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Abstract

Employing credit default swap (CDS) data for a sample of 52 major banks across 18 countries from 2008 to 2016, this paper investigates determinants of the outstanding net notional amount of CDS on banks. We provide evidence for trading-specific, fundamental bank-specific as well as macroeconomic and institutional determinants of bank CDS trading. Our study fills an important gap since empirical studies have only focused on sovereign and corporate CDS yet. In addition, the analysis at hand provides important implications for both academic research and practitioners.

Keywords: credit default swaps, outstanding CDS net notional, CDS trading, default insurance, banking, Depository Trust and Clearing Corporation (DTCC)

JEL Classification: G10, G12, G21

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1 Introduction

Without a doubt, the credit default swap (CDS) is one of the most discussed and fastest growing financial innovations in the last decades. The market has grown to one of the biggest derivative markets with an outstanding notional of approximately $9,931 billions in the second half of 2016.[1] The rapid growth of the CDS market is fostered by the versatility of this product (da Silva et al., 2015). Hence, next to hedging, CDS are used in arbitrage trades and speculation (Oehmke and Zawadowski, 2016). In addition, as compared to the corresponding bond market, CDS are a very cost efficient way to diversify credit risk, which may result in higher financial stability (Bessembinder et al., 2009). In contrast, French et al. (2010) argue that large CDS exposures may create substantial systemic risks in the financial sector. This may result in end clients buying and dealers selling net protection in the CDS market (Brunnermeier et al., 2013). Accordingly, if systemically important financial institutions are affected by unhedged positions, systemic risk arises (da Silva et al., 2015).

Nowadays, investors predominantly see CDS spreads as an indicator for measuring the default risk of corporate firms and sovereigns alike (e.g., Greatrex, 2009; Longstaff et al., 2011). Furthermore, as most traders in the CDS market are highly sophisticated (e.g., hedge funds, banks, asset managers and insurers), the market has gained importance in the price discovery process (Acharya and Johnson, 2007). However, most transactions in the CDS market are traded over-the-counter and the market could be described as opaque regarding the disclosure of trading volumes and price information (da Silva et al., 2015). Therefore, in the aftermath of the global financial crisis regulatory supervisors claimed the introduction of a central clearing, higher regulation and standardization in the CDS market, which was implemented by the International Swap and Derivatives Association's (ISDA) 'Big Bang Protocol' in 2009.

Just before the intervention of the ISDA, the Depository Trust and Clearing Corporation (DTCC) started reporting disaggregated CDS data on single-name gross

[1] The data is retrieved from the OTC derivatives statistics provided by the Bank for International Settlements. (https://stats.bis.org)

and net notional amounts in the fourth quarter of 2008. Up to this date, academic research mainly focused on studies investigating the price (e.g., Collin-Dufresne et al., 2001; Benkert, 2004; Pelster and Vilsmeier, 2018), the flow of information to and from the CDS market (e.g., Blanco et al., 2005; Das et al., 2014; Hilscher et al., 2015) as well as the consequences of the CDS market introduction to firms (e.g., Ashcraft and Santos, 2009; Saretto and Tookes, 2013; Subrahmanyam et al., 2014).[2] In contrast, academic literature focusing on why investors trade in the CDS market is scarce, although, for different markets, related studies show that non-price data contains further information that cannot be obtained from price data (see e.g., Blume et al., 1994; de Launois and Van Oppens, 2005; Lo and Wang, 2009; Fodor et al., 2011). Accordingly, Augustin et al. (2014) emphasize that non-price data have to be analyzed in order to better understand the CDS market. In this context, Shachar (2012) and Biswas et al. (2015) focus on liquidity related questions, Siriwardane (2018) analyzes the risk-bearing capacity of the corporate CDS market and Du et al. (2018) examine counterparty risks in the CDS market.

Furthermore and in contrast to the aforementioned studies, Berg and Streitz (2015) as well as Augustin et al. (2016) analyze the CDS net notional outstanding in the sovereign CDS market while the most related studies to our analysis are provided by da Silva et al. (2015) and Oehmke and Zawadowski (2016) who investigate the CDS net notional outstanding in the corporate CDS market to identify determinants of CDS trading. Berg and Streitz (2015) show that sovereign CDS markets are, in relation to the corresponding country's debt, generally larger in smaller countries, in countries that exhibit a rating which is just above the investment grade and in countries with weaker creditor rights. Augustin et al. (2016) argue that debt is one of the main determinants of the net notional amount in the sovereign CDS market. Furthermore, they identify four channels (shocks to credit risk, debt issued by the government, news and sentiment and a regulatory channel) which may explain the change of the CDS trading volume of sovereigns. As regards the most related studies to our analysis, da Silva et al. (2015) examine the dynamics of CDS net and gross notional amounts of 317 US and 210 European firms on a weekly basis from

[2] For a comprehensive overview of the CDS literature see Augustin et al. (2014).

October 31, 2008 to October 10, 2014. They find that asymmetric information about a firm's credit risk is a trigger for the dynamics of CDS net notional. They further show that common factors (e.g., investors' risk aversion, macroeconomic environment) have even a greater impact on the trading dynamics in the CDS market. Oehmke and Zawadowski (2016) focus on the corporate CDS market in the US by analyzing 496 firms on a monthly basis from October 2008 to December 2012. They investigate the determinants of the CDS net notional amounts and highlight four different trading motives for CDS investors, i.e. hedging, speculation, arbitrage and standardization in the underlying bond market.

The study at hand differs from the previous studies in two aspects. First, we shed a brighter light on the determinants of *bank* CDSs. Second, we analyze whether fundamental data is exploited by CDS investors in the banking sector. We argue that fundamental data affects CDS trading on banks through a risk channel. In this context, we consider theories from the the bank risk (taking) literature suggesting that higher bank risks should lead to higher hedging incentives and to higher speculation incentives due to rising CDS prices. Our analysis is important since banks play an essential role for the stability of the financial market and the real economy, which could especially be observed during the financial crisis in 2007/08 (see e.g., Acharya and Schnabl, 2010; De Haas et al., 2011; Cetorelli and Goldberg, 2011) and during the ongoing European Sovereign Debt Crisis (see e.g., Lane, 2012; Mody and Sandri, 2012; Brunnermeier et al., 2016). Furthermore, banks are susceptible to many types of risk (e.g., credit risk, interest rate risk, liquidity risk) (Jorion, 2009) and exhibit a large counterparty risk since they are the top liquidity providers in over-the-counter markets (da Silva et al., 2015). Thus, depending on their risk aversion and portfolio composition, it may be rational for (institutional) investors to hedge their portfolio against bank risks by means of CDSs. In contrast, it may also be beneficial for investors to speculate on these banks since increasing bank risk should lead to rising bank CDS prices.

Against this background, we employ a sample of annual data from 52 major banks across 18 countries from 2008 to 2016 in order to analyze the impact of CDS trading-specific, fundamental bank-specific, macroeconomic and institutional determinants on the outstanding net notional amount of CDS. We provide evidence that hedging is one of the most important determinants of trading bank CDSs. Furthermore, exploiting arbitrage opportunities, a lower standardization in the underlying bond market as well as a higher CDS tail risk trigger trading in the CDS market. We additionally find that investors use fundamental data for their decision to buy CDSs as an insurance against bank defaults. Furthermore, we show that investors in the CDS market do not speculate against larger banks but rather smaller banks. Finally, we control for macroeconomic and institutional variables in further analyses and find that these variables are additional key determinants for an outstanding CDS net notional on banks.

The remainder of the paper is organized as follows. Section 2 presents the data and Section 3 introduces the empirical methodology. The empirical results are provided in Section 4. While Section 4.1 discusses the results of our baseline analysis, Section 4.2 presents the results from robustness checks and Section 4.3 provides the results from controlling for macroeconomic and institutional determinants. Finally, Section 5 summarizes and concludes.

2 Data

Table 1 presents the geographical distribution of banks in our sample and Table 2 provides notes on variables and data sources. The descriptive statistics are presented in Table 3. Table 4 presents the correlation matrix of variables which are employed in our baseline regression.[3]

2.1 Outstanding CDS net notional amount on banks

Our sample comprises annual data from 2008 to 2016. We retrieve data on net notional amounts outstanding on bank CDS from the Depository Trust and Clearing Corporation (DTCC). The DTCC collects data directly from major dealers and captures around 95% of globally traded CDS positions and CDS trading. The data on outstanding positions in the

[3] As we use 30 variables in total, we do not provide the full correlation matrix in this study but will provide it on request.

CDS market, i.e. CDS net notional and gross notional amounts, is weekly disclosed in US dollars for the top 1000 reference entities. On average, the amount from these top reference entities covers about 98% of the gross notional amount outstanding in the CDS market (da Silva et al., 2015). The CDS gross notional reflects the total amount outstanding, including long and short positions that are mutually exclusive, whereas the net notional is the maximum possible transfer of funds between sellers and buyers of net protection in the CDS market. The net notional amount outstanding is considered to be the economically most meaningful measure of aggregate risk transfer (Oehmke and Zawadowski, 2016). It also provides a direct indication of the net insured interest, and is therefore analoguous to open interest in futures and options markets (Augustin et al., 2016). Accordingly, we focus on net notional amounts outstanding on banks as our dependent variable. We include the ratio of a banks net notional amount outstanding to a bank's total assets since we observe that the CDS net notional scales with bank size.

We average weekly outstanding net notional amounts per bank and year.[4] Furthermore, we exclude all state-owned or non-listed banks as well as banks with less than four consecutive weekly data points. If a bank drops out of the DTCC database due to a default, it remains in our database up to the relevant year. If two banks merge, the acquirer remains in our sample whereas the acquired bank drops out of the sample after the year of the merger to account for a probable survivorship bias. These corrections lead to a sample of 52 major banks from 18 countries (Table 1), i.e. 464 observations on CDS net notional amounts on banks.

Subsequently, data from the DTCC is hand-matched with further CDS data from IHS Markit, fundamental data from Orbis Bank Focus/Bankscope (provided by Bureau van Dijk), stock and bond market data from EIKON, Datastream and IBES (all provided by Thomson Reuters) as well as macro and institutional data from the World Bank's WDI database, Thomson Reuters, the International Monetary Fund's IFS database as well as the Financial Stability Board (FSB). Quantities in currencies other than US dollars are converted to US dollars, using the prevailing foreign exchange rate.

[4]We focus on yearly data since most balance sheet data is only available on an annual basis.

2.2 Explanatory variables

We focus on CDS trading-specific and fundamental bank-specific determinants of the CDS net notional outstanding on banks in our baseline analysis. As mentioned above, the main trading motives being analyzed in related studies are insurable interest, bond market fragmentation, speculation, arbitrage and market risk. In our study, we further include fundamental data and utilize the well-established CAMEL model[5] extended by a bank's business model. In addition, we gradually add macroeconomic and institutional determinants during further analyses.

2.2.1 CDS trading-specific determinants

To begin with and as discussed in Section 1, risk-hedging describes a well-accepted motive for investors to buy CDS. We proxy the hedging incentive by the ratio of outstanding bonds to total assets per bank and year (*Bond ratio*).[6] A higher volume on outstanding bonds to total assets means higher insurable interest since the outstanding CDS net notional on banks should rise with higher bond ratios (Oehmke and Zawadowski, 2016). We expect a positive impact of the bond ratio on the CDS net notional outstanding on banks.

Furthermore, we include a bond fragmentation measure (*Bond frag.*) following the methodology provided by Oehmke and Zawadowski (2016).[7] This measure controls for the fact that CDS contracts are more standardized than bond contracts. Usually, bonds are fragmented into many different issues whereas CDSs are standardized contracts. As investors can choose between the CDS market and the underlying bond market, the CDS market should be more beneficial if constraints in the bond market exist. Since standardization differences should increase with a higher fragmentation of the bond market, we expect a positive impact of bond fragmentation on the outstanding CDS net notional on banks.

[5]CAMEL is an acronym for a bank's capital adequacy, asset quality, management soundness, earnings capacity and liquidity.

[6]We construct this variable by summing up the volume of all outstanding bonds per bank and year with a maturity of more than one-year. Subsequently, the result is divided by a bank's total assets.

[7]The technical details of the construction of the bond fragmentation measure are provided in the Technical Appendix B.1.

Next to hedging, speculation describes another important trading motive for investors in the CDS market. Investors may express their views about the default probability of a bank even if they do not have an exposure to the reference entity (Fostel and Geanakoplos, 2012; Che and Sethi, 2014). We employ a measure of disagreement on one-year analysts' earnings forecasts per share (*Disagr.*) to proxy speculation as suggested by Oehmke and Zawadowski (2016).[8] The higher the dispersion of the earnings prospects with regard to banks, the more analysts take views in the credit market since a disagreement about default probabilities should naturally be related to disagreement about earnings (Oehmke and Zawadowski, 2016). We expect that, speculation on future earnings of banks and on credit risk should increase the outstanding CDS net notional on banks.

In addition, we control for a bank's market risk which is proxied by the tail risk of a bank's CDS log-spread change with the corresponding CDS index log-spread change. We use the upper tail dependence coefficient suggesting that higher CDS spreads indicate a higher risk exposure of the underlying bank (*UTD CDS*). We calculate this measure following Schmidt and Stadtmüller (2006) who present a non-parametric estimation technique of the tail dependence coefficient.[9] As shown by Meine et al. (2016), investors in the bank CDS market protect themselves against extreme downside risks while protection sellers of contracts on banks require a premium for bearing the risk of a joint tail event in the financial market. Thus, the upper tail dependence measures the susceptibility of a bank to defaults in economic downturns and a higher upper tail dependence of CDS spread changes sets an incentive to investors to buy net protection against extreme tail events. Accordingly, we expect a positive impact of tail risk on the outstanding CDS net notional amounts on banks.

[8] Following Oehmke and Zawadowski (2016) the measure is calculated as the ratio of a bank's standard deviation of one-year earnings forecasts to the stock price if the stock price is above one, and it is set to missing otherwise. Dividing through the stock price ensures that the measure adjusts for a bank's equity cushion. We also control for two-year earnings forecasts. Since the results are generally reiterated, we do not report the results but provide them on request.

[9] We employ this procedure instead of choosing a particular copula model to avoid an estimation bias due to misspecification of the copula (Weiß et al., 2014). We use the CDX North America Investment Grade, iTraxx Asia ex Japan, iTraxx Australia, iTraxx Europe and iTraxx Japan as proxies for the business environment for the corresponding banks in these regions to calculate the tail dependence coefficient. The technical details of the non-parametric estimation are provided in the Technical Appendix B.2.

Finally, arbitrage is measured by the negative (*Neg. basis*) and positive (*Pos. basis*) CDS-bond basis[10], which is the difference between the five-year CDS spread and the underlying bond yield over the risk-free rate[11]. From a theoretical perspective, a portfolio of a long (short) bond position and a long (short) CDS position should result in the risk-free rate and thus, the basis should be zero (or close to zero). Deviations of the basis in capital markets can be used by arbitrageurs by means of positive or negative basis trades. As mentioned above, both arbitrage strategies imply either a short or a long position in a CDS contract and should increase the outstanding CDS net notional on banks.

2.2.2 Fundamental bank-specific determinants

We additionally examine the impact of a bank's fundamental data on an investor's decision to buy net protection by means of CDSs. We employ the well-established CAMEL model and extend it by a measure of a bank's business model. CAMEL describes a rating system, which is widely used by bank supervisory authorities (e.g., the Federal Reserve (Fed), the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC)). CAMEL measures the condition of a bank by means of five fundamental bank-specific determinants: capital adequacy, asset quality, management soundness, earnings capacity and liquidity (West, 1985). From an investor's perspective, the latest information available is the annual financial statement from the past year. Therefore, we lag the CAMEL variables and the proxy for a bank's business model by one year. Additionally, lagging by one period helps to avoid multicollinearity issues (see Section 3).

[10]The basis is calculated following Blanco et al. (2005). We employ five-year CDS spreads since they are the most liquid CDS spreads in the market (see amongst others Jorion and Zhang, 2007). Since bonds are not a standardized product like CDSs, we need to calculate the corresponding five-year bond spreads for each bank. As no bond generally corresponds to the five-year maturity of CDS contracts, we select all bonds with a remaining maturity of one to five years and all bonds with a remaining maturity over five to ten years. If we find at least one pair of bonds, we interpolate the yields to a five-year maturity. Otherwise we set our variable to missing, which explains the lower observation number for this variable (see Table 3). We repeat this procedure on a quarterly basis and average the positive and negative basis per year. For reasons of interpretation, we multiply the negative basis by minus one. As a consequence, a higher negative (as well as positive) basis means higher arbitrage opportunities.

[11]We employ the U.S. 3-months T-Bill as a proxy for the risk-free rate. The data is directly obtained from the U.S. Department of the Treasury (`https://www.treasury.gov`).

To begin with, capital adequacy is proxied by the leverage ratio (*Leverage*) while higher ratios indicate less capitalized banks. A higher leverage ratio raises a bank's probability of default and thus, should lead to a higher risk exposure, which may be hedged or exploited by investors through CDSs (Merton, 1974; Keeton and Morris, 1987; Wheelock and Wilson, 2000; Gambacorta and Mistrulli, 2004; Berger and Bouwman, 2013; Demirgüç-Kunt et al., 2013). However, a higher leverage ratio may also result in stronger debt covenants, which may discipline bank managers (Jensen and Meckling, 1976; Calomiris and Kahn, 1991; Rajan and Zingales, 1995; Diamond and Rajan, 2001). Accordingly, as debt covenants may force bank managers to negotiate future investment projects with the bank's debt holders (e.g., investors holding bonds), high-risk investment projects with a negative net present value are less likely, which should result in a lower outstanding CDS net notional on higher levered banks. Against this background, the impact of the leverage ratio on the outstanding CDS net notional on banks is not distinct.

We further include a bank's loan loss reserves to gross loans (*LLR*) as a proxy for asset quality while higher values of this ratio indicate a lower loan portfolio quality (e.g., Altunbas et al., 2007; Tabak et al., 2012; Farruggio and Uhde, 2015). Since a decrease in loan portfolio quality results in higher bank risk (Keeton and Morris, 1987), we suggest a stronger incentive to investors to trade bank CDSs and hence, expect a positive impact of the measure of loan loss reserves on the outstanding CDS net notional on banks. Against this background, we suggest a stronger incentive to investors to trade bank CDS and hence, expect a positive impact of the measure of loan loss reserves on the outstanding CDS net notional on banks.

In a next step, we employ a bank's cost-to-income ratio (*CIR*) as a proxy for the efficiency of a bank's management while a higher cost-to-income ratio implies higher inefficiency. Results from related theoretical and empirical studies are mixed. Known as the 'bad management' hypothesis Berger and DeYoung (1997) suggest that banks with managers who exhibit poor skills in credit scoring, estimating collateral-values and controlling and monitoring borrowers exhibit higher operating expenses and a lower loan portfolio quality. If this is true, greater cost inefficiency should be positively associated with the outstanding CDS net notional on banks. In contrast, following the 'skimping' hypothesis it is suggested that the extent of resources, which is established to underwrite and monitor loans may have an impact on the loan portfolio quality (Berger and DeYoung, 1997). Hence, it is shown that a bank's management operates more cost-efficiently in the short run, whereas future loan performance may decrease and credit risk may increase in the long run if a bank reduces its management resources. Against this background, the impact of the cost-to-income ratio on the amount of outstanding CDS net notional on banks is ambiguous.

Turning to a bank's earnings capacity, we include the return on average assets ($ROAA$). Higher returns suggest a higher earnings capacity. Following the 'bad management' and the 'gambling for resurrection' hypothesis, we suggest that more profitable and well-managed banks may have a more accurate credit monitoring and credit scoring processes, may assess the value of collaterals more precisely and may be less prone to engage in risky (credit) investments (Berger and DeYoung, 1997; Williams, 2004). In sum, we expect a negative impact of the return on average assets on the outstanding CDS net notional on banks.

Furthermore, we control for a bank's liquidity position by including the ratio of liquid assets to total deposits and short-term funding (*Liquid assets*). A higher ratio of this proxy indicates a higher bank liquidity. Theoretical arguments provided by Cebenoyan and Strahan (2004) and Wagner (2007) suggest that growing liquidity risk buffers set an incentive for an excessive risk-taking behavior of bank managers. In contrast, Wagner (2007) as well as Demirgüç-Kunt et al. (2013) argue that liquidity risk buffers mitigate banks' susceptibility to liquidity shocks. Taking these arguments into account, the impact of liquid assets on the outstanding CDS net notional on banks is ambiguous.

Finally, we employ a bank's business model (*Business model*), which is built as non-interest income to net interest income. This variable indicates whether a bank engages in fee-based businesses (like investment banking) or trading activities next to the traditional deposit taking and lending business. Higher values of the measure indicate a more diversified business model. Studies provided by Allen and Jagtiani (2000), Davis and

Tuori (2000), Smith et al. (2003), Stiroh (2004) as well as Altunbas et al. (2011) suggest that investors may benefit from a higher diversification of a bank's business model. In this context, higher diversification leads to a lower dependency on specific business segments and a decreased cyclical variation in bank profits and revenues which may result in a better risk-return structure especially in times of low interest rates when banks strongly depend on alternative sources of capital. Accordingly, both additional and more diversified sources of income may lower banks' individual idiosyncratic risk. In contrast, it is argued that non-interest income (especially trading revenue) is more volatile than interest income, especially in times of financial turmoil (DeYoung and Roland, 2001; Fraser et al., 2002; Stiroh, 2004; Baele et al., 2007; Altunbas et al., 2011). In addition, the correlation between the two sources of income has increased over the last decades due to overlapping business units and substitution effects resulting in a lack of diversification and broader systemic risk exposure (De Jonghe, 2010; Brunnermeier et al., 2012). Thus, the impact of the business model on the outstanding CDS net notional on banks is not clear.

2.2.3 Macroeconomic and institutional determinants

Next to CDS trading-specific and fundamental bank-specific variables, we include various well-accepted variables, which control for the macroeconomic and institutional environment during further sensitivity analyses in Section 4.3. Empirical evidence suggests that the price of a CDS contract reacts to both, macroeconomic information (Kim et al., 2015) and specific information concerning the reference entity (Zhang and Zhang, 2013). This is due to the fact that the business cycle heavily influences overall default rates, default correlations and recovery rates (da Silva et al., 2015). Accordingly, we include macroeconomic controls for the economic growth, the state of the economy, foreign borrowing, the price level, the development of the credit market and the financial wealth on a country level. As regards the institutional environment, we control for the systemic importance of a bank as determined by banking regulators. In addition, we analyze the impact of the inclusion of a bank in the corresponding regional main CDS index. Finally, we include a bank's stock trading volume as a proxy for equity trading.

Economic growth is proxied by the one-year lagged slope of the yield curve (*Yield curve*), which is calculated as a country's ten-year government bond yield minus the two-year government bond yield. This proxy is a widely used leading indicator for future prospects of an economy (e.g. Estrella and Hardouvelis, 1991; Wheelock and Wohar, 2009; Adrian et al., 2010). Gropp et al. (2014) argue that a rising slope of the yield curve negatively effects loan spreads and that banks demand a lower spread on loans when economic prospects brighten and hence, credit risk decreases. In addition, further related studies argue that a growing economy is likely to be associated with a higher level of incomes and revenues, reduced financial distress and an improved debt service (Louzis et al., 2012; Ghosh, 2015; Dimitrios et al., 2016). Therefore, we expect a negative impact of economic growth on the outstanding CDS net notional on banks.

The state of the economy is determined by the change of a country's gross domestic product (*Change in GDP*). This proxy should control for the variations in trading CDS net notional on banks due to differences between the countries' economic environment. Since an increase in the GDP may foster stability in the banking sector (Michalak and Uhde, 2012; Schaeck and Čihák, 2012) investors may more engage in bank CDSs when a country's GDP decreases. Therefore, we expect a decrease in the outstanding CDS net notional on banks under a prospering economy.

Furthermore, we employ the ratio of a country's government deficit to the corresponding GDP (*Government deficit to GDP*) to proxy the debt increase of a country. Studies from Demirgüç-Kunt and Detragiache (1998) as well as Demirgüç-Kunt and Huizinga (2013) reveal that recessions are associated with a higher probability of bank defaults since a higher government deficit decreases the probability of governmental banks bailouts (e.g., through governmental capital injections). In addition and as observed in the 2009-2012 European Sovereign Debt Crisis, Brunnermeier et al. (2016) suggest that an ongoing government deficit may result in a deterioration of sovereign creditworthiness which in turn reduces the market value of the banks' holdings of domestic sovereign debt. This may lead to investors perceiving a lower solvency and banks facing restricted lending activities. Accordingly, it is more likely for CDS investors to seek protection or to speculate on banks when the government deficit is high resulting in a higher amount of the outstanding CDS net notional on banks.

In a next step, we include the foreign exchange return (*FX return*). Demirgüç-Kunt and Detragiache (1998) as well as von Hagen and Ho (2007) argue that an unexpected depreciation of the foreign exchange rate may increase bank risk. This is due to the fact that higher foreign exchange returns may jeopardize bank profitability when banks borrow in foreign currency and lend in local currency. Moreover, Demirgüç-Kunt and Detragiache (1998) suggest that banks, which borrow abroad, may choose to issue domestic loans in foreign currency and thus, cancel the open position. In this case, the foreign exchange risk is shifted to borrowers and an unexpected depreciation would still have a negative impact on the profitability of a bank by increasing bank risk. Similarly, Kaufman (2000) suggests that the depreciation of countries' foreign exchange rates is related to banking crises. If foreign currency creditors perceive that domestic debtors (e.g., banks) may be unable to repay them in full and on time when the local currency depreciates, they will attempt to withdraw their funds. This may result in undercapitalized banks and higher bank risk. Taking these arguments into account, we expect a positive relationship between a country's foreign exchange rate depreciation and the outstanding CDS net notional on banks.

We employ a country's inflation rate (*Inflation*) to control for a country's price level. In general, high inflation rates yield to higher interest rates and are associated with higher net interest margins and profitability (Uhde and Heimeshoff, 2009; Tan and Floros, 2012). In contrast, Perry (1992) suggests that the effect of inflation on a bank's performance depends on whether inflation is anticipated correctly by the bank or not. He finds a positive relationship between inflation and the performance of a bank if the interest rates are constantly and properly adjusted to the inflation rate. However, unexpectedly rising and volatile inflation rates may cause cash flow difficulties for borrowers which may result in an early termination of loans and possible loan defaults (Perry, 1992; Hoggarth et al., 2001). Hence, if banks slowly adjust their interest rates, costs may increase faster than revenues, which yields to more risky banks and a higher trading incentive to investors in the CDS market. Additionally, Demirgüç-Kunt and Huizinga (1999) suggest that banks in developed countries are less profitable when inflation is high. Moreover, Demirgüç-Kunt and Detragiache (1998, 2000) provide evidence that higher inflation rates may increase the likelihood of systemic problems in the banking sector. Against this background, the impact of a change in inflation rates on the outstanding CDS net notional is ambiguous.

Furthermore, we employ the ratio of domestic credit to the private sector by banks to GDP (*Domestic credit*) to control for the development of a country's credit market. Following the 'boom and bust' hypothesis, excessive credit growth is a reliable indicator of a turmoil in banking systems due to decreasing capital ratios (Demirgüç-Kunt and Detragiache, 1998; Schaeck et al., 2009; Uhde and Heimeshoff, 2009). In contrast, Čihák et al. (2012) propose that the former argument is only true in case of an 'excessive' credit growth. They rather suggest that moderately growing credit markets indicate that banks are well-developing. Taking both lines of argumentation into account, the impact of domestic credit on the amount of outstanding CDS net notional on banks is not clear.

In a next step, we employ a dummy variable that indicates whether the return of the corresponding country's main stock index is positive (bull market) in the respective year, or not (bear market) (*Stock market*). Positive stock markets may increase financial wealth, may increase the value of shares used as collaterals and may improve the ability of borrowers to service their debt which may result in lower default probabilities and decreasing bank risk (Nkusu, 2011; Beck et al., 2015; da Silva et al., 2015). Hence, we expect a negative impact of the stock index measure on the outstanding CDS net notional on banks.

Turning to a bank's institutional environment, we include a dummy variable that takes on the value of one if a bank is classified as a global systemically important bank (*G-SIB*) by the Financial Stability Board (FSB), and zero otherwise. Theoretical and empirical arguments suggest that G-SIBs exhibit positive wealth effects after having been classified as 'too-big-to-fail' (O'hara and Shaw, 1990). Furthermore, these banks are required to hold additional capital buffers that protect them against external shocks (Boyd and De Nicolo, 2005). Moreover, 'too-big-to-fail' banks exhibit higher ratings in general and lower bank risk caused by the guarantee of the government which is also reflected by low CDS spreads as compared to non-G-SIBs (Morgan and Stiroh, 2005; Demirgüç-Kunt and Huizinga, 2013). In addition, if it is true that G-SIBs are typically larger in size, higher economies of scale and scope (Allen and Liu, 2007; Berger et al., 2007) as well as greater loan portfolio diversification opportunities (Demsetz and Strahan, 1997; Carletti and Hartmann, 2003) describe further aspects that may reduce an investor's inventive to buy default insurance against G-SIBs. In contrast, it is shown that regulators are often reluctant to close or liquidate G-SIBs, which may set an incentive to these banks to take on excessive excessive risks in anticipation of government bailouts (e.g. Farhi and Tirole, 2012; Laeven et al., 2016). Accordingly, the effect of the G-SIB classification on the outstanding CDS net notional on banks is not distinct.

We additionally employ a dummy variable that specifies whether a bank is listed in the corresponding regional main CDS index or not (*Main CDS index*).[12] Since the main CDS indices only include the most liquid firms (banks) per region, we argue that these firms (banks) are most likely to play a major role in the corresponding markets. In addition, portfolio managers trade CDS indices through exchange traded funds (ETFs) or simply by copying the CDS index which may result in higher outstanding CDS net notional on these banks as compared to non-index members.

Finally, we include the stock trading volume (STV) per bank and year to measure the level of equity trading. The relationship between trading and information flows is analyzed in several theoretical and empirical studies (e.g., Mitchell and Mulherin, 1994; Bessembinder et al., 1996; Chordia et al., 2007). As regards CDS, Hilscher et al. (2015) show that information flows from equity markets to CDS markets. Norden and Weber (2009) provide empirical evidence that stock returns clearly lead CDS spreads during the price discovery process. In sum, a higher stock trading volume may result in a higher willingness of CDS investors to trade, and to take positions based on their expectations in the equity market (da Silva et al., 2015). Therefore, we expect a positive impact of equity trading on the outstanding CDS net notional on banks.

[12]The respective CDS indices used are the CDX North America Investment Grade, iTraxx Asia ex Japan, iTraxx Australia, iTraxx Europe and iTraxx Japan.

3 Empirical model

We employ a linear model on panel data in order to analyze the determinants of the amount of the outstanding CDS net notional on banks. The regression model for our baseline regressions is specified as

$$y_{it} = \alpha_i + \sum_{j=1}^{M} \beta_j x_{j,it}^{(1)} + \sum_{k=1}^{N} \gamma_k x_{k,it-1}^{(2)} + \epsilon_{it}, \tag{1}$$

where y_{it} is the outstanding CDS net notional on bank i in a respective year t and $x_{j,it}^{(1)}$ are the M CDS trading-specific control variables as described in Section 2.2.1. $x_{k,it-1}^{(2)}$ denote the N one-period lagged fundamental bank-specific control variables as described in Section 2.2.2. The error term of the linear model is represented by ϵ_{it}. α_i as well as β_j and γ_k denote the parameters to be estimated.

We employ a bank-specific fixed effects model including time dummies to control for time-specific effects (e.g., trends in banking regulation or common shocks to the banking sector). Additionally, we utilize clustered robust standard errors at the bank level to address a possible downward bias originating from different aggregation levels of our variables (Moulton, 1990). Following Greene (2003), we use the modified Wald test to control for groupwise heteroskedasticity. The null hypothesis of homoskedasticity is clearly rejected suggesting that the use of robust standard errors is appropriate.[13] Since the Hausman test (Hausman, 1978) is not applicable under heteroskedasticity, a generalization of the Hausman test proposed by Arellano (1993) is used to test for the adequacy of our model. The test strongly rejects the null of using random effects, supporting our model choice. Furthermore, we control for possible multicollinearity between our independent variables. Since the variance inflation factor (VIF) of all independent variables is close to one (mean VIF is 1.29), we rule out that our results are biased by multicollinearity.

[13]Petersen (2009) shows that too few clusters may bias the results even when clustered in the right dimension. In this case, he proposes to address the time-dependence parametrically and cluster at bank-level. Nevertheless, we implement double-clustered standard errors with 52 bank and only 9 time clusters in order to verify whether the clustered-robust standard errors are correctly specified. Since the results remain robust, we do not present them in this paper but provide them on request.

4 Empirical results

We provide baseline regression results and results from robustness checks in Tables 5 and 6. Results from further analyses, which additionally control for the macroeconomic and institutional environment are shown in Tables 7 and 8. Table 9 shows the economic materiality of the determinants from our baseline and sensitivity analyses.

4.1 Results from baseline regressions

To begin with, results from our baseline regression in specification (1) reveals that the bond ratio has a positive impact on the CDS net notional ratio at the 1% level, indicating that an increase in a bank's debt financing by issuing a higher share of bonds provides a hedging incentive to investors by means of CDS. The high significance level remains robust in most of the further regression specifications confirming that hedging is a key determinant for investors to buy CDSs as a default insurance against bank risk.

As further shown, bond fragmentation enters the regression significantly positive at the 10%-level. As discussed in Section 2.2.1, investors might use the CDS market as an alternative trading venue to the bond market, especially if a bank issues many different bonds. As a consequence, more trading volume is shifted from the bond market to the CDS market, which might be due to a higher standardization and regulation level in the CDS market (Oehmke and Zawadowski, 2016).

Furthermore and in line with theoretical arguments, we find a significantly positive relationship between the upper tail dependence and the outstanding CDS net notional on banks. As expected, a higher upper tail dependence sets an incentive to investors to buy net protection via CDS in order to hedge their positions against banks with extreme tail risks (da Silva et al., 2015; Meine et al., 2016).

Finally and corresponding to findings from Oehmke and Zawadowski (2016), we provide evidence that the negative basis has a significantly positive impact on the CDS net notional ratio suggesting that investors perform arbitrage strategies.[14] In contrast,

[14]Note that the negative basis is multiplied by minus one. Hence, higher values indicate greater arbitrage opportunities.

we do not observe a significant effect of the positive basis. Taking into account the two possible arbitrage strategies (Section 2.2.1), the negative basis trade can be performed through a long position in a CDS and a long position in the corresponding bond, whereas the positive basis trade requires short positions in both the CDS and the bond market. However, since long positions are much easier to trade in terms of fees and regulations, this might explain why we observe a significant impact of the negative basis only.

Turning to fundamental bank-specific variables, regression specification (1) initially reveals that a higher leverage ratio decreases the outstanding CDS net notional on banks which supports results provided by Oehmke and Zawadowski (2016) who analyze outstanding CDS net notionals on US corporate firms. Our finding also corresponds to related studies from Jensen and Meckling (1976), Calomiris and Kahn (1991), Rajan and Zingales (1995) as well as Diamond and Rajan (2001) who provide evidence that a higher leverage ratio results in stronger debt covenants which in turn may discipline bank managers. In contrast, our results do not support findings provided by Merton (1974), Keeton and Morris (1987), Wheelock and Wilson (2000), Gambacorta and Mistrulli (2004), Berger and Bouwman (2013) and Demirgüç-Kunt et al. (2013) suggesting that a higher leverage ratio may lead to higher bank risk and higher probability of default which is hedged by CDS investors.

As expected, we further provide evidence that a bank's credit risk exposure, as measured by the ratio of loan loss reserves to gross loans, has a significantly positive impact on the outstanding CDS net notional on banks at the 1%-level. A higher loan loss ratio indicates lower loan portfolio quality and hence, a higher exposure to credit risk (Keeton and Morris, 1987). Accordingly, a higher credit risk exposure may trigger the trading of CDS on banks.

Finally, regression specification (1) reveals that a bank's business model has a positive impact on the outstanding CDS net notional on banks. Our finding does not support results from related studies provided by Allen and Jagtiani (2000), Davis and Tuori (2000), Smith et al. (2003), Stiroh (2004) as well as Altunbas et al. (2011) suggesting that a more diversified business model leads to less trading in the bank CDS market due to less volatile revenues and a better risk-return structure. Rather, our results are in line with findings provided by DeYoung and Roland (2001), Stiroh (2004), Baele et al. (2007), De Jonghe (2010), Altunbas et al. (2011) as well as Brunnermeier et al. (2012) indicating that a more diversified business model may lead to higher systemic risk due to higher correlations between the traditional and the fee-based sources of revenues of a bank, especially in times of financial crises. If this is true, the investor's incentive to buy CDSs on banks increases.

4.2 Results from robustness checks

Results from further robustness checks are presented by regression specifications (2) to (9) in Table 5 and regression specifications (1) to (4) in Table 6.

To begin with, even though we include the one-year lagged leverage ratio one may argue that the bond ratio and leverage ratio describe partly the same issue. Therefore and following Oehmke and Zawadowski (2016), we use the total bond volume (*Bonds*) instead of the bond ratio as a proxy for hedging in regression specification (2) from Table 5. As shown, since the coefficient of total bond volume exhibits a significant and positive sign while significances and signs from further control variables are generally reiterated, the analysis reveals that our baseline result remains robust even when controlling for a different hedging measure.

By means of regression specification (3) and (4) (Table 5) we distinguish between bonds which are issued by the parent bank (*Bond ratio (parent)*) and via subsidiaries (*Bond ratio (subs)*) respectively. As shown, both direct issues by the parent bank and issues via subsidiaries have a significantly positive impact on the outstanding CDS net notional on banks at the 5%-level. Our finding does not fully correspond to results provided by Oehmke and Zawadowski (2016), who do not provide any evidence of a significant relationship between bonds issued by subsidiaries and the outstanding CDS net notional on US firms. Rather, our finding may be explained by the fact that many banks from our sample have subsidiaries which are responsible for bond trading activities.[15]

[15] Approximately 36% of the total bond issues in our sample are issued via subsidiaries, while approximately 89% of all banks issue at least one bond per year via a subsidiary.

We initially substitute the *bond ratio* by the bank's *debt ratio* in regression specification (5). The debt ratio is built as the ratio of total debt to total assets per bank and year. As shown by specification (5), we do not find any significant relationship between the debt ratio and the CDS net notional. Subsequently, we add *non-bond debt* to our baseline model in regression specification (6). This measure is constructed as the amount of total debt outstanding minus outstanding bonds divided by total assets. As shown, also non-bond debt enters the regression insignificantly. Taking this into account, both results suggest that bonds are a main determinant of the outstanding CDS net notional on banks.

As a further step, we substitute bond fragmentation by debt fragmentation (*Debt frag.*) in regression specification (7). As shown, this measure enters the regression insignificantly positive indicating that bond fragmentation rather than debt fragmentation triggers an investor's decision to buy an insurance against bank default.

We proceed and substitute three different risk proxys for (tail risk, debt position and credit risk) as used in our baseline analysis by measures for the overall (market) risk, namely the *probability of default* in regression specification (1) and the *CDS spread volatility* in regression specification (2) from Table 6. As expected, both measures enter the regression significantly positive indicating that uncertainty about future bank defaults increases the willingness for investors to hedge against or to speculate on more likely defaults.

Finally, we control for the nexus between bank size, speculation or hedging and the outstanding CDS net notional on banks in regression specifications (3) and (4) from Table 6. Since larger distressed banks are more likely to be rescued by governments following the 'too-big-to-fail' doctrine (O'hara and Shaw, 1990), it might not be reasonable for CDS investors to hedge or speculate on these banks. To control for the effect of bank size, we create a dummy variable that takes on the value of one if a bank is below the median of total assets in the respective year, and zero otherwise (*Low size*). Subsequently, the dummy variable is interacted with our hedging and speculation measures, respectively. As expected, the interaction variable of speculation and size enters regression (8) significantly positive at the 5%-level suggesting that speculation on smaller (not 'too-big-to-fail') banks in our sample increases the outstanding CDS net notional. In contrast, we do not provide any empirical evidence concerning the relationship between hedging, bank size and changes in the outstanding CDS net notional.

4.3 Results from macroeconomic and institutional determinants

In the following, we perform further analyses to control for the impact of the macroeconomic and institutional environment on the outstanding CDS net notional on banks. Respective results are presented in Tables 7 and 8. To be upfront with it, our baseline findings concerning CDS trading- and fundamental bank-specific determinants are generally reiterated even when including macroeconomic and institutional control variables.

4.3.1 Macroeconomic determinants

We initially include the one-period lagged slope of the yield curve in regression specification (1) in Table 7 to investigate how bank default insurance is affected by economic growth. As shown, the coefficient enters the regression significantly negative at the 5%-level suggesting that investors less insure against bank defaults during a prospering economy. Our finding may be explained by the fact that a rising slope of the yield curve results in lower credit risk, higher level of incomes and revenues, reduced financial distress and an improved debt service (Gropp et al., 2014).

Furthermore, as shown by regression specification (2), the current state of the economy, as measured by a country's change in GDP, has a significantly negative impact on the outstanding CDS net notional on banks. A higher GDP may result in a more stable economy, which may also lead to a higher banking stability (Louzis et al., 2012; Michalak and Uhde, 2012; Schaeck and Čihák, 2012; Ghosh, 2015; Dimitrios et al., 2016). If this is true, we provide empirical evidence that investors buy less default insurance in times of economic boom phases and silent banking markets.

In a next step, we control for a country's debt increase by employing the ratio of government deficit to GDP in regression specification (3). As shown, this variable enters the regression significantly positive at the 10%-level indicating that CDS investors in the banking sector seek protection during phases of government deficits. Our result corresponds to findings provided by Demirgüç-Kunt and Detragiache (1998), Demirgüç-Kunt and Huizinga (2013) as well as Brunnermeier et al. (2016) suggesting that recessions may increase the probability of bank defaults since governmental aid is less likely during economic downturns.

Regression specification (4) reveals that the foreign exchange return has a significantly positive impact on the outstanding CDS net notional on banks. Higher returns from the foreign exchange rate indicate a depreciation of the local currency. We suggest that the depreciation of the foreign exchange rate may jeopardize bank profitability when banks borrow in foreign currency and lend in domestic currency (Demirgüç-Kunt and Detragiache, 1998; von Hagen and Ho, 2007). In addition, depreciation may result in undercapitalized banks due to the fact that creditors may withdraw their funds when they assume that banks are not able to repay them completely (Kaufman, 2000). This may yield to less profitable and undercapitalized banks, which in turn results in higher bank risks and thus to a stronger trading incentive for bank CDS investors.

Furthermore, as reported by regression specification (6), domestic credit exhibits a significantly negative sign. Hence, we do not support the 'boom and bust' hypothesis proposing that 'excessive' growth in domestic credit may lead to higher bank risk due to decreasing capital ratios (Demirgüç-Kunt and Detragiache, 1998; Schaeck et al., 2009; Uhde and Heimeshoff, 2009). In contrast supporting results from Čihák et al. (2012), our finding suggests that (moderately) growing credit markets[16] indicate well-developing banking markets and less system-wide bank risk. If this is true, investors in well-developed and less risky banking markets may have a lower incentive to use bank CDSs as hedging instrument.

Finally, we investigate if differences in the countries levels of financial wealth may have an effect on the outstanding CDS net notional on banks. As expected, a higher country's financial wealth (measured as positive stock market index return) has a significantly

[16]See the descriptive statistics in Table 3.

negative impact on the outstanding CDS net notional on banks. Our finding can be explained by the fact that positive stock markets increase financial wealth, the value of collaterals and the ability of borrowers to service their debt obligations. As a result, banks may exhibit a decreasing risk exposure and lower default probabilities, which in turn leads to a decreasing demand for default insurance on banks by means of CDSs (Nkusu, 2011; Beck et al., 2015).

4.3.2 Institutional determinants

Turning to the institutional environment, we initially control for the systemic importance of a bank in regression specification (1) in Table 8. Following the FSB's G-SIB classification, we employ a dummy variable that specifies whether a bank is classified as G-SIB or not. As shown, the dummy variable enters the respective regression specification (1) significantly negative at the 5%-level indicating that the outstanding CDS net notional decreases for banks being classified as a G-SIB. This result was expected since G-SIBs are forced by regulators to hold additional capital buffers to protect them from external shocks (Boyd and De Nicolo, 2005). Moreover, 'too-big-to-fail' banks exhibit higher ratings in general and lower bank risk caused by the guarantee of the government (Morgan and Stiroh, 2005; Demirgüç-Kunt and Huizinga, 2013). In addition, if it is true that G-SIBs are typically larger in size[17], higher economies of scale and scope in general (Allen and Liu, 2007; Berger et al., 2007) as well as the ability to diversify loan portfolios more efficiently (Demsetz and Strahan, 1997; Carletti and Hartmann, 2003) describe further aspects that may reduce an investor's inventive to buy default insurance against G-SIBs.

In a next step, we control whether a bank is a constituent of the regional main CDS index, i.e. we control for the importance of a bank for the regional market. As shown in regression specification (2), the dummy variable has a significantly positive impact on the outstanding CDS net notional on banks, which is in line with results provided by Oehmke and Zawadowski (2016) for US corporate firms. Our results may be explained by the fact that the index-inclusion is attended with higher outstanding CDS net notional on banks

[17]In our sample the mean size of G-SIBs as measured by total assets is approximately $1,489 billions, whereas the mean is about $393 billions for non-G-SIBs.

due to investors who copy-trade the respective CDS indices or trade with exchange traded funds.

Finally, we include a bank's total stock trading volume per year. As shown by regression specification (3), this measure enters the regression significantly positive at the 10%-level suggesting that investors stronger engage in CDS trading when the stock trading volume of a bank is high. Accordingly, and in line with da Silva et al. (2015), our result suggests that investors in the bank CDS market take positions based on their expectations in the equity market. Hence, we find that trading in the bank CDS market is pro-cyclical to trading in the stock market, which may be due to the fact that information flows from equity to CDS markets (Norden and Weber, 2009; Hilscher et al., 2015).

5 Summary and conclusion

Employing a sample of 52 major banks across 18 countries between 2008 and 2016, this paper empirically investigates determinants of the outstanding CDS net notional amounts on banks. We provide evidence for CDS trading- and fundamental bank-specific determinants and additionally show that even macroeconomic and institutional determinants have an impact of an investor's decision to hedge or to speculate on bank risk.

To be more precisely, we initially find that investors trade bank CDS due to hedging motives, arbitrage opportunities through negative basis trades, a higher standardization as compared to the underlying bond market and in cases of a rising CDS tail risk. Furthermore, we provide evidence that a bank's fundamental data affects bank CDS trading through a risk channel. Accordingly, we find that a bank's credit risk, its leverage and its business model have an impact on the investor's decision to employ CDSs as a default insurance or speculation instrument. Finally, our analysis reveals that a country's macroeconomic and institutional environment additionally affects CDS trading on banks. Hence, it is empirically shown in this study that the outstanding CDS net notional decreases in growing economies, with an appreciation of the local currency and with a stable development of the credit market. In addition, we provide evidence that trading in the bank CDS market is anti-cyclical to a country's business climate. As regards the institutional framework, our study reveals that banks being listed as a G-SIB exhibit less outstanding CDS net notional as compared to non-G-SIBs. In contrast, the fact that a bank is listed in the corresponding regional CDS main index has a positive effect on trading bank CDSs. Finally, we provide empirical evidence that the outstanding CDS net notional on banks is pro-cyclical as compared to the trading volume in equity markets.

Against the background of our empirical results, we provide important implications for academia and practitioners. Since the CDS market is still very opaque, we shed a brighter light on the trading motives of a CDS investor in the banking sector. Focusing on banks is important since they are the top liquidity providers in over-the-counter markets and exhibit a variety of risks that may result in credit deteriorations or even defaults. These changes in the credit quality may be insured or may be exploited by investors through CDSs.

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A Empirical Appendix

Table 1: Geographical distribution of banks in the sample

Region	Country	Bank
Americas	USA	Bank Of America Corporation
		Capital One Financial Corporation
		Citigroup Inc.
		JPMorgan Chase & Co.
		Morgan Stanley
		The Goldman Sachs Group, Inc.
		Wells Fargo & Company
Asia	India	Icici Bank Limited
	Japan	Mizuho Bank, Ltd.
		Nomura Securities Co., Ltd.
		Orix Corporation
		Resona Bank, Limited
		Sumitomo Mitsui Banking Corporation
		The Bank Of Tokyo-Mitsubishi UFJ, Ltd.
	Kazakhstan	JSC Kazkommertsbank
	Korea	Kookmin Bank
	Singapore	DBS Bank Ltd.
		Oversea-Chinese Banking Corporation Limited
		United Overseas Bank Limited
Australia & New Zealand	Australia	Australia And New Zealand Banking Group Ltd.
		Commonwealth Bank Of Australia
		Macquarie Bank Limited
		National Australia Bank Limited
		Westpac Banking Corporation
Europe	Belgium	BNP Paribas Fortis
		Dexia
	Denmark	Danske Bank A/S
	France	BNP Paribas
		Crédit Agricole SA
		Natixis
		Société Générale

Table 1: Geographical distribution of banks in the sample (continued)

Region	Country	Bank
	Germany	Commerzbank AG
		Deutsche Bank AG
Europe	Italy	Banca Monte Dei Paschi Di Siena S.P.A.
		Banca Poplare Di Milano Soc. Coop. A R.L.
		Banco Popolare Societa Cooperativa
		Intesa Sanpaolo S.P.A.
		Mediobanca Banca Di Credito Finanziario S.P.A.
		Unicredit, S.P.A.
	Netherlands	ING Bank N.V.
	Portugal	Banco Comercial Portugues, S.A.
		Novo Banco, S.A. (former Banco Espírito Santo)
	Russia	Sberbank
	Spain	Banco Bilbao Vizcaya Argentaria, S.A.
		Banco Santander, S.A.
	Switzerland	Credit Suisse Group AG
		UBS AG
	UK	Barclays Bank PLC
		HSBC Bank PLC
		Lloyds Bank PLC
		Standard Chartered Bank
		The Royal Bank Of Scotland PLC

Table 2: Notes on variables and data sources

Variable	Proxy	Description	Source
Dependent variable			
NN ratio	Default insurance	Ratio of the yearly-averaged outstanding CDS net notional on banks to total assets per bank and year in percent.	DTCC, Bankscope, Orbis Bank Focus
CDS trading-specific variables			
Bond ratio	Insurable interest	Ratio of the outstanding notional of bonds issued by the parent company and via subsidiaries with a maturity of more than one year to total assets.	Thomson Reuters EIKON, Orbis Bank Focus, Bankscope
Bond frag.	Fragmentation	Logarithm of the Herfindahl-Hirschman index of bonds issued by the parent bank and subsidiaries orthogonalized with respect to the logarithm of bonds issued by the parent bank and via subsidiaries. The result is multiplied by minus one.	Own calc. following Oehmke and Zawadowski (2016)
Disagr.	Speculation	Standard deviation of analysts' one-year earnings per share forecast divided by the stock price if the stock price is greater than one.	Thomson Reuters Datastream, IBES, own calc. following Oehmke and Zawadowski (2016)
UTD CDS	Tail risk	Upper tail dependence between a bank's individual CDS log-spreads and the corresponding market index log-spreads.	Markit, own calc. following Schmidt and Stadtmüller (2006)

Table 2: Notes on variables and data sources (continued)

Variable	Proxy	Description	Source
Neg./Pos. basis	Arbitrage	Yearly averaged negative/positive basis of five year CDS spreads and corresponding five year corporate bond yields in percent. Yields for corporate bonds are interpolated when necessary.	Markit, Thomson Reuters EIKON, own calc. following Blanco et al. (2005)
Fundamental bank-specific variables			
Leverage$_{t-1}$	Capital	Ratio of the accounting value of a bank's total debt to total equity lagged by one year.	Orbis Bank Focus, Bankscope
LLR$_{t-1}$	Loan portfolio	Ratio of the accounting value of a bank's loan loss reserves to gross loans lagged by one year.	Orbis Bank Focus, Bankscope
CIR$_{t-1}$	Management efficiency	Ratio of the accounting value of a bank's total cost to total income lagged by one year.	Orbis Bank Focus, Bankscope
ROAA$_{t-1}$	Earnings	Ratio of the accounting value of a bank's return on average assets lagged by one year.	Orbis Bank Focus, Bankscope
Liquid assets$_{t-1}$	Liquidity & funding	Ratio of the accounting value of a bank's liquid assets to total deposits and short-term funding lagged by one year.	Orbis Bank Focus, Bankscope
Business model$_{t-1}$	Business model	Ratio of the accounting value of a bank's non-interest income to net interest income lagged by one year.	Orbis Bank Focus, Bankscope
Variables as used in robustness checks			
Bond ratio (parent)	Insurable interest	Ratio of the outstanding notional of bonds issued by the parent bank with a maturity of more than one year to total assets.	Thomson Reuters EIKON, Orbis Bank Focus, Bankscope

Table 2: Notes on variables and data sources (continued)

Variable	Proxy	Description	Source
Bond ratio (subs)		Ratio of the outstanding notional of bonds issued by via subsidiaries with a maturity of more than one year to total assets.	Thomson Reuters EIKON, Orbis Bank Focus, Bankscope
Bonds		Outstanding notional of bonds issued by the parent bank and via subsidiaries with a maturity of more than one year in billions of US dollars.	Thomson Reuters EIKON
Debt ratio		Ratio of the outstanding notional of debt issued by the parent bank and via subsidiaries of the bank with a maturity of more than one year to total assets.	Thomson Reuters EIKON, Orbis Bank Focus, Bankscope
Non-bond debt ratio		Outstanding notional of debt minus outstanding bonds issued by both, the parent bank and via subsidiaries divided by total assets.	Thomson Reuters EIKON, Orbis Bank Focus, Bankscope
Debt frag.	Fragmentation	Logarithm of the Herfindahl-Hirschman index of debt issued by the parent bank and subsidiaries orthogonalized with respect to the logarithm of debt issued by the parent bank and via subsidiaries. The result is multiplied by minus one.	Own calc. following Oehmke and Zawadowski (2016)
Probability of default	Market risk	Probability of default calculated as the ratio of the respective yearly CDS spread divided by the loss given default in percent. The loss given default is calculated as one minus the recovery rate.	Markit, own calc. following Hull (2012)
CDS spread volatility		Annualized five year CDS log-spread volatility estimated with a GARCH(1,1) model.	Markit, own calc.
Bottom half size	Size	Dummy variable that takes on the value of one if the total assets of the respective bank are below the median of the sample.	Orbis Bank Focus, Bankscope

Table 2: Notes on variables and data sources (continued)

Variable	Proxy	Description	Source
Macroeconomic variables			
Yield curve$_{t-1}$	Economic growth	Slope of the yield curve calculated as the 10 year government bond yield minus the 2 year government bond yield per country and year, lagged by one year and expressed in percent.	Thomson Reuters EIKON
Change in GDP	State of the economy	Yearly change of the gross domestic product in trillions of US dollars per country and year.	World Bank's WDI
Government deficit to GDP	Debt increase	Ratio of the government deficit per country and year to the corresponding GDP in percent. If there is a surplus, the variable is set to zero.	World Bank's WDI
FX return	Foreign borrowing	Annualized foreign exchange rate return calculated from the local currency exchange rate to US dollars per country and year for non-US banks. For US banks the annualized return of the nominal effective exchange rate is used.	International Monetary Fund's IFS
Inflation	Price level	Yearly inflation rate per country and year in percent.	World Bank's WDI
Domestic credit	Development of the credit market	Domestic credit to private sector provided by banks per country and year to the corresponding GDP in percent.	
Stock market	Financial wealth	Dummy variable that takes on the value of one if the main stock market index return of the respective year and country is positive, and zero otherwise.	Thomson Reuters Datastream

Table 2: Notes on variables and data sources (continued)

Variable	Proxy	Description	Source
Institutional environment			
G-SIB	Systemic importance	Dummy variable indicating whether a bank is classified as a global systemically important bank according to the Financial Stability Board.	Financial Stability Board
Main CDS index	Regional importance	Dummy variable indicating whether a bank is a constituent of the corresponding regional CDS main index.	Markit, own calc.
STV	Equity trading	Proxy for equity trading on the corresponding bank. Measured as the volume of stock trading per bank and year in billions of US dollars.	Thomson Reuters Datastream

Table 3: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable					
NN ratio	464	.286	.4034	.0127	4.1861
CDS trading-specific variables					
Bond ratio	464	.031	.0521	0	.3903
Bond frag.	463	.0073	.2929	-1.1866	1.3985
Disagr.	441	.1264	.7565	0	10.9003
UTD CDS	462	.4955	.1563	0	.806
Neg. basis	430	1.3114	1.4743	0	9.9377
Pos. basis	430	1.1518	2.5455	0	27.2423
Fundamental bank-specific variables					
Leverage$_{t-1}$	456	.1934	.1678	.033	2.3133
LLR$_{t-1}$	444	.4098	3.3394	.0001	66.2505
CIR$_{t-1}$	462	.7728	.1531	.5132	2.3201
ROAA$_{t-1}$	462	.0047	.0089	-.053	.1093
Liquid assets$_{t-1}$	462	.4794	.4904	.0316	5.5897
Business model$_{t-1}$	462	.0153	.0896	-1.4662	.7483
Variables as used in robustness checks					
Bonds	464	17.3444	28.6798	0	292.7204
Bond ratio (parent)	464	.0254	.0496	0	.3795
Bond ratio (subs)	464	.0056	.0084	0	.0545
Debt ratio	464	.2551	.3362	.0003	2.9373
Non-bond debt ratio	464	.2241	.3319	0	2.9155
Debt frag.	464	.0058	.3008	-1.6679	1.6826
Probability of default	464	2.7759	2.9517	.5566	28.3652
CDS Spread Volatility	464	.8034	.5888	.201	4.5956
Bottom half of size	464	.5022	.5005	0	1
Country-specific variables					
Yield curve$_{t-1}$	464	1.3918	.8442	-2.839	3.647
Change in GDP	464	.0646	.3013	-1.0475	.7276
Government deficit to GDP	464	3.2631	2.6663	0	10.2041
FX return	464	.0777	.1947	-.6302	1.5431
Inflation	464	1.5248	2.5783	-1.9	23.64
Domestic credit	464	1.0609	.4035	.3077	2.1808
Stock market	464	.5259	.4999	0	1
Institutional environment					
G-SIB	464	.4579	.4988	0	1
Main CDS index	464	.6509	.4772	0	1
STV	455	7.5245	12.9861	.0007	120.1079

Table 4: Correlation matrix

	NN ratio	Bond ratio	Bond frag.	Disagr.	UTD CDS	Neg. basis	Pos. basis	Leverage$_{t-1}$	LLR$_{t-1}$	CIR$_{t-1}$	ROAA$_{t-1}$	Liquid assets$_{t-1}$	Business model$_{t-1}$
NN ratio	1.00												
Bond ratio	0.14***	1.00											
Bond frag.	0.08*	-0.03	1.00										
Disagr.	0.32***	-0.00	-0.04	1.00									
UTD CDS	-0.14***	0.12**	0.06	-0.23***	1.00								
Neg. basis	-0.18***	-0.20***	-0.04	-0.11**	-0.00	1.00							
Pos. basis	0.35***	0.17***	0.10**	0.21***	-0.06	-0.31***	1.00						
Leverage$_{t-1}$	-0.16***	-0.07	0.00	0.00	0.02	-0.01	-0.09*	1.00					
LLR$_{t-1}$	0.15***	0.01	0.02	-0.01	-0.06	0.02	-0.03	0.01	1.00				
CIR$_{t-1}$	-0.02	0.07	-0.00	0.06	0.12***	0.08*	-0.04	0.36***	0.05	1.00			
ROAA$_{t-1}$	0.06	-0.19***	0.06	-0.13***	-0.05	-0.04	0.10**	-0.27***	0.04	-0.42***	1.00		
Liquid assets$_{t-1}$	-0.03	-0.13***	0.00	0.07	-0.00	0.14***	-0.21***	0.08*	0.02	0.36***	-0.04	1.00	
Business model$_{t-1}$	0.03	-0.01	-0.10**	0.18***	-0.04	-0.02	-0.02	-0.02	0.03	0.05	0.01	0.22***	1.00

* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Baseline regressions and robustness checks (1)

	(1) NN ratio	(2) NN ratio	(3) NN ratio	(4) NN ratio	(5) NN ratio	(6) NN ratio	(7) NN ratio
Bond ratio	0.7215***					0.7332***	0.6891***
	(0.004)					(0.004)	(0.006)
Bond frag.	0.0691*	0.0649*	0.0702*	0.0443	0.0672*	0.0694*	
	(0.081)	(0.093)	(0.076)	(0.196)	(0.083)	(0.079)	
Disagr. 1Y FC	0.1699	0.1693	0.1696	0.1707	0.1690	0.1697	0.1696
	(0.183)	(0.185)	(0.184)	(0.172)	(0.185)	(0.185)	(0.188)
UTD CDS	0.1669*	0.1887**	0.1751*	0.1618*	0.1908**	0.1628*	0.1650*
	(0.079)	(0.042)	(0.068)	(0.064)	(0.040)	(0.081)	(0.078)
Neg. basis	0.0154**	0.0139**	0.0151**	0.0121*	0.0135*	0.0154**	0.0138**
	(0.027)	(0.045)	(0.027)	(0.050)	(0.051)	(0.028)	(0.047)
Pos. basis	-0.0032	-0.0013	-0.0025	-0.0010	-0.0006	-0.0031	-0.0029
	(0.554)	(0.817)	(0.646)	(0.861)	(0.921)	(0.563)	(0.606)
Leverage_{t-1}	-0.0904*	-0.0917*	-0.0944*	-0.0613*	-0.0970*	-0.0933*	-0.0918*
	(0.065)	(0.068)	(0.067)	(0.079)	(0.072)	(0.065)	(0.059)
LLR_{t-1}	0.0087***	0.0087***	0.0087***	0.0086***	0.0088***	0.0088***	0.0085***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CIR_{t-1}	0.0852	0.0909	0.0897	0.0809	0.0981	0.0836	0.0842
	(0.472)	(0.449)	(0.453)	(0.488)	(0.413)	(0.479)	(0.475)
ROAA_{t-1}	-0.2877	-0.3880	-0.2771	-0.9479	-0.4138	-0.3421	-0.2641
	(0.887)	(0.851)	(0.891)	(0.682)	(0.843)	(0.865)	(0.885)
$\text{Liquid assets}_{t-1}$	-0.0441	-0.0457	-0.0485	-0.0290	-0.0519	-0.0326	-0.0384
	(0.548)	(0.559)	(0.510)	(0.721)	(0.537)	(0.696)	(0.605)
$\text{Business model}_{t-1}$	0.0428*	0.0412*	0.0433*	0.0376	0.0429*	0.0426*	0.0208
	(0.075)	(0.087)	(0.072)	(0.111)	(0.075)	(0.078)	(0.218)
Bonds		0.0004*					
		(0.085)					
Bond ratio (parent)			0.5421**				
			(0.012)				
Bond ratio (sub)				7.6447**			
				(0.023)			
Debt ratio					-0.0038		
					(0.901)		
Non-bond debt						-0.0175	
						(0.500)	
Debt frag.							0.0328
							(0.159)
Bank FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Cluster bank level	YES	YES	YES	YES	YES	YES	YES
N	388	388	388	388	388	388	388
No. of Groups	52	52	52	52	52	52	52
R^2	0.2896	0.2485	0.2886	0.2024	0.2615	0.2909	0.2897

The panel model estimated is $\text{NN ratio}_{i=\text{bank},t=\text{time}} = \alpha_i + \beta_1 \text{Bond ratio}_{i,t} + \beta_2 \text{Bond frag.}_{i,t} + \beta_3 \text{Disagr.}_{i,t} + \beta_4 \text{UTD CDS}_{i,t} + \beta_5 \text{Neg. basis}_{i,t} + \beta_6 \text{Pos. basis}_{i,t} + \gamma_1 \text{Leverage}_{i,t-1} + \gamma_2 \text{LLR}_{i,t-1} + \gamma_3 \text{CIR}_{i,t-1} + \gamma_4 \text{ROAA}_{i,t-1} + +\gamma_5 \text{Liquid assets}_{i,t-1} + \gamma_6 \text{Business model}_{i,t-1}$. The bond ratio is substituted by the outstanding total bond volume in specification (2), the ratio of bonds being directly issued by the parent bank to total assets in specification (3), the ratio of bonds being issued by subsidiaries to total assets in specification (4) and the debt ratio in specification (5). In specification (6) we additionally include a bank's non-bond debt. The bond fragmentation measure is replaced by debt fragmentation in specification (7). Constant term is included but not reported. Heteroscedasticity consistent P-values are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

Table 6: Baseline regressions and robustness checks (2)

	(1) NN ratio	(2) NN ratio	(3) NN ratio	(4) NN ratio
Bond ratio	0.6750***	0.7657***	0.6934***	0.7764**
	(0.000)	(0.000)	(0.003)	(0.025)
Bond frag.	0.0919*	0.0831	0.0660*	0.0692*
	(0.091)	(0.124)	(0.085)	(0.089)
Disagr. 1Y FC	0.0714	0.0742	-0.1026*	0.1707
	(0.296)	(0.270)	(0.052)	(0.183)
UTD CDS			0.1608*	0.1656*
			(0.090)	(0.091)
Neg. basis	0.0143*	0.0149**	0.0137**	0.0153**
	(0.077)	(0.041)	(0.040)	(0.030)
Pos. basis	-0.0154	-0.0006	-0.0026	-0.0031
	(0.231)	(0.936)	(0.634)	(0.565)
Leverage_{t-1}			-0.0968*	-0.0954*
			(0.056)	(0.058)
LLR_{t-1}			0.0093***	0.0092***
			(0.000)	(0.000)
CIR_{t-1}	0.0644	0.0700	0.1094	0.0857
	(0.356)	(0.313)	(0.349)	(0.469)
ROAA_{t-1}	0.5915	0.3392	-0.2975	-0.2807
	(0.734)	(0.854)	(0.882)	(0.890)
$\text{Liquid assets}_{t-1}$	-0.1051**	-0.0992*	-0.0466	-0.0465
	(0.041)	(0.073)	(0.531)	(0.535)
$\text{Business model}_{t-1}$	0.0048	0.0191	0.0427*	0.0435*
	(0.938)	(0.766)	(0.074)	(0.088)
Probability of default	0.0225*			
	(0.074)			
CDS spread volatility		0.0814**		
		(0.043)		
Bottom half of size			-0.0768	-0.0361
			(0.242)	(0.531)
Disagr. × Bottom half of size			0.2778**	
			(0.040)	
Bond ratio × Bottom half of size				-0.2241
				(0.690)
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Cluster bank level	YES	YES	YES	YES
N	408	408	388	388
No. of Groups	52	52	52	52
R^2	0.2088	0.1560	0.2360	0.2682

The empirical model and parameters are defined in Table 5. The variables controlling for different types of risk (tail risk, debt position and credit risk) are substituted by the probability of default and the CDS spread volatility in regression specifications (1) and (2), respectively. Regression specification (2) and (4) control for speculation and bank size as well as hedging and bank size, respectively. Constant term is included but not reported. Heteroscedasticity consistent P-values are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

Table 7: Macroeconomic environment

	(1) NN ratio	(2) NN ratio	(3) NN ratio	(4) NN ratio	(5) NN ratio	(6) NN ratio	(7) NN ratio
Bond ratio	0.7168***	0.6883***	0.7273***	0.7169***	0.6665***	0.7298***	0.7243***
	(0.007)	(0.004)	(0.002)	(0.004)	(0.003)	(0.005)	(0.006)
Bond frag.	0.0643*	0.0688*	0.0718*	0.0673*	0.0647*	0.0645	0.0680*
	(0.073)	(0.082)	(0.072)	(0.084)	(0.078)	(0.107)	(0.084)
Disagr	0.1685	0.1711	0.1729	0.1722	0.1510	0.1683	0.1711
	(0.183)	(0.178)	(0.177)	(0.169)	(0.176)	(0.189)	(0.181)
UTD CDS	0.1652	0.1847*	0.1532*	0.2027**	0.1725*	0.1658*	0.1851*
	(0.108)	(0.051)	(0.088)	(0.037)	(0.057)	(0.081)	(0.058)
Neg. basis	0.0143**	0.0155**	0.0144**	0.0154**	0.0149**	0.0137*	0.0146**
	(0.047)	(0.027)	(0.035)	(0.029)	(0.027)	(0.053)	(0.035)
Pos. basis	-0.0042	-0.0036	-0.0025	-0.0047	-0.0031	-0.0014	-0.0043
	(0.424)	(0.503)	(0.658)	(0.372)	(0.549)	(0.800)	(0.413)
Leverage_{t-1}	-0.0870**	-0.0825*	-0.0859*	-0.0829*	-0.0737	-0.0791*	-0.0791*
	(0.047)	(0.092)	(0.063)	(0.088)	(0.135)	(0.070)	(0.083)
LLR_{t-1}	0.0089***	0.0084***	0.0085***	0.0090***	0.0087***	0.0084***	0.0087***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CIR_{t-1}	0.1061	0.0948	0.0936	0.1154	0.0679	0.0287	0.0582
	(0.349)	(0.417)	(0.434)	(0.361)	(0.533)	(0.804)	(0.622)
ROAA_{t-1}	-0.0655	-0.2079	0.0189	-0.2331	-0.5913	-0.3757	-0.5409
	(0.975)	(0.915)	(0.992)	(0.910)	(0.761)	(0.847)	(0.795)
$\text{Liquid assets}_{t-1}$	-0.0534	-0.0351	-0.0423	-0.0548	-0.0523	-0.0513	-0.0287
	(0.474)	(0.634)	(0.551)	(0.474)	(0.496)	(0.469)	(0.692)
$\text{Business model}_{t-1}$	0.0482**	0.0413*	0.0327	0.0442*	0.0432*	0.0433*	0.0439*
	(0.048)	(0.081)	(0.212)	(0.064)	(0.062)	(0.068)	(0.066)
Yield curve_{t-1}	-0.0413**						
	(0.019)						
Change in GDP		-0.0486*					
		(0.066)					
Government deficit to GDP			0.0116*				
			(0.078)				
FX return				0.1484**			
				(0.022)			
Inflation					0.0162		
					(0.288)		
Domestic credit						-0.1450*	
						(0.076)	
Stock market (dummy)							-0.0437**
							(0.028)
Bank FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Cluster bank level	YES	YES	YES	YES	YES	YES	YES
N	388	388	388	388	388	387	388
No. of Groups	52	52	52	52	52	52	52
R^2	0.3001	0.2710	0.3164	0.2673	0.3506	0.3018	0.2847

The empirical model and parameters are defined in Table 5. Regression specification (1) includes the slope of the yield curve, regression specification (2) controls for the change in GDP, regression specification (3) employs the government deficit to GDP, regression specification (4) includes foreign exchange returns, regression specification (5) controls for the inflation rate, regression specification (6) employs the development of the credit market (domestic credit) and regression specification (7) includes a dummy variable indicating a positive stock market development. Constant term is included but not reported. Heteroscedasticity consistent P-values are in parenthesis.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8: Institutional environment

	(1) NN ratio	(2) NN ratio	(3) NN ratio
Bond ratio	0.6550***	0.6593**	0.7115***
	(0.008)	(0.019)	(0.003)
Bond frag.	0.0701*	0.0544	0.0730*
	(0.075)	(0.142)	(0.068)
Disagr.	0.1703	0.1741	0.1728
	(0.182)	(0.168)	(0.179)
UTD CDS	0.1695*	0.1564*	0.1291
	(0.075)	(0.080)	(0.147)
Neg. basis	0.0152**	0.0126**	0.0129*
	(0.028)	(0.047)	(0.054)
Pos. basis	-0.0032	-0.0056	-0.0039
	(0.543)	(0.316)	(0.469)
Leverage$_{t-1}$	-0.0789*	-0.0935**	-0.0713*
	(0.054)	(0.042)	(0.086)
LLR$_{t-1}$	0.0086***	0.0086***	0.0079***
	(0.000)	(0.000)	(0.000)
CIR$_{t-1}$	0.0766	0.0671	0.1319
	(0.511)	(0.579)	(0.222)
ROAA$_{t-1}$	-0.3451	-0.6922	0.6142
	(0.866)	(0.748)	(0.708)
Liquid assets$_{t-1}$	-0.0443	-0.0395	-0.0660
	(0.551)	(0.591)	(0.345)
Business model$_{t-1}$	0.0424*	0.0406*	0.0412*
	(0.077)	(0.084)	(0.091)
G-SIB (dummy)	-0.0757**		
	(0.018)		
Main CDS index (dummy)		0.1139*	
		(0.066)	
STV			0.0019*
			(0.085)
Bank FE	YES	YES	YES
Time FE	YES	YES	YES
Cluster bank level	YES	YES	YES
N	388	388	379
No. of Groups	52	52	51
R^2	0.2847	0.2293	0.2739

The empirical model and parameters are defined in Table 5. Regression specification (1) includes a dummy variable indicating whether a bank is categorized as a G-SIB, regression specification (2) employs a dummy variable indicating the affiliation to the regional CDS main index and regression specification (3) controls for the stock trading volume of the respective bank per year (STV). Constant term is included but not reported. Heteroscedasticity consistent P-values are in parenthesis.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 9: Economic materiality

Variable	Coefficient	Corresponding absolute change in NN (c.p.)
CDS trading-specific variables		
1 pp increase in Bond ratio	0.7215	64.2073 Mio. USD
1 pp increase in Bond frag.	0.0691	6.1493 Mio. USD
1 pp increase in UTD CDS	0.1699	15.1196 Mio. USD
1 pp increase in Neg. basis	0.0154	137.0467 Mio. USD
Fundamental bank-specific variables		
1 pp increase in Leverage$_{t-1}$	-0.0904	-8.0448 Mio. USD
1 pp increase in LLR$_{t-1}$	0.0087	0.7742 Mio. USD
1 pp increase in Business model$_{t-1}$	0.0428	3.8088 Mio. USD
Macroeconomic variables		
1 pp increase in Yield curve$_{t-1}$	-0.0413	-383.5527 Mio. USD
1 pp increase in Change in GDP	-0.0486	-4.3250 Mio. USD
1 pp increase in Government deficit to GDP	0.0116	103.2230 Mio. USD
1 pp increase in FX return	0.1484	13.2063 Mio. USD
1 pp increase in Domestic credit	0.0162	144.1660 Mio. USD
Stock market (dummy)	-0.1450	-1,290.3746 Mio. USD
Institutional variables		
G-SIB (dummy)	-0.0757	-673.6645 Mio. USD
Main CDS index (dummy)	0.1139	1,013.6115 Mio. USD
1 billion USD increase in STV	0.0019	16.9084 Mio. USD

This table shows the economic materiality of all statistically significant variables from our baseline and sensitivity analyses. As regards the dummy variables, the average ceteris paribus increase/decrease in the CDS net notional is presented when the dummy variable takes on the value of one. The average ceteris paribus increase/decrease in the CDS net notional for all other variables is specified for a percentage point (pp) increase of the respective variable.

B Technical Appendix

B.1 Construction of the bond fragmentation measure

In what follows, the construction of the bond fragmantation measure is described following Oehmke and Zawadowski (2016). For this purpose, the Herfindahl-Hirschman-Index (HHI) of each bank's outstanding bond j in our sample is constructed by summing the squared ratio of each bond's dollar amount $b_{i,j}$ to the total dollar amount of bonds bank i has outstanding:

$$HHI_i = \sum_{j=1}^{N} \left(\frac{b_{i,j}}{B_i} \right)^2, \tag{2}$$

where $B_i = \sum_{j=1}^{N} b_{i,j}$ is the overall dollar amount of bonds outstanding. Subsequently, the natural logarithm of the Herfindahl-Hirschman-measure is orthogonalized by the natural logarithm of a bank's outstanding bonds.[18] This is done for two reasons. First, to improve the distributional properties and, second, to adjust for the relationship between total issuance of bonds and number of bond issues (Oehmke and Zawadowski, 2016). Finally, the measure is multiplied by minus one, to make sure that a higher value of the measure means higher fragmentation. According to Oehmke and Zawadowski (2016), this measure is attractive due to two reasons. First, it is less affected by the demand for trading as compared to liquidity measures and second, it is very unlikely to be endogenous to CDS trading ((bank) managers do not intentionally choose the fragmentation of their bank's bond issues to affect CDS trading activities).

B.2 Estimation of the upper tail dependence coefficient of CDS spreads

In the following, the estimation of the upper tail dependence coefficient is described following the nonparametric approach of Schmidt and Stadtmüller (2006). The upper tail dependence is estimated nonparametrically using the fact that the tail dependence between two random variables is governed by the copula of the variables' bivariate joint

[18] We regress log HHI on the log of bond's outstanding and take the residual as our fragmentation measure.

distribution. Let (X_1, X_2) be two random variables with continuous distribution function for which we wish to estimate the coefficient of upper tail dependence. Since the regulatory conditions of Sklar's theorem are fulfilled with continuous distribution of the random variables, we let their unique copula be C. The upper tail dependence can be expressed using the upper tail copula as a function on $\bar{\mathbb{R}}_+^2$ as

$$\lambda_U(x, y) = \lim_{t \to \infty} t\tilde{C}(\frac{x}{t}, \frac{y}{t}). \tag{3}$$

where $\tilde{C}(x, y) = x + y - 1 + C(1 - x, 1 - y)$ denotes the survival copula of C and the upper tail dependence coefficient is defined as $\lambda_U(1, 1)$.

Let now be $(X^{(1)}, Y^{(1)}), \ldots, (X^{(n)}, Y^{(n)})$ independent and identically distributed random vectors with a joint distribution function F, marginal distribution functions G and H as well as C a copula.

The empirical copula C_n can then be expressed as

$$C_n(a, b) = F_n(G_n^{-1}(a), H_n^{-1}(b)),\ (a, b) \in [0, 1]^2, \tag{4}$$

where F_n, G_n and H_n are the empirical distribution functions corresponding to F, G and H.

The empirical survival copula is defined as

$$\tilde{C}_n(a, b) = \tilde{F}_n(\tilde{G}_n^{-1}(a), \tilde{H}_n^{-1}(b)),\ (a, b) \in [0, 1]^2, \tag{5}$$

with

$$\tilde{F}_n = \frac{1}{n} \sum_{j=1}^{n} \mathbb{1}_{\left\{X^{(j)} > x, Y^{(j)} > y\right\}}$$

and $\tilde{G}_n = 1 - G_n$ as well as $\tilde{H}_n = 1 - H_n$.

Let further $R^j_{n,X}$ and $R^j_{n,Y}$ be the rank of $X^{(j)}$ and $Y^{(j)}$ with $j = 1, \ldots, n$. Finally, the coefficient of the upper tail dependence can be estimated as

$$\hat{\lambda}_{U,n}(x, y) = \frac{n}{k}\tilde{C}_n\left(\frac{kx}{n}, \frac{ky}{n}\right) \approx \frac{1}{k}\sum_{j=1}^{n} \mathbb{1}_{\left\{R^j_{n,X} > m-kx \text{ and } R^j_{n,Y} > m-ky\right\}}, \tag{6}$$

with some parameter $k \in \{1, \ldots, n\}$ which is chosen by the use of a plateau-finding algorithm.[19] As mentioned above, the upper tail dependence coefficient is then obtained by calculating $\hat{\lambda}_{U,n}(1, 1)$.

[19]For a discussion of the optimal k and the algorithm to use see Frahm et al. (2005) and Schmidt and Stadtmüller (2006).