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Determinants of CDS trading on major banks

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Abstract: This paper empirically investigates determinants of the outstanding net notional amount of credit default swaps (CDSs) contracts written on banks. We extend and complement the previous literature dealing with CDS trading by analyzing a comprehensive set of CDS trading-specific, bank-fundamental, macroeconomic and bank-institutional determinants. We find that risk hedging clearly dominates an investor's speculation and arbitrage motive, while the latter, however, exhibits the strongest impact on the outstanding net notional amount of bank CDSs. Furthermore, being classified as a G-SIB, being a constituent of the main CDS index and the equity trading volume may significantly explain changes in the outstanding CDS net notional on banks. The analysis at hand provides important implications for both academics and practitioners, since understanding the trading motives of bank CDS investors provides a deeper insight into the opaque CDS market.

Keywords: banking, outstanding CDS net notional, determinants of bank CDS trading
JEL Classification: G10, G12, G21

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1. Introduction

The market for credit default swaps (CDSs) has grown to one of the biggest derivative markets during the last decades (BIS, 2022). The rapid growth is clearly fostered by the versatility of this derivative, i.e. next to employing CDS as a cost-efficient instrument to hedge credit risk, CDS are also used in arbitrage trades and for speculation purposes (da Silva et al., 2015; Oehmke and Zawadowski, 2016).

Nevertheless, as investors predominantly hold CDSs to hedge against credit risk (Greatrex, 2009; Longstaff et al., 2011), most academic studies have analyzed if CDS spreads are a reliable indicator for a change in firm and sovereign default risk (e.g., Collin-Dufresne et al., 2001; Benkert, 2004; Pelster and Vilsmeier, 2018) and if CDS spreads for banks and non-financial firms (Raunig and Scheicher, 2009). In contrast, although it is well-known from related markets (e.g., the bond market) that non-spread (non-price) data may also determine an investor's decision to hold financial instruments (e.g., Fodor et al., 2011), far fewer studies have focused on further factors beyond CDS spreads. For instance, Shachar (2012) and Biswas et al. (2015) analyze the CDS market liquidity, Siriwardane (2019) investigates the risk-bearing capacity of the CDS market and Du et al. (2018) examine counterparty risks in the CDS market.

So far, the *change in the CDS net notional outstanding*, and hence trading dynamics and potential *trading motives* of investors, have been the least explored. Augustin et al. (2016) provide evidence that the level of national debt per country may affect the net notional amount of sovereign CDSs in respective countries. Furthermore, they identify four channels (shocks to credit risk, debt issued by the government, news and sentiment and a regulatory channel) which may explain a change in the trading volume of sovereign CDSs. Similarly, Berg and Streitz (2015) empirically show that sovereign CDS markets are generally larger in smaller countries, in countries that exhibit a rating which is above the investment grade and in countries with weaker creditor rights.

The most related studies to our analysis are provided by da Silva et al. (2015) as well as Oehmke and Zawadowski (2016) who investigate the CDS net notional outstanding in the corporate CDS market in order to identify determinants of CDS trading. To begin with, da Silva et al. (2015) examine changes in the CDS net and gross notional amounts outstanding of 317 US and 210 European non-bank firms between 2008 and 2014. They find that asymmetric information with regard to the firms' credit risk portfolios is a strong trigger of the CDS net notional. Furthermore, it is shown that common factors, such as investor risk aversion and the macroeconomic environment, have even a greater impact on the trading dynamics in the US and European corporate CDS market. Oehmke and Zawadowski (2016) focus on the US corporate CDS market by analyzing the CDS net notional outstanding of 496 non-financial and financial firms from 2008 to 2012. Without distinguishing between non-financial and financial firms, and without a specific focus on banks, their analysis reveals that hedging, speculation, arbitrage transactions and standardization in the underlying bond market describe main trading motives for investors in the US corporate CDS market.

The study at hand extends both most related studies since it is, to the best of our knowledge, the first comprehensive empirical analysis of the determinants of the outstanding volume of CDSs contracts written on *banks*. Explicitly focusing on banks in the CDS context is important for at least three reasons. *First*, the threat of maturity mismatches in the loan and deposit business, a volatile fee-based income from the investment banking as well as a typically high leverage ratio leads to banks exhibiting a greater variety of risks and different triggers of the default risk as compared to non-bank firms (e.g., Raunig and Scheicher, 2009). If this is true, investors may have a strong incentive to employ CDSs to hedge against or to speculate on bank risk.

Second and related to the former aspect, banks are usually more heavily regulated than other firms. However, bank deposits are insured by governmental deposit guarantees and solvent bank have access to the central bank acting as a 'lender of last resort'. Furthermore, as learned from the

Global Financial Crisis (2007/08) and European Sovereign Debt Crisis (beginning in 2012) regulators may be reluctant to close or liquidate banks, in particular if they assumed to be "too big to fail", which may set an incentive to these banks to take on excessive risks in anticipation of a government bailout. In turn, such an implicit government guarantee may destroy market discipline and hence, result in a weaker risk perception by investors in the bank CDS market.

Third, as the CDS market is still very opaque, we shed a brighter light on the CDS market by investigating a large variety of (bank-)specific determinants that may have an impact on an investor's decision to trade bank CDSs.

The analysis at hand employs CDS data from 52 major banks across 18 countries between 2008 and 2016. In line with the related studies provided by da Silva et al. (2015) and Oehmke and Zawadowski (2016), we investigate the impact of CDS trading-specific determinants in a first step. In a second step, we extend and complement the previous studies by examining a comprehensive set of fundamental bank-specific as well as macroeconomic and institutional determinants with a special focus on bank CDS trading.

Our analysis initially reveals that fundamental bank data, such as a bank's tail risk, capital adequacy, loan portfolio quality and business model, may determine an investor's decision to trade bank CDSs. In this context, risk hedging clearly dominates an investor's speculation and arbitrage motive, while the latter, however, exhibits the strongest impact on the outstanding net notional amount of bank CDSs. Moreover, further CDS trading-specific, macroeconomic indicators and bank-institutional factors, such as being classified as a G-SIB, being a constituent of the main CDS index and the equity trading volume, significantly explain changes in the outstanding CDS net notional on banks. In sum, our analysis provides important implications for both academics and practitioners, since understanding the trading motives of bank CDS investors provides a deeper insight into the opaque CDS market.

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 outcomes of our baseline analysis, Section 4.2 presents the findings 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. Figure 1 and 2 illustrate the development of the outstanding CDS net notional in our sample. Finally, Table 4 presents the correlation matrix of variables which are employed in our baseline regression.[1]

2.1 Outstanding CDS net notional amount on banks

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

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1 As we employ 30 variables in total, we do not provide the full correlation matrix in this paper but will provide it on request.

outstanding is considered to be the economically most viable measure for aggregated risk transfer (Oehmke and Zawadowski, 2016). It also provides a direct indication of the net insured interest, and is therefore analogous to open interest in futures and options markets (Augustin et al., 2016). Accordingly, we focus on the amount of the outstanding CDS net notional on banks as our dependent variable.

In a first step, we average weekly outstanding net notional amounts per bank and year and include the ratio of a bank's net notional amount outstanding to a bank's total assets per bank and year (*NN ratio*) in our regressions as we observe that the CDS net notional scales with bank size.[2]

In a second step, 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 until the year of default. 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. As shown in Table 1, these corrections lead to a sample of 52 major banks from 18 countries.

In a final step, data from the DTCC is hand-matched with (i) further CDS data from IHS Markit, (ii) fundamental data from Orbis Bank Focus/Bankscope (provided by Bureau van Dijk), (iii) stock and bond market data from EIKON, Datastream and IBES (all provided by Thomson Reuters) as well as (iv) macroeconomic 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.

As indicated by Table 3, the *NN ratio* for our sample of banks reaches it maximum at 4.1861 percent and its minimum at 0.0127 percent while the mean value exhibits 0.2860 percent. In addition, the average unscaled outstanding CDS net notional per year for our sample of banks is

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2 We are forced to focus on yearly data since most bank balance sheet data is only available on an annual basis.

illustrated in Figure 1. The figure shows that the CDS net notional outstanding is decreasing since the *Global Financial Crisis* from 2007 and 2008. Nevertheless, the average bank in our sample still exhibits about one billion USD of outstanding CDS net notional in 2016. Figure 2 additionally indicates the development of the outstanding CDS net notional in different regions over the sample period. Again, the downward trend is identified in this illustration. However, it is striking that the Asian market (without Japan) exhibits the strongest decrease, whereas the American market has a fairly high ratio throughout the entire time period as compared to the remaining regions.

2.2 Explanatory variables

2.2.1 CDS trading-specific determinants

As discussed in Section 1, the risk position to be hedged, bond market fragmentation, the speculation and arbitrage motive as well as market risk have been empirically identified as the main CDS trading motives for corporate CDS markets (da Silva et al., 2015; Oehmke and Zawadowski, 2016). Accordingly, we adopt these determinants for our sample of banks and employ proxies as described in the following.

To begin with, we include the ratio of outstanding bonds to total assets per bank and year (*Bond ratio*) to control for a CDS investor's motive to hedge against a bank's credit and default risk.[3] Since a higher volume of the bond ratio indicates a higher risk exposure to be hedged, we expect a positive impact of the bond ratio on the amount of the outstanding CDS net notional on banks.

Furthermore, we include a measure of bond fragmentation (*Bond fragmentation*) following the methodology provided by Oehmke and Zawadowski (2016).[4] This measure controls for the fact that CDS contracts are more standardized than bond contracts. Usually, bonds are fragmented into

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[3] 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.

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

many different issues whereas CDSs are standardized contracts. As investors can choose between the CDS market for banks and the underlying bond market, the bank 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.

Next to hedging, speculation describes another important trading motive of investors in the bank 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 (*Disagreement*) to proxy speculation.[5] We argue that analysts take more views in the credit market if the dispersion of the earnings prospects for banks increases. This is due to the fact that disagreements about bank default probabilities should naturally be related to disagreements about future earnings. Accordingly, we expect that speculation on future earnings and hence, default probabilities should increase the outstanding CDS net notional on banks.

Furthermore, 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 (*UTD CDS*). We employ the upper tail dependence coefficient suggesting that higher CDS spreads indicate a higher risk exposure of the underlying bank. The UTD CDS measure is calculated following Schmidt and Stadtmüller (2006) who present a non-parametric estimation technique of the tail dependence coefficient.[6] As shown by Meine et al. (2016), investors in the bank CDS market protect themselves

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5 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. Scaling by 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 in this paper but provide them on request.

6 We employ this procedure instead of choosing a particular copula model to avoid an estimation bias due to a misspecification of the copula (Weiß et al., 2014). We use the CDX North America Investment Grade, iTraxx

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 a default in economic downturns. In addition, 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 on banks.

Finally, we control for a bank CDS investor's arbitrage motive, which is proxied by the negative (*Neg. basis*) and positive (*Pos. basis*) CDS-bond basis[7], i.e. the difference between the five-year CDS spread and the underlying bond yield over the risk-free rate[8]. 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). In practice, deviations of the basis are used by arbitrageurs through positive or negative basis trades. As mentioned above, both arbitrage strategies imply either a short or a long position in a CDS contract and thus, should increase the outstanding CDS net notional on banks.

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.

7 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). Unlike CDS, bonds are not standardized so that we have to calculate the corresponding five-year bond spreads for each bank. Accordingly, 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 measure as compared to all other variables (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) CDS-bond basis means higher arbitrage opportunities.

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

2.2.2 Fundamental bank-specific determinants

We proceed by examining the impact of a bank's fundamental data on an investor's decision to buy net protection by means of CDSs. To control for bank fundamental data, we follow the CAMEL rating, which is widely used by bank supervisory authorities, and which is well-accepted in empirical studies on bank risk (e.g., Citterio, 2020). Next to proxies for a bank's capital adequacy, asset quality, management efficiency, earnings capacity and liquidity position, we additionally include a measure of a bank's business model. As the annual financial statement of the past year is the latest information available from an investor's perspective, we lag all bank-specific variables by one year respectively. Moreover, lagging by one period helps to avoid multicollinearity issues.

To begin with, we proxy capital adequacy by a bank's leverage ratio (*Leverage*), with higher ratios indicating less capitalized banks. The impact of the leverage ratio on the outstanding CDS net notional on banks is not clear. On the one hand, a higher leverage ratio raises a bank's probability of default, which may be hedged 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). On the other hand, 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. If this is true, a higher leverage ratio may affect the outstanding CDS net notional negatively.

We further include a ratio of *loan loss reserves to gross loans* as a proxy for a bank's asset quality, with higher values indicating 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 induces an increase in credit risk (Keeton and Morris, 1987), we expect a positive impact of the ratio on the outstanding CDS net notional on banks.

Introducing the efficiency of a bank's management, we employ a bank's cost-to-income ratio (*CIR*), while a higher ratio implies a higher bank (management) inefficiency.[9] Results from related theoretical and empirical studies are mixed. Following the 'bad management' hypothesis, Berger and DeYoung (1997) suggest that banks with managers, who exhibit poor skills in credit scoring, in estimating collateral-values and in controlling and monitoring borrowers, exhibit higher operating expenses and a lower loan portfolio quality. Accordingly, greater cost inefficiency should be positively associated with the outstanding CDS net notional on banks. However, following the 'skimping' hypothesis (Berger and DeYoung, 1997), it is also shown that a bank's management operates more cost-efficiently in the short run, if management resources are reduced. If this is true, the relationship between the outstanding CDS net notional and bank efficiency is negative on a short term.

Turning to a bank's earnings capacity, we employ the return on average assets (*ROAA*) as a proxy. Advocates of the 'bad management' and the 'gambling for resurrection' hypothesis postulate that more profitable and well- managed banks may have 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). Taking this into account, the impact of the ROAA measure on an investor's decision to buy net protection by means of bank CDSs should be negative.

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[9] We are aware of the fact that the cost-to-income ratio is only a rough measure of the efficiency of a bank's (risk) management. Unfortunately, more precise management data is not available, especially for the European banks in our sample. Taking this into account, we argue that the efficiency of a bank's (risk) management is reflected in the bank's cost structure and follow related studies employing the cost-to-income ratio as well (e.g., Louzis et al., 2012; Farruggio and Uhde, 2015).

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*). Theoretical predictions provided by Cebenoyan and Strahan (2004) as well as Wagner (2007) suggest that growing liquidity risk-buffers may incentivize bank managers to an excessive risk-taking behavior. In contrast, Demirgüç-Kunt et al. (2013) empirically demonstrate that liquidity risk buffers mitigate a bank's susceptibility to liquidity shocks. Against this background, liquidity may affect the outstanding CDS net notional on banks negatively or positively.

Finally, we employ a bank's business model (*Business model*), which is built as the ratio of non-interest income to net interest income. Constructing the ratio this way, it indicates to which extent a bank engages in fee-based businesses (esp. investment banking) or trading activities next to the traditional deposit taking and lending business. As a consequence, higher ratios indicate a more diversified bank business model. The impact of a bank's business model on the outstanding CDS net notional is ambiguous. 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 stronger diversification of a bank's business model. In this context, stronger diversification leads to a lower dependency on specific business segments and a smaller cyclical variation in bank profits. Both effects induce a better risk-return structure, especially in times of low interest rates when banks strongly depend on alternative sources of capital. In contrast, it is also argued that non-interest income is more volatile than interest income, especially in times of financial crises (DeYoung and Roland, 2001; Fraser et al., 2002; Stiroh, 2004; Baele et al., 2007; Altunbas et al., 2011). In addition, as the correlation between fee- and interest-based income has increased over the last decades due to overlapping business units and substitution effects, the risk diversification effect has become weaker (De Jonghe, 2010; Brunnermeier et al., 2012).

2.2.3 Macroeconomic and institutional determinants

Macroeconomic determinants

Next to CDS trading-specific and fundamental bank-specific variables, we include various well-accepted variables that control for the macroeconomic and institutional environment of the CDS and banking market. Empirical evidence suggests that the CDS *price* reacts to both, specific information concerning the reference entity (Zhang and Zhang, 2013) and information on the macroeconomic and institutional environment of a bank (Kim et al., 2015). 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 control for the impact of the macroeconomic and institutional framework on bank CDS *trading*. We include measures of economic growth, the state of the economy, foreign borrowing, the price level, the development of the credit market and the financial wealth of a country level as macroeconomic control variables. As regards the institutional environment, we control for the systemic importance of a bank as classified by banking regulators. In addition, we consider if a bank is a constituent of the corresponding regional main CDS index. Finally, we employ a bank's stock trading volume as a proxy for equity trading.

Introducing measures of the macroeconomic environment, we initially proxy economic growth by the one-year lagged slope of the yield curve (*Yield curve*). Calculated as a country's ten-year government bond yield minus the two-year government bond yield, this ratio is a widely used and 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 affects 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 show that a growing economy is likely to be associated with an improved debt service, higher bank returns and reduced financial distress (Louzis et al., 2012; Ghosh, 2015; Dimitrios et al., 2016). Against this background, we expect a negative impact of economic growth on the outstanding CDS net notional on banks.

In a next step, we proxy the state of the economy by the change of a country's gross domestic product (*Change in GDP*) and thus, control for the variation in trading CDS net notional on banks due to differences in the sample countries' economic development. Since it is argued and empirically shown that an increase in the GDP may foster stability in the banking sector (Michalak and Uhde, 2012; Schaeck and Čihák, 2012), 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 control for a country's sovereign debt exposure. Empirical evidence on the so-called 'Sovereign-Bank Diabolic Loop' suggests that an increase in sovereign debt raises a bank's default risk since an increase in government deficit decreases the probability of a governmental bank bailout (e.g., through governmental capital injections). In addition and as observed during European Sovereign Debt Crisis beginning in 2012, an ongoing government deficit may result in a deterioration of sovereign creditworthiness, which in turn reduces the market value of sovereign bonds held in the banking book (Demirgüç-Kunt and Detragiache, 1998; Demirgüç-Kunt and Huizinga, 2013; Brunnermeier et al., 2016). Against this background, we argue that CDS investors are more prone to seek protection against bank defaults by means of CDSs under an increasing government deficit.

We proceed and include the foreign exchange return (*FX return*) as another macroeconomic control variable. Basically, an increase in foreign exchange rates may jeopardize a bank's profitability if the bank borrows in foreign currency and lends in local currency (e.g., von Hagen and Ho, 2007). Moreover, banks borrowing 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 so that an unexpected depreciation would still have a negative impact on the bank's profitability but may additionally increase credit risk (Demirgüç-Kunt and Detragiache, 1998). Similarly, Kaufman (2000) suggests that the depreciation of countries' foreign exchange rates may induce financial distress at banks. Hence, 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 hence, higher bank risk. Against this background, we expect a positive relationship between a country's foreign exchange rate depreciation and the outstanding CDS net notional on banks.

We further control for a country's inflation rate (*Inflation*). The relationship between a change in inflation rates and a change in the outstanding CDS net notional on banks is not distinct. Rather, it depends on the impact of a change in inflation rates on a bank's interest margins and loan portfolio risk. On the one hand, an increase in inflation rates may result in rising interest rates and, ceteris paribus, net interest margins, if banks are able to stronger pass through higher rates to debtors than creditors (Uhde and Heimeshoff, 2009; Tan and Floros, 2012). Obviously, this effect depends on a bank's market power in the loan and deposit market and whether inflation is anticipated correctly or not (Perry, 1992; Demirgüç-Kunt and Huizinga, 1999; Demirgüç- Kunt and Detragiache, 1998, 2000). On the other hand, unexpectedly rising or volatile inflation rates may cause cash flow difficulties for borrowers which may result in an early termination of loans and loan defaults (Perry, 1992; Hoggarth et al., 2001).

Next, we employ the ratio of domestic credit to the private sector by banks to GDP (*Domestic credit*) in order to control for the development of a country's loan 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.

Finally, we employ a dummy variable (*Stock market*) that takes on the value of one if the return of a country's main stock market index is positive (bull market), and zero otherwise (bear market). From a bank's point of view, positive stock market returns may increase the value of shares used as collaterals for loans and may raise financial wealth (Nkusu, 2011; Beck et al., 2015; da Silva et al., 2015). Moreover, investors may less engage in CDS trades for speculation or arbitrage purposes if the stock market turns out to be a profitable alternative trading venue. Against this background, we expect a negative impact of the stock market measure on the outstanding CDS net notional on banks.

Institutional determinants

Turning to a bank's institutional environment, we initially 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. Banks, being classified as G-SIBs, can generally be described as 'too-big-to-fail' as their default would have a significant impact on the banking sector and real economy as a whole. Therefore, regulators are often reluctant to close or liquidate G-SIBs. In addition, such an implicit government guarantee may result in a weaker risk perception by investors, which is reflected by lower spreads of CDS written on G-SIBs as compared to non-G-SIBs (Morgan and Stiroh, 2005; Demirgüç-Kunt and Huizinga, 2013). Taking this into account, we expect a negative impact of the G-SIB classification on the outstanding CDS net notional on banks.

We further employ a dummy variable that specifies whether a bank is listed in the corresponding regional main CDS index or not (*Main CDS index*).[10] 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 a higher outstanding CDS net notional on these banks as compared to non-index members.

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

3. Empirical model

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

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

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

where y_{it} is the outstanding CDS net notional to total assets 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. $x_{k,it-1}^{(2)}$ denotes 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 y_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 employ 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.[11] Since the Hausman test (Hausman, 1978) is not applicable under heteroskedasticity, a generalization of the Hausman test proposed by Arellano (1993) is used to control for the adequacy of our model. The test strongly rejects the null of using random effects, supporting our model choice.

Finally, 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 biasedby multicollinearity.

4. Empirical results

We provide baseline regression results and findings from robustness checks in Tables 5 and 6. Results from further analyses, which additionally control for the macroeconomic and institutional

[11] Petersen (2009) shows that too few clusters may bias the results even when clustered in the right dimension. In this case, it is suggested to address the time-dependence parametrically and cluster at the 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.

environment, are shown in Tables 7 and 8 respectively. Finally, Table 9 reports the economic materiality of the determinants from our regression results.

4.1 Results from the baseline regression

CDS trading-specific determinants

Beginning with CDS trading-specific determinants, regression specification (1) in Table 5 reveals a significantly positive impact of the *Bond ratio* on the CDS net notional ratio, indicating that an increase in a bank's debt financing by issuing bonds may provide a hedging incentive for investors by means of CDS. Moreover, the high significance at the 1%-level of the *Bond ratio*-coefficient remains robust in most of the further regression specifications suggesting that hedging is a key determinant for investors to engage in bank CDS trading.

Introducing *Bond fragmentation*, this variable enters the regression significantly positive at the 10%-level. Our finding suggests that investors may partially replace the bond market with the bank CDS market as an alternative trading venue if bond fragmentation increases. In this case, the CDS market becomes more beneficial and trading volume is shifted from the bond market to the CDS market due to a higher standardization of the CDS market (Oehmke and Zawadowski, 2016).

Specification (1) further reports a significantly positive impact of the upper tail dependence (*UTD CDS*) between a bank's individual CDS log-spreads and the corresponding market index log-spreads on the outstanding CDS net notional on banks. This result underlines theoretical predictions suggesting that investors buy net protection via CDS in order to protect themselves against extreme downside risks and hedge their positions against banks with extreme tail risks (da Silva et al., 2015; Meine et al., 2016).

Finally, observing a significantly positive impact of the negative basis (*Neg. basis*) on the bank's CDS net notional, this finding implies that investors in bank CDS may exploit arbitrage opportunities through negative basis trades.[12] In this context, Table 9 points to the strong economic impact of a rising negative basis. Hence, an increase of the negative basis by one percentage point raises the CDS net notional by $137 million indicating that the arbitrage-motive may have a stronger impact on bank CDS trading than the origin purpose of hedging against risk.[13]

Fundamental bank-specific determinants

Turning to fundamental bank-specific variables, regression specification (1) initially reports a significantly negative impact of the leverage ratio (*Leverage*) on the outstanding CDS net notional on banks. Hence, in contrast to our finding from the more specific *bond ratio* measure, we find that an increase in debt financing in general does not trigger (but reduces) CDS trading on banks. Our result confirms theoretical predictions that a higher leverage ratio may force (institutional) debt capital providers to negotiate stricter credit covenants, which in turn discipline bank managers (Jensen and Meckling, 1976; Calomiris and Kahn, 1991; Rajan and Zingales, 1995; Diamond and Rajan, 2001). Accordingly, as stricter debt covenants force bank managers to negotiate future investment projects with the bank's debt providers, high-risk investment projects with a negative net present value may be less likely.

Turning to a bank's loan portfolio quality, which is measured by the ratio of *loan loss reserves to gross loans*, this variable has a significantly positive impact on the outstanding CDS net notional on banks at the 1%-level. This result was expected since a lower loan portfolio quality is accompanied by a higher exposure to credit risk (Keeton and Morris, 1987). Interestingly in this

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

13 Note, that we do not observe any statistically significant impact of the *positive basis*. This might be due to the fact that 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. Thus, as long positions are much easier to trade in terms of fees and regulations during a negative basis trade, this might explain why we observe a significant impact of the negative basis only.

context, as shown by Table 9, an increase of one percentage point in a bank's loan loss reserves to gross loans raises the outstanding CDS net notional by only about $0.77 million.

Finally, regression specification (1) reveals a significantly positive relationship between a bank's business model (*Business model*) and the outstanding CDS net notional on banks. Taking this into account, our finding does not support previous theoretical predictions and empirical evidence that a more diversified business model may result in less volatile bank profits and a better risk-return structure (Allen and Jagtiani, 2000; Davis and Tuori, 2000; Smith et al., 2003; Stiroh, 2004; Altunbas et al., 2011). Rather, the finding at hand suggests that a more diversified business model may increase a bank's risk exposure, which may be due to more volatile fee-based income from investment banking and a shrinking diversification effect from stronger correlated fee- and interest-based income over the last decades (DeYoung and Roland, 2001; Stiroh, 2004; Baele et al., 2007; De Jonghe, 2010; Altunbas et al., 2011; Brunnermeier et al., 2012).

4.2 Results from robustness checks

We provide results from the variety of robustness checks in regression specifications (2) to (7) in Table 5 and regression specifications (1) to (4) in Table 6. The variables used for the robustness checks are described in greater detail in Table 2.

Alternative CDS trading-specific determinants

To begin with, one may argue that the bond ratio and leverage ratio are very similar measures of a bank's debt financing. Taking this into account, we perform a variety of robustness checks. To begin with, we initially substitute the *Bond ratio* from specification (1) by the volume of total bonds outstanding (*Bonds*) in specification (2) in Table 5. As shown, *Bonds* enters the regression significantly positive (while significances and signs from further control variables are generally reiterated) indicating that the baseline result remains robust even when controlling for a different hedging measure.

In regression specification (3) and (4) we distinguish between bonds that are issued by the parent bank (*Bond ratio (parent)*), and bonds that issued via subsidiaries (*Bond ratio (subs)*).[14] The regressions reveal that both, direct issues by the parent bank and issues via subsidiaries may have a significantly positive impact on the outstanding CDS at the 5%-level, respectively. Accordingly, both robustness checks reiterate our baseline finding that a stronger debt-financing through bonds may incentivize investors to hedge against credit risk by means of bank CDSs.

In a next step, we initially substitute the *Bond ratio* by a 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 a measure of *Non-bond debt* to our baseline model in regression specification (6). This variable is constructed as the amount of total debt outstanding minus outstanding bonds divided by total assets. As indicated, also *Non-bond debt* enters the regression insignificantly. Overall, results from these robustness checks underline our previous finding that is not debt capital but rather issued bonds outstanding that describe a key incentive for an investor to hedge against credit risk by means of bank CDS.

Finally, we replace the measure of *Bond fragmentation* by *Debt fragmentation* in regression specification (7). *Debt fragmentation* is calculated the same way as *Bond fragmentation* but refers to a bank's total debt including bonds. Corresponding to our findings from regressions (5) and (6), *Debt fragmentation* enters the regression insignificantly, indicating that bond fragmentation rather than debt fragmentation triggers CDS trading on banks.

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[14] 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.

Alternative fundamental bank-specific determinants

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

Furthermore, we control for the nexus between bank size and an investor's hedging and speculation motive in regression specifications (3) and (4). We argue, that it might not be reasonable for CDS investors to hedge or speculate, if larger distressed banks are more likely to be rescued by governments following the 'too-big-to-fail' doctrine (O'hara and Shaw, 1990). To control for the effect of bank size, we create a dummy variable that takes on the value of one if a bank's value of total assets is below the sample median of total assets in the respective year, and zero otherwise (*Bottom half of size*). Subsequently, the dummy variable is interacted with the hedging measure (*Bond ratio*) and speculation measure (*Disagreement*), respectively. As expected, the interaction variable of speculation and size enters regression (4) 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 on these banks. However, as reported by regression (3), we do not provide any evidence concerning a possible nexus between hedging, bank size and changes in the outstanding CDS net notional.

4.3 Results from macroeconomic and institutional determinants

In this final section, we discuss results from further analyses that focus on the impact of the macroeconomic and institutional environment on a change in the outstanding CDS net notional on banks. Variables used for these analyses are described in detail in Table 2 while regression results are presented in Tables 7 and 8. Overall, our baseline findings from CDS trading- and fundamental bank-specific determinants are generally reiterated even when including macroeconomic and institutional control variables. In addition, we empirically identify several macroeconomic and institutional factors as further determinants that may affect an investor's decision to engage in the trading of bank CDSs.

Macroeconomic determinants

Among the macroeconomic factors, we initially include the one-period lagged slope of the *yield curve* in regression specification (1) in Table 7. As shown, the coefficient of our measure enters the regression significantly negative at the 5%-level suggesting that investors insure less against bank defaults by means of CDSs during a prospering economy. This finding was expected and may be traced back to the fact that, typically, loan default risk decreases whereas bank profitability increases during economic upturns (Gropp et al., 2014).

Similarly, and as shown by regression specification (2), we provide evidence for a significantly negative relationship between a country's *change in GDP* and the outstanding CDS net notional on domestic banks. Our result indiates that investors hold less CDS contracts in times of economic upturns, which might be due to the fact economic upswings are typically accompanied by a more stable banking sector (Louzis et al., 2012; Michalak and Uhde, 2012; Schaeck and Čihák, 2012; Ghosh, 2015; Dimitrios et al., 2016).

In a next step, we control for a country's sovereign debt exposure 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 bank CDS investors may seek stronger protection against bank defaults under increasing sovereign debt. Our result may be explained by the 'Sovereign-Bank Diabolic Loop' suggesting that the value of sovereign bonds in the banking book may decrease and bank defaults may increase if the sovereign creditworthiness deteriorates and bank bail-outs are less likely under high government deficits (Demirgüç-Kunt and Detragiache, 1998; Demirgüç-Kunt and Huizinga, 2013; Brunnermeier et al., 2016).

Introducing the exchange rate risk, regression specification (4) reports that the *FX return* exhibits a significantly positive coefficient. Taking into account that higher returns from a foreign exchange rate indicate a depreciation of the local currency, bank profitability may be jeopardized when banks borrow in foreign currency and lend in domestic currency (Demirgüç-Kunt and Detragiache, 1998; von Hagen and Ho, 2007). In addition, a depreciation may provoke an undercapitalization of banks if creditors withdraw their funds, expecting that banks are not able to repay them in full (Kaufman, 2000). Both, shrinking profits and an undercapitalization increase a bank's default risk and thus, provide a stronger incentive for investors to hedge by means of CDSs.

Next, we include the measure of *domestic credit* in regression specification (6) in order to control for the development of the local credit market. As shown, this variable significantly reduces the outstanding CDS net notional on banks. Hence, our result is not in line with the 'boom and bust' hypothesis proposing that 'excessive' growth in the domestic credit market may lead to higher bank risk due to decreasing capital ratios (Demirgüç-Kunt and Detragiache, 1998; Schaeck et al., 2009; Uhde and Heimeshoff, 2009). Rather, our finding underlines previous evidence provided by Čihák et al. (2012) that a (moderately) growing credit market may be reliable indicator of a well-developing banking market and less system-wide bank risk so that investors are less incentivized to employ bank CDSs as hedging instruments.

Finally, *Stock market* enters regression specification significantly negative at the 5%-level suggesting that positive stock market index returns may reduce the outstanding CDS net notional on banks. From a bank's point of view, a positive development of the stock market may increase the value of stock-based collaterals and raise a bank's financial wealth (Nkusu, 2011; Beck et al., 2015), which in turn reduces an investor's incentive to buy default insurance by means of CDSs. Moreover, and referring to the high economic materiality as reported by Table 9, we additionally suggest that investors may less engage in CDS trades for speculation or arbitrage purposes if the stock market turns out to be a profitable alternative trading venue.

Institutional determinants

Turning to a bank's institutional environment, we initially control if our baseline results differ for global systemically important banks (*G-SIBs*) in our sample. As shown in Table 8, the dummy variable enters the respective regression specification (1) significantly negative at the 5%-level indicating that the outstanding CDS net notional may decrease if a bank is classified as a G-SIB. This finding may be explained by the fact that G-SIBs are typically claimed as 'too-big-to-fail', so that CDS investors may perceive G-SIBs as less risky since they operate under a governmental financial safety net (Morgan and Stiroh, 2005; Demirgüç-Kunt and Huizinga, 2013).

In a next step, we control whether our baseline findings change for those banks in our sample that are constituents of the regional *main CDS index*, i.e. we control if an investor's decision to hold CDSs depends on the importance of a bank for the regional market. As reported by regression specification (2), the dummy variable turns out to be significantly positive suggesting that the local importance of a bank may indeed determine the amount of bank CDS trading. Considering the high economic materiality of our dummy as reported by Table 9, the increase in the outstanding CDS net notional on constituent banks may be traced back to the fact that especially portfolio managers trade CDS indices through exchange traded funds (ETFs) or simply by copying a CDS index.

Finally, the level of equity trading per bank as measures by the total *stock trading volume* per year enters regression specification (3) significantly positive at the 10%-level indicating that an increase in the trading volume of a bank's stocks incentivizes investors to trade CDSs that are written on this bank. Our result implies that investors in the bank CDS market may trade and take positions based on their expectations in the equity market, which is in line with the finding that information flows from equity to CDS markets (Norden and Weber, 2009; Hilscher et al.,2015).

5. Summary and implications

Employing 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 CDSs contracts written on banks. We extend and complement the previous literature dealing with CDS trading (da Silva et al., 2015; Oehmke and Zawadowski, 2016) by analyzing a comprehensive set of CDS trading-specific, fundamental bank-specific as well as macroeconomic and institutional determinants with a focus on bank CDS trading. We find that, next to well-discussed determinants for CDS trading on non-financial firms, a bank's tail risk, capital adequacy, loan portfolio and business model, may affect the outstanding CDS net notional. In this context, risk hedging clearly dominates an investor's speculation and arbitrage motive, while the latter, however, exhibits the strongest impact on the outstanding net notional amount of bank CDSs. Moreover, further CDS trading-specific, macroeconomic indicators and bank-institutional factors, such as being classified as a G-SIB, being a constituent of the main CDS index and the equity trading volume, significantly explain changes in the outstanding CDS net notional on banks.

Overall, results from the analysis at hand provide important implications for academics and practitioners. Since the CDS market is still very opaque, our findings shed a brighter light on the trading motives of investors in the banks CDS market. Focusing on banks is important since they are the top liquidity providers in over-the-counter markets and typically exhibit a larger variety of financial risks as compared to non-financial firms. Taking this into account, analyzing the trading motives of bank CDS investors may be helpful to avoid high systemic risks from large unhedged CDS positions written on banks.

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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

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

Region	Country	Bank
Europe	Germany	Commerzbank AG
		Deutsche Bank AG
	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 Esp´ırito 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.	DTCC, Bankscope, Orbis Bank Focus
CDS trading-specific variables			
Bond ratio	Hedging	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 fragmentation	Fragmentation	Measure of bond 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)
Disagreement	Speculation	Measure of disagreement. Standard deviation of analysts' one-year earnings per share forecasts 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)
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. For reasons of interpretation, the negative basis is multiplied by minus one. As a consequence, a higher negative (as well as positive) CDS-bond basis reflects higher arbitrage opportunities.	Markit, Thomson Reuters EIKON, own calc. following Blanco et al. (2005)

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

Variable	Proxy	Description	Source
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
Loan loss $reserves_{t-1}$	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

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

Variable	Proxy	Description	Source
Variables used in robustness checks			
Bonds	Hedging	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, Orbis Bank Focus, Bankscope
Bond ratio (parent)		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
Bond ratio (subs)		Ratio of the outstanding notional of bonds issued by subsidiaries with a maturity of more than one year to total assets.	Thomson Reuters EIKON
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 fragmentation	Fragmentation	Measure of debt 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 which is 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 of size	Size	Dummy variable that takes on the value of one if the value of the total assets of a bank are below the median value of the entire sample of banks, and zero otherwise.	Orbis Bank Focus, Bankscope

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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.	World Bank's WDI
Stock market	Financial wealth	Dummy variable that takes on the value of one if the return of a country's main stock market index is positive (bull market), and zero otherwise (bear market).	Thomson Reuters Datastream

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

Variable	Proxy	Description	Source
Institutional environment			
G-SIB	Systemic importance	Dummy variable that takes on the value of one if a bank is classified as global systemically important according to the Financial Stability Board criteria, and zero otherwise.	Financial Stability Board
Main CDS index	Regional importance	Dummy variable that takes on the value of one if a bank is a constituent of the regional CDS index, and zero otherwise.	Markit, own calc.
Stock trading volume	Equity trading	Measure of the stock trading value. 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

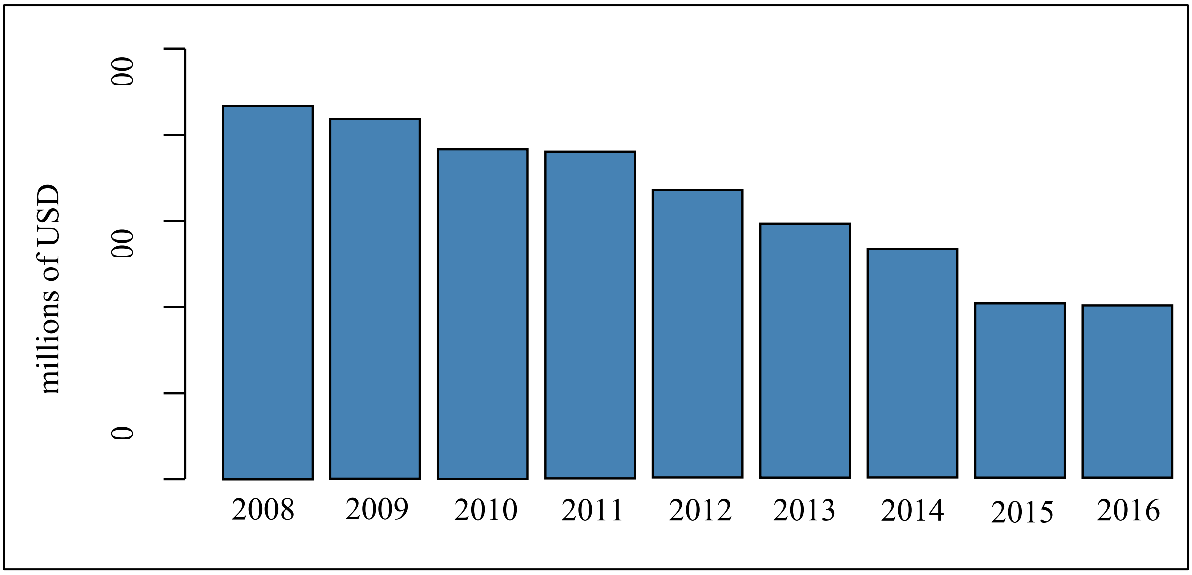
Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable					
NN ratio	464	0.2860	0.4034	0.0127	4.1861
CDS trading-specific variables					
Bond ratio	464	0.0310	0.0521	0.0000	0.3903
Bond fragmentation	463	0.0073	0.2929	–1.1866	1.3985
Disagreement	441	0.1264	0.7565	0.0000	10.9003
UTD CDS	462	0.4955	0.1563	0.0000	0.8060
Neg. basis	430	1.3114	1.4743	0.0000	9.9377
Pos. basis	430	1.1518	2.5455	0.0000	27.2423
Fundamental bank-specific variables					
Leverage_{t-1}	456	0.1934	0.1678	0.0330	2.3133
$\text{Loan loss reserves}_{-1}$	444	0.4098	3.3394	0.0001	66.2505
CIR_{t-1}	462	0.7728	0.1531	0.5132	2.3201
ROAA_{t-1}	462	0.0047	0.0089	–0.0530	0.1093
$\text{Liquid assets}_{t-1}$	462	0.4794	0.4904	0.0316	5.5897
$\text{Business model}_{t-1}$	462	0.0153	0.0896	–1.4662	0.7483
Variables as used in robustness checks					
Bonds	464	17.3444	28.6798	0.0000	292.7204
Bond ratio (parent)	464	0.0254	0.0496	0.0000	0.3795
Bond ratio (subs)	464	0.0056	0.0084	0.0000	0.0545
Debt ratio	464	0.2551	0.3362	0.0003	2.9373
Non-bond debt ratio	464	0.2241	0.3319	0.0000	2.9155
Debt fragmentation	464	0.0058	0.3008	–1.6679	1.6826
Probability of default	464	2.7759	2.9517	0.5566	28.3652
CDS Spread Volatility	464	0.8034	0.5888	0.2010	4.5956
Bottom half of size	464	0.5022	0.5005	0.0000	1.0000
Country-specific variables					
Yield curve_{t-1}	464	1.3918	0.8442	–2.8390	3.6470
Change in GDP	464	0.0646	0.3013	–1.0475	0.7276
Government deficit to GDP	464	3.2631	2.6663	0.0000	10.2041
FX return	464	0.0777	0.1947	–0.6302	1.5431
Inflation	464	1.5248	2.5783	–1.9000	23.6400
Domestic credit	464	1.0609	0.4035	0.3077	2.1808
Stock market	464	0.5259	0.4999	0.0000	0.0000
Institutional environment					
G-SIB	464	0.4579	0.4988	0.0000	1.0000
Main CDS index	464	0.6509	0.4772	0.0000	1.0000
Stock trading volume	455	7.5245	12.9861	0.0007	120.1079

Table 4: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) NN ratio	1.00												
(2) Bond ratio	0.14***	1.00											
(3) Bond fragmentation	0.08*	–0.03	1.00										
(4) Disagreement	0.32***	–0.00	–0.04	1.00									
(5) UTD CDS	–0.14***	0.12**	0.06	–0.23***	1.00								
(6) Neg. basis	–0.18***	–0.20***	–0.04	–0.11**	–0.00	1.00							
(7) Pos. basis	0.35***	0.17***	0.10**	0.21***	–0.06	–0.31***	1.00						
(8) Leverage$_{t-1}$	–0.16***	–0.07	0.00	0.00	0.02	–0.01	–0.09*	1.00					
(9) Loan loss reserves$_{t-1}$	0.15***	0.01	0.02	–0.01	–0.06	0.02	–0.03	0.01	1.00				
(10) CIR$_{t-1}$	–0.02	0.07	–0.00	0.06	0.12***	0.08*	–0.04	0.36***	0.05	1.00			
(11) 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		
(12) 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	
(13) 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

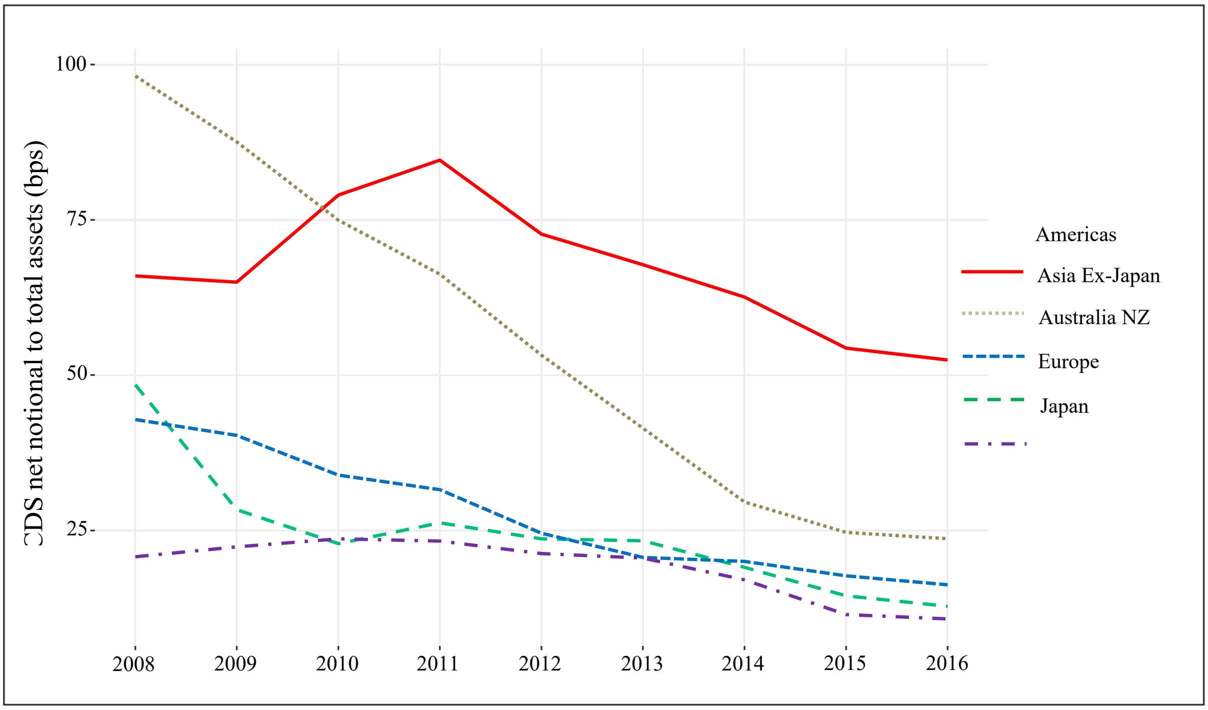
***,**,* indicate statistical significance at the one-, five- and ten-percent level.

Figure 1: Average outstanding CDS net notional



This figure illustrates the average outstanding CDS net notional of all banks in our sample per year.

Figure 2: Average ratio of the outstanding CDS net notional to total assets per region



This figure illustrates the average ratio of the outstanding CDS net notional to total assets of all banks in our sample per year and region.

Table 5: Baseline regression and robustness checks for CDS trading-specific determinants

	(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 fragmentation	0.0691*	0.0649*	0.0702*	0.0443	0.0672*	0.0694*	
	(0.081)	(0.093)	(0.076)	(0.196)	(0.083)	(0.079)	
Disagreement	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)	(0.06)	(0.09)
$\text{Loan loss reserves}_{t-1}$	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 (subs)				7.6447**			
				(0.023)			
Debt ratio					–0.0038		
					(0.901)		
Non-bond debt						–0.0175	
						(0.500)	
Debt fragmentation							0.0328
							(0.159)
Bank FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Cluster at bank level	YES	YES	YES	YES	YES	YES	YES
No. of obs.	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 linear fixed-effects panel model estimated by regression specifications (1) – (7) is $\text{NN ratio}_{(i=\text{bank},\, t=\text{time})} = \alpha_i + \beta_1 \text{ Bond ratio}_{i,t} + \beta_2 \text{ Bond fragmentation}_{i,t} + \beta_3 \text{ Disagreement}_{i,t} + \beta_4 \text{ UTD CDS}_{i,t} + \beta_5 \text{ Neg. basis}_{i,t} + \beta_6 \text{ Pos. basis}_{i,t} + \gamma_1 \text{ Leverage}_{i,t-1} + \gamma_2 \text{ Loan loss reserves}_{,t-1} + \gamma_3 \text{ CIR}_{i,t-1} + \gamma_4 \text{ ROAA}_{i,t-1} + \gamma_5 \text{ Liquid assets}_{i,t-1} + \gamma_6 \text{ Business model}_{i,t-1} + \varepsilon_{i,t}$. The *Bond ratio* from baseline regression (1) is substituted by the outstanding total bond volume (*Bonds*) in specification (2), by the ratio of bonds directly issued by the parent bank (*Bond ratio (parent)*) in specification (3), by the ratio of bonds issued by subsidiaries (*Bond ratio (subs)*) in specification (4) and by the *Debt ratio* in specification (5). In specification (6), we additionally include a measure of the banks' *non-bond debt*. Finally, the bond fragmentation measure is replaced by a *debt fragmentation* measure in specification (7). Constant term is included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***,**,* indicate statistical significance at the one-, five- and ten-percent level.

Table 6: Robustness checks for fundamental bank-specific determinants

	(1) NN Ratio	(2) NN Ratio	(3) NN Ratio	(4) NN Ratio
Bond ratio	0.6750***	0.7657***	0.7764**	0.6934***
	(0.000)	(0.000)	(0.025)	(0.003)
Bond fragmentation	0.0919*	0.0831	0.0692*	0.0660*
	(0.091)	(0.124)	(0.089)	(0.085)
Disagreement	0.0714	0.0742	0.1707	–0.1026*
	(0.296)	(0.270)	(0.183)	(0.052)
UTD CDS			0.1656*	0.1608*
			(0.091)	(0.090)
Neg. basis	0.0143*	0.0149**	0.0153**	0.0137**
	(0.077)	(0.041)	(0.030)	(0.040)
Pos. basis	–0.0154	–0.0006	–0.0031	–0.0026
	(0.231)	(0.936)	(0.565)	(0.634)
Leverage_{t-1}			–0.0954*	–0.0968*
			(0.058)	(0.056)
$\text{Loan loss reserves}_{t-1}$			0.0092***	0.0093***
			(0.000)	(0.000)
CIR_{t-1}	0.0644	0.0700	0.0857	0.1094
	(0.356)	(0.313)	(0.469)	(0.349)
ROAA_{t-1}	0.5915	0.3392	–0.2807	–0.2975
	(0.734)	(0.854)	(0.890)	(0.882)
$\text{Liquid assets}_{t-1}$	–0.1051**	–0.0992*	–0.0465	–0.0466
	(0.041)	(0.073)	(0.535)	(0.531)
$\text{Business model}_{t-1}$	0.0048	0.0191	0.0435*	0.0427*
	(0.938)	(0.766)	(0.088)	(0.074)
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)
Bond ratio * Bottom half of size			–0.2241	
			(0.690)	
Disagreement * Bottom half of size				0.2778**
				(0.040)
Bank FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Cluster at bank level	YES	YES	YES	YES
No. of obs.	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. Variables controlling for the different types of risk (*UTD CDS*, *Leverage* and *Loan loss reserves*) are substituted by the *Probability of default* and the *CDS spread volatility* in regression specifications (1) and (2), respectively. Regression specification (3) and (4) control for a relationship between bank size, the hedging and speculation motive respectively by means of interaction variables. Constant term is included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***,**,* indicate statistical significance at the one-, five- and ten-percent level.

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 fragmentation	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)
Disagreement	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)
$\text{Loan loss reserves}_{t-1}$	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 at bank level	YES	YES	YES	YES	YES	YES	YES
No. of obs.	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) adds the one-year lagged slope of the yield curve, specification (2) controls for the change in a country's GDP, specification (3) employs the government deficit to GDP, regression specification (4) includes foreign exchange returns, specification (5) controls for the inflation rate, regression specification (6) adds the development of the domestic credit market and 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. ***,**,* indicate statistical significance at the one-, five- and ten-percent level.

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 fragmentation	0.0701*	0.0544	0.0730*
	(0.075)	(0.142)	(0.068)
Disagreement	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)
$\text{Loan loss reserves}_{t-1}$	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)
$\text{Liquid assets}_{t-1}$	–0.0443	–0.0395	–0.0660
	(0.551)	(0.591)	(0.345)
$\text{Business model}_{t-1}$	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)	
Sock trading volume			0.0019*
			(0.085)
Bank FE	YES	YES	YES
Time FE	YES	YES	YES
Cluster at bank level	YES	YES	YES
No. of obs.	408	408	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) adds a dummy variable indicating whether a bank from our sample is categorized as a global systemically important bank (G-SIB), specification (2) employs a dummy variable indicating the affiliation of a bank to the regional CDS main index and regression specification (3) controls for a bank's stock trading volume. Constant term is included but not reported. Heteroscedasticity consistent P-values are in parenthesis. ***,**,* indicate statistical significance at the one-, five- and ten-percent level.

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 fragmentation	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 Loan loss reserves_{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 stock trading volume	0.0019	16.9084 mio. USD

This table shows the economic materiality of all statistically significant variables from our regressions (except robustness checks). As regards the dummy variables, the average ceteris paribus increase or decrease in the CDS net notional is presented when the dummy variable takes on the value of one. The average ceteris paribus increase or 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

The bond fragmentation measure is constructed following Oehmke and Zawadowski (2016). For this purpose, the Herfindahl-Hirschman-Index (HHI) of each bank's outstanding bond j in our sample is calculated 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 thenatural logarithm of a bank's outstanding bonds.[15] 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 toCDS 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

The estimation of the upper tail dependence coefficient follows the nonparametric approach

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

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 distribution. Let (X_1, X_2) be two random variables with continuous distribution functions 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 $\overline{\mathbb{R}}_+^2$ as

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

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 $\left(X^{(1)}, Y^{(1)}\right), \dots, \left(X^{(n)}, Y^{(n)}\right)$ 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

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

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

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

with

$$\tilde{F}_n = \frac{1}{n}\sum_{j=1}^{n} \mathbb{1}_{\{X^{(j)}>x \text{ and } Y^{(j)}>y\}}, \tag{6}$$

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

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

$$\tilde{\lambda}_{U,n}(x,y) = \frac{n}{k}\tilde{C}_n\left(\frac{kx}{n}, \frac{ky}{n}\right) \approx \frac{1}{k}\sum_{j=1}^{n} \mathbb{1}_{\left\{R^j_{n,X}>m-kx \text{ and } R^j_{n,Y}>m-ky\right\}}, \tag{7}$$

with some parameter $k \in \{1, \dots, n\}$ which is chosen by the use of a plateau-finding algorithm.[16] As mentioned above, the upper tail dependence coefficient is then obtained by calculating $\tilde{\lambda}_{U,n}(1,1)$.

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