for the ULR, as well as a negative minimum (i.e. over-insurance, at least with respect to syndicated loan exposures). As the sample becomes more restrictive, the average ULR increases, reaching 104% for the sampe of CDS active banks and CDS traded firms.

The average balance sheet size of banks in our sample amounts to (in logs) 19.79, with the largest bank in our sample being HSBC and the bank with the smallest amounts of total assets being Banco Português de Investimento. Leverage is defined as the ratio of total bank assets to equity. Banks in our sample show an average leverage of 19.15, with a substantial maximum at 425.02 and minimum of almost purely equity-financing (i.e. leverage close to 1).[30] We observe an average amount of wholesale funding in relation to total assets of 32.54%, with some banks showing zero wholesale funding, while one bank depends more strongly on wholesale funding

[29] We performed tests for all four samples to check whether ULR is statistically significantly different from 1, and for all samples we reject the null hypothesis that $ULR = 1$ at 1% significance.

[30] We observe for very few banks a negative value of book equity, which would imply a leverage of infinity. We replace these observations with the maximum value of leverage observed in our sample, namely 425.02.

with a ratio of 122.09%.[31] Returns for our sample banks are on average positive, with an average return on assets ratio of 0.25%.

Finally, around 32% of all syndicated loans that we observe are granted from a bank to a firm within the same country, and the share of domestic loans decreases as the sample becomes more restrictive.

4.2. Main regression results

We now provide regression results for the hypotheses outlined above. We absorb all time-constant bank factors by including *bank* fixed effects as well as all factors that are constant for all loans by including *time* fixed effects. By including firm fixed effects, we also account for all firm specific characteristics that stay constant through time. In some regressions, we fully control for demand by adding $firm \cdot time$ fixed effects that control for all factors that vary on the firm-time dimension. In our most saturated specifications for Hypotheses 4 and 5, we control for both $firm \cdot time$ and $bank \cdot time$ fixed effects, thereby controlling for all observed and unobserved time-varying bank- and firm-specific characteristics.[32]

Hypothesis 1: Firm risk. We present results for Hypothesis 1 in Table 2. As market CDS spreads are the key variable for testing the hypothesis, the regressions only apply to *Samples 3* (CDS traded firms) and *4* (CDS active banks and CDS traded firms). The table presents results from estimating Equation 3 with *bank*, *firm* and *time* fixed effects, as well as bank-specific controls:[33] Columns (1) and (3) present results for *S3* and *S4* respectively, excluding index market activity as a control variable, whereas columns (2) and (4) control for potential index hedging by including the bank-level index market activity indicator.

We start by noting that, in line with Hypothesis 1, we find the uninsured loan ratio of bank i with respect to firm j is smaller the larger the market CDS quote of firm j. In other words, banks are more likely to hedge their credit exposures to riskier firms. The negative sign, as well as its magnitude, is consistent across the two samples. The coefficients are, however, relatively small.

As shown in columns (2) and (4), when including the control for banks' index market activity, the coefficient for the CDS quote becomes insignificant in *Sample 3*, while presenting weaker statistical significance in *Sample 4*. Portfolio and proxy hedging via the index market seems to take some explanatory power away from the standard CDS quote. Banks that are active participants in the index market tend to have a smaller share of loans uninsured in the single-name market. In the regressions that follow we will always control for index market activity.

Hypothesis 2: Bank health and hedging/speculating behavior. Results for our second hypothesis are presented in Table 3. The overall message is that healthier banks tend to insure larger shares of their syndicated credit exposures. Columns (1)-(2) refer to our broadest sample (*S1*), whereas columns (3)-(5) present results for the narrowest sample of CDS active banks and CDS

[31] Note that this wholesale funding ratio larger than 100% is due to negative equity.

[32] Note that we correct our sample for singleton groups, i. e. , groups with only one observation. We display in the tables the number of observations that were used to calculate cluster-robust standard errors i. e. the respective sample excluding singletons.

[33] In order to focus on the effect of CDS, we do not include the coefficients for the bank controls. The sign, magnitude and statistical significance of these are in line with the tables that follow.

Table 2: Firm Risk

	(1)	(2)	(3)	(4)
$CDS_{j,t-1}$	-0.000**	-0.000	-0.000**	-0.000*
	(-2.131)	(-1.403)	(-2.463)	(-1.964)
$IMA_{i,t}$		-0.008***		-0.006***
		(-7.649)		(-6.153)
R^2	0.280	0.295	0.299	0.308
N	90800	90800	77918	77918
Sample	$S3$	$S3$	$S4$	$S4$
Bank controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓

OLS regressions for Equation (3). The dependent variable is the ULR_{ijt} defined in (2). Bank controls include: Size (log of total assets), wholesale funding to asset ratio, TIER1 ratio, leverage (total assets over equity) and return on assets. All variables are lagged by one period except for $IMA_{i,t}$. $CDS_{j,t-1}$ stands for the lagged CDS quote of firm j. $IMA_{i,t}$ stands for the index market activity defined above. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

traded firms (*S4*). For both samples we explore a specification with *bank*, $firm$ and $time$ fixed effects,[34] as well as a more saturated specification which controls for all firm-specific time-varying characteristics through $firm \cdot time$ fixed effects.

Throughout all specifications, we find that the coefficient on leverage is statistically insignificant. For the regressions on *Sample 1*, the sign reverses compared to *Sample 4* and the magnitudes become negligible. We obtain a positive and statistically highly significant coefficient for a bank's share of wholesale funding to total assets in all specifications and for both samples, which indicates that banks with a higher funding risk (stronger reliance on wholesale funding) insure less of their credit risk. The coefficient of banks' return on average assets is throughout all specifications negative and highly significant: More profitable banks insure more often their loans than less profitable banks. The effect is quantitatively stronger in the narrow sample of CDS active banks and CDS traded firms. Larger banks tend to have a smaller share of loans uninsured, as do banks that are active in the index market. As shown in Appendix B, these results are consistent across samples, and are quantitatively stronger for the narrower samples. The only exception is bank size, which turns out to be insignificant in *Sample 4*.

[34] Running the same regressions as in columns (1), (3) and (4) without *bank* fixed effects yields the same message in terms of sign, magnitude and significance of the coefficients, but exhibits a somewhat smaller R^2 (between 5% and 10% smaller for columns (1) and (3)-(4) respectively).

Table 3: Bank Health / Capital Relief

	(1)	(2)	(3)	(4)	(5)
$Size_{i,t-1}$	-0.009***	-0.009***	-0.033	-0.051	-0.087
	(-4.673)	(-3.983)	(-0.500)	(-0.648)	(-1.217)
$Tier1_{i,t-1}$	-0.001***	-0.001***	-0.026***	-0.025***	-0.025***
	(-8.795)	(-10.160)	(-6.223)	(-6.579)	(-6.414)
$LEV_{i,t-1}$	0.000	0.000	-0.005	-0.004	-0.003
	(0.076)	(0.542)	(-0.949)	(-0.696)	(-0.647)
$WF_{i,t-1}$	0.002***	0.002***	0.028***	0.030***	0.027***
	(4.840)	(5.662)	(12.004)	(9.988)	(-12.506)
$ROA_{i,t-1}$	-0.004***	-0.005***	-0.080***	-0.077***	-0.077***
	(-4.350)	(-4.220)	(-6.542)	(-5.447)	(-6.530)
$IMA_{i,t}$	-0.001***	-0.001***	-0.006***	-0.006***	-0.007***
	(-8.951)	(-9.686)	(-6.836)	(-6.153)	(-7.373)
$CDS_{j,t-1}$				-0.000*	
				(-1.964)	
R^2	0.167	0.248	0.305	0.308	0.378
N	1097434	976947	96174	77918	93335
Sample	$S1$	$S1$	$S4$	$S4$	$S4$
Bank FE	✓	✓	✓	✓	✓
Time FE	✓		✓	✓	
Firm FE	✓		✓	✓	
Firm · Time FE		✓			✓

Notes: OLS regressions for Equation (3). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Overall, these results are in line with our expectation, and unambiguously support Hypothesis 2: Weaker banks (presumably with a lower charter value) appear to have lower incentives to insure their loans. Note that our setting allows us to control for many dimensions using fixed effects. In this way, the results from the specification where we include $firm \cdot time$ fixed effects imply that, within the set of loans granted in the same month to the same firm by different banks, banks with weaker balance sheets tend to insure a smaller fraction of the loan using credit default swaps.

Hypothesis 3: Capital relief. As can also be seen in Table 3, we do not find support for the capital relief hypothesis. Under the latter, one would expect to see banks with lower regulatory capital ratios having higher incentives to use the CDS market in order to hedge their credit risk exposures, thereby obtaining capital relief via a sort of risk-weighting arbitrage. In the context of our empirical setting, this should translate into a positive coefficient for the TIER1 ratio: higher regulatory capital ratios should be associated with a higher share of the loan being uninsured. To the contrary, we observe a negative sign: A larger TIER1 ratio is associated with a smaller share of the loan being uninsured, i.e. a larger share of the loan being insured.[35] These results are in contrast to those of Hasan and Wu (2016), who use a similar empirical design but a very different data set: Whereas they focus on 6 large U.S. bank holding companies (presumably all dealer banks), we work with a significantly larger group of European banks, ranging from 1022 in the broadest sample to 142 in the narrowest, including banks with very different business models. Furthermore, these banks come from many different countries.

The results hold in all samples, and become even stronger in the narrower samples, in particular the one focusing on CDS active banks and CDS traded firms (*S4*). They are also stronger whenever we control for all observed and unobserved time-varying firm-specific characteristics, which contain, but are not limited to, borrower riskiness.

The findings from Hypotheses 2 and 3 are complementary, and they point to stronger banks (i.e. better capitalized, funded through more stable sources, etc.) being more inclined to hedge larger portions of their credit risk exposures. Taken together, these findings speak to the literature on bank capital risk aversion mentioned earlier, by pointing towards better capitalized banks being more risk averse.

Hypothesis 4: Cross-border hedging. Next, we test for Hypothesis 4 and present the regression results in Table 4. For the domestic loan dummy, we find a negative and significant coefficient. This implies that, controlling for a series of bank characteristics and different fixed effects, banks are more likely to hedge their domestic loans relative to similar foreign loans. This result also holds if we control for firm observable and unobservable time-invariant and time-varying characteristics, including firms' risk. When we specifically control for firm risk through the CDS spread in *S4*, we find that this variable is significant and negative, yet the domestic dummy retains its significance and magnitude. Thus, comparing a bank lending to two firms of virtually identical characteristics (including the same level of riskiness), we find that the loan to the domestic firm is hedged to a larger extent than the loan to the firm abroad. This could point to banks trying to overcome their home bias, diversifying out of their home market in credit terms. Furthermore, the result survives the specification in which we control for all bank- and firm-specific time-varying characteristics, and thereby exploit the within-bank, within-firm variation. In this way we compare two loans granted by virtually the same bank to the same hypothetical firm, where the only difference stems from one loan being granted within the borders of the country whereas another loan is made cross-border. Note that $bank \cdot time$ fixed effects absorb all time-varying bank characteristics, so we cannot estimate coefficients for the bank balance sheet variables as well as the indicator for index market activity. The result that domestic loans are more likely to be hedged than similar cross-border loans is also present throughout all the four samples we consider (see Appendix B).

This finding is not in line with our original expectation as laid out in Hypothesis 4. An explanation for this result might be the following: The negative coefficient also implies that bank double-up the credit risk less often. However, as banks typically have more loans to domestic firms given individually rather than in a syndicate, they might be less willing to double-up idiosyncratic risks but rather diversify the loan portfolio (which is domestically less expensive in terms of collecting soft information).

It is worth noting that all the results pertaining to the previous hypotheses continue to hold in this expanded specification, across all samples and fixed effects combinations.

[35]One could argue that the results found for leverage and TIER1 ratio are driven by including both variables simultaneously. In untabulated results, we find that this is not the case.

Table 4: Cross-border hedging

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Size_{i,t-1}$	-0.009***	-0.009***		-0.033	-0.051	-0.087	
	(-4.680)	(-3.992)		(-0.498)	(-0.649)	(-1.217)	
$Tier1_{i,t-1}$	-0.001***	-0.001***		-0.026***	-0.025***	-0.025***	
	(-8.802)	(-10.173)		(-6.222)	(-6.583)	(-6.413)	
$LEV_{i,t-1}$	0.000	0.000		-0.005	-0.004	-0.003	
	(0.076)	(0.544)		(-0.952)	(-0.699)	(-0.649)	
$WF_{i,t-1}$	0.002***	0.002***		0.028***	0.030***	0.027***	
	(4.840)	(5.664)		(11.996)	-9.983	-12.502	
$ROA_{i,t-1}$	-0.004***	-0.005***		-0.080***	-0.077***	-0.076***	
	(-4.350)	(-4.219)		(-6.536)	(-5.441)	(-6.526)	
$DOM_{i,j}$	-0.001***	-0.001***	-0.001***	-0.012***	-0.013***	-0.011**	-0.008**
	(-4.931)	(-4.698)	(-3.946)	(-2.987)	(-3.346)	(-2.744)	(-2.219)
$IMA_{i,t}$	-0.001***	-0.001***		-0.006***	-0.006***	-0.007***	
	(-8.951)	(-9.686)		(-6.837)	(-6.153)	(-7.375)	
$CDS_{j,t-1}$					-0.000*		
					(-1.959)		
R^2	0.167	0.248	0.259	0.305	0.308	0.378	0.42
N	1097434	976947	1081842	96174	77918	93335	98104
Sample	$S1$	$S1$	$S1$	$S4$	$S4$	$S4$	$S4$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (4). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets (i.e. size), $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Hypothesis 5: CDS and asymmetric information externalities. Table 5 presents the regression results pertaining to Hypothesis 5 by estimating Equation 5. The set-up of the table is similar to that of Table 4: the first three columns present results for the different specifications within the sample of European banks (*S1*), whereas the last four columns present results for different specifications using the sample of CDS active banks and CDS traded firms (*S4*).

Table 5: CDS and asymmetric information externalities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Size_{i,t-1}$	-0.009***	-0.009***		-0.032	-0.050	-0.086	
	(-4.683)	(-3.996)		(-0.484)	(-0.641)	(-1.207)	
$Tier1_{i,t-1}$	-0.001***	-0.001***		-0.026***	-0.025***	-0.025***	
	(-8.801)	(-10.171)		(-6.216)	(-6.583)	(-6.403)	
$LEV_{i,t-1}$	0.000	0.000		-0.005	-0.004	-0.003	
	(0.076)	(0.546)		(-0.951)	(-0.697)	(-0.647)	
$WF_{i,t-1}$	0.002***	0.002***		0.028***	0.030***	0.027***	
	(4.838)	(5.662)		(12.010)	(9.989)	(12.517)	
$ROA_{i,t-1}$	-0.004***	-0.005***		-0.080***	-0.077***	-0.076***	
	(-4.353)	(-4.220)		(-6.547)	(-5.460)	(-6.530)	
$DOM_{i,j}$	-0.001***	-0.001***	-0.001***	-0.010**	-0.010***	-0.009**	-0.006*
	(-4.739)	(-4.391)	(-3.544)	(-2.572)	(-2.868)	(-2.299)	(-1.744)
$LA_{i,j}$	-0.002***	-0.002***	-0.002***	-0.020***	-0.027***	-0.020***	-0.019***
	(-6.396)	(-7.503)	(-8.660)	(-9.014)	(-6.417)	(-9.890)	(-9.504)
$IMA_{i,t}$	-0.001***	-0.001***		-0.006***	-0.006***	-0.007***	
	(-8.951)	(-9.686)		(-6.842)	(-6.153)	(-7.379)	
$CDS_{j,t-1}$					-0.000*		
					(-1.915)		
R^2	0.167	0.248	0.259	0.305	0.308	0.378	0.42
N	1097434	976947	1081842	96174	77918	93335	98104
Sample	$S1$	$S1$	$S1$	$S4$	$S4$	$S4$	$S4$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (5). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets (i.e. size), $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). $LA_{i,j}$ is a dummy indicating whether bank i is a lead arranger in the loan being granted. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Controlling for borrowers' characteristics using $firm$ fixed effects or $firm \cdot time$ fixed effects, we obtain a negative and significant coefficient for the lead arranger dummy. Comparing two banks lending to the same firm, with one bank being a lead arranger while the other is not, we find that the former tends to buy more net protection on its loans than the non lead arranger bank. Thus, our finding confirms Hypothesis 5. In columns (3) and (7), we again explore the within-bank variation using $bank \cdot time$ fixed effects. We thus compare two loans granted by virtually the same bank, where one loan was given as a lead arranger whereas the second loan was not. The negative coefficient for the lead arranger dummy remains in place, both in terms of statistical significance and magnitude. This further confirms our results on Hypothesis 5, i.e. banks buy more protection on loans for which they act as lead arrangers. Note again that we cannot estimate coefficients for our bank balance sheet variables due to the inclusion of $bank \cdot time$ fixed effects. As with the results using the domestic dummy, our finding on lead arrangers being more likely to hedge similar exposures than non lead arrangers is consistent across the different samples considered, as shown in Appendix B for *Samples S2* and *S3*.

These results point to a possible negative externality the CDS market imposes on the syndicated loan market. Due to the structure of syndicates, there are issues of both moral hazard and adverse selection, as reviewed above. While the syndicated loan market presents some features that allow lead arrangers to signal commitment and thereby mitigate information asymmetries, our finding that lead arrangers shed their credit risk via CDS (while retaining control rights over the loan) may undermine such signaling mechanisms. Depending on the lead arranger's overall position vis-à-vis the borrower (which we do not see), the fact that the CDS market is OTC may thus provide opportunities to anonymously reduce their credit risk. These results are in line with the findings in Amiram et al. (2017). In unreported results, we also confirm one of their key findings, namely that the loan share retained by lead arrangers is larger for CDS traded firms than non-CDS traded firms.

All results regarding Hypotheses 2, 3 and 4 remain robust to this expanded specification, and continue to hold across samples: Banks with a higher charter value (i.e. healthier banks) tend to hedge their loans more often, banks do not seem to use the CDS market for capital relief purposes, and cross-border loans are more likely to be doubled up.

4.3. Do speculators differ?

Having tackled our main hypotheses, we now take our main dependent variable and split it in order to evaluate whether the characteristics of banks that use the market to double-up on their credit risk exposures differs from those banks which do not double-up. We term the former as "speculators"/position takers.

As noted earlier, the uninsured loan ratio defined in Equation 2 can be in different ranges. Negative readings of this indicator point to possible over-insurance, namely net protection buying over and above the initial credit exposure, at least regarding the syndicated loan exposure. Values between zero and one indicate that the bank is, at least partially, hedging its exposure. Values of the ULR equal to one signal that the bank neither buys nor sells protection on the syndicated lending exposure. Finally, the most relevant region for the analysis in this section refers to when the ULR is larger than one. In such scenario, banks are using CDS markets to increase (i.e. "double up") rather than reduce their credit exposure.

We split the ULR into two regions: when $ULR > 1$ we term this "doubling-up", and whenever $ULR \leq 1$ we label this "hedging".[36] The main goal is to assess whether there exist nuances in the main findings described in the previous section if we account for the possibility that "speculators" might be different than the rest.

Due to space considerations we only present results that expand on Tables 2 and 5. We expand these tables by interacting both doubling-up and non-doubling-up dummy indicators with all the regressors. In this way we can interpret the doubling-up and non-doubling-up interactions as level effects.

Table 6 presents the results on firm risk. We first note that there is a difference in sign for the market CDS spreads depending on whether they refer to banks that double-up credit risk exposures versus banks that do not. For banks that use the market to speculate on a borrowing firm, higher CDS spreads are associated with a higher ULR, i. e., more speculation/position taking. The result we obtained for Hypothesis 1, namely that larger CDS spreads lead to a smaller uninsured loan ratio, applies strongly for the banks that do not use the market for doubling-up. Contrary to the results shown in Table 2, the inclusion of the control for the activity undertaken in the index market does not take away much significance from the CDS spreads. Furthermore, in this refined specification the indicator of index market activity turns out to be positive (and largely insignificant) for the banks that do not double-up. The strongly significant negative sign we found before seems to be driven by "speculator" banks, i.e. those that use the CDS market to double-up on their credit risk exposures.

[36] In the regressions, we will refer for convenience to this second alternative as "insurance" though this is obviously, strictly speaking, a misnomer: whenever $ULR = 1$ banks are neither doubling-up nor insuring/hedging.

Table 6: Doubling-up versus Insurance — Firm risk

	(1)	(2)	(3)	(4)
$DU \cdot CDS_{j,t-1}$	0.000**	0.000*	0.000**	0.000*
	(2.592)	(1.933)	(2.353)	(1.766)
$DU \cdot IMA_{i,t}$		-0.014***		-0.013***
		(-8.528)		(-7.482)
$IN \cdot CDS_{j,t-1}$	-0.000***	-0.000*	-0.000***	-0.000**
	(-2.826)	(-1.814)	(-3.518)	(-2.553)
$IN \cdot IMA_{i,t}$		0.000		0.001*
		(0.817)		(1.747)
R^2	0.358	0.382	0.370	0.389
N	90800	90800	77918	77918
Sample	$S3$	$S3$	$S4$	$S4$
Bank controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓

Notes: OLS regressions for Equation (3), expanded with doubling-up/non-doubling-up dummies. The dependent variable is the ULR_{ijt} defined in (2). Bank controls include: size (log of total assets), wholesale funding to asset ratio, TIER1 ratio, leverage (total assets over equity) and return on assets. All variables are lagged by one period except for $IMA_{i,t}$. $CDS_{j,t-1}$ stands for the lagged CDS quote of firm j. $IMA_{i,t}$ stands for the index market activity defined above. DU (IN) indicates a dummy that captures the presence of doubling-up (not doubling-up), as discussed in the main text. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table 7 presents the results for the remaining variables. Regardless of doubling-up versus non doubling-up considerations, more profitable banks tend to have smaller shares of their loans uninsured: return on assets is consistently negative for both interactions, across fixed effects combinations and samples (including *S2* and *S3*, presented in Appendix B). Something similar applies to wholesale funding, which remains positive and significant across samples and specifications, regardless of whether there is doubling-up or not.

Leverage remains insignificant across samples and specifications, with the only exception of *Sample 3* (see Appendix B): When looking at the sample of CDS traded firms, banks with higher leverage that use the CDS market to speculate tend to have a larger share of their loans uninsured.

The results found in the previous section regarding domestic/cross-border credit seem to be driven by those participants using the market for speculation. Within the set of players that use the market for hedging purposes, loans are insured to a larger extent if the bank is granting cross-border credit. Note that when interacting both double-up and non-double-up dummies the interpretation of the coefficients is not the same as before. In particular for the domestic and lead arranger dummies the results that carry more weight are in columns (3) and (7), when we control for $bank \cdot time$ and $firm \cdot time$ fixed effects. For instance for the lead arranger case, we virtually compare two loans by the same bank to the same firm, and *for both loans the bank uses the market to either hedge or double-up risk*; the only difference stems therefore from the bank being lead arranger in one of the loans and not in the other. When we do not include $bank \cdot time$ but *bank* fixed effects, we are comparing two banks that are identical with respect to any time-constant factors (i.e. culture, business model) but might differ in terms of time-varying factors. While we control for some of these time-varying bank-specific factors, this is potentially not sufficient and this might bias results, especially in this case where we distinguish between different ULR regions.

Table 7: Doubling-Up versus Insurance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DU \cdot Size_{i,t-1}$	-0.007***	-0.007***		-0.038	-0.056	-0.070	
	(-4.179)	(-4.949)		(-0.831)	(-0.986)	(-1.465)	
$DU \cdot Tier1_{i,t-1}$	0.025***	0.022***		0.006	0.008	0.004	
	(8.180)	(6.930)		(1.344)	(1.641)	(1.010)	
$DU \cdot LEV_{i,t-1}$	0.004	0.005**		0.003	0.002	0.004	
	(1.667)	(2.091)		(0.581)	(0.327)	(0.902)	
$DU \cdot WF_{i,t-1}$	0.000	0.000		0.017***	0.018***	0.015***	
	(0.123)	(0.490)		(7.686)	(6.385)	(7.651)	
$DU \cdot ROA_{i,t-1}$	-0.226***	-0.212***		-0.224***	-0.223***	-0.216***	
	(-13.812)	(-13.245)		(-12.520)	(-10.442)	(-13.338)	
$DU \cdot IMA_{i,t}$	-0.018***	-0.018***		-0.014***	-0.013***	-0.015***	
	(-9.699)	(-9.053)		(-8.569)	(-7.462)	(-8.553)	
$DU \cdot CDS_{j,t-1}$					0.000		
					(1.003)		
$DU \cdot DOM_{i,j}$	-0.113***	-0.107***	-0.097***	-0.098***	-0.082***	-0.092***	-0.052***
	(-9.252)	(-8.719)	(-7.159)	(-12.221)	(-9.715)	(-11.491)	(-8.244)
$DU \cdot LA_{i,j}$	-0.106***	-0.106***	0.206***	-0.106***	-0.110***	-0.107***	0.087***
	(-22.032)	(-27.239)	(12.973)	(-22.301)	(-18.224)	(-27.259)	(27.127)
$IN \cdot Size_{i,t-1}$	-0.007***	-0.007***		-0.035	-0.053	-0.068	
	(-4.248)	(-5.350)		(-0.774)	(-0.926)	(-1.423)	
$IN \cdot Tier1_{i,t-1}$	-0.000***	-0.000***		-0.018***	-0.018***	-0.017***	
	(-5.130)	(-5.649)		(-5.469)	(-5.484)	(-5.413)	
$IN \cdot LEV_{i,t-1}$	-0.000	-0.000		-0.005	-0.004	-0.004	
	(-0.755)	(-0.526)		(-1.569)	(-1.180)	(-1.359)	
$IN \cdot WF_{i,t-1}$	0.001***	0.001***		0.018***	0.019***	0.017***	
	(4.470)	(4.731)		(8.510)	(6.904)	(8.459)	
$IN \cdot ROA_{i,t-1}$	-0.001**	-0.001**		-0.023***	-0.021**	-0.023***	
	(-2.768)	(-2.532)		(-2.924)	(-2.408)	(-2.836)	
$IN \cdot IMA_{i,t-1}$	0.000*	0.000*		0.001*	0.001*	0.001**	
	(1.774)	(1.872)		(2.014)	(1.715)	(2.246)	
$IN \cdot CDS_{j,t-1}$					-0.000		
					(-1.496)		
$IN \cdot DOM_{i,j}$	0.000	-0.000	0.001***	0.010***	0.004	0.009***	0.003
	(0.268)	(-0.473)	(9.789)	(4.348)	(1.511)	(3.856)	(1.350)
$IN \cdot LA_{i,j}$	-0.000	-0.000	-0.008***	0.007***	0.003	0.007***	-0.059***
	(-0.588)	(-0.217)	(-11.890)	(2.935)	(0.775)	(3.471)	(-16.361)
R^2	0.368	0.432	0.292	0.399	0.396	0.464	0.431
N	1097434	976947	1081842	96174	77918	93335	98104
Sample	$S1$	$S1$	$S1$	$S4$	$S4$	$S4$	$S4$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (5), expanded with doubling-up/non-doubling-up dummies. The dependent variable is the ULR_{ijt} defined in (2). $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index of market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). $LA_{i,j}$ is a dummy indicating whether bank i is a lead arranger in the loan being granted. DU (IN) indicates a dummy that captures the presence of doubling-up (not doubling-up), as discussed in the main text. t-statistics are given in parentheses; clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Finally, we find some evidence that large banks tend to insure less regardless of whether they use the market for either doubling-up or not, whereas banks that are very active in the index market insure less if they are already using the single-name market for speculative purposes.

4.4. Dealers versus non-dealers

As noted in Appendix A, the CDS market is quite concentrated around a relatively small set of dealer banks. These intermediaries account for a substantial share of transactions, and by their very nature typically run matched books, with net to gross exposures relatively small, yet exhibiting high market activity. Our control for the activity in the index market could be seen as a proxy for the behavior of dealers, which are also very active in this market. Yet, one could single out individually the dealers and allow for the different variables we have analyzed having a different impact on the share of uninsured loans, depending on whether the bank in question is a dealer or not.

Table 8 presents the results focusing on market CDS spreads of borrowing firms, which as before refer to the samples of CDS traded firms (*S3*) and CDS active banks and CDS traded firms (*S4*). For non-dealer banks, the larger the CDS spread of borrowing firms, the more likely they are to have a higher share of the loan insured. Dealer banks, on the contrary, exhibit the opposite behavior. However, the coefficient on dealer banks is either marginally significant (*S3*) or directly insignificant (*S4*). In unreported regressions we also observe that the different impact of CDS spreads between non-dealers and dealers is negative and statistically significant at the 1% level.

This result is in line with the nature of the dealer business: dealer banks' protection buying and selling are less likely to be closely associated to CDS spreads, since they operate in the market to intermediate and accommodate the hedging/speculating needs of end customers. Non-dealer banks, on the other hand, are more likely to enter the market with the more concrete purpose of hedging a specific exposure.[37]

Participation in the index market also has a different impact depending on whether the bank is a dealer or not. In particular, for dealer banks, larger index market activity is associated with a smaller share of the loan being uninsured, whereas the opposite holds, though with a significantly smaller magnitude, for non-dealer banks. The difference between non-dealers and dealers is in fact positive and significant.

Table 9 presents the results for the remaining variables, for samples *S1* and *S4*. The effect of wholesale funding on the uninsured loan ratio remains positive for both dealers and non-dealers, though the magnitude is 3 to 5 times larger for the former. The difference between non-dealers and dealers (not reported) is indeed negative and highly significant. The effect of leverage is significantly different between dealers and non-dealers, and the sign reverses from negative for the former to positive for the latter. This implies that for dealer banks higher leverage is associated with a smaller share of uninsured loan, whereas the opposite holds for non-dealer banks. In terms of profitability, the negative coefficient found in the baseline regressions applies for dealer banks, whereas for non-dealer banks the coefficient on return on assets is positive yet insignificant across most specifications.[38]

When it comes to the result on the capital relief hypothesis, we observe that it continues to hold for both dealers and non-dealers, as the sign of the TIER1 ratio remains negative and statistically significant. However, the magnitude is significantly larger for dealer than non-dealer banks, especially in *sample S4*.

Lead arrangers, regardless of whether they are dealer or non-dealer banks, continue to insure larger shares of their credit risk exposures. Hypothesis 5 therefore holds for both types of banks. In *sample S1*, the difference between non-dealers and dealers is significant (though small), whereas for *sample S4*, it is insignificant.

[37]This result is further confirmed in column (5) of Table 9.

[38]The difference between non-dealers and dealers in terms of the effect of profitability on the uninsured loan ratio is positive and significant.

Table 8: Firm Risk — Dealers versus non-dealers

	(1)	(2)	(3)	(4)
$D \cdot CDS_{j,t-1}$	0.000*	0.000*	0.000	0.000
	(1.841)	(1.843)	(1.088)	(1.111)
$ND \cdot CDS_{j,t-1}$	-0.000***	-0.000**	-0.000***	-0.000***
	(-2.822)	(-2.635)	(-3.951)	(-3.776)
$D \cdot IMA_{i,t}$		-0.008***		-0.007***
		(-3.628)		(-3.414)
$ND \cdot IMA_{i,t}$		0.001***		0.000*
		(3.815)		(1.840)
R^2	0.313	0.319	0.321	0.327
N	90800	90800	77918	77918
Sample	$S3$	$S3$	$S4$	$S4$
Bank controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓

Notes: OLS regressions for Equation (3), expanded with doubling-up/non-doubling-up dummies. The dependent variable is the ULR_{ijt} defined in (2). Bank controls include: size (log of total assets), wholesale funding to asset ratio, TIER1 ratio, leverage (total assets over equity) and return on assets. All variables are lagged by one period except for $IMA_{i,t}$. $CDS_{j,t-1}$ stands for the lagged CDS quote of firm j. $IMA_{i,t}$ stands for the index market activity defined above. D (ND) indicates a dummy that captures whether the bank is (is not) a dealer. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Finally, for domestic versus cross-border lending, the message is less clear-cut for non-dealers. Dealer banks tend to hedge more their domestic exposures (i.e. the sign of the $Dealer * DOM$ interaction is negative and significant across specifications and samples). For non-dealer banks the same holds for the sample of CDS active banks and CDS traded firms (*S4*), but reverses sign for the broadest sample (columns (1)-(3)). The difference between non-dealers and dealers in terms of the effect of the domestic credit dummy is positive and significant for *S1*, and largely insignificant for *S4*.

Table 9: Dealers versus non-dealers — Expanded specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D \cdot Size_{i,t-1}$	-0.016	-0.023		-0.039	0.055	-0.117	
	(-0.343)	(-0.380)		(-0.194)	(0.269)	(-0.539)	
$ND \cdot Size_{i,t-1}$	-0.007***	-0.013***		-0.253***	-0.346***	-0.289***	
	(-4.304)	(-6.027)		(-7.639)	(-5.868)	(-8.470)	
$D \cdot Tier1_{i,t-1}$	-0.003	-0.005*		-0.030***	-0.032***	-0.029***	
	(-1.553)	(-1.994)		(-3.269)	(-3.337)	(-3.084)	
$ND \cdot Tier1_{i,t-1}$	-0.000***	-0.000***		-0.006***	-0.005***	-0.007***	
	(-5.103)	(-6.663)		(-3.208)	(-4.287)	(-4.013)	
$D \cdot LEV_{i,t-1}$	-0.005***	-0.005***		-0.033***	-0.037***	-0.031***	
	(-3.269)	(-3.198)		(-4.711)	(-5.671)	(-4.494)	
$ND \cdot LEV_{i,t-1}$	0.000	0.000*		0.010***	0.017***	0.009***	
	(1.554)	(1.966)		(7.973)	(5.482)	(7.393)	
$D \cdot WF_{i,t-1}$	0.005***	0.007***		0.047***	0.052***	0.048***	
	(13.219)	(12.631)		(13.173)	(11.668)	(12.002)	
$ND \cdot WF_{i,t-1}$	0.001***	0.001***		0.013***	0.015***	0.012***	
	(4.794)	(4.856)		(6.328)	(5.661)	(6.404)	
$D \cdot ROA_{i,t-1}$	-0.068***	-0.069***		-0.327***	-0.280***	-0.301***	
	(-4.876)	(-4.247)		(-3.874)	(-3.294)	(-3.550)	
$ND \cdot ROA_{i,t-1}$	-0.000***	-0.000		0.010	0.016	0.008	
	(-3.667)	(-1.040)		(1.228)	(1.325)	(1.311)	
$D \cdot DOM_{i,j}$	-0.008***	-0.008***	-0.007***	-0.012***	-0.006*	-0.010**	-0.005
	(-6.852)	(-6.746)	(-5.928)	(-3.058)	(-1.926)	(-2.615)	(-1.245)
$ND \cdot DOM_{i,j}$	0.001***	0.001***	0.001***	-0.008*	-0.012***	-0.008**	-0.007**
	(10.808)	(10.281)	(13.446)	(-2.042)	(-2.971)	(-2.120)	(-2.094)
$D \cdot LA_{i,j}$	-0.005***	-0.005***	-0.005***	-0.018***	-0.024***	-0.018***	-0.017***
	(-5.062)	(-5.418)	(-5.712)	(-6.171)	(-4.215)	(-6.791)	(-6.385)
$ND \cdot LA_{i,j}$	-0.000**	-0.000***	-0.000**	-0.021***	-0.028***	-0.022***	-0.021***
	(-2.058)	(-3.059)	(-2.574)	(-9.125)	(-8.361)	(-9.191)	(-9.675)
$D \cdot IMA_{i,t}$	-0.001***	-0.002***		-0.008***	-0.007***	-0.008***	
	(-4.214)	(-4.344)		(-3.601)	(-3.412)	(-3.832)	
$ND \cdot IMA_{i,t}$	0.000***	-0.000		0.000***	0.000*	0.000	
	(4.135)	(-0.061)		(3.338)	(1.756)	(0.337)	
$D \cdot CDS_{j,t-1}$					0.000		
					(1.140)		
$ND \cdot CDS_{j,t-1}$					-0.000***		
					(-3.680)		
R^2	0.173	0.253	0.259	0.323	0.328	0.394	0.420
N	1097434	976947	1081842	96174	77918	93335	98104
Sample	$S1$	$S1$	$S1$	$S4$	$S4$	$S4$	$S4$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (5), expanded with doubling-up/non-doubling-up dummies. The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). $LA_{i,j}$ is a dummy indicating whether bank i is a lead arranger in the loan being granted. D (ND) indicates a dummy that captures whether the bank is (is not) a dealer. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

5. Concluding remarks

Since their inception in the early 1990s, CDS have been viewed in very different ways. On one hand, former Federal Reserve Chairman Alan Greenspan identified them as leading to the "development of a far more flexible, efficient, and hence resilient financial system";[39] on the other extreme, famous investor George Soros tagged them as "toxic" and "poisonous".[40] While the jury is still out, any assessment of the benefits or drawbacks of such instruments will hinge upon how market participants, in particular banks, use them.

In this paper, we combine a unique dataset on bilateral CDS positions with loan-level data from the syndicated loan market and balance sheet data for banks. We use these data to identify the relation between the usage of credit default swaps and bank, borrower and loan characteristics. Our dataset is the richest to date within this literature: In our broadest sample we analyze the behavior of 1022 banks from 28 countries that lend to 14660 different firms from 144 countries. Given the richness of our data, we can look at different subsamples, focusing alternatively on CDS active banks, CDS traded borrowers, and combinations of both. Furthermore, the data allow us to use different fixed effects combinations to disentangle the relevant mechanisms at play. We use the data to construct a measure of the share of uninsured loans, and use it in a panel setting to shed light on how banks use the CDS market.

We first document that the share of uninsured syndicated loans is suggestive of banks not using the CDS market for the purpose it is often claimed to fulfill, namely the hedging of credit risk. This is particularly the case for the sub-sample of CDS active European banks and CDS traded firms, and is in line with recent evidence presented for the U.S. by Caglio et al. (2016). We then show that banks are more likely to hedge the exposures to relatively riskier firms. However, when controlling for portfolio/proxy hedging via the activity undertaken in the index market, this result is somewhat moderated.

We find that banks that are riskier in terms of leverage, credit risk, and funding risk, as well as banks with a poorer performance in terms of returns on assets, have a significantly larger share of loans not insured using CDS, relative to their less risky/better performing counterparts. Our result is robust to controlling for both observed and unobserved, time-varying, firm heterogeneity through $time \cdot firm$ fixed effects and for observed and unobserved, time-constant, bank heterogeneity through *bank* fixed effects. This finding is in line with Keeley (1990), who argues that declining bank charter values cause banks to increase default risk.

Contrary to the previous literature (Hasan and Wu (2016), Shan et al. (2016)), we do not find evidence that banks use CDS for capital relief purposes. The fact that we are able to match loans and CDS buying/selling at the transaction level (relative to Shan et al. (2016)) and that we have very broad coverage in terms of banks and countries (relative to Hasan and Wu (2016), who use a sample of six large US dealer banks) provides substantial validity to our findings. Furthermore, we show that this result holds for both dealers and non-dealers separately.

We also show that domestic loans are more likely to be hedged than are cross-country exposures (that is, due to factors such as home bias, domestic idiosyncratic risk is less likely to be doubled up). Finally, consistent with Amiram et al. (2017), we provide evidence suggesting that the CDS market may exert negative externalities on the syndicated loan market: The lead arranger of a syndicated loan in a syndicate tends to insure a larger share of its credit risk than non-lead arrangers, reducing the skin in the game that the lead arranger has in the lending relation. Both of these latter results remain in place when we explore within-bank and within-firm variation by controlling for both $bank \cdot time$ and $firm \cdot time$ fixed effects.

[39] See "Economic Flexibility", speech given before the HM Treasury Enterprise Conference in January 26, 2004.
[40] See "One way to stop bear raids", Wall Street Journal, March 24, 2009.

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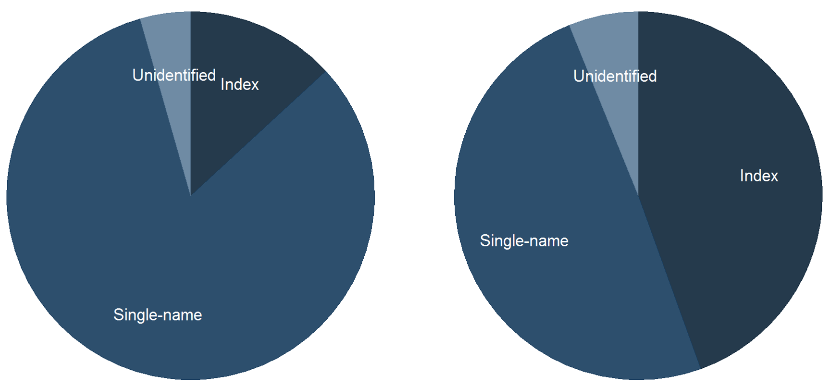
Appendix A. CDS data cleaning and charts

The purpose of the cleaning procedure for the CDS data is twofold: first, it allows us to identify and eliminate erroneous/inconsistent observations, and second, it helps us narrow down the object of study to the single-name NFC market for which at least one counterparty is a financial institution.

The processing of the raw data follows very closely the template outlined in Abad et al. (2016). We start by dropping outliers featuring implausible values, which typically involve a misreported currency or plainly a "fat fingers" mistake. We also drop observations in which the ISIN identifier is misreported, as well as observations with missing mark-to-market values. Using the trade IDs, we identify those duplicates which have inconsistent notionals, counterparty IDs, intragroup flag, maturity, counterparty side or reference entity. As we cannot trust such inconsistent observations, and we have no sensible reason to pick one over the other, we drop both. For the remaining, self-consistent, duplicate observations, we eliminate only one. We exclude all reported trades which are intragroup, have missing information on the reference entity (or the entity is not identified via an ISIN), and we drop the index market. Finally, we also exclude total return swaps, thereby focusing on credit default swaps.



(a) # trades

(b) Notional

Figure A.1: Shares by market – DTCC TSR end April 2016. # Trades: 829,439 – Notional (€bln): 7,952. Notes: own calculations based on DTCC and Bloomberg.

Using data from the TSR of end April 2016, Figure A.1 presents a snapshot of the market in terms of trades and notional before dropping observations not belonging to the single-name market.

In Figure A.2 we zoom in on the single-name market, and see the distribution by reference entity type, both in terms of trades and notional amount outstanding. While the NFC market accounts for roughly 70% of the market in terms of trades, this share is reduced to circa 45% when we weight trades by notional, on account of the notable increase of the government market for CDS, which features larger volumes.

Figure A.3, in turn, narrows the analysis further by focusing only on the single-name market for NFCs (all subsequent figures preserve this focus). The left panel shows that the consumer sector takes the largest share of the market in terms of notional, followed by communications, industrial and energy & utilities. The right panel shows that the market is quite concentrated in terms of reference entities: the 50 top-ranked reference entities account for roughly 70% of the total notional traded in this market.

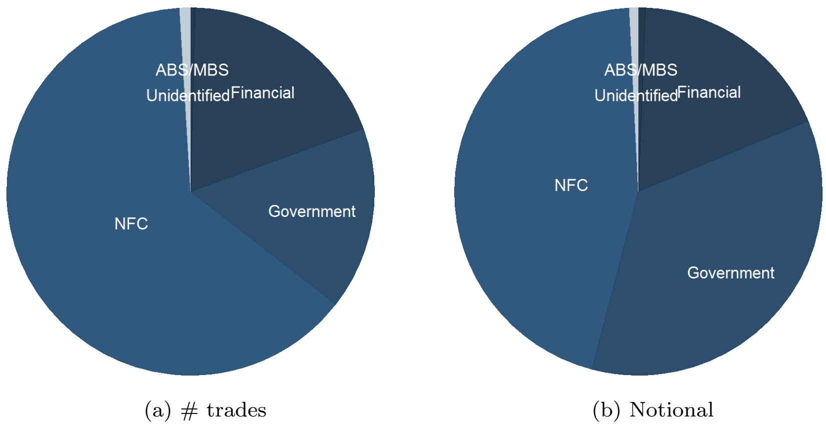


Figure A.2: Shares by underlying type, single-name market – DTCC TSR end April 2016. # Trades: 681,401 – Notional (€bln): 3,906. Notes: own calculations based on DTCC and Bloomberg.

Figure A.4 shows that the distribution of effective dates is concentrated around 2014-2016, both in terms of trades and trades wieghted by notional. This is not surprising, given the nature of the data we obtain from DTCC.

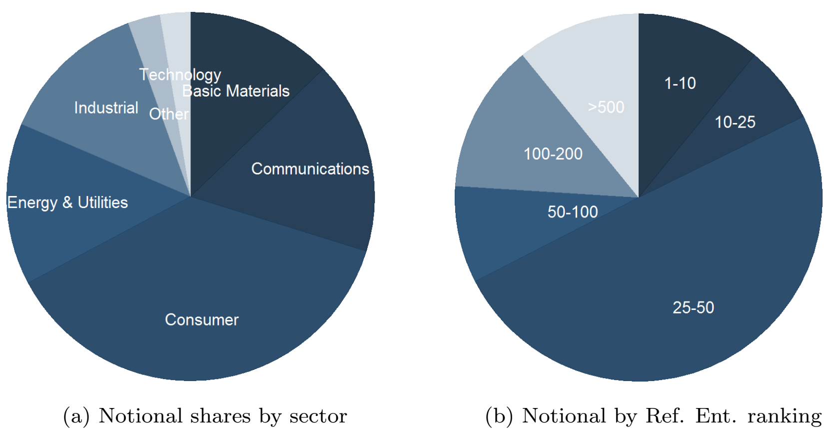
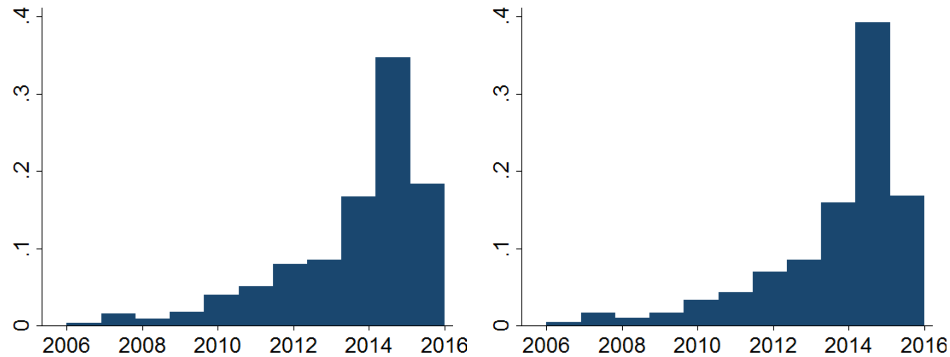


Figure A.3: Notional shares by subsector (left) and notional by reference entity ranking (right), NFC market – DTCC TSR end April 2016. # Trades: 443,068 – Notional (€bln): 1,825. Notes: own calculations based on DTCC and Bloomberg.

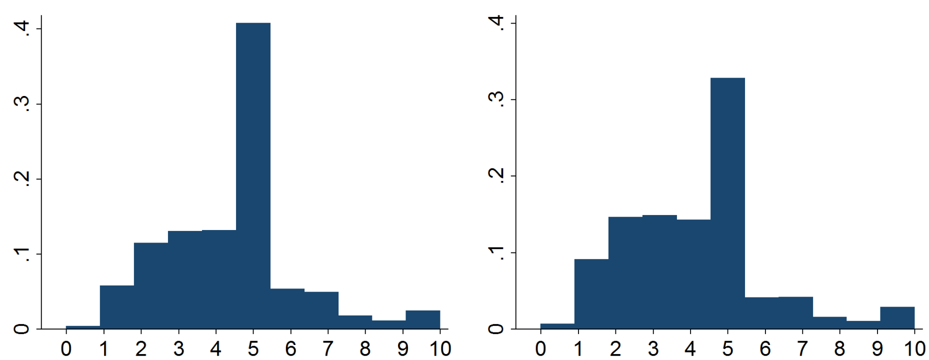


(a) # trades (b) Notional

Figure A.4: Distribution of effective dates – DTCC TSR end April 2016. Notes: own calculations based on DTCC.

As is well known, the CDS market is very standardised at the five year mark. Figure A.5 presents evidence of this. Both in terms of number of trades, as well as in terms of notional, the largest share of the market is taken by five year CDS. Furthermore, around 85% of the market is concentrated within the one to five year range.

Finally, Table A.1 presents the bilateral positions by counterparty sector for the single-name market for non-financial corporations. The market is very concentrated in the activity of intermediaries, who deal close to 60% of the notional between themselves. We focus our analysis on all trades in which at least one intermediary is involved (i.e. the first row and column).[41]



(a) # trades (b) Notional

Figure A.5: Distribution of maturities – DTCC TSR end April 2016. Notes: own calculations based on DTCC and Bloomberg.

[41] Other financials includes hedge funds and other non-bank financial institutions. ICPFs denotes Insurance Companies and Pension Funds. The large share of *Other* is explained by the presence of some Central Clearing Counterparties (CCPs). Note that some cells in the table cannot be shown due to confidentiality reasons. The numbers for such cells are, however, marginal.

Buy \ Sell	Intermediaries	Other financials	ICPFs	Non-financial	Other	Total
Intermediaries	59.1%	6.2%	0.3%	0.6%	8.1%	**74.3%**
Other financials	7.9%	(*)	(*)	0.0%	(*)	**8.6%**
ICPFs	0.3%	0.0%	0.0%	(*)	0.0%	**0.3%**
Non-financial	0.8%	0.0%	(*)	0.0%	0.0%	**0.8%**
Other	15.6%	(*)	0.0%	0.0%	(*)	**15.9%**
Total	**83.7%**	**6.9%**	**0.4%**	**0.6%**	**8.4%**	**100.0%**

Table A.1: Bilateral positions on NFCs, by counterparty sector. DTCC TSR end April 2016. Notes: own calculations based on DTCC, Bloomberg and self-constructed LEI library. (*): not shown for confidentiality reasons.

Appendix B. Additional results for baseline analysis: Samples *2* and *3*

In this appendix we present additional results regarding Hypotheses 2, 3, 4 and 5 for the subsample of CDS active banks (*S2*) and CDS traded firms (*S3*).

Table B.1: Bank health and CDS activity — *Samples 2 & 3*

	(1)	(2)	(3)	(4)	(5)
$Size_{i,t-1}$	-0.015***	-0.015**	-0.091***	-0.129**	-0.112***
	(-3.275)	(-2.647)	(-4.168)	(-2.312)	(-5.229)
$Tier1_{i,t-1}$	-0.003***	-0.003***	-0.007***	-0.007***	-0.006***
	(-5.261)	(-5.585)	(-6.874)	(-6.797)	(-7.674)
$LEV_{i,t-1}$	-0.000	0.000	0.000	0.002	0.001
	(-0.169)	(0.068)	(0.144)	(0.476)	(0.448)
$WF_{i,t-1}$	0.003***	0.003***	0.019***	0.019***	0.019***
	(6.843)	(7.912)	(6.347)	(7.085)	(6.694)
$ROA_{i,t-1}$	-0.011***	-0.015***	-0.067***	-0.070***	-0.061***
	(-6.635)	(-7.751)	(-5.836)	(-6.701)	(-5.331)
$IMA_{i,t}$	-0.001***	-0.001***	-0.008***	-0.008***	-0.008***
	(-7.749)	(-8.483)	(-8.287)	(-7.649)	(-8.821)
$CDS_{j,t-1}$				-0.000	
				(-1.403)	
R^2	0.180	0.262	0.292	0.295	0.364
N	830818	699724	112155	90800	109475
Sample	*S2*	*S2*	*S3*	*S3*	*S3*
Bank FE	✓	✓	✓	✓	✓
Time FE	✓		✓	✓	
Firm FE	✓		✓	✓	
Firm · Time FE		✓			✓

Notes: OLS regressions for Equation (3). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table B.2: Cross-border hedging — *Samples 2 & 3*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Size_{i,t-1}$	-0.015***	-0.015**		-0.091***	-0.129**	-0.112***	
	(-3.280)	(-2.654)		(-4.164)	(-2.309)	(-5.231)	
$Tier1_{i,t-1}$	-0.003***	-0.003***		-0.007***	-0.007***	-0.006***	
	(-5.263)	(-5.583)		(-6.876)	(-6.805)	(-7.680)	
$LEV_{i,t-1}$	-0.000	0.000		0.000	0.002	0.001	
	(-0.169)	(0.068)		(0.142)	(0.472)	(0.449)	
$WF_{i,t-1}$	0.003***	0.003***		0.019***	0.019***	0.019***	
	(6.841)	(7.919)		(6.348)	(7.085)	(6.695)	
$ROA_{i,t-1}$	-0.011***	-0.015***		-0.067***	-0.070***	-0.061***	
	(-6.634)	(-7.750)		(-5.837)	(-6.705)	(-5.332)	
$DOM_{i,j}$	-0.002***	-0.002***	-0.001***	-0.009***	-0.011***	-0.008**	-0.005*
	(-4.129)	(-4.137)	(-3.689)	(-2.897)	(-3.544)	(-2.638)	(-1.799)
$IMA_{i,t}$	-0.001***	-0.001***		-0.008***	-0.008***	-0.008***	
	(-7.748)	(-8.481)		(-8.287)	(-7.649)	(-8.822)	
$CDS_{j,t-1}$					-0.000		
					(-1.410)		
R^2	0.180	0.262	0.274	0.292	0.295	0.364	0.411
N	830818	699724	764421	112155	90800	109475	115204
Sample	$S2$	$S2$	$S2$	$S3$	$S3$	$S3$	$S3$
Bank FE	✓	✓		✓	✓		
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓		✓	✓	
Bank·Time FE			✓			✓	

Notes: OLS regressions for Equation (4). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table B.3: CDS and asymmetric information externalities — *Samples 2 & 3*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Size_{i,t-1}$	-0.015***	-0.015**		-0.090***	-0.128**	-0.111***	
	(-3.287)	(-2.662)		(-4.138)	(-2.302)	(-5.203)	
$Tier1_{i,t-1}$	-0.003***	-0.003***		-0.007***	-0.007***	-0.006***	
	(-5.260)	(-5.581)		(-6.884)	(-6.818)	(-7.692)	
$LEV_{i,t-1}$	-0.000	0.000		0.000	0.002	0.001	
	(-0.167)	(0.070)		(0.140)	(0.471)	(0.448)	
$WF_{i,t-1}$	0.003***	0.003***		0.019***	0.019***	0.019***	
	(6.840)	(7.915)		(6.347)	(7.073)	(6.694)	
$ROA_{i,t-1}$	-0.011***	-0.015***		-0.067***	-0.070***	-0.061***	
	(-6.630)	(-7.747)		(-5.833)	(-6.700)	(-5.329)	
$DOM_{i,j}$	-0.002***	-0.002***	-0.001***	-0.007**	-0.008***	-0.006**	-0.003
	(-3.948)	(-3.914)	(-3.347)	(-2.434)	(-3.048)	(-2.136)	(-1.238)
$LA_{i,j}$	-0.002***	-0.002***	-0.002***	-0.018***	-0.024***	-0.017***	-0.016***
	(-5.792)	(-6.552)	(-7.316)	(-9.321)	(-6.433)	(-10.235)	(-9.754)
$IMA_{i,t}$	-0.001***	-0.001***		-0.008***	-0.008***	-0.008***	
	(-7.748)	(-8.481)		(-8.291)	(-7.647)	(-8.825)	
$CDS_{j,t-1}$					-0.000		
					(-1.343)		
R^2	0.180	0.262	0.274	0.292	0.295	0.364	0.412
N	830818	699724	764421	112155	90800	109475	115204
Sample	$S2$	$S2$	$S2$	$S3$	$S3$	$S3$	$S3$
Bank FE	✓	✓		✓	✓		
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓		✓	✓	
Bank·Time FE			✓			✓	

Notes: OLS regressions for Equation (4). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). $LA_{i,j}$ is a dummy indicating whether bank i is a lead arranger in the loan being granted. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table B.4: Lead Arranger — Double-Up vs. Insurance (*Samples 2 & 3*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DU \cdot Size_{i,t-1}$	-0.011***	-0.012***		-0.076***	-0.085*	-0.086***	
	(-3.105)	(-2.898)		(-4.494)	(-2.003)	(-5.426)	
$DU \cdot Tier1_{i,t-1}$	0.023***	0.020***		0.019***	0.020***	0.017***	
	(7.439)	(6.025)		(5.825)	(5.503)	(5.451)	
$DU \cdot LEV_{i,t-1}$	0.004	0.005*		0.007***	0.006	0.008***	
	(1.608)	(1.992)		(2.946)	(1.461)	(3.383)	
$DU \cdot WF_{i,t-1}$	0.001	0.001		0.010***	0.010***	0.010***	
	(1.094)	(1.604)		(4.449)	(4.692)	(4.745)	
$DU \cdot ROA_{i,t-1}$	-0.225***	-0.211***		-0.234***	-0.237***	-0.222***	
	(-13.563)	(-12.889)		(-13.685)	(-12.085)	(-14.152)	
$DU \cdot IMA_{i,t}$	-0.018***	-0.018***		-0.015***	-0.014***	-0.016***	
	(-9.624)	(-8.956)		(-9.567)	(-8.479)	(-9.506)	
$DU \cdot CDA_{j,t-1}$					0.000		
					(1.118)		
$DU \cdot DOM_{i,j}$	-0.114***	-0.108***	-0.096***	-0.098***	-0.083***	-0.093***	-0.051***
	(-9.213)	(-8.569)	(-6.906)	(-12.728)	(-10.019)	(-12.122)	(-8.804)
$DU \cdot LA_{i,j}$	-0.109***	-0.110***	0.206***	-0.103***	-0.108***	-0.104***	0.093***
	(-22.712)	(-27.783)	(13.260)	(-22.484)	(-18.620)	(-27.889)	(28.762)
$IN \cdot Size_{i,t-1}$	-0.011***	-0.012***		-0.074***	-0.083*	-0.084***	
	(-3.064)	(-2.998)		(-4.184)	(-1.918)	(-5.041)	
$IN \cdot Tier1_{i,t-1}$	-0.002***	-0.002***		-0.004***	-0.005***	-0.004***	
	(-4.354)	(-4.430)		(-5.110)	(-4.932)	(-5.491)	
$IN \cdot LEV_{i,t-1}$	-0.000	-0.000		-0.000	-0.000	-0.000	
	(-0.739)	(-0.812)		(-0.549)	(-0.042)	(-0.318)	
$IN \cdot WF_{i,t-1}$	0.002***	0.002***		0.011***	0.012***	0.011***	
	(5.897)	(6.251)		(5.139)	(5.351)	(5.285)	
$IN \cdot ROA_{i,t-1}$	-0.003***	-0.004***		-0.025***	-0.026***	-0.021***	
	(-2.939)	(-2.951)		(-3.313)	(-3.886)	(-2.840)	
$IN \cdot IMA_{i,t-1}$	0.000***	0.000***		0.001	0.000	0.001	
	(2.986)	(3.006)		(0.966)	(0.762)	(1.190)	
$IN \cdot CDS_{i,j}$					-0.000		
					(-0.955)		
$IN \cdot DOM_{i,j}$	-0.000	-0.000	0.001***	0.010***	0.004**	0.009***	0.004**
	(-0.691)	(-1.397)	(10.420)	(6.290)	(2.455)	(5.582)	(2.573)
$IN \cdot LA_{i,j}$	0.001**	0.001**	-0.012***	0.004**	0.001	0.005**	-0.050***
	(2.201)	(2.633)	(-11.399)	(2.090)	(0.158)	(2.694)	(-16.205)
R^2	0.378	0.444	0.305	0.392	0.388	0.455	0.423
N	830818	699724	764421	112155	90800	109475	115204
Sample	$S2$	$S2$	$S2$	$S3$	$S3$	$S3$	$S3$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (5), expanded with doubling-up/non-doubling-up dummies. The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). $LA_{i,j}$ is a dummy indicating whether bank i is a lead arranger in the loan being granted. DU (IN) indicates a dummy that captures the presence of doubling-up (not doubling-up), as discussed in the main text. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Appendix C. Robustness check: Restricted Dealscan sample

As noted in the main text, in order to assign facility amounts to the different banks participating in the syndicates, we use the lender share variable whenever available, which gives an exact break-up of the contribution of each bank to the facility. Using the lender share data available, we construct average shares by "lender role type", distinguishing between the different top-tiers of arrangers versus plain "Participants", and use these average shares to distribute the lending in the syndicates for which we do not observe the lender shares. To test that this approach is robust, we present here the main regressions of the paper but using instead only those Dealscan observations which provide the loan share.

Table C.1: Firm Risk — Given loan shares

	(1)	(2)	(3)	(4)
$CDS_{j,t-1}$	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.999)	(-4.002)	(-5.778)	(-4.854)
$IMA_{i,t}$		-0.000***		-0.000***
		(-7.338)		(-5.831)
R^2	0.330	0.349	0.349	0.361
N	38326	38326	33651	33651
Sample	$S3$	$S3$	$S4$	$S4$
Bank controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓

Notes: OLS regressions for Equation (3). The dependent variable is the ULR_{ijt} defined in (2). Bank controls include: size (log of total assets), wholesale funding to asset ratio, TIER1 ratio, leverage (total assets over equity) and return on assets. All variables are lagged by one period except for $IMA_{i,t}$. $CDS_{j,t-1}$ stands for the lagged CDS quote of firm j. $IMA_{i,t}$ stands for the index market activity defined above. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table C.2: Firm Risk — Double-Up vs. Insurance for given loan shares

	(1)	(2)	(3)	(4)
$DU \cdot CDS_{j,t-1}$	0.000	0.000	0.000	0.000
	(1.093)	(0.318)	(0.790)	(0.022)
$DU \cdot IMA_{i,t}$		-0.000***		-0.000***
		(-8.348)		(-7.194)
$IN \cdot CDS_{j,t-1}$	-0.000***	-0.000***	-0.000***	-0.000***
	(-4.495)	(-3.619)	(-4.859)	(-3.388)
$IN \cdot IMA_{i,t}$		0.000		0.000
		(0.438)		(1.426)
R^2	0.398	0.425	0.409	0.431
N	38326	38326	33651	33651
Sample	3	$S3$	$S4$	$S4$
Bank controls	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓

Notes: OLS regressions for Equation (3), expanded with doubling-up/non-doubling-up dummies. The dependent variable is the ULR_{ijt} defined in (2). Bank controls include: size (log of total assets), wholesale funding to asset ratio, TIER1 ratio, leverage (total assets over equity) and return on assets. All variables are lagged by one period except for $IMA_{i,t}$. $CDS_{j,t-1}$ stands for the lagged CDS quote of firm j. $IMA_{i,t}$ stands for the index market activity defined above. DU (IN) indicates a dummy that captures the presence of doubling-up (not doubling-up), as discussed in the main text. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table C.3: Bank Health — Given loan shares

	(1)	(2)	(3)	(4)	(5)
$Size_{i,t-1}$	-0.000***	-0.000***	-0.003	-0.002	-0.003*
	(-5.212)	(-4.113)	(-1.372)	(-1.260)	(-1.791)
$TIER1_{i,t-1}$	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(-9.080)	(-9.615)	(-7.074)	(-7.318)	(-6.974)
$LEV_{i,t-1}$	-0.000	0.000	-0.000	-0.000	-0.000
	(-0.107)	(0.560)	(-0.269)	(-0.408)	(-0.033)
$WF_{i,t-1}$	0.000***	0.000***	0.001***	0.001***	0.001***
	(4.977)	(6.064)	(11.233)	(10.888)	(10.911)
$ROA_{i,t-1}$	-0.000***	-0.000***	-0.002***	-0.002***	-0.002***
	(-5.679)	(-4.995)	(-5.771)	(-5.179)	(-5.128)
$IMA_{i,t}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-9.364)	(-9.756)	(-6.279)	(-5.831)	(-6.454)
$CDS_{j,t-1}$				-0.000***	
				(-4.854)	
R^2	0.203	0.284	0.351	0.361	0.419
N	341393	301196	40079	33651	38542
Sample	$S1$	$S1$	$S4$	$S4$	$S4$
Bank FE	✓	✓	✓	✓	✓
Time FE	✓		✓	✓	
Firm FE	✓		✓	✓	
Firm · Time FE		✓			✓

Notes: OLS regressions for Equation (3). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $ln(Totalassets)_{i,t-1}$ stands for the logarithm of total assets (i.e. size), $Tier1Ratio_{i,t-1}$ for the TIER1 regulatory capital ratio, $WholesaleFunding_{i,t-1}$ for the wholesale funding to assets ratio, $Leverage_{i,t-1}$ for total assets over equity, $ROAA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. . t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table C.4: Cross-border hedging — Given loan shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Size_{i,t-1}$	-0.000***	-0.000***		-0.003	-0.002	-0.003*	
	(-5.213)	(-4.122)		(-1.393)	(-1.292)	(-1.821)	
$TIER1_{i,t-1}$	-0.000***	-0.000***		-0.001***	-0.001***	-0.001***	
	(-9.079)	(-9.614)		(-7.075)	(-7.329)	(-6.974)	
$LEV_{i,t-1}$	-0.000	0.000		-0.000	-0.000	-0.000	
	(-0.107)	(0.561)		(-0.263)	(-0.407)	(-0.027)	
$WF_{i,t-1}$	0.000***	0.000***		0.001***	0.001***	0.001***	
	(4.976)	(6.062)		(11.240)	(10.897)	(10.924)	
$ROA_{i,t-1}$	-0.000***	-0.000***		-0.002***	-0.002***	-0.002***	
	(-5.679)	(-4.997)		(-5.775)	(-5.183)	(-5.134)	
$DOM_{i,j}$	-0.000*	-0.000***	0.000	-0.001***	-0.001***	-0.001***	-0.001***
	(-1.774)	(-4.608)	(0.969)	(-6.760)	(-6.307)	(-6.967)	(-9.345)
$IMA_{i,t}$	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***	
	(-9.364)	(-9.756)		(-6.274)	(-5.826)	(-6.446)	
$CDS_{j,t-1}$					-0.000***		
					(-4.859)		
R^2	0.203	0.284	0.302	0.351	0.361	0.420	0.440
N	341393	301196	337747	40079	33651	38542	40098
Sample	$S1$	$S1$	$S1$	$S4$	$S4$	$S4$	$S4$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (4). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $ln(Totalassets)_{i,t-1}$ stands for the logarithm of total assets (i.e. size), $Tier1Ratio_{i,t-1}$ for the TIER1 regulatory capital ratio, $WholesaleFunding_{i,t-1}$ for the wholesale funding to assets ratio, $Leverage_{i,t-1}$ for total assets over equity, $ROAA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table C.5: Lead Arranger — Given loan shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Size_{i,t-1}$	-0.000***	-0.000***		-0.003	-0.002	-0.003*	
	(-5.214)	(-4.117)		(-1.384)	(-1.283)	(-1.817)	
$TIER1_{i,t-1}$	-0.000***	-0.000***		-0.001***	-0.001***	-0.001***	
	(-9.080)	(-9.617)		(-7.073)	(-7.333)	(-6.977)	
$LEV_{i,t-1}$	-0.000	0.000		-0.000	-0.000	-0.000	
	(-0.107)	(0.560)		(-0.266)	(-0.411)	(-0.029)	
$WF_{i,t-1}$	0.000***	0.000***		0.001***	0.001***	0.001***	
	(4.976)	(6.061)		(11.240)	(10.897)	(10.929)	
$ROA_{i,t-1}$	-0.000***	-0.000***		-0.002***	-0.002***	-0.002***	
	(-5.673)	(-4.990)		(-5.787)	(-5.188)	(-5.135)	
$DOM_{i,j}$	-0.000	-0.000***	0.000	-0.001***	-0.001***	-0.001***	-0.001***
	(-1.590)	(-4.011)	(1.287)	(-6.110)	(-5.800)	(-6.374)	(-8.338)
$LA_{i,j}$	0.000	0.000	-0.000	-0.000***	-0.001***	-0.000***	-0.000***
	(0.243)	(0.517)	(-0.114)	(-6.172)	(-9.702)	(-4.521)	(-4.892)
$IMA_{i,t}$	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***	
	(-9.364)	(-9.756)		(-6.281)	(-5.830)	(-6.452)	
$CDS_{j,t-1}$					-0.000***		
					(-4.765)		
R^2	0.203	0.284	0.302	0.351	0.362	0.420	0.440
N	341393	301196	337747	40079	33651	38542	40098
Sample	$S1$	$S1$	$S1$	$S4$	$S4$	$S4$	$S4$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (5). The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $ln(Totalassets)_{i,t-1}$ stands for the logarithm of total assets (i.e. size), $Tier1Ratio_{i,t-1}$ for the TIER1 regulatory capital ratio, $WholesaleFunding_{i,t-1}$ for the wholesale funding to assets ratio, $Leverage_{i,t-1}$ for total assets over equity, $ROAA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). $LA_{i,j}$ is a dummy indicating whether bank i is a lead arranger in the loan being granted. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.

Table C.6: Lead Arranger — Double-Up vs. Insurance — Given loan shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$DU \cdot Size_{i,t-1}$	-0.000***	-0.000***		-0.003*	-0.003*	-0.003**	
	(-4.902)	(-4.352)		(-1.872)	(-1.861)	(-2.069)	
$DU \cdot Tier1_{i,t-1}$	0.001***	0.000***		0.000	0.000	0.000	
	(6.277)	(5.104)		(1.250)	(1.153)	(1.113)	
$DU \cdot LEV_{i,t-1}$	0.000	0.000		0.000	-0.000	0.000	
	(0.163)	(0.527)		(0.080)	(-0.274)	(0.281)	
$DU \cdot WF_{i,t-1}$	0.000*	0.000**		0.000***	0.001***	0.000***	
	(1.707)	(2.411)		(7.073)	(6.877)	(7.600)	
$DU \cdot ROA_{i,t-1}$	-0.006***	-0.005***		-0.005***	-0.006***	-0.005***	
	(-11.625)	(-11.534)		(-9.926)	(-10.034)	(-8.754)	
$DU \cdot IMA_{i,t}$	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***	
	(-10.838)	(-9.915)		(-8.195)	(-7.238)	(-8.171)	
$DU \cdot CDS_{j,t-1}$					-0.000		
					(-0.140)		
$DU \cdot DOM_{i,j}$	-0.001***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.437)	(-5.002)	(-4.444)	(-5.082)	(-5.005)	(-5.570)	(-5.429)
$DU \cdot LA_{i,j}$	-0.001***	-0.001***	0.004***	-0.001***	-0.001***	-0.001***	0.001***
	(-4.216)	(-3.471)	(7.259)	(-4.252)	(-4.267)	(-3.332)	(5.409)
$IN \cdot Size_{i,t-1}$	-0.000***	-0.000***		-0.002*	-0.002*	-0.003*	
	(-4.396)	(-5.036)		(-1.718)	(-1.714)	(-1.952)	
$IN \cdot Tier1_{i,t-1}$	-0.000***	-0.000***		-0.001***	-0.001***	-0.000***	
	(-5.222)	(-5.438)		(-5.923)	(-6.081)	(-5.273)	
$IN \cdot LEV_{i,t-1}$	-0.000	0.000		-0.000	-0.000	-0.000	
	(-0.380)	(0.045)		(-0.503)	(-0.564)	(-0.426)	
$IN \cdot WF_{i,t-1}$	0.000***	0.000***		0.000***	0.000***	0.000***	
	(4.285)	(4.873)		(7.481)	(7.106)	(7.358)	
$IN \cdot ROA_{i,t-1}$	-0.000***	-0.000**		-0.001***	-0.000*	-0.000**	
	(-3.213)	(-2.520)		(-2.959)	(-1.908)	(-2.291)	
$IN \cdot IMA_{i,t}$	0.000	0.000**		0.000	0.000	0.000**	
	(1.504)	(2.119)		(1.652)	(1.432)	(2.495)	
$IN \cdot CDS_{j,t-1}$					-0.000***		
					(-3.164)		
$IN \cdot DOM_{i,j}$	-0.000***	-0.000***	0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(-6.693)	(-8.066)	(4.542)	(-4.811)	(-4.583)	(-4.988)	(-8.878)
$IN \cdot LA_{i,j}$	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000	-0.001***
	(-4.701)	(-4.104)	(-18.702)	(-2.128)	(-3.455)	(-1.464)	(-19.983)
R^2	0.402	0.461	0.321	0.429	0.432	0.491	0.448
N	341393	301196	337747	40079	33651	38542	40098
Sample	$S1$	$S1$	$S1$	$S4$	$S4$	$S4$	$S4$
Bank FE	✓	✓		✓	✓	✓	
Time FE	✓			✓	✓		
Firm FE	✓			✓	✓		
Firm·Time FE		✓	✓			✓	✓
Bank·Time FE			✓				✓

Notes: OLS regressions for Equation (5), expanded with doubling-up/non-doubling-up dummies. The dependent variable is the ULR_{ijt} defined in (2). All variables are lagged by one period except for $IMA_{i,t}$. $Size_{i,t-1}$ stands for the logarithm of total assets, $Tier1_{i,t-1}$ for the TIER1 regulatory capital ratio, $WF_{i,t-1}$ for the wholesale funding to assets ratio, $LEV_{i,t-1}$ for total assets over equity, $ROA_{i,t-1}$ for the return on average assets, $CDS_{j,t-1}$ for the CDS quote of firm j and $IMA_{i,t}$ for the index market activity defined above. $DOM_{i,j}$ is a dummy indicating whether the loan is domestic (1) versus cross-border (0). $LA_{i,j}$ is a dummy indicating whether bank i is a lead arranger in the loan being granted. DU (IN) indicates a dummy that captures the presence of doubling-up (not doubling-up), as discussed in the main text. t-statistics are given in parentheses; SE are clustered at the time level. ***, **, * indicate significance at the 1%, 5% and 10% levels.