Mitigating Counterparty Risk*

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Abstract

This paper provides initial evidence on counterparty risk-mitigation activities of financial institutions on the basis of Depository Trust and Clearing Corporation's (DTCC) proprietary bilateral credit default swap transactions and positions. We show that financial institutions that are active buyers of protection from a specific counterparty undertake successive contracts and purchase protection written on them, even avoiding wrong-way risk mitigation. Higher stock return and CDS price volatility, lower past stock returns, and higher CDS prices of the counterparty are shown to have an increasing effect on the hedging behaviour against the counterparty. As the current regulatory frameworks explicitly formulate any protection purchase on the counterparty would diminish the required capital, this type of risk mitigation could follow regulatory capital relief motives and provides a viable hedging instrument beyond receiving coverage through collateral.

Keywords: Credit default swaps, DTCC, OTC markets, hedging, Basel III, CRR.

JEL classification: G11, G21, G23.

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1 Introduction

The past decade has witnessed the emergence of counterparty credit risk as one of the potential factors contributing to the systemic nature of the global financial crisis. The Lehman default spread initial fear as to whether this would trigger a "domino effect" among major dealers involved in a bilateral relationship through financial derivatives, including credit default swaps (CDSs). Nevertheless, extensive government support and supervisory actions have prevented a systemic breakdown of the financial system. What remains from the peak period of the crisis is the need to take a closer look at bilateral counterparty credit risk-taking activities of global actors in order to see whether such fears were substantiated.

In this paper we provide extensive empirical evidence confirming the existence of trading activities for mitigating counterparty risk. We make use of the Depository Trust & Clearing Corporation's (DTCC) proprietary dataset on CDS transactions and outstanding positions between November 2006 and February 2012 in order to explore the hedging behavior of banks participating in the market. Specifically, we investigate whether banks or financial institutions that are active buyers of protection from a counterparty undertake successive contracts and purchase protection written on these global players. Our rich dataset, which includes the number of contracts bought and sold from counterparties with specific identities, enables us to identify whether (and how) banks active in the CDS market mitigate their counterparty credit risk positions against global dealers.

The market for credit default swaps is a perfect laboratory for analyzing how counterparty risk is priced and managed within a system of major dealers. J.P. Morgan was the pioneer developer of the product in the 1990s, which was initially thought of as an instrument for hedging the credit risk associated with loans and bonds.[1] When the Federal Reserve issued a statement in 1996 suggesting hedging with credit derivatives as a means of reducing necessary capital, this provided a further catalyst for market development. The CDS market has grown

[1] J.P. Morgan initiated an annual payment to the European Bank for Reconstruction and Development (EBRD), making it possible for the credit risk of a credit line extended to Exxon to be transferred to EBRD.

significantly since 2001, as the trading of company or sovereign-specific default risk through credit derivatives has spread globally.

The systemic role of CDSs was of particular interest during the financial crisis, as the market was criticized for creating a highly dependent default correlation structure among participants. The all-time peak value of global outstanding notional amounts of CDSs in 2007 gradually reduced during and after the crisis as a result of bilateral netting, trade compression and maturing contracts. The recent creation of central counterparties has already mitigated counterparty risk to a certain extent, as the credit default swap markets currently possess a standardized trading architecture thanks to the "Big Bang" and "Small Bang" protocols issued in 2009. However, even if central clearing phased out the creation of further counterparty risk, it did not eliminate the necessity of regularly mitigating it; such that the Basel III regulations and its European implementation, the Capital Requirements Regulation (CRR), explicitly incentivize purchasing protection on counterparties as a way of risk mitigation.

Within this laboratory of all CDS transactions and positions of the last decade, we focus on the bilateral trading activities of banks and financial institutions in the OTC market. This focus enables us to identify counterparty risk mitigation activities in the absence of a central counterparty, therefore allowing us to see whether (and how) financial institutions manage their counterparty risk. Consequently, the paper points to an additional cost of not having central clearing, which has not been articulated in the literature so far.

The key results are as follows. First, we find evidence that counterparty risk is managed over weekly and/or monthly horizons. The financial institutions in our dataset purchase protection *on* global financial counterparties once they are protection buyers *from* them. In line with previous literature, the economic significance of our results indicates a hedge proportion of 4-15%, implying that the high degree of collateralization diminishes the need to fully mitigate counterparty risk. This hedge proportion should also be read as the extent to which the purchaser of protection would like to cover any unhedged losses beyond the recovery of underlying in case of a default. Second, the dealers in the dataset exhibit a different counterparty risk-mitigation behavior to that of non-dealers. Non-dealers are identified as actively hedging their counterparty risk only at longer, monthly intervals, whereas dealers are shown to be managing this risk by hedging over both short and longer horizons. Third, all specifications with the transaction-level dataset provide robust results even with the inclusion of time(week/month) fixed effects or counterparty-time(week/month) pair fixed effects that control for any aggregate factors, which may simultaneously drive protection bought from the counterparty today and protection bought on the counterparty in the future. Fourth, we utilize also a position-level dataset in order to carve out the causal effects of an exogenous price shock on all underlyings of the bank-counterparty pairs. This identification strategy enables us to show that the results are robust each time a price shock increases the counterparty risk of our sample banks. Finally, when managing counterparty risk, our financial institutions avoid wrong-way risk mitigation by purchasing protection from counterparties that do not belong to the same country as the global dealer on which protection is sought. This indeed provides evidence on the careful risk management policies of financial institutions. Overall, the evidence provided is an indication that mitigation of counterparty risk could follow regulatory capital relief motives, since Basel III and the European CRR explicitly formulate any protection purchase on the counterparty to be subtracted from the exposure for regulatory capital calculation.

Related Literature

By providing initial evidence of counterparty risk-mitigating activities at the contract level, this paper adds to the scarce empirical literature. This has been made possible by the DTCC dataset, which enables us to uniquely identify the protection purchase activities on the counterparties to which our banks are most heavily exposed. Arora, Gandhi, and Longstaff (2012) was the first study to focus on the price effects of counterparty risk. They showed that as the credit risk of 14 major CDS dealers increases, the price at which these dealers sell protection decreases. Nevertheless, the effect in question is of negligible magnitude. The CDS price of the dealers needs to increase by 645 basis points for it to cause a one basis point price decline of the CDS sold. The authors document the market practice of full collateralization in the CDS market as a key reason for this extremely small magnitude. In this paper, we provide significant evidence of managing counterparty risk-mitigation activities that go beyond the prevailing emphasis on collateralization in the market, and extend the results of Arora et al. on pricing to management of counterparty risk.

In a similar effort, a recent paper by Du, Gadgil, Gordy, and Vega (2016) confirms the findings of Arora et al. (2012), demonstrating that counterparty risk does not affect any CDS contract pricing. On the other hand, they provide evidence indicating that the participants prefer to trade with counterparties whose default risk is low and less correlated with those of the underlying entities. Our paper complements their findings on showing the financial institutions' preference to hedge counterparties with lower past stock returns, higher stock return volatility and higher CDS volatility, while they avoid wrong-way risk mitigation. Interestingly, their finding that central clearing is associated with lower spreads contradicts the results of Loon and Zhong (2014), who attribute the higher spreads to the added value of central clearing to the mitigation of counterparty risk. Overall, our paper adds to the growing literature on bilateral counterparty risk-taking activities through its insights based on OTC transactions in the DTCC dataset.

There is also a growing body of theoretical analysis that draws attention to regulatory capital relief motives of banks for purchasing protection through CDS. Klingler and Lando (2015) concentrate only on sovereign states as counterparties and build a model to argue that banks find it necessary to purchase CDS written on their sovereign counterparties in order to hedge their counterparty risk. Our analysis provides granular evidence that the authors' theory could be well extended to any counterparty, since Basel III and CRR regulations do not limit capital relief for any type of counterparty. Yorulmazer (2013) focuses in his model also on the regulatory capital relief through CDS purchases. He draws attention to adverse effects of these incentives that lead to excessive risk-taking. Our study takes up the debate on these regulatory motives and aims at providing first empirical evidence on risk mitigation.[2]

Finally, our paper contributes to the expanding strand of literature that utilizes DTCC data to analyze various features of credit default swaps, although they do not focus directly on counterparty risk. As outlined by Augustin, Subrahmanyam, Tang, and Wang (2014), the CDS literature is growing; however there is a recent tendency to utilize transaction and position-level data to the extent of availability. In one of the first papers with CDS transaction data from the DTCC, Gehde-Trapp, Gündüz, and Nasev (2015) consider whether microstructural frictions are priced in CDS transactions. They find that larger transactions have a higher price impact and that traders charge higher premiums not for compensating asymmetric information, but rather as a price for liquidity provision. In effect, buy-side investors are charged higher prices than major CDS dealers for demanding liquidity. Shachar (2012) also uses transaction-based DTCC data and examines an aggregation of end-of-day inventory changes. Oehmke and Zawadowski (2017) explain net notional CDS outstanding by bonds outstanding of the same entity through the usage of aggregate public DTCC information, in order to interpret hedging and speculation effects. Recently, Biswas, Nikolova, and Stahel (2015) estimate transaction costs showing that effective spreads are larger for actively traded CDS. The transaction costs of the bonds they reference are not necessarily higher in terms of the effective spreads; for large trade sizes, trading bonds is cheaper. Focusing on an entirely different research question, Gündüz, Ongena, Tümer-Alkan, and Yu (2017) couple proprietary CDS positions from DTCC with a credit register containing bilateral bank-firm credit exposures, concluding that there has been an increase in hedging activity with CDS for credit lending relationships to riskier firms following the Small Bang event.

This paper is organized as follows. Section 2 introduces the counterparty risk that exists in OTC markets. In Section 3, we provide a description of our DTCC transaction and

[2]Other important theoretical analyses on counterparty risk include Cooper and Mello (1991), Duffie and Huang (1996), Jarrow and Yu (2001), Hull and White (2001), and Kraft and Steffensen (2007). More recently, Duffie and Zhu (2011), Biais, Heider, and Hoerova (2016), Acharya and Bisin (2014) and Duffie, Scheicher, and Vuillemey (2015) have studied the impact of central clearing.

position-level datasets. Next, in Section 4 we present our empirical results, which provide evidence of the counterparty risk-mitigation activities in OTC markets. Section 5 sets out our conclusions.

2 Counterparty Risk in the CDS Market

A single-name CDS trade can be thought of as an act of purchasing protection against the default of a certain underlying reference entity from a protection seller, who contrarily is interested in increasing its credit risk exposure on the entity. Once both parties have agreed on a credit risk transfer, the protection buyer is basically insured against the default of the reference entity, whereas now the seller of the protection bears the default risk. If a "credit event" in line with the circumstances of default according to the protocols of International Swaps and Derivatives Association (ISDA) occurs prior to the contract maturity, the seller is obliged to transfer the full notional amount in exchange for post-default deliverable bonds of the reference entity. Meanwhile, the buyer of the contract makes quarterly installments to the seller, so-called "CDS premium" payments, as a typical insurance fee. Figure 1 shows the basic structure of a CDS transaction.

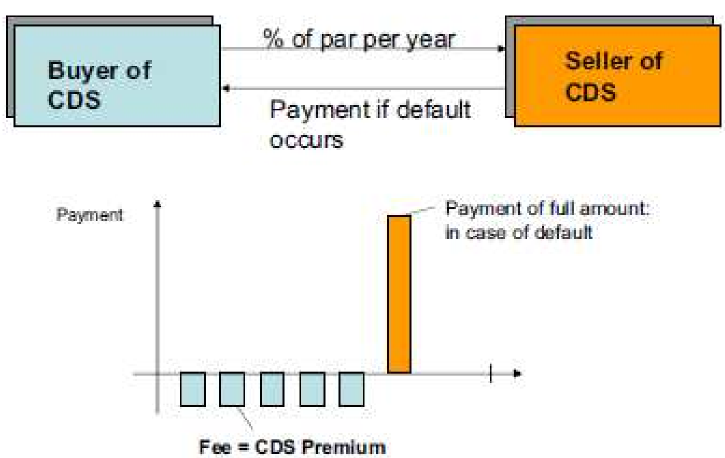

Figure 1: A typical CDS transaction that transfers the underlying reference entity's default risk.

The risk of the protection buyer not receiving the notional payment due to financial constraints of the seller, even if the reference entity defaults, can be referred to as the "counterparty risk" in CDS contracts. If the counterparty faces financial difficulties in parallel to the reference entity, there is a danger that the buyer of the initial protection will not receive his notional payment. Nevertheless, counterparty risk persists not just during a credit event relating to the reference entity but at any time when the counterparty is in financial trouble, since marking-to-market agreements and the need to post additional collateral can threaten its position as a viable reverse side of the contract. In order to assess their expected loss from the default of their counterparties, financial institutions calculate their *credit valuation adjustment* or CVA, which is counterparty-specific and is a product of the probability of default, loss given default and expected net exposure for the counterparty. An increase in CVA is deducted from the reported income of dealers, so that there is a general interest in keeping the counterparty-specific credit exposure at lower levels. Moreover, this counterparty-specific credit risk has also been introduced as a capital charge under the Basel III regulations (Basel Committee on Banking Supervision (2011)).

How can the buyer protect himself against the possibility of deteriorating counterparty credibility? Typically, ISDA master agreements and protocols provide a framework for a healthy bilateral relationship between transacting parties. Most importantly, the high degree of collateralization in the CDS market secures the system against any derailing. In this paper, we specifically look at the counterparty risk-mitigation activity of buyers of protection who might prefer to actively manage their risk above and beyond master agreements and collateralization. Specifically, we investigate whether German banks that are active buyers of CDS protection from one global counterparty undertake successive contracts and purchase protection written on these global players. Providing significant evidence on mitigation of counterparty risk even only on bilateral CDS exposures indicates that a much higher degree of counterparty risk mitigation should be taking place if exposures from interest rate and FX swaps were included.

Our analysis has implications for the degree of hedging CVA accounts as well, since any counterparty-specific credit risk exposure, including interest rate or FX swaps, needs to be mitigated for accounting purposes. Besides risk-mitigation motives, there is a regulatory incentive following Basel III and its European implementation, the CRR (Capital Requirements Regulation (CRR) (2013)). According to Basel III, banks can alleviate the contribution to RWA that arises through any counterparty credit risk exposure by purchasing protection on their counterparties. Similarly, CRR Article 386 specifically refers to mitigation of CVA risk such that banks and financial institutions could also get capital relief from regulatory requirements through purchasing a single-name or index CDS on their counterparties, since any protection purchase on the counterparty is subtracted from the exposure for regulatory CVA capital calculation (CRR, Article 384). The evidence we provide is an indication that hedging of counterparty risk follows not only risk-mitigation motives but regulatory capital relief motives as well.

Figure 2 provides an illustrative example of possible time $t+1$ activity for Bank AAA, which faces the counterparty risk of Bank BBB after a trade at time t.

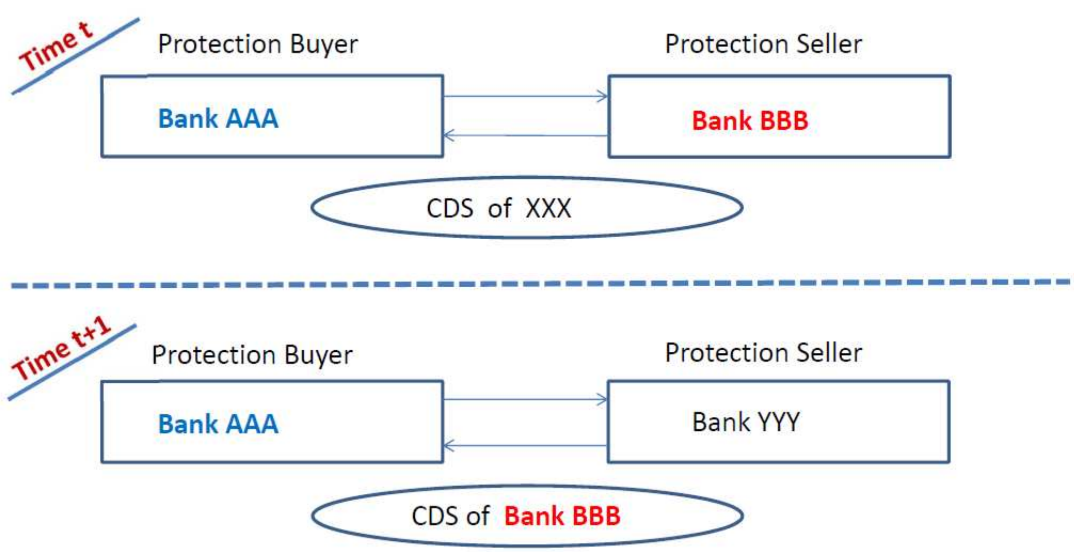

Figure 2: Active counterparty risk mitigation by Bank AAA.

Testing whether Bank AAA actively takes action to mitigate counterparty risk of Bank BBB at $t+1$ is central to our analysis. Such an investigation could not have been made in the past, as bilateral transaction data on CDS has only recently become available through trade repositories. Our proprietary DTCC data on CDS transactions is presented in the next section.

3 Bank-Specific Credit Default Swap Data from the DTCC

3.1 Transaction-Level Dataset

There is a vast amount of literature based on daily CDS composite prices or quotes that look at an aggregated set of information on credit risk. Since the trading of credit default swaps was primarily achieved on the over-the-counter market prior to the introduction of central counterparties, empirical research in financial literature was limited to depending on this type of composite data. The recent formation of trade repositories has made it possible to analyze bank activities not only for regulation purposes, but also in the world of academia.

The DTCC pioneered in the trade repository market with its Trade Information Warehouse (TIW), which actively started capturing transactions in 2008. In parallel, all earlier trades that are still open have been frontloaded, which means that they were transferred to TIW after their inception. The DTCC thereby estimates its coverage for all globally traded single-name CDS to stand at 95% and 99%, respectively, in terms of number of contracts and notional amounts (Gündüz et al. (2017)). A summary of the growing academic literature using TIW data of the DTCC can be found in Acharya, Gündüz, and Johnson (2017).

The DTCC provided access to all CDS transactions of German banks and financial institutions, as well as the positions associated with these transactions. Our baseline transaction-level dataset encompasses all new trades from November 2006 to February 2012. These are the actual new CDS transactions bought (sold) by German financial institutions from (to) any global counterparty, as well as any CDS contracts bought or sold on these counterparties where they are a reference entity. The DTCC tags financial institutions in the CDS market as "dealer" or "buyside". Prior research shows that counterparties tagged as "dealers" by the DTCC are either on the buy (85%) or the sell side (89%) of a CDS trade. The full universe of TIW positions confirms this high concentration (89% for being on the buy or sell side) with publicly available data (Gündüz et al. (2017)). Since our sample includes all the trading activity with these global dealers, it is highly representative of the global CDS trading which is known to have dealer dominance. Moreover, focusing on dealers as the counterparties for German financial institutions has the advantage of avoiding the usage of transactions by counterparties that rarely trade and/or are rarely traded as a reference entity.

A group of 25 German banks and financial institutions reside in our sample, the aim being to look at their counterparty risk-mitigation behavior. Their names could not be explicitly mentioned due to confidentiality reasons. On the other hand, Table 1 consists of the 21 counterparties that DTCC tags as global dealers.[3,4]

All of the new CDS protection bought from these dealers, as well as all of the new CDS bought on these dealers as reference entities, will be investigated concurrently in this study. Figures 3 and 4 shed light on the time series development of the counterparty risk-taking and mitigation activities of German banks on global dealers. In Figure 3, it can be seen that purchasing protection from dealers reached an all-time high of 600 new contracts during the week of September 15-19, 2008, at the peak of the subprime mortgage crisis when Lehman Brothers defaulted, and then partly slowed down towards the end of our sample period. We term this type of transactions as "SEL", where the global counterparty acts as the *seller* of the contract. Similarly, Figure 4 shows that purchasing protection on dealers reached a value of 235 new contracts during the same week in which Lehman Brothers defaulted, but as the

[3] It should be noted that these include the G14 dealers: Bank of America-Merrill Lynch, Barclays Capital, BNP Paribas, Citi, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan, Morgan Stanley, RBS, Société Générale, UBS, and Wells Fargo Bank. Peltonen, Scheicher, and Vuillemey (2014) provide empirical evidence that the CDS market is centered around G14 dealers.

[4] It should be noted that Deutsche Bank AG and Commerzbank AG are present in both samples. For our purposes, they will serve as German banks when their counterparty risk-taking behavior on dealers is being investigated, and as dealers against other German banks and financial institutions whenever they act as counterparties for the remaining 23 institutions included in our German sample.

Table 1: List of 21 global dealers in our sample that act as counterparties.

Banco Santander, S.A.
Bank of America Corporation
Barclays Bank PLC
BNP Paribas
Citigroup Inc.
Commerzbank AG
Crédit Agricole SA
Credit Suisse Group
Deutsche Bank AG
HSBC Bank PLC
JPMorgan Chase & Co.
Lehman Brothers Holdings Inc.
Morgan Stanley
Natixis
Nomura Holdings, Inc.
Royal Bank of Scotland Group PLC
Société Générale
The Goldman Sachs Group, Inc.
UBS AG
UniCredit S.p.A.
Wells Fargo & Co.

tensions in the financial markets eased, the number of new contracts purchased on global counterparties decreased as well. In the following, we will term these type of transactions as "RED", where the global counterparty acts as the *reference entity* of the contract.[5]

Table 2 shows basic statistics of the transaction dataset from the perspective of German financial institutions. Although we will initially focus on protection purchase from global dealers, the protection sold to these dealers is important to arrive at a net purchasing amount. Within the 2006-2012 period, the institutions in our sample bought (sold) 49,814 (55,442) contracts from (to) 21 global dealers. German banks are net sellers of protection, as evidenced by these figures and the total volume of contracts. German banks bought 316,201 EUR million of CDS over an eight-year interval, while selling 340,215 EUR million worth of CDS in notional terms to global dealers over the same period.

The main question that we aim to answer lies in identifying the relationship between

[5]The RED abbreviation comes from Markit company's notation for "Reference Entity Database"

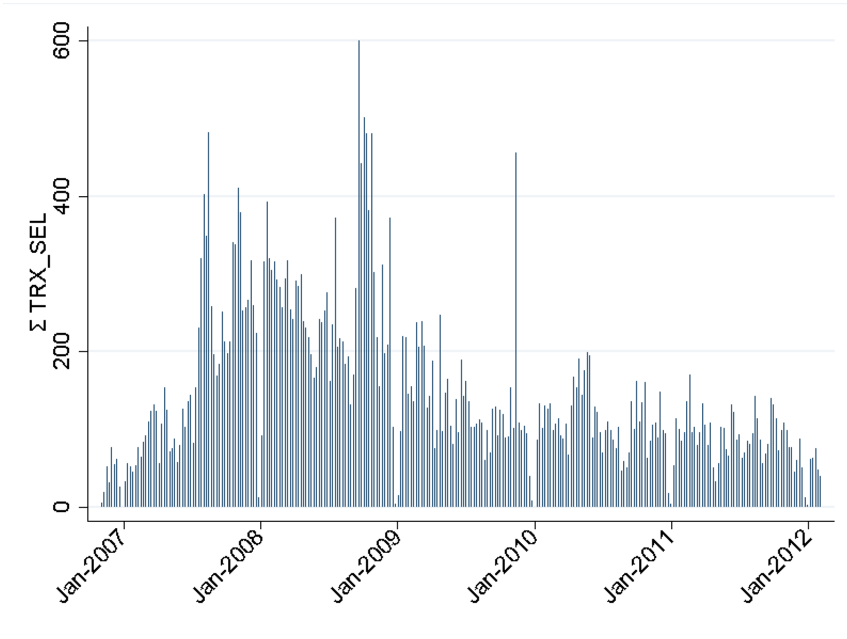

Figure 3: Time series development of weekly aggregate SEL-type transactions

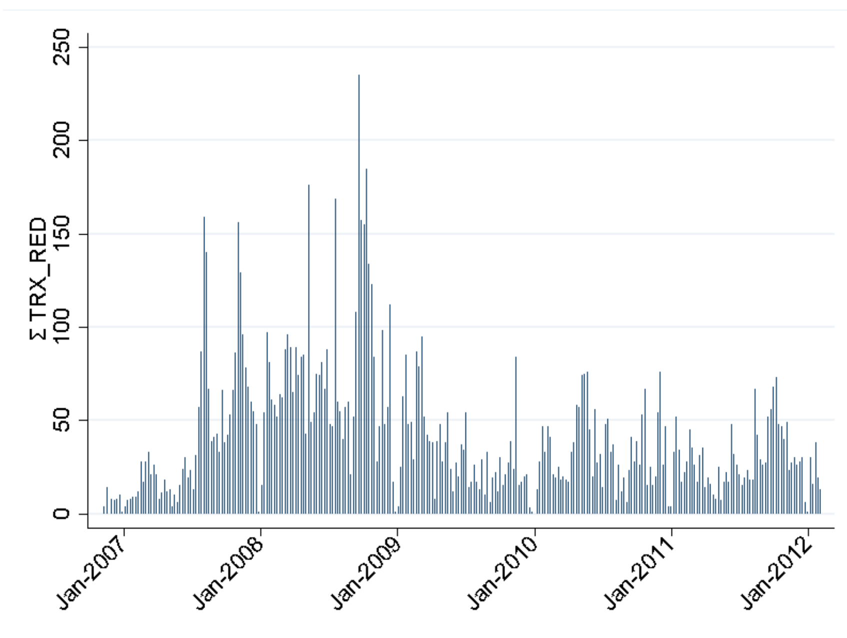

Figure 4: Time series development of weekly aggregate RED-type transactions

SEL and RED types of transactions. In doing this we will use the cumulative number of new contracts in monthly buckets of SEL and RED type of transactions (Figures 5 and 6, respectively), or alternatively in weekly buckets of SEL and RED transactions (Figures 7 and 8, respectively). These four figures indicate how the aggregate number of new contracts are highly correlated with the aggregate notional amounts of these contracts. The main reason for this is the increasing dominance of standardized CDS contracts with fixed notional amounts over the years. As a result of the observation that the correlation coefficients between the two series are between 0.95 and 0.98 for these four figures, and that the choice of the variable (notional amount or number of contracts) matters relatively little due to standard contract size, we provide the results with the number of new contracts.

The balance sheet and financial characteristics of the 21 global dealers that act as counterparties are presented in Table 3. In addition to our main interest, that is, whether SEL type of transactions are followed by RED transactions, we would also like to understand whether certain financial features of the global dealers cause German banks to undertake more hedging of their risk. It can be seen that the global dealers in our sample have quite a large asset size (an average of 1.2 EUR trillion), are highly leveraged, and do not have liquidity constraints in the median. Since our observation period encompasses the subprime mortgage crisis, the very high maximum values for stock volatility and CDS price levels coincide with the peak of the financial crisis in 2008. Although some global counterparties may be safe, as a minimum CDS price of 4 bps indicates, an average CDS price value of 122 bps and a standard devaition of 88 bps show that the variation in dealer riskiness is quite high.

Table 2: Descriptive statistics derived from transaction-level dataset

Number of contracts traded by German banks		Volume [EUR million] of contracts traded by German banks	
bought	sold	bought	sold
49,814	55,442	316,201	340,215

This table presents the basic statistics acquired from the transaction-level dataset, which covers the period between November 2006 and February 2012.

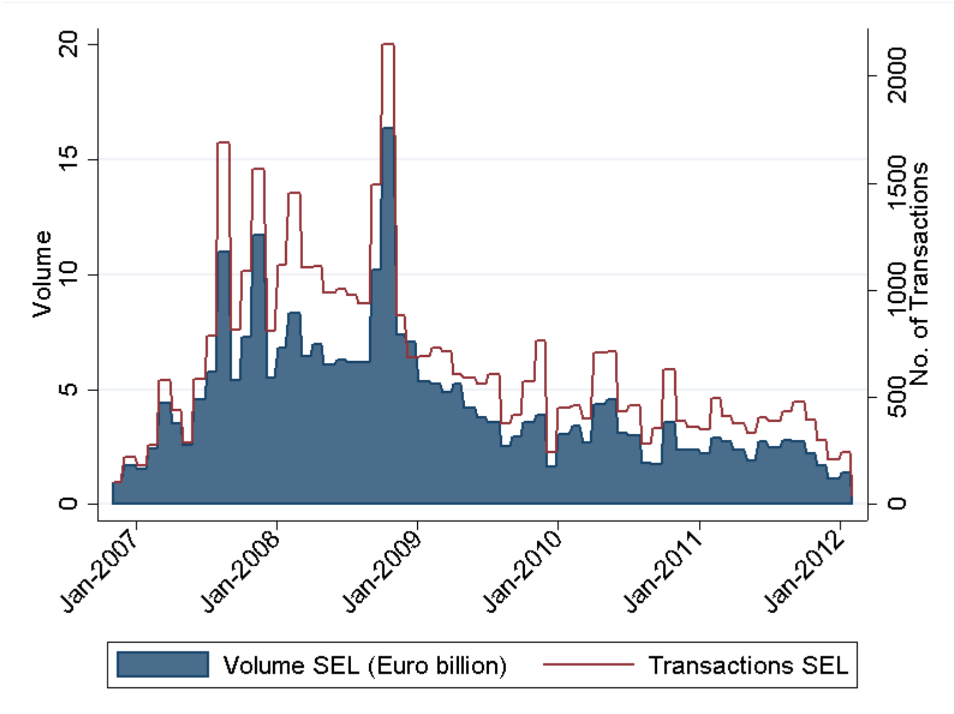

Figure 5: Volume and number of SEL transactions, aggregated in monthly buckets

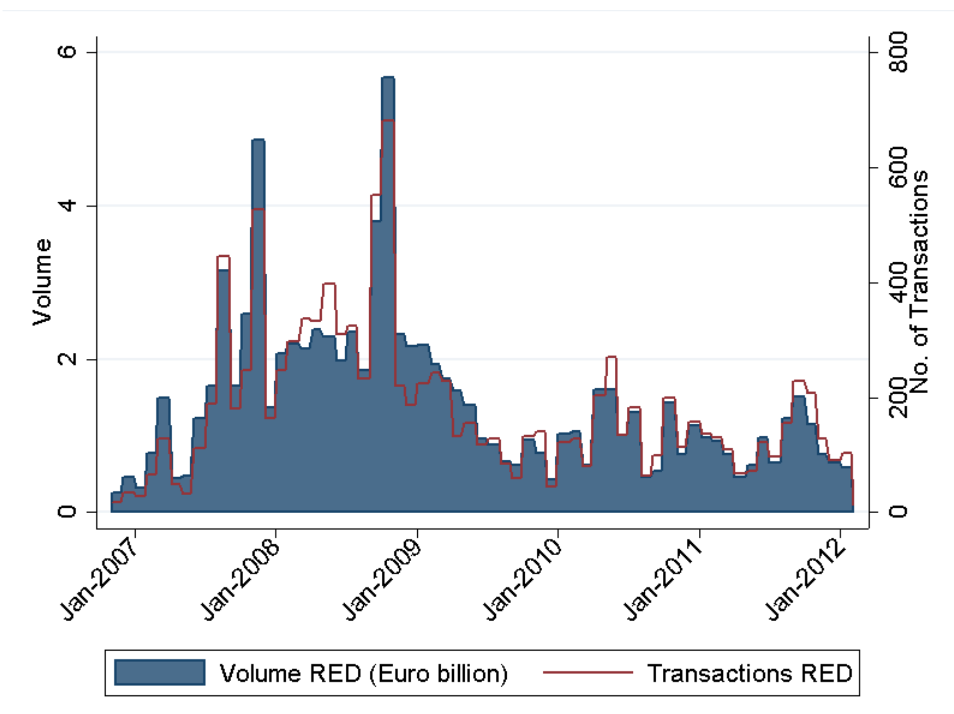

Figure 6: Volume and number of RED transactions, aggregated in monthly buckets

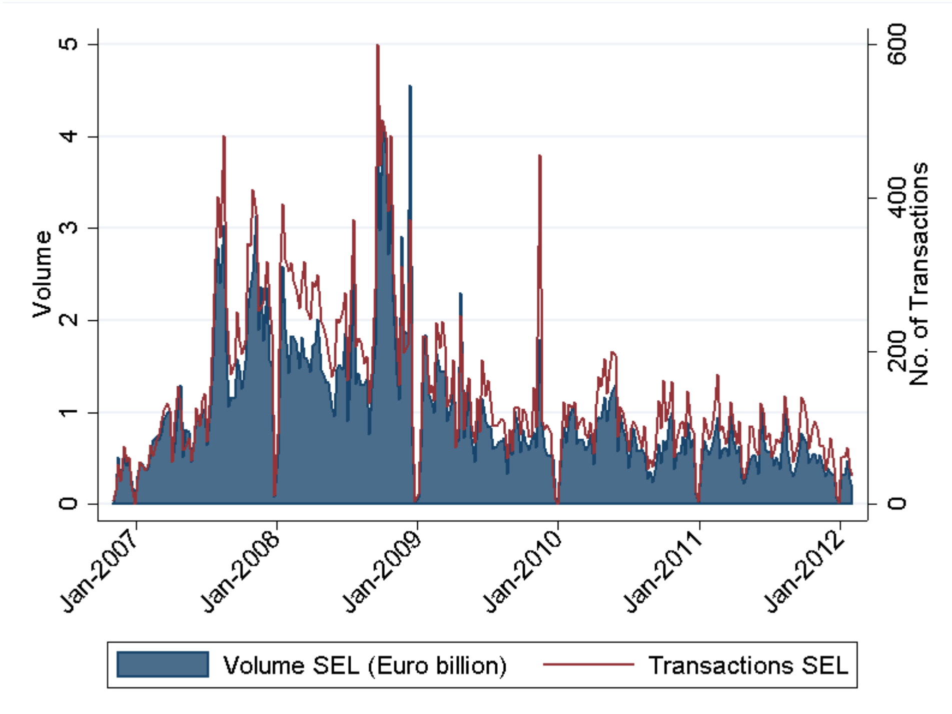

Figure 7: Volume and number of SEL transactions, aggregated in weekly buckets

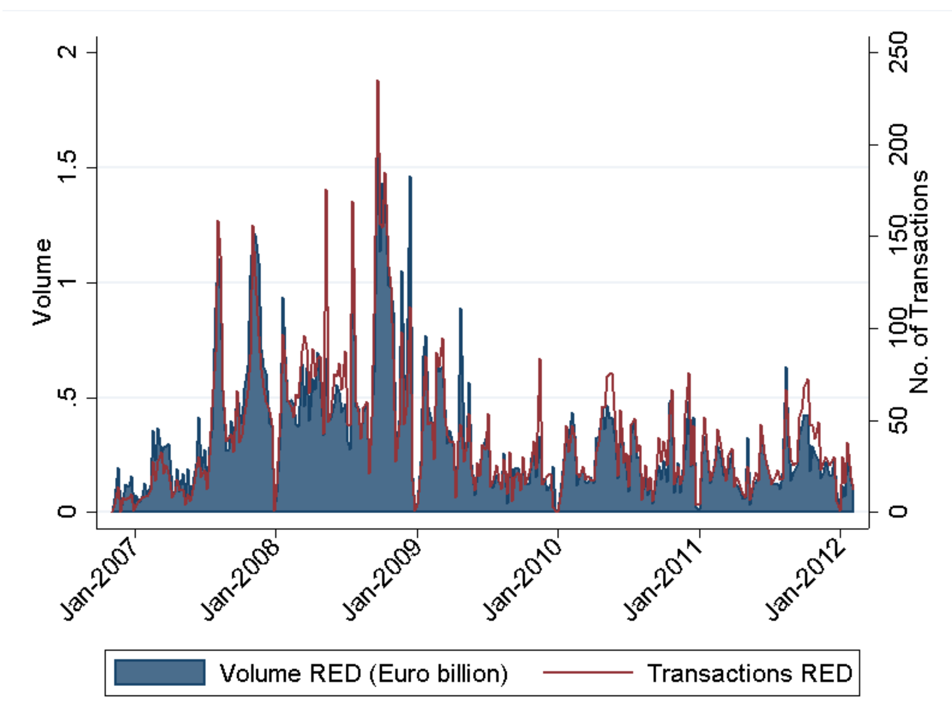

Figure 8: Volume and number of RED transactions, aggregated in weekly buckets

Table 3: Summary statistics for financial variables of 21 global dealers

VARIABLES	N	Mean	S.D.	Min	10^{th}	50^{th}	90^{th}	Max
Total Assets (EUR billion)	5,318	1,235.20	556.75	156.35	548.87	1,162.32	1,957.75	3,027.84
Capital Structure	5,318	0.95	0.02	0.89	0.91	0.95	0.98	0.99
Current Ratio	5,318	1.17	0.56	0.26	0.60	1.09	1.80	4.77
Stock Return (%)	5,318	-0.15	2.10	-42.98	-1.87	-0.11	1.60	16.75
Stock Volatility	5,318	1.48	2.03	0.01	0.17	0.85	3.42	25.24
CDS Volatility (bps)	5,318	7.08	13.40	0.01	0.90	4.30	14.43	411.00
CDS Price (bps)	5,318	122.07	88.18	4.28	29.66	106.30	217.36	1,182.35

This table contains summary statistics for financial variables of 21 global dealers as counterparties. Listed in the table are weekly summary statistics (number of observations, mean, standard deviation, minimum, 10^{th}, 50^{th} and 90^{th} percentiles, and maximum) in the sample period between November 2006 and February 2012. Quarterly values for Total Assets, Captial Structure and Current Ratio are repeated in this table as weekly observations, since the following regression analyses makes use of weekly data points. Total Assets of the 21 global counterparties are in billion euros. Capital Structure is defined as total liabilities divided by total assets. Current Ratio is defined as one-year liquid assets (marketable securities, other short-term investments, cash and cash-near items) over one-year liabilities (short-term borrowing, securities sold as repos, short-term liabilities and customer accounts). Stock Return and Stock Volatility are defined as geometric average of trading week stock return and the standard deviation of trading week stock returns of the global counterparty, respectively. CDS Volatility is the standard deviation of CDS price levels of the trading week, whereas CDS price is the arithmetic average CDS spread level of the same week. Data sources are Bankscope, Bloomberg and Markit.

3.2 Position-Level Dataset

The position-level dataset from DTCC provides an alternative answer to the research question. In contrast to the "flow" information provided by the transaction-level dataset, the position-level dataset contains "stock" information. These snapshots encompass the January 2008 to February 2012 weekly CDS positions of all the above-mentioned 25 financial institutions. Although the DTCC started building its database in 2008, the position dataset contains all the prior transactions that are frontloaded as well. Moreover, this dataset serves as a perfect tool for testing the robustness of the transaction-level results, since all other types of CDS transactions, such as assignments, amendments, and terminations are now embedded in the information in the number of open contracts. Moreover, the maturity of each new transaction is automatically accounted for when all open trades in the position level dataset are considered.

Table 4 Panel A provides basic descriptive statistics on the weekly average number of open contracts of banks and institutions in our sample on dealer banks as the underlying, and on dealer banks as the counterparty. Although the confidential nature of the data does not allow for the disclosure of bank-level statistics, the aggregated statistics already show the proportional dominance of dealer banks acting as a counterparty, as opposed to their credit risk being traded by the institutions in our sample. In an average week there are 710 (698) open CDS contracts where the dealer bank acted as a seller (buyer) against our 25 institutions, whereas these institutions traded the credit risk of dealers by only 42 (41) open CDS contracts by buying (selling) their CDS where they are a reference entity.

Similarly, Panel B of Table 4 presents statistics on the weekly average of the total volume of open contracts for the financial institutions in our sample. It is evident that German banks do not predominantly take long or short positions on dealer banks as the underlying on aggregate terms as the average long volume (351.19 EUR million) and the average short volume (353.56 EUR million) are not far apart. On the other hand, the German banks are net sellers of protection to 21 global dealers, indulging in a net selling of 255.38 EUR million when weekly average volumes of open contracts are considered.

Table 4: Descriptive statistics derived from position-level dataset

Panel A: Weekly average of number of open contracts by German banks			
Dealer banks as counterparty		Dealer banks as underlying	
bought from	sold to	bought on	sold on
710.32	697.53	42.06	41.07

Panel B: Weekly average of total volume [EUR million] of open contracts					
Dealer banks as counterparty			Dealer banks as underlying		
bought from	sold to	net	bought on	sold on	net
7,414.61	7,670.00	-255.38	351.19	353.56	-2.37

This table presents the basic statistics acquired from the position-level dataset, which covers the period between January 2008 and February 2012.

Naturally, our position-level dataset only enables tracking of CDS positions in the form of weekly snapshots. These might not reveal actual risk-taking activity, as contracts that mature automatically drop from this dataset, thus lowering the respective number and volume of contracts. Although it may be argued that maturing bought contracts would, on average, be equivalent to maturing sold contracts, the position-level dataset will be an ideal tool to be utilized in Section 4.3 for a better identification through price shocks to the individual position with the counterparty. All in all, both datasets will be important sources for understanding risk-taking activities by the financial institutions in our sample. The findings from the two datasets would complement each other in this manner.

4 Empirical Analysis

4.1 Evidence of Risk Mitigation from Baseline Transaction Datasets

We are initially interested in the trading activity in rolling weeks or months. Our selection of alternative time intervals overlaps with the margin period at risk for CVA calculation. The so-called "cure period" is the time that elapses between when the counterparty ceases to post collateral and the financial institution is able to hedge this uncovered risk. This can be regarded as the actual grace period in which no collateral is posted and the institution is exposed to naked counterparty risk, and therefore the institution takes action in order to cover remaining exposure. In practice, a cure period of 10 to 25 business days is typical. It is initially hypothesized that the banks and financial institutions in our sample undertake trading activity in the form of CDS purchasing on a global counterparty as an underlying entity following a month of CDS purchases from that same global counterparty. By collecting the flow information in monthly buckets, any successive hedging activity can be identified at rolling intervals.[6] The first specification we examine is as follows:

$$\sum_{k=1}^{4} RED_{i,j,t+k} = a_0 + a_1 \sum_{k=0}^{3} SEL_{i,j,t-k} + a_2 X_{j,t} + FE + \epsilon_{i,j,t} \tag{1}$$

where SEL is the cumulative number of contracts bought by the German bank i when the counterparty j acts as a seller between (and including) weeks $t = 0$ and $t = -3$, and RED is

[6] In this way, the rolling methodology could also capture any chain of consecutive hedging on each next counterparty.

the cumulative number of contracts bought by the German bank i where the counterparty j is a reference entity between (and including) weeks t=4 and t=1. We expect a positive coefficient for a_1 if the banks i aim at hedging their risk on counterparties j on monthly rolling horizons. Vector X represents the counterparty-specific variables such as total assets, capital structure, current ratio (of their last quarter), geometric average stock return and volatility (in their last month), and average CDS price and volatility (in their last month). All specifications are alternatively tested using bank fixed effects, counterparty fixed effects and bank-counterparty pair fixed effects. In this way, we are able to address any idiosyncratic effects arising from our banks and their counterparties. In addition, all specifications include time(month) fixed effects or counterparty-time(month) pair fixed effects in order to control for any aggregate factors that may simultaneously drive protection bought from the counterparty today and protection bought on the counterparty in the future. All errors are clustered at the bank level. As a robustness check, we also cluster the errors at the bank-counterparty pair level as an alternative.

Table 5 presents the results of the baseline dataset of monthly cumulative rolling transactions. The main variable of interest, the monthly lagged cumulative new transactions of protection bought from the counterparty is positive, and always significant in explaining the following month's cumulative new protections bought on the counterparty. Even the highly constraining bank-counterparty pair fixed effect (with more than 200 dummies) in specifications (3),(4),(8) and (9) does not diminish the significance of the main variable of interest. It is important to underline that the significance is also persistent, regardless of whether the errors are clustered at bank level (with 24-25 clusters) or bank-counterparty pair level (with more than 200 clusters).[7] Finally, the a_1 parameter, which is significantly positive even in specification (5), ensures that accounting for counterparty-specific time-variant effects does not alter the results, and addresses any endogeneity concerns by showing that the results are

[7]When there is a small number of clusters, or when there are very unbalanced cluster sizes, the inference using the cluster-robust estimator may be biased. As long as bank-level clustering is undertaken, our dealer banks have a higher number of observations than non-dealer banks, which makes it necessary to check the robustness of the results to bank-counterparty pair clustering.

Table 5: Mitigation of counterparty risk – Monthly rolling intervals of cumulative new transactions

VARIABLES	(1) Σ TRX_RED	(2) Σ TRX_RED	(3) Σ TRX_RED	(4) Σ TRX_RED	(5) Σ TRX_RED	(6) Σ TRX_RED	(7) Σ TRX_RED	(8) Σ TRX_RED	(9) Σ TRX_RED
L4.Σ TRX_SEL	0.0954***	0.147***	0.0491***	0.0491**	0.155***	0.0796***	0.146***	0.0364***	0.0364**
	(0.0113)	(0.0114)	(0.00674)	(0.0205)	(0.00842)	(0.00827)	(0.0131)	(0.0103)	(0.0152)
TOT_ASSETS (QLAG) (e-10)						4.85	9.41	-0.477	-0.477
						(3.26)	(8.02)	(4.25)	(9.06)
CAP_STRUCTURE (QLAG)						-15.63	56.72	110.0*	110.0**
						(12.58)	(42.83)	(62.01)	(46.31)
CURRENT_RATIO (QLAG)						1.001	-0.304*	-0.429***	-0.429
						(0.712)	(0.154)	(0.137)	(0.292)
L4.STOCK_RETURN						-49.22	-38.44	-46.45*	-46.45***
						(31.12)	(25.32)	(26.20)	(14.82)
L4.STOCK_VOLATILITY						0.172	-0.337**	0.0343	0.0343
						(0.142)	(0.147)	(0.0656)	(0.322)
L4.CDS_VOLATILITY						0.0241	0.0132	0.0177	0.0177
						(0.0361)	(0.0217)	(0.0236)	(0.0463)
L4.CDS_PRICE (e-4)						160.0*	75.7	103.0	103.0***
						(91.9)	(45.3)	(61.5)	(34.9)
Constant	-5.868***	3.826**	-11.16***	-11.16***	1.086	6.000	-51.89	-117.4*	-117.4***
	(0.261)	(1.549)	(0.460)	(0.832)	(0.667)	(10.51)	(43.24)	(60.71)	(44.47)
Observations	12057	12057	12057	12057	12057	9486	9486	9486	9486
Adjusted R^2	0.341	0.355	0.142	0.142	0.453	0.380	0.347	0.176	0.176
Bank FE/#	YES/25	NO	NO	NO	NO	YES/24	NO	NO	NO
Cparty FE/#	NO	YES/21	NO	NO	NO	NO	YES/20	NO	NO
Month FE/#	YES/65	YES/65	YES/65	YES/65	NO	YES/65	YES/65	YES/65	YES/65
Bank-Cparty FE/#	NO	NO	YES/219	YES/219	NO	NO	NO	YES/208	YES/208
Cparty-Month FE/#	NO	NO	NO	NO	YES/1172	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty

This table presents the coefficients from fixed-effect regressions with bank, counterparty, bank-counterparty pair, month and counterparty-month pair fixed effects. Columns (1) and (6) present the coefficients for linear regressions with fixed effects on the German banks (bank FE) and time (month FE), whereas the coefficients presented in columns (2) and (7) are based on linear regressions with global dealer bank (counterparty FE) and time (month) fixed effects. Regression results presented in columns (3), (4), (8) and (9) use bank-counterparty pair in addition to month fixed effects. Column (5) presents the coefficient for linear regression with counterparty-month pair fixed effect. The time horizon is from November 2006 to February 2012 and the difference between two units of time is one week. Σ TRX_RED is the number of new transactions within the following four weeks where the German bank serves as the buyer and the global counterparty as the underlying. Σ TRX_SEL contains the number of new transactions entered within this week and the three previous weeks where the German bank serves as the buyer and the global counterparty as the seller. The variables TOT_ASSETS, CAP_STRUCTURE, and CURRENT_RATIO contain the total assets, the capital structure and the current ratio of the counterparty lagged by one quarter. The variables STOCK_RETURN and STOCK_VOLATILITY contain the geometric average stock return and the standard deviation of the weekly stock return of the counterparty in the past month, respectively. CDS_PRICE contains the CDS spread level of the past month, whereas CDS_VOLATILITY is the standard deviation of the CDS price within the last month. Robust standard errors clustered at either bank or bank-counterparty pair level are in parentheses. The symbols $***$, $**$, and $*$ indicate significance levels of 1%, 5% and 10%, respectively.

not driven by counterparty-specific or aggregate factors in certain months.[8]

Moreover, what we may refer to as the “hedge proportion” is at economically reasonable levels. For each contract bought from counterparties, $4-15\%$ of contracts are bought on the counterparties. These values provide a good estimate for the counterparty risk-mitigation activity beyond any usage of collateral and any expected retained amount due to recovery in case of a default. The high extent of collateralization in the CDS market is documented in Arora et al. (2012), such that collateral agreements were included in 74% of CDS contracts that were executed in 2008. The economic significance of the hedge proportion can be interpreted in terms of the expected recovery from the underlying and the non-collateralized portion for an average trade. A standard assumption for the average recovery of a corporate bond would be at the 40% level. Hence, the buyer of the CDS would receive 60% of the notional amount as a payoff from the seller, in case of a default of the reference entity. With a back-of-the-envelope calculation, if the buyer of the CDS has received collateral for 74% of the contracts with the seller, counterparty risk could be further hedged for a remaining 15.6% of the contracts, which is a value close to the maximum hedge proportion revealed by our coefficients.

Given that the transaction-level data enables a fine picture of risk-taking activity, one can consider a weekly cumulation of buckets with a view to identify short-term trading activities.

$$RED_{i,j,t+1} = a_0 + a_1 SEL_{i,j,t} + a_2 X_{j,t} + FE + \epsilon_{i,j,t} \tag{2}$$

The specification in Equation (2) would collect all transactions on weekly rolling horizons. All other variables are identical to the first specification. The results in Table 6 mirror the findings in Table 5 such that new transactions of protections bought from the counterparty positively explain the following week’s new protections bought on the counterparty. In Table

[8] An alternative specification that was looked at used the net (bought - sold) number of new transactions traded with/on the counterparty. The main variable of interest was still significantly positive, and the magnitude was naturally lower. The results are therefore robust when protections sold to/on the counterparty are considered.

6, all nine specifications (with an exception of specification (5)) include time(week) fixed effects in order to control for any aggregate factors that may simultaneously drive protection bought from the counterparty today and protection bought on the counterparty in the following weeks. Specification (5) alternatively provides the results with counterparty-week fixed effects. The a_1 parameter, which is robustly positive in all nine cases, once again confirms that accounting for time-variant effects does not alter the results, and that the results are not driven by counterparty-specific or aggregate shocks in certain weeks.

The regressions with the weekly baseline dataset deliver further interesting observations. The full specifications ((6)-(9)) reveal that protection purchase activity is prevalent on counterparties that have a larger asset size. While the evidence on the current ratio and leverage is not conclusive, a decrease in the past week's stock returns and a higher stock return volatility leads to increased protection purchase on the counterparty. Most importantly, there is strong evidence that the CDS of riskier counterparties that have a higher CDS price level are purchased more. These intuitive results contribute to the analysis of counterparty risk mitigation.

An interesting extension to Table 6 is to include interacting variables with the protection bought from the counterparty. These interaction terms would show which attributes of the counterparty complement the explanation of the hedging behavior of our financial institutions. Table 7 provides this analysis based on bank, counterparty, and bank-counterparty pair fixed effects, in addition to the time (week) fixed effects in each specification. The interacting variables indicate that lower past stock returns and increased stock volatility of the counterparty encourage the banks to purchase more CDS protection on these counterparties, possibly as insurance during turbulent times that the counterparty might be facing. The CDS price volatility of the counterparty has a similar effect on protection purchasing on these counterparties. All these variables indicate a higher degree of risk mitigation by the financial institutions.

Table 6: Mitigation of counterparty risk – Weekly rolling intervals of new transactions

VARIABLES	(1) TRX_RED	(2) TRX_RED	(3) TRX_RED	(4) TRX_RED	(5) TRX_RED	(6) TRX_RED	(7) TRX_RED	(8) TRX_RED	(9) TRX_RED
L.TRX_SEL	0.0607***	0.0891***	0.0317***	0.0317**	0.114***	0.0496***	0.0858***	0.0266***	0.0266**
	(0.0213)	(0.0220)	(0.00977)	(0.0147)	(0.0197)	(0.0154)	(0.0229)	(0.00884)	(0.0115)
TOT_ASSETS (QLAG) (e-10)						2.60***	5.02**	1.19	1.19
						(0.928)	(2.03)	(2.17)	(3.12)
CAP_STRUCTURE (QLAG)						-6.372**	23.04	42.20***	42.20***
						(2.887)	(16.72)	(12.41)	(13.24)
CURRENT_RATIO (QLAG)						0.353**	-0.146***	-0.219***	-0.219*
						(0.153)	(0.0492)	(0.0370)	(0.127)
L.STOCK_RETURN						-3.647	-3.129**	-2.006*	-2.006
						(2.249)	(1.437)	(1.072)	(5.464)
L.STOCK_VOLATILITY						0.103	0.0329	0.0970*	0.0970
						(0.0694)	(0.0537)	(0.0535)	(0.0753)
L.CDS_VOLATILITY						0.00864	0.00440	0.00600	0.00600
						(0.0101)	(0.00808)	(0.00686)	(0.00766)
L.CDS_PRICE (e-4)						101.0**	79.3**	83.0***	83.0***
						(37.1)	(28.8)	(29.2)	(25.0)
Constant	-2.296***	-0.0318	-2.730***	-2.730***	0.578	2.880	-22.41	-43.26***	-43.26***
	(0.118)	(0.752)	(0.106)	(0.104)	(0.370)	(2.345)	(16.80)	(12.21)	(12.81)
Observations	6725	6725	6725	6725	6725	5318	5318	5318	5318
Adjusted R^2	0.191	0.212	0.112	0.112	0.138	0.257	0.225	0.157	0.157
Bank FE/#	YES/25	NO	NO	NO	NO	YES/24	NO	NO	NO
Cparty FE/#	NO	YES/21	NO	NO	NO	NO	YES/20	NO	NO
Week FE/#	YES/275	YES/275	YES/275	YES/275	NO	YES/275	YES/275	YES/275	YES/275
Bank-Cparty FE/#	NO	NO	YES/221	YES/221	NO	NO	NO	YES/208	YES/208
Cparty-Week FE/#	NO	NO	NO	NO	YES/4075	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty

This table presents the coefficients from fixed-effect regressions with bank, counterparty, bank-counterparty pair, week and counterparty-week pair fixed effects. Columns (1) and (6) present the coefficients for linear regressions with fixed effects on the German banks (bank FE) and time (week FE), whereas the coefficients presented in columns (2) and (7) are based on linear regressions with global dealer bank (counterparty FE) and time (week) fixed effects. Regression results presented in columns (3), (4), (8) and (9) use bank-counterparty pair in addition to week fixed effects. Column (5) presents the coefficient for linear regression with counterparty-week pair fixed effect. The time horizon is from November 2006 to February 2012 and the difference between two units of time is one week. TRX_RED is the number of new transactions within the current week where the German bank serves as the buyer and the counterparty is the underlying. TRX_SEL contains the number of new transactions entered within the past week where the German bank serves as the buyer and the counterparty as the seller. The variables STOCK_RETURN and STOCK_VOLATILITY contain the geometric average stock return and the standard deviation of the weekly stock return of the counterparty in the past week, respectively. CDS_PRICE contains the CDS spread level of the past week, whereas CDS_VOLATILITY is the standard deviation of the CDS price within the last week. All other variables are defined similarly as in Table 5. Robust standard errors clustered at either bank or bank-counterparty pair level are in parentheses. The symbols $***$, $**$, and $*$ indicate significance levels of 1%, 5% and 10%, respectively.

Table 7: Mitigation of counterparty risk – Weekly rolling intervals of new transactions (interactions)

VARIABLES	(1) TRX_RED	(2) TRX_RED	(3) TRX_RED	(4) TRX_RED
L.TRX_SEL	0.00317	0.0205	0.000326	0.000326
	(0.0184)	(0.0318)	(0.00492)	(0.0136)
TOT_ASSETS (QLAG) (e-10)	2.52**	4.89**	1.38	1.38
	(95.6)	(1.84)	(2.06)	(3.02)
CAP_STRUCTURE (QLAG)	-6.595**	23.34	39.75***	39.75***
	(3.179)	(14.89)	(12.38)	(12.46)
CURRENT_RATIO (QLAG)	0.356**	-0.162***	-0.220***	-0.220*
	(0.159)	(0.0552)	(0.0426)	(0.123)
L.STOCK_RETURN	-0.662	-0.676	1.560	1.560
	(1.385)	(0.905)	(0.964)	(5.757)
L.STOCK_VOLATILITY	0.00672	-0.0931***	-0.0191	-0.0191
	(0.0449)	(0.0224)	(0.0213)	(0.0486)
L.CDS_VOLATILITY	-0.00717*	-0.0105***	-0.0116***	-0.0116**
	(0.00359)	(0.00363)	(0.00236)	(0.00584)
L.CDS_PRICE (e-4)	88.4**	53.1	84.0**	84.0***
	(41.8)	(40.4)	(37.3)	(24.2)
L.TRX_SEL*L.STOCK_RETURN	-0.183***	-0.0756	-0.264***	-0.264
	(0.0450)	(0.0719)	(0.0236)	(0.222)
L.TRX_SEL*L.STOCK_VOLATILITY	0.00885***	0.0102***	0.00837***	0.00837***
	(0.00154)	(0.00208)	(0.000793)	(0.00205)
L.TRX_SEL*L.CDS_VOLATILITY	0.00145***	0.00130***	0.00179***	0.00179***
	(0.000191)	(0.000269)	(0.0000763)	(0.000382)
L.TRX_SEL*L.CDS_PRICE (e-4)	1.65	3.11	-0.465	-0.465
	(1.17)	(2.76)	(0.921)	(1.41)
Constant	3.392	-22.49	-40.67***	-40.67***
	(2.606)	(15.15)	(12.32)	(12.03)
Observations	5318	5318	5318	5318
Adjusted R^2	0.279	0.257	0.177	0.177
Bank FE/#	YES/25	NO	NO	NO
Cparty FE/#	NO	YES/20	NO	NO
Week FE/#	YES/275	YES/275	YES/275	YES/275
Bank-Cparty FE/#	NO	NO	YES/208	YES/208
Error Clustering	Bank	Bank	Bank	Bank-Cparty

This table presents the coefficients from fixed-effect regressions with bank, counterparty, week, and bank-counterparty pair fixed effects. Column (1) presents the coefficients for linear regressions with fixed effects on the German banks (bank FE), whereas the coefficients presented in column (2) are based on linear regressions with global dealer bank (counterparty) fixed effects. The regression results presented in columns (3) and (4) use bank-counterparty pair fixed effects for estimation. All columns, additionally, share week fixed effects. The time horizon is from November 2006 to February 2012 and the difference between two units of time is one week. TRX_RED is the number of new transactions within the week where the German bank serves as the buyer and the counterparty is the underlying. TRX_SEL contains the number of new transactions entered within this week where the German bank serves as the buyer and the counterparty as the seller. All other variables are defined as in Table 6. Robust standard errors clustered at either bank or bank-counterparty pair level are in parentheses. The symbols $***$, $**$, and $*$ indicate significance levels of 1%, 5% and 10%, respectively.

4.2 Evidence of Risk Mitigation by Dealers and Non-Dealers

Below, we separately analyze the counterparty risk-mitigation activities exhibited by German dealers and non-dealers in our sample. Dealers and non-dealers may display different hedging/risk-mitigation behaviour, since dealers are more active in trading and would be more interested in short-term risk taking than non-dealers. Table 8 provides the results on weekly rolling new transactions from Equation (2), separating German dealers and non-dealers in Panels A and B, respectively.

Panel A of Table 8 presents the risk-mitigation activity of dealers. The weekly lagged new transactions of protections bought from the counterparty remain partly significant in explaining the following week's new protections bought on the counterparty. Most importantly, the coefficient of interest is highly significant in specification (5), which utilizes the very strong counterparty-week fixed effects in order to control for any endogeneity. Higher leverage, lower past stock returns and higher CDS price levels of the counterparty lead to increased protection purchases on the respective counterparty by German dealers. On the other hand, we see a different picture when we look at Panel B. There is no evidence of hedging behaviour by non-dealers in weekly intervals, which is observed from the insignificant TRX_SEL coefficient. Since non-dealers are active in CDS trading markets to a lesser degree, this finding overlaps with the intuition that non-dealers might not be active in counterparty risk-taking and mitigation on such short horizons. Still, higher leverage and short-term past stock performance seem to be decisive for non-dealers' decisions regarding the purchase of CDS on respective global dealers. The lower the past performance of the global player, the greater the extent of protection bought on counterparties by non-dealers.

Table 9 replicates the setup used in Table 8, but this time with monthly intervals. The interesting insight provided by Table 9 Panel B is that, unlike the results with the weekly intervals in Table 8, non-dealers are shown to be more active in mitigating their risk on monthly horizons. This result builds on the insignificance of the short-term mitigation effects shown in Table 8, and indicates that since non-dealers are active in CDS trading markets to a lesser degree, they might be managing their counterparty risk-taking and mitigation on longer horizons. On the other hand, in Panel A of Table 9, we observe that the dealers are to a certain degree still active with respect to risk mitigation over longer periods. This result can be interpreted as indicating that the risk-taking activity of dealers spans both short and

Table 8: Mitigation of counterparty risk – Weekly rolling intervals of new transactions, dealers v non-dealers

VARIABLES	(1) TRX_RED	(2) TRX_RED	(3) TRX_RED	(4) TRX_RED	(5) TRX_RED	(6) TRX_RED	(7) TRX_RED	(8) TRX_RED	(9) TRX_RED
Panel A. German banks and investment firms acting as dealers									
L.TRX_SEL	0.0802**	0.0909	0.0372	0.0372*	0.141***	0.0638	0.0901	0.0322	0.0322**
	(0.00521)	(0.0595)	(0.0182)	(0.0194)	(1.32e-09)	(0.0165)	(0.0682)	(0.0250)	(0.0158)
TOT_ASSETS (QLAG) (e-10)						2.73	7.25**	3.91	3.91
						(1.11)	(0.283)	(2.59)	(3.60)
CAP_STRUCTURE (QLAG)						-8.533	30.01	45.08	45.08***
						(3.642)	(30.01)	(15.68)	(12.45)
CURRENT_RATIO (QLAG)						0.496	-0.128	-0.218	-0.218
						(0.174)	(0.0243)	(0.0394)	(0.142)
L.STOCK_RETURN						-3.079	-2.831**	-1.072	-1.072
						(3.338)	(0.0993)	(0.999)	(8.351)
L.STOCK_VOLATILITY						0.144	0.0720	0.124	0.124
						(0.113)	(0.114)	(0.0780)	(0.0829)
L.CDS_VOLATILITY						0.0155	0.0101	0.0102	0.0102
						(0.0148)	(0.00946)	(0.00835)	(0.00928)
L.CDS_PRICE (e-4)						116.0	86.5	88.6	88.6***
						(45.4)	(36.1)	(35.9)	(25.6)
Constant	-1.851*	-0.751	-2.234**	-2.234***	0.654	4.623	-29.97	-45.68	-45.68***
	(0.166)	(1.484)	(0.175)	(0.111)	(0.509)	(2.652)	(30.19)	(15.58)	(12.10)
Observations	4862	4862	4862	4862	4862	3851	3851	3851	3851
Adjusted R^2	0.173	0.250	0.140	0.140	0.052	0.255	0.270	0.187	0.187
Bank FE/#	YES/2	NO	NO	NO	NO	YES/2	NO	NO	NO
Cparty FE/#	NO	YES/21	NO	NO	NO	NO	YES/20	NO	NO
Week FE/#	YES/275	YES/275	YES/275	YES/275	NO	YES/275	YES/275	YES/275	YES/275
Bank-Cparty FE/#	NO	NO	YES/40	YES/40	NO	NO	NO	YES/38	YES/38
Week-Cparty FE/#	NO	NO	NO	NO	YES/3927	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty
Panel B. German banks and investment firms acting as non-dealers									
L.TRX_SEL	-0.00000567	0.000316	0.000104	0.000104	-0.00246	0.000145	0.000144	-0.000128	-0.000128
	(0.000254)	(0.000555)	(0.000331)	(0.000267)	(0.0120)	(0.000218)	(0.000452)	(0.000384)	(0.000419)
TOT_ASSETS (QLAG) (e-10)						-0.185	-0.406	-0.440	-0.440
						(0.113)	(0.285)	(0.285)	(0.792)
CAP_STRUCTURE (QLAG)						0.734***	4.956***	4.093***	4.093
						(0.260)	(1.669)	(1.344)	(2.886)
CURRENT_RATIO (QLAG)						0.0431*	0.0103	0.0205	0.0205
						(0.0231)	(0.0185)	(0.0204)	(0.0267)
L.STOCK_RETURN						-2.234**	-2.083**	-2.020**	-2.020*
						(0.939)	(0.915)	(0.890)	(1.199)
L.STOCK_VOLATILITY						-0.00141	-0.0106	-0.00887	-0.00887
						(0.00503)	(0.00662)	(0.00558)	(0.00944)
L.CDS_VOLATILITY						0.00389	0.00349	0.00401	0.00401
						(0.00301)	(0.00294)	(0.00320)	(0.00289)
L.CDS_PRICE (e-4)						-2.67	-3.38	-4.31	-4.31
						(4.15)	(6.12)	(7.35)	(5.35)
Constant	-0.161***	0.0337**	-0.0398***	-0.0398***	0.0740**	-0.759***	-4.443***	-3.723***	-3.723
	(0.00814)	(0.0157)	(0.00700)	(0.0107)	(0.0286)	(0.227)	(1.488)	(1.283)	(2.724)
Observations	1863	1863	1863	1863	1863	1467	1467	1467	1467
Adjusted R^2	0.016	0.006	0.001	0.001	-0.026	0.061	0.040	0.042	0.042
Bank FE/#	YES/23	NO	NO	NO	NO	YES/23	NO	NO	NO
Cparty FE/#	NO	YES/19	NO	NO	NO	NO	YES/18	NO	NO
Week FE/#	YES/254	YES/254	YES/254	YES/254	NO	YES/247	YES/247	YES/247	YES/247
Bank-Cparty FE/#	NO	NO	YES/181	YES/181	NO	NO	NO	YES/170	YES/170
Week-Cparty FE/#	NO	NO	NO	NO	YES/1328	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty

Table 9: Mitigation of counterparty risk – Monthly rolling intervals of cumulative new transactions, dealers v non-dealers

VARIABLES	(1) Σ TRX_RED	(2) Σ TRX_RED	(3) Σ TRX_RED	(4) Σ TRX_RED	(5) Σ TRX_RED	(6) Σ TRX_RED	(7) Σ TRX_RED	(8) Σ TRX_RED	(9) Σ TRX_RED
Panel A. German banks and investment firms that are dealers									
L4.Σ TRX_SEL	0.102**	0.132	0.0445	0.0445*	0.159	0.0783	0.131	0.0299	0.0299*
	(0.00583)	(0.0574)	(0.0228)	(0.0240)	(0.0282)	(0.0223)	(0.0686)	(0.0327)	(0.0176)
TOT_ASSETS (QLAG) (e-10)						8.89	24.1	10.9	10.9
						(5.07)	(7.03)	(8.78)	(12.8)
CAP_STRUCTURE (QLAG)						-25.69	90.88	144.1	144.1***
						(22.78)	(101.6)	(97.23)	(51.38)
CURRENT_RATIO (QLAG)						2.048	-0.105**	-0.338	-0.338
						(1.158)	(0.00251)	(0.0990)	(0.425)
L4.STOCK_RETURN						-85.57	-75.44	-69.82	-69.82***
						(55.74)	(41.18)	(40.59)	(22.40)
L4.STOCK_VOLATILITY						0.316	-0.315	0.0595	0.0595
						(0.394)	(0.143)	(0.182)	(0.416)
L4.CDS_VOLATILITY						0.0470	0.0151	0.0191	0.0191
						(0.0855)	(0.0449)	(0.0464)	(0.0686)
L4.CDS_PRICE (e-4)						252.0	161.0	176.0	176.0***
						(151.0)	(92.3)	(99.3)	(48.2)
Constant	-5.034**	0.539	-9.339*	-9.339***	2.000	13.14	-89.72	-149.2	-149.2***
	(0.368)	(5.200)	(0.940)	(0.793)	(1.810)	(17.77)	(103.9)	(95.96)	(49.54)
Observations	6832	6832	6832	6832	6832	5400	5400	5400	5400
Adjusted R^2	0.298	0.383	0.195	0.195	0.533	0.369	0.387	0.245	0.245
Bank FE/#	YES/2	NO	NO	NO	NO	YES/2	NO	NO	NO
Cparty FE/#	NO	YES/21	NO	NO	NO	NO	YES/20	NO	NO
Month FE/#	YES/65	YES/65	YES/65	YES/65	NO	YES/65	YES/65	YES/65	YES/65
Bank-Cparty FE/#	NO	NO	YES/40	YES/40	NO	NO	NO	YES/38	YES/38
Month-Cparty FE/#	NO	NO	NO	NO	YES/1158	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty
Panel B. German banks and investment firms that are non-dealers									
L4.Σ TRX_SEL	0.00704***	0.00758***	0.00745***	0.00745***	0.0110***	0.00714***	0.00741***	0.00731***	0.00731***
	(0.000782)	(0.000555)	(0.000444)	(0.000855)	(0.000960)	(0.000269)	(0.000527)	(0.000399)	(0.000793)
TOT_ASSETS (QLAG) (e-10)						-0.276	-1.62	-1.74	-1.74
						(0.326)	(1.04)	(1.49)	(1.88)
CAP_STRUCTURE (QLAG)						0.397	7.972	9.756	9.756
						(1.609)	(5.716)	(6.147)	(7.272)
CURRENT_RATIO (QLAG)						-0.0164	-0.0369*	-0.0324***	-0.0324
						(0.0436)	(0.0198)	(0.0111)	(0.0254)
L4.STOCK_RETURN						-5.299***	-4.505***	-4.957***	-4.957***
						(1.771)	(1.362)	(1.399)	(1.749)
L4.STOCK_VOLATILITY						0.0263*	0.00882	0.0192	0.0192
						(0.0143)	(0.0231)	(0.0241)	(0.0271)
L4.CDS_VOLATILITY						0.000504	0.00148	0.000166	0.000166
						(0.00208)	(0.00221)	(0.00185)	(0.00256)
L4.CDS_PRICE (e-4)						0.660	-6.46	-5.59	-5.59
						(3.74)	(7.89)	(8.12)	(6.83)
Constant	-0.272*	0.0386	0.0581	0.0581	0.173**	-0.447	-7.188	-8.750	-8.750
	(0.137)	(0.132)	(0.0661)	(0.0594)	(0.0676)	(1.465)	(5.259)	(5.588)	(6.760)
Observations	5225	5225	5225	5225	5225	4086	4086	4086	4086
Adjusted R^2	0.114	0.085	0.066	0.066	0.324	0.152	0.120	0.108	0.108
Bank FE/#	YES/23	NO	NO	NO	NO	YES/23	NO	NO	NO
Cparty FE/#	NO	YES/19	NO	NO	NO	NO	YES/18	NO	NO
Month FE/#	YES/63	YES/63	YES/63	YES/63	NO	YES/63	YES/63	YES/63	YES/63
Bank-Cparty FE/#	NO	NO	YES/179	YES/179	NO	NO	NO	YES/170	YES/170
Month-Cparty FE/#	NO	NO	NO	NO	YES/709	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty

longer horizons as revealed by Panels A in Tables 8 and 9.

One way to interpret the results in Tables 8 and 9 is that the accumulation of counterparty risk might be slower for non-dealers in comparison to that of dealers. Non-dealers might be waiting to hedge until the open interest hits a certain level or ratio, and this might be the reason why they hedge less frequently. Another possibility might be the lower turnus of risk management meetings at non-dealer institutions, which could fix hedging action deadlines to a less frequent extent.

4.3 Identification through an Exogenous Shock on the Underlying

The previous two subsections made use of the transaction-level CDS dataset together with bank, counterparty or bank-counterparty pair fixed effects, and relied on time (week/month) or counterparty-time pair fixed effects to address any endogeneity that could have been caused by aggregate or counterparty-specific time-variant factors, which may simultaneously drive protection bought from the global dealer today and protection bought on the global dealer on a future week or month.

An alternative robust way to address this issue is to make use of price shocks on underlyings, whose protection are being purchased by our sample banks and financial institutions from the global counterparties at the SEL time step. An ideal identification could be achieved through looking at the CDS price change of each underlying u in all trading activities between the German banks and their counterparties, and multiplying this value with the current net position of the same bank i with the same counterparty j on this underlying u ("NETSELPOS"). The value in Equation 3 could be viewed as an individual shock ("INDSHOCK") to the counterparty risk of the bank with respect to a given underlying u.

$$INDSHOCK_{i,j,u,t} = NETSELPOS_{i,j,u,t-1} * (CDS\_PRICE_{u,t} - CDS\_PRICE_{u,t-1}) \quad (3)$$

In order to reach the aggregate shock to the counterparty risk of a bank with respect to all underlyings, the individual shocks in Equation 3 could be aggregated across all underlyings

u that are traded between a bank-counterparty pair.

$$SHOCK_{i,j,t} = \sum^{u} INDSHOCK_{i,j,u,t} \tag{4}$$

The variable $SHOCK_{i,j,t}$ provides a valuable exogenous shock on counterparty risk of bank i on counterparty j, which enables the consecutive actions of bank i on trading the CDS of counterparty j to be independently interpreted from any endogeneity. Table 10 Panel A introduces $\Sigma SHOCK_{i,j,t}$ as a new explanatory variable, where past four weeks of price shocks on all underlyings are aggregated. In the first (second) part of the panel the dependent variable is the cumulative number of new protection contracts,"TRX_RED" (cumulative volume of new protection, "VOL_RED") purchased on the counterparty during the immediately following four weeks. We make use of the following specifications in Equations 5 and 6, alternatively with (1) bank and month FE, (2) counterparty and month FE, and (3) counterparty-month pair FE. The fourth and fifth specifications add the typical counterparty-specific controls that were used previously into specifications (1) and (2).

$$\sum_{k=1}^{4} TRX\_RED_{i,j,t+k} = a_0 + a_1 \sum_{k=0}^{3} SHOCK_{i,j,t-k} + a_2 X_{j,t} + FE + \epsilon_{i,j,t} \tag{5}$$

$$\sum_{k=1}^{4} VOL\_RED_{i,j,t+k} = a_0 + a_1 \sum_{k=0}^{3} SHOCK_{i,j,t-k} + a_2 X_{j,t} + FE + \epsilon_{i,j,t} \tag{6}$$

The results in Table 10 Panel A indicate that both dependent variables, number of new contracts and notional amount purchased on the counterparty, are explained by the exogenous increase in the counterparty risk of the global dealer, revealed by the price shock on the CDS underlyings in prior weeks. In economic terms, a 100 bps aggregate CDS price deterioration (increase) in 10 EUR billion of an aggregate net sold position to the counterparty results in purchase of 3.25-6.69 additional contracts bought on the counterparty in order to mitigate the counterparty risk emerging from the price shock. Similarly, the second part of Panel A reveals that the same conditions result in a protection purchase of 18.5-38.7 EUR million on the counterparty.[9]

Panel B shows the effects of weekly price shocks on our sample banks' behaviour on purchase of protection on the counterparty (Equations 7 and 8). The same pattern of mitigation of counterparty risk due to exogenous price shocks on the underlying are once again observed, albeit at a lesser economic extent.

$$TRX\_RED_{i,j,t+1} = a_0 + a_1 SHOCK_{i,j,t} + a_2 X_{j,t} + FE + \epsilon_{i,j,t} \tag{7}$$

$$VOL\_RED_{i,j,t+1} = a_0 + a_1 SHOCK_{i,j,t} + a_2 X_{j,t} + FE + \epsilon_{i,j,t} \tag{8}$$

Overall, the results in this section underline once again the robustness of the results when an exogenous shock is used for a better identification.

4.4 Robustness

This section provides the results for alternative monthly and weekly specifications. We specifically look at whether German banks hedge their counterparty risk from correct parties (no wrong-way risk), and whether results are robust when (i) contemporaneous months and weeks of hedging activity are analyzed, and (ii) non-overlapping monthly specifications are used.[10] Table 11 reports the results of these checks by tabulating only the main variable of interest for monthly and weekly specifications in Panels A and B, respectively.

4.4.1 Wrong-Way Risk

"Wrong-way risk" arises when banks intend to mitigate their counterparty risk through the purchase of protection on their counterparty from a third party that is highly correlated with their initial counterparty. For instance, if a German bank purchases protection on a Japanese counterparty from another Japanese third party, it can be suggested that wrong-way risk mitigation occurs. In order to see whether German financial institutions mitigate

[9] A one standard deviation shock would have a value of 62.8 billion, which is a value close to this scenario.

[10] In undocumented results, our main finding is shown to be also robust when only observations of non-zero hedging activity are utilized.

Table 10: Mitigation of counterparty risk – Identification through an Exogenous Shock

Panel A. Monthly rolling intervals of new transactions					
VARIABLES	(1) Σ TRX_RED	(2) Σ TRX_RED	(3) Σ TRX_RED	(4) Σ TRX_RED	(5) Σ TRX_RED
Σ SHOCK	0.0325***	0.0371*	0.0669***	0.0339***	0.0497*
	(0.0014)	(0.019)	(0.0086)	(0.0053)	(0.024)
Observations	6230	6230	6230	4021	4021
Adjusted R^2	0.238	0.225	0.340	0.362	0.277
VARIABLES	(1) Σ VOL_RED	(2) Σ VOL_RED	(3) Σ VOL_RED	(4) Σ VOL_RED	(5) Σ VOL_RED
Σ SHOCK	0.185***	0.211	0.387***	0.159***	0.270
	(0.016)	(0.148)	(0.048)	(0.030)	(0.176)
Observations	6230	6230	6230	4021	4021
Adjusted R^2	0.259	0.229	0.341	0.383	0.271
Controls	NO	NO	NO	YES	YES
Bank FE/#	YES/8	NO	NO	YES/6	NO
Cparty FE/#	NO	YES/21	NO	NO	YES/20
Month FE/#	YES/50	YES/50	NO	YES/49	YES/49
Cparty-Month FE/#	NO	NO	YES/982	NO	NO
Panel B. Weekly rolling intervals of new transactions					
VARIABLES	(1) TRX_RED	(2) TRX_RED	(3) TRX_RED	(4) TRX_RED	(5) TRX_RED
SHOCK	0.00286	0.00576***	0.0197***	0.00679**	0.0110**
	(0.0031)	(0.0020)	(0.0046)	(0.0030)	(0.0044)
Observations	11087	11087	11087	6525	6525
Adjusted R^2	0.162	0.079	0.108	0.226	0.110
VARIABLES	(1) VOL_RED	(2) VOL_RED	(3) VOL_RED	(4) VOL_RED	(5) VOL_RED
SHOCK	0.0169	0.0376***	0.112***	0.0199	0.0504*
	(0.014)	(0.0093)	(0.022)	(0.015)	(0.027)
Observations	11087	11087	11087	6525	6525
Adjusted R^2	0.166	0.080	0.060	0.225	0.101
Controls	NO	NO	NO	YES	YES
Bank FE/#	YES/25	NO	NO	YES/19	NO
Cparty FE/#	NO	YES/21	NO	NO	YES/20
Week FE/#	YES/214	YES/214	NO	YES/213	YES/213
Cparty-Week FE/#	NO	NO	YES/4272	NO	NO

This table presents the coefficients from fixed-effect regressions with bank, counterparty, time (month or week) and counterparty-time pair fixed effects. Column (1) and (4) present the coefficients for linear regressions with fixed effects on the German banks (bank FE), whereas the coefficients presented in column (2) and (5) are based on linear regressions with international dealer bank (counterparty) fixed effects, all sharing, in addition, time fixed effects. The regression results presented in columns (3) use counterparty-time pair fixed effects for estimation. The time horizon is from November 2006 to February 2012 and the difference between two units of time is one week. In Panel A, Σ TRX_RED is the number while Σ VOL_RED is the volume of new transactions within the following four weeks, where the German bank serves as the buyer and the counterparty is the underlying. Σ SHOCK is the cumulative product between NETSELPOS and Δ RED_PRICE from the first to the fourth lag. In Panel B, TRX_RED is the number while VOL_RED is the volume of new transactions within the week, where the German bank serves as the buyer and the counterparty is the underlying. SHOCK is composed of lagged NETSELPOS times Δ RED_PRICE. All the other variables are defined as in Table 5 and 6 and are not tabulated for brevity. Robust standard errors clustered at bank level are in parentheses. The symbols $***$, $**$, and $*$ indicate significance levels of 1%, 5% and 10%, respectively.

Table 11: Robustness checks

Panel A. Monthly rolling intervals of new transactions

VARIABLES	(1) Σ TRX_RED	(2) Σ TRX_RED	(3) Σ TRX_RED	(4) Σ TRX_RED	(5) Σ TRX_RED	(6) Σ TRX_RED	(7) Σ TRX_RED	(8) Σ TRX_RED	(9) Σ TRX_RED
Baseline (Table 5): L4.Σ TRX_SEL	0.104***	0.147***	0.0694***	0.0694***	0.148***	0.0873***	0.146***	0.0472**	0.0472***
Case 1 (No WWR): L4.Σ TRX_SEL	0.0398***	0.0798***	0.0205***	0.0205*	0.0849***	0.0265***	0.0726***	0.0106	0.0106
Case 2 (Contemporaneous Month): Σ TRX_SEL	0.124***	0.168***	0.0892***	0.0892***	0.180***	0.116***	0.182***	0.0830***	0.0830**
Case 3 (Non-Overlapping Months): L4.Σ TRX_SEL	0.101***	0.151***	0.0557***	0.0557**	0.162***	0.0863***	0.151***	0.0442***	0.0442**
Controls	NO	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	YES	NO	NO	NO	NO	YES	NO	NO	NO
Counterparty FE	NO	YES	NO	NO	NO	NO	YES	NO	NO
Time (Month or Week) FE	YES	YES	YES	YES	NO	YES	YES	YES	YES
Bank-Cparty FE	NO	NO	YES	YES	NO	NO	NO	YES	YES
Cparty-Time FE	NO	NO	NO	NO	YES	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty

Panel B. Weekly rolling intervals of new transactions

VARIABLES	(1) TRX_RED	(2) TRX_RED	(3) TRX_RED	(4) TRX_RED	(5) TRX_RED	(6) TRX_RED	(7) TRX_RED	(8) TRX_RED	(9) TRX_RED
Baseline (Table 6): L.TRX_SEL	0.0607***	0.0891***	0.0317***	0.0317**	0.114***	0.0496***	0.0858***	0.0359**	0.0359**
Case 1 (No WWR): L.TRX_SEL	0.0215***	0.0437***	0.00855**	0.00855	0.0587***	0.0141***	0.0380***	0.00457	0.00457
Case 2 (Contemporaneous Week): TRX_SEL	0.0848***	0.110***	0.0584***	0.0584***	0.138***	0.0841***	0.129***	0.0543***	0.0543***
Controls	NO	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	YES	NO	NO	NO	NO	YES	NO	NO	NO
Counterparty FE	NO	YES	NO	NO	NO	NO	YES	NO	NO
Time (Month or Week) FE	YES	YES	YES	YES	NO	YES	YES	YES	YES
Bank-Cparty FE	NO	NO	YES	YES	NO	NO	NO	YES	YES
Cparty-Time FE	NO	NO	NO	NO	YES	NO	NO	NO	NO
Error Clustering	Bank	Bank	Bank	Bank-Cparty	Bank	Bank	Bank	Bank	Bank-Cparty

This table presents the coefficients from fixed-effect regressions with bank, counterparty, time (month or week), bank-counterparty and counterparty-time pair fixed effects. Columns (1) and (6) present the coefficients for linear regressions with fixed effects on the German banks (bank FE), whereas the coefficients presented in columns (2) and (7) are based on linear regressions with international dealer bank (counterparty) fixed effects, both sets of regressions sharing, in addition, time fixed effects. Regression results presented in columns (3), (4), (8) and (9) use bank-counterparty pair fixed effects for estimation in addition to time fixed effects. Column (5) presents the coefficient for linear regression with counterparty-time pair fixed effect. The time horizon is from November 2006 to February 2012 and the difference between two units of time is one week. In Panel A, Σ TRX_RED is the number of new transactions within the following four weeks where the German bank serves as the buyer and the counterparty is the underlying. L4.Σ TRX_SEL contains the number of new transactions entered within this week and the three previous weeks where the German bank serves as the buyer and the counterparty as the seller. In Panel B, TRX_RED is the number of new transactions within the current week where the German bank serves as the buyer and the counterparty is the underlying. L.TRX_SEL contains the number of new transactions entered within the past week where the German bank serves as the buyer and the counterparty as the seller. All the other variables are defined as in Table 5 (for Panel A) and 6 (for Panel B) and are not tabulated for brevity. Robust standard errors clustered at either bank or bank-counterparty pair level. The symbols $***$, $**$, and $*$ indicate significance levels of 1%, 5% and 10%, respectively.

counterparty risk keeping in mind the need to avoid wrong-way risk, we remove all the same country hedging activity and see if the results still hold. Hence, all protection purchases on, e.g., US dealers, from another US financial institution, are removed from the sample. Cases 1 in Panels A and B of Table 11 show that although the hedge proportion is lower, there is indeed significant evidence for German financial institutions to be avoiding wrong-way risk mitigation.

4.4.2 Contemporaneous months and weeks

It could be argued that risk-mitigation activity takes place directly in the same weeks or months whenever counterparty risk occurs, due to immediate reaction of the dealer desks. Cases 2 in Panels A and B of Table 11 provide evidence that risk mitigation takes place even in the contemporaneous months and weeks. Interestingly, the hedge proportion is much higher when compared to baseline results in Tables 5 and 6, which gives rise to the possibility that risk mitigation is immediately undertaken as well.

4.4.3 Non-overlapping months

One argument could be that the results might be spurious due to autocorrelated usage of weeks in monthly rolling intervals. If overlapping weeks are rolled over, double counting of information might emerge. In order to avoid this concern, Case 3 in Panel A of Table 11 generates results with non-overlapping rolling of monthly intervals. The coefficients of interest indicate an even slightly higher hedge proportion in some specifications compared to the baseline results in Table 5.

5 Conclusion and Policy Implications

This paper provides initial evidence of counterparty risk-mitigation activity on the part of financial institutions. Our sample banks and financial institutions manage their counterparty risk on weekly or monthly horizons as evidenced both by transaction-level and position-level information. Trading-intensive dealer banks are found to be more active in hedging, over both short and longer horizons, whereas non-dealer banks appear to manage this risk only over longer, monthly intervals. Higher stock return and CDS price volatility, lower past stock returns, and higher CDS prices of the counterparty are shown to boost hedging behaviour on the counterparty. The sample banks are also shown to mitigate their counterparty risk by keeping in mind to avoid wrong-way hedging. Finally, we further document the robustness of our main finding through identifying the risk mitigation activity when an exogenous price shock increases the counterparty risk of our sample banks.

The analysis provided in this study has implications regarding the ongoing debate on regulating the OTC market and further phasing in central clearing, which would seemingly eliminate the necessity of bilateral trading and diminish counterparty risk. We show that risk-mitigation is taking place in the OTC market despite the high level of collateralization indicated by recent studies, and that purchasing protection on the reference entities of counterparties seems to be a reliable method in circumstances where collateral alone provides insufficient protection. Players in the market are able to tentatively hedge their counterparty risk through CDSs in the OTC market regardless of whether they are a central clearing member. Given that we are able to show evidence on hedging in the CDS market that encompasses only a part of counterparty risk-taking activity, we expect that even a much higher degree of counterparty risk mitigation could be evidenced if exposures from interest rate and FX swaps were included. Altogether, the analysis in the paper points to an additional cost of not having central clearing, which has not been articulated in the literature.

We argue in this study that regulatory capital relief motives could actively accentuate this type of risk mitigation. Since Basel III and its European implementation, the CRR, explicitly formulate that any protection purchase on the counterparty would diminish the required regulatory CVA capital, future work should study whether such an incentive might create adverse effects that lead to excessive risk-taking. In the end, it is in the best interest of regulators to set the right incentives for market participants and clearing houses for an optimal design of the capital regulation of CDSs.

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