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The determinants of global bank credit-default-swap spreads

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Abstract

Using a sample of 161 global banks in 23 countries, we examine the applicability of structural models and bank fundamentals to price global bank credit risk. First, we find that variables predicted by structural models (leverage, volatility, and risk-free rate) are significantly associated with bank CDS spreads. Second, some CAMELS indicators, including asset quality, cost efficiency, and sensitivity to market risk, contain incremental information for bank CDS prices. Moreover, leverage and asset quality have had a stronger impact on bank CDS since the onset of the recent financial crisis. Banks in countries with lower stock market volatility and/or more financial conglomerates restrictions tend to have lower CDS spreads. Deposit insurance appears to have an adverse effect on CDS spreads, indicating a moral hazard problem.

Keywords: Bank credit default swaps, structural models, CAMELS, global banks

JEL code: G21, G13, G15

The Determinants of Global Bank Credit-Default-Swap Spreads

1. Introduction

Banks took center stage during the recent global financial crisis, which prompted efforts to develop early warning systems that could identify institutions likely to default. As the recent financial crisis shows, one warning sign could be widening credit default swap (CDS) spreads, which usually reflect increased financial stress and default risk, making them early indicators of real failures. In this paper, we explore the determinants of CDS spreads for banks around the world. Are the variables predicted by the structural models, which usually apply to *nonfinancial* firms, also relevant for pricing bank CDS? Do financial-soundness indicators (CAMELS ratings, in particular) have incremental explanatory power for bank CDS spreads? Around the world, what economic, institutional, and regulatory factors explain the variations in bank CDS spreads?

CDSs, especially corporate CDSs, have received a lot of attention in academia and the business world since the emergence of new derivatives in the late 1990s. CDSs with banks as the underlying reference entities attracted somewhat delayed but heated attention after the financial crisis. Specifically, market observers have noted that bank CDS spreads reflect banks' default risk during the crisis. However, it is still not clear what determines CDS spread levels across banks around the world.

Researchers widely use structural models to price credit risk in corporations. Specifically, leverage, volatility, and risk-free rates are significant determinants of the levels of and changes in corporate yield spreads (Duffee, 1998; Collin-Dufresne et al., 2001, etc.). Benkert (2004) shows that the structural model can also apply to CDS pricing. Ericsson, Jacobs, and Oviedo (2009) find that leverage, volatility, and the risk-free rate are major determinants of corporate CDS premia using a sample of 94 North American companies from 1999 to 2002. They find that the explanatory power of the theoretical variables for CDS spreads of industrial firms is approximately 60%, which provides further evidence of the credit-spread puzzle indicating that structural variables can only explain a moderate portion of credit-spread variability (Huang and Huang, 2012; Collin-Dufresne et al., 2001). It is suggested that adding the common systematic risk component and the default probability over business cycles may help to overcome the restraints of the time-invariant assumptions in the structural models (Collin-Dufresne et al. 2001; Chen et al., 2009).

Traditionally, researchers exclude banks from empirical investigations in the credit risk literature. Due to special business models, asset-liability structures, and regulatory requirements on capital adequacy, the leverage ratios of banks are generally high and lack in variation. Such limited variation in leverage could exaggerate the credit-spread puzzle in the banking industry. However, some banks may choose to hold additional levels of capital buffers in excess of the regulatory requirement and hence have lower leverage to reduce the probability that they have to raise costly equity or suffer from exogenous shocks in case they occur (Barth, 2006; Berger et al., 1995; Brewer et al., 2008; Diamond and Rajan, 2000; Flannery, 1994; Tian, Yang, and Zhang, 2013). Therefore, banks can have optimal leverage ratios cross-sectionally just as nonfinancial firms do. In addition, it has been argued that banks increased their leverage substantially since the lending boom of the early 2000s, which fueled the run-up to the sub-prime crises. Hence, there should be also time-series variations in bank leverage over the past decade. It is ultimately an empirical question to determine whether the relevance of leverage in explaining firm credit risk carries over to financial institutions.

However, the empirical evidence on capital structure outside the U.S. banking industry is limited due to the data availability. Annaert et al. (2013) shows that the Merton-model variables can explain bank credit-spread changes for 31 EU banks. One concern with their empirical estimations is that they use the bank stock return as a proxy for financial leverage. In fact, stock return fails to serve as a direct measure of bank's debt-equity level since it captures both upside and downside movements that might be totally unrelated to the bank capitalization.

In our paper, we construct the market-value based leverage following the credit risk literature, and we examine whether structural variables can explain CDS spreads for financial firms. We find that all three variables are statistically and economically significant for bank CDS spreads and robust to our model specifications. To be specific, a standard deviation increase in *leverage* is associated with widening of CDS spreads by 110bp, and a standard deviation increase in *equity-return volatility* is associated with an increase in raw CDS spread of 175bps. However, the variables predicted by the structural model without controlling for time and bank fixed effects can explain only about 20% of the variation of bank CDS spreads, indicating that the credit-spread puzzle is more evident for banks than corporations.

Alternatively, bank regulators traditionally use the CAMELS rating system, which is based on ratio analyses of financial statements, to monitor banks' overall financial soundness.[1] A CAMELS rating should incorporate important information regarding bank fundamentals and credit risk. The literature finds that CAMELS indicators predict bank failures (e.g., King et al., 2006). For 22 European Large Complex Financial Institutions (LCFI) over 2004-2008, Otker-Robe and Podpiera (2010) find that business models, earnings potential, and overall economic uncertainty affect bank CDS spreads. However, they caution that the generalization of their results to other banks and countries might require adjustments since their analysis is for

[1] CAMELS stands for Capital adequacy, Asset quality, Management quality, Earnings potential, Liquidity, and Sensitivity to systematic risk.

European LCFI only, which have limited variations in many aspects.[2] Chiaramonte and Casu (2013) find that bank CDS spreads reflect the risk captured by some bank balance-sheet ratios for a sample of 57 banks, mostly European banks. They also find the accounting measure of leverage (equity/total assets) is not significant. Both studies point out the importance of CAMELS indicators, but they do not consider theoretical determinants of structural models and country-level factors.

With a large sample of 161 large, medium, and small financial institutions in 22 countries spanning 2001-2011, which encompasses both the pre-financial crisis and crisis periods, we test whether the earlier findings for CAMELS can be generalized to a wide range of global banks, and whether CAMELS have incremental explanatory power above and beyond the structural variables. We find that asset quality (measured by loan-loss provisions to total loans), management quality (measured by cost efficiency), and cost of funds (measured by interest expense to total liabilities) are significantly associated with bank CDS spreads, even controlling for structural model variables. Including both structural variables and CAMELS improves the model fit from 20% to 30%, suggesting that structural variables and CAMELS indicators contain complementary information about bank credit risk.

Because our cross-country sample varies widely in terms of economic development, institutions, banking structure, and regulations, we account for those country differences using GDP per capita, stock market volatility, yield slope, country governance, banking concentration, financial conglomerates restriction, entry barrier, and deposit insurance adoption. We find that stock market volatility, which reflects systematic risk and risk aversion, is indeed a significant determinant of bank CDS across countries. This result is also consistent with Tang and Yan

[2] They note that the book-value based leverage in their study is not significant due to its high persistence and little variation across the LCFIs during the sample period.

(2006) that manifest the significant impact of macroeconomic conditions on credit spread. The empirical literature on credit-spread puzzle relies mostly on time-series data within the U.S. nonfinancial firms. Our cross-country evidence supports the claim that adding the common systematic risk component helps to address the credit-spread puzzle in bank CDS.[3]

In addition, more stringent financial conglomerate restriction in a country is associated with narrower bank CDS spreads, consistent with the findings of Beltratti and Stulz (2012) that large banks from countries with more restrictions on bank activities perform better and cut back on lending less during the recent crisis. However, adopting explicit deposit insurance statistically and significantly increases banks' credit risk. This result is consistent with the "moral hazard" view that deposit insurance diminishes depositors' incentives and efforts to monitor bank activities, which in turn increases the likelihood of bank default.

Furthermore, we examine the impact of the financial crisis. Our regression confirms that global bank CDS spreads witness a dramatic widening since the onset of the recent financial crisis after controlling for bank and country factors. Moreover, leverage and asset quality have a much stronger impact on bank CDS spread after the crisis.

Our paper contributes to the CDS literature in several ways. First, we test the usefulness of structural variables for pricing bank credit risk. Earlier studies focus on CDS price drivers in industrial companies; we extend the literature by confirming the applicability of structural models to financial institutions. Second, we apply risk measures widely used in the banking industry, CAMELS variables, to examine whether they provide incremental information to price bank credit risk beyond structural variables. Third, our study is based on a comprehensive set of global banks over the past decade. The sample of international banks has greater cross-sectional

[3] In a related paper, Eichengreen et al. (2012) apply the principal component analysis to CDS spreads of 45 large global financial institutions. They find that the share of the variance accounted for by the common components is quite high before the financial crisis.

and time-wise variations relative to earlier studies that focus on a single country or region. Thus, our study should shed light on what drives global bank CDS spreads and whether those factors apply more broadly. In a related cross-country study, Beltratti and Stulz (2012) investigate how bank performance during the crisis is affected by accounting ratios and bank regulations before the financial crisis. While their paper uses during-crisis buy-and-hold stock returns to measure both upside and downside risk, our paper primarily focuses on the downside risk that is captured by the CDS spreads.

The remainder of this study is organized as follows. Section 2 reviews literature and develops the main hypothesis. Section 3 provides data descriptions. Section 4 discusses research methodology and presents our results. Section 5 concludes.

2. Hypothesis Development

CDS spreads are a direct and an excellent measure of default risk. The buyer pays a premium (the CDS spread), and the seller agrees to compensate the buyer for any loss in the event that the reference entities (corporations or banks) default. CDSs are homogeneous and standardized contracts. Unlike bonds, there is no need to select a benchmark risk-free interest rate to calculate the credit spread, and there are no short-selling restrictions. Liquidity and tax treatment also have less effect on CDS prices than on corporate bonds (Driessen, 2005). Moreover, several studies find that CDS spreads incorporate default-related information in an efficient way relative to the bond and stock markets and the rating agencies (Blanco et al., 2005; Hull et al., 2004; Fung et al. 2008; Norden and Weber, 2004; Rodríguez-Moreno and Pena, 2013).

A CDS contract allows sellers to collect annual payments, which are quoted in basis points, on a notional bond value of $10 million. In the event that the bond issuer defaults, the buyer will receive full compensation from the sellers. The CDS spread is thus an indicator of credit risk for the underlying entities. For example, the five-year CDS spread for Goldman Sachs widened by 23bp in 2011 from 115bp to 138bp. This means that a contract buyer will pay \$138,000 instead of \$115,000 every year for the next five years to insure \$10 million of Goldman debt against a default.

2.1. Structural Model Variables

Structural models of default by Merton (1974) offer an economically intuitive framework for credit-risk pricing and have been widely used to analyze corporate credit spreads. Default occurs when the value of its assets is below the default boundary at the bond's maturity. The value of a risky bond is related to the variance in the firm's return on assets and leverage, as well as to the variance in risk-free interest rates. Benkert (2004) shows that this theory also applies to CDS pricing. Ericsson et al. (2009) test the usefulness of the structural model in this way and find that all three factors are indeed important determinants of CDS spreads. The explanatory power of these three variables is about 50%-60%.

In general, however, banks have different asset and liability structures from corporations due to their different business models. Specifically, they rely on deposits and other sources to fund their assets. Therefore, their leverage ratios are considerably greater than those in other corporate sectors, and there is less variation among banks. On the one hand, the ability to draw on more deposits is a signal of greater growth potential. On the other hand, too much debt relative to equity can lead a bank to fail. So it is an empirical issue whether leverage is a significant determinant of credit risk in banks. Distinct from prior studies on bank CDS spreads that use the balance-sheet leverage ratio (e.g., Otker-Robe and Podpiera, 2010; Chiaramonte and Casu, 2013) or stock returns as a proxy for leverage (Annaert et al., 2013), we use the market-based financial leverage, defined as the book value of liabilities to the sum of the book value of liabilities and the market value of equity.

Following the empirical credit risk literature, we use equity return volatility to proxy for assets volatility, which is calculated as the historical standard deviation of bank's daily equity returns in a particular year. We expect that bank CDS spread is positively related to equity return volatility, which increases the default likelihood.

The 10-year government bond yield is used to proxy for risk-free rate (Ericsson et al., 2009).[4] Interest rates are positively related to economic growth and negatively related to default likelihood. Therefore a negative relationship is expected between risk-free rate and CDS spreads for a given country. However, the relationship could be positive across countries because banks have higher borrowing costs in countries with greater risk-free rates.

Although credit-risk modeling widely uses structural models, there is a so-called credit-spread puzzle; that is, the models are generally unable to explain why they fail to predict the high excess returns corporate bondholders historically receive (Huang and Huang, 2012; Collin-Dufresne et al., 2001). The puzzle suggests that either the assumption of time-invariant default probabilities and recovery rates of the Merton model need to be relaxed, or that factors other than default and recovery risk affect credit spreads. Factors could be the variability of risk premiums and the default probability over business cycles.

Collin-Dufresne et al. (2001) suggest that a single market-wide component is the driving force behind historical spreads. Chen, Collin-Dufresne, and Goldstein (2009) also show that the credit-spread puzzle can be addressed by adding factors that explain the equity-premium puzzle, such as common systematic risk factors. The credit-spread puzzle in the context of bank credit spread could be more pronounced and more challenging to address, however.

[4] We also use 2-year and 5-year yields for robustness check. Results are similar.

In turn, we first test whether the factors predicted by structural models are significant determinants of bank CDS spreads. We then attempt to investigate what additional factors explain credit spreads for banks.

2.2. CAMELS Indicators

Due to the differing business models between banks and non-financial firms, a bank's loan quality, capital adequacy, asset liquidity position, and cost of funds, among other things, may provide incremental information about its credit risk. Therefore, we account for bank fundamentals using the CAMELS rating system, which bank supervisory authorities traditionally use to classify a bank's overall condition and predict bank failures (Cole and White, 2011; Jin, Kanagaretnam, and Lobo, 2011) . Moreover, we examine whether these bank fundamentals have incremental explanatory power beyond the structural variables.

The six factors of CAMELS system are capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk. The system helps regulators identify banks that need attention. The ratings are not public (to prevent bank runs when institutions receive CAMELS rating downgrades). Institutions with deteriorating situations and declining CAMELS ratings are subject to ever-increasing supervisory scrutiny. Failed institutions are eventually resolved via a formal resolution process designed to protect retail depositors. Although there are several measures to proxy for each element of the CAMELS indicators, we select the most commonly used with the highest number of observations to avoid multicollinearity problems.[5]

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[5] For example, loan-loss provisions to total loans and nonperforming loans ratios are both proxies for asset quality. Their correlations are 47.5%, which is significant at the 1% level. As the first variable has 707 observations and the second has only 630 observations, we use loan-loss provisions in our main analysis. As a robustness check, we also conduct analysis using an alternative set of CAMELS variables, including Tier 1 capital ratios, share of nonperforming loans to total loans, the trading income to total revenue ratio, ROA, and the wholesale funds to total liabilities. The results are similar.

For these reasons, capital adequacy is crucial. It provides a cushion against fluctuations in earnings so that banks can continue to operate in periods of loss. It also supports growth as a free source of funds and provides protection against insolvency. In addition to meeting regulatory capital requirements, maintaining additional capital beyond the statutory requirements is critical for banks to survive during a crisis and better cope with exogenous shocks (Tian, Yang, and Zhang, 2013). Thus, capital adequacy should be a critical determinant of bank credit risk. Accordingly, we use *Z-scores* to measure capital adequacy. Z-score equals the return on assets plus the capital-asset ratio, divided by the standard deviation of asset returns. We expect that Z-score is correlated negatively with the bank CDS spread (i.e., banks with more capital have lower credit risk).

Asset quality measures the quality and trends of all major assets of a bank, such as loans, investments, and other assets that could adversely affect a bank's financial condition. It assesses the bank's management of credit risk, such as the quality of loan underwriting, the ability to properly administer its assets, and the timely collection of problem assets. We use *loan-loss provisions to total loans* to proxy for asset quality. Banks with higher asset quality (lower loan-loss provisions for a bank's problem loans) should have lower credit risk and therefore lower CDS spreads.

Management quality assesses whether a bank can correctly diagnose and respond to financial stress. Quality management can better identify, measure, monitor, and control the risks of a bank's activities and ensure its safe and sound operation with lower credit risk than other banks, all else equal. We use *cost efficiency*, which is the ratio of operating expenses to total revenues, as a proxy for management quality. We expect this ratio to be negatively related to bank CDS spreads.

Earnings reflect a bank's income-producing ability. It is essential for a bank to remain viable, fund growth, and sustain and increase capital. Therefore, a bank with higher return on its assets/equity is probably more financially sound and has lower default risk. We use *ROE* (return on equity) to measure earnings potential. Banks with higher earnings potential should have lower CDS spreads.

Liquidity enables a bank to meet present and future cash flow needs efficiently without adversely affecting daily operations, funding needs, liabilities payments, and survival. We use *liquid assets to total assets* as proxies for bank liquidity. Presumably, a higher liquid asset ratio should be negatively related to CDS spread. Thus, we expect that CDS spreads correlate negatively with *liquid assets to total assets*.

The last element of the CAMELS system is sensitivity to market risk, especially interest-rate risk, which is the sensitivity of all loans and deposits to relatively abrupt and unexpected shifts in interest rates. We use the ratio of interest expense to total liabilities to measure the bank's liability funding costs as a proxy for interest rate risk. Banks with higher *cost of funds* are more sensitive to changes in interest rates and therefore are more vulnerable to changes in market conditions. A higher *cost of funds* may also indicate that a bank has problems in maintaining liquidity and needs to take higher risks in order to cover funding costs. Therefore, we expect that banks with high *cost of funds* have higher CDS spreads.

Taken together, we expect that banks with lower CDS spreads have higher capital adequacy, asset quality, management quality, earnings potential, liquidity position, and lower sensitivity to market risk.

2.3. Country-Level Economic, Governance, and Regulation Factors

Our sample includes a number of countries that are likely to have different business cycles and systematic risk, which should affect credit risk levels and credit risk premia in general and bank CDS spreads in particular. Moreover, banking performance, stability, structure, and regulations are often correlated with economic development (Demirguc-Kunt, Laeven, and Levine, 2004; La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998). Therefore, we control for economic-development and market-condition differences across countries using the natural log of GDP per capita, country governance indicator, stock market volatility, and yield slope. We use the country in which a bank is incorporated to assign the country-level variables.

GDP per capita is from the World Development Indicator database (WDI).[6] *Country governance indicator* is from the Worldwide Governance Indicators dataset. Countries with higher GDP per capita are expected to carry lower country risk. We also expect that banks in countries with better governance make better risk-taking decisions and have lower default probability (Beltratti and Stulz, 2012). *Stock market volatility* is the historical standard deviation of a country's stock index in a particular year. Lower stock market volatility indicates less economic uncertainty, lower default risk, and credit risk premia (Tang and Yan, 2010). *Slope of the yield curve* is calculated as the difference between the return on 10-year government bonds and the return on two-year government bonds. A higher slope of the yield term structure is generally associated with better economic growth prospects and lower default risk. Therefore, we expect banks to have lower CDS spreads if they are domiciled in a country with higher GDP, lower stock market volatility, and higher slope of yield.

Finally, we also include in our analysis bank concentration, regulation and restriction, and deposit-insurance systems. We measure *bank industry concentration* as the fraction of bank

[6] We also use *GDP growth rate* to replace *GDP per capita*, which is not significant in all regressions, and so we report results for regressions using *GDP per capita*.

assets held by the five largest commercial banks in the country. We compute this using the Bankscope database.[7] Banks would earn monopoly rents in more concentrated banking systems and thus are less likely to take more risks (Gorton and Rosen, 1995). However, more concentrated banking systems could also carry greater systemic risks. Indeed, Beltratti and Stulz (2012) find that the worst-performing banks during the financial crisis come from countries with higher bank concentration. So it is an empirical question to test the relationship between bank concentration and CDS spreads.

Following Barth et al. (2004, 2006, 2008), we use two measures to proxy for a country's bank regulation and restriction. The first variable, *financial conglomerates restriction*, measures the extent to which banks may own and control nonfinancial firms, the extent to which nonfinancial firms may own and control banks, and the extent to which nonbank financial firms may own and control banks. A higher index value indicates that the country's banking regulation favors traditional banking rather than financial conglomerates. The second variable, *entry barrier*, is the fraction of bank entry applications denied. Lax regulation would lead banks to take more risks and undergo poor performance. Beltratti and Stulz (2012) find that the better-performing banks come from significantly more tightly regulated countries (more restrictions on banking activities), so we expect a negative relationship between bank CDS spreads and restriction.

The last variable is the deposit insurance scheme, which aims to prevent banking runs and promote financial stability, but which may also lead to moral hazard problems. Our information on deposit insurance is collected from the "Comprehensive Deposit Insurance

[7] Considering that the Bankscope coverage increases over the sample period, the change in coverage might drive the change in concentration measure. To mitigate such biases, we use an alternative measure of concentration in an unreported test by averaging the annual concentration value over the sample period. The results remain robust. In addition, our results remain unaffected after using other measures of concentration, such as the fraction of bank deposits held by the three largest commercial banks or the HHI of bank assets (or deposits) in a given country.

around the World" dataset of the World Bank and the 2010 annual survey results of International Association of Deposit Insurers (IADI, www.iadi.org). We construct a dummy variable, *Explicit*, which equals 1 if a country has an explicit deposit insurance system, and 0 otherwise. The deposit insurance system can lead to banks taking higher risks, so its relationship with bank CDS spread is ambiguous.

3. Data

Our bank CDS spread data is from MarkIt, which provides comprehensive coverage for over 3,000 firms and banks around the world. This database is widely used for research on CDSs. Because CDSs are over-the-counter contracts, their maturities are negotiable; they range from a few months to 10 years or more, although five years is the most common horizon. In this paper, we use only five-year spreads because these contracts are the most liquid and constitute over 85% of the entire CDS market.

We then carefully match the name of the bank CDS entities to Fitch-IBCA Ltd's Bankscope via a combination of algorithmic matching and manual checking.[8] Bankscope provides the most comprehensive bank-level world-wide data set with balance sheet and income statement information for both public and private banks across a wide range of countries.

These procedures render a sample of 968 bank-year observations for 222 banks in 26 countries from 2001 to 2011.[9] The lack of bank stock return data in some cases reduces the sample to 707 bank-year observations for 161 banks in 23 countries during the sample years. As stock return volatility and leverage are key determinants of CDS spreads according to the structural model, most of our analysis is based on this main sample (707 observations). We also

[8] Matching global bank CDS and Bankscope data is based on bank name and a series of identification information, such as country, state, city, etc.

[9] Our analysis is conducted in bank-year observations because, unlike the Fed's Call Report data, the BankScope dataset only has annual frequency. It therefore limits our key explanatory factors such as structural variables and CAMELS variables to a yearly basis.

conduct robustness checks using the expanded sample of 968 observations for the models with no structural variables.

As discussed, CAMELS ratings consider capital adequacy, asset quality, management quality, earnings potential, liquidity, and sensitivity to market risk. We use Z-score to measure capital adequacy, loan-loss provisions as a percentage of total loans to measure quality of bank assets, cost efficiency to proxy for management quality, ROE to capture earnings potential, and liquid assets as a percentage of total assets to gauge liquidity/funding position.[10] Then we use alternative indicators for each CAMELS category as a robustness check.

Table 1 displays the distribution of our main samples by year, region, and bank specialization. With the growth of the CDS market, the number of observations increases from 20 banks in 2001 to 100 in 2007 and 2008. The number declines after 2008, likely due to CDS market consolidation after the financial crisis. The sample coverage of 23 countries spans the following regions (with the number of banks in brackets): Africa (1), Asia Pacific excluding Japan (17), Australia (11), EU (53), Eastern Europe (5), Japan (23), and North America (51). The United States has 46 banks in our sample, followed by Japan with 25 banks, Italy with 13 banks, Germany with 11 banks, and Australia with 10 banks. Other countries have fewer than 10 banks, including China, which has four banks in our sample.

[Insert Table 1 here]

Panel A of Table 2 presents summary statistics for key variables in the regressions. In our sample, the average year-end CDS spread is 195 basis points (and the median is 75 basis points). The standard deviation reaches over 500, showing the vast variation between good times when banks' credit risk was negligible and the crisis period when banks' credit risk skyrocketed. We

[10] The Z-score measures the distance from insolvency. It is inversely related to bank insolvency risk, that is, whether banks have enough capital to deal with potential loss (Laeven and Levine, 2010).

also calculate the average of CDS spread for each year as an alternative; the mean and median are 175 and 81, respectively. The statistics of Cook's D suggest that there are no highly influential data points for CDS spread worth checking for validity. The average bank leverage is 90%. The daily equity-return volatility has an average of 2.69%. The average 10-year government bond yield is 3.62%.

In terms of bank CAMELS indicators, we find that the banks are mainly large or medium and that the mean (median) book value of their assets is $428 billion (median is $132 billion). In our sample, 41% of banks are commercial banks. On average, a sample bank has a Z-score of 21.24, loan-loss provisions to total loans of 0.02%, cost efficiency of 63.12%, ROE of 0.04, and liquid assets to total assets of 15%. The average cost of funds is 2.33%.

The table also shows great variation in terms of bank characteristics, key country economic and governance indicators, bank concentration structure, regulation and restriction variables. 93% of observations in our sample are in countries with explicit deposit insurance schemes.[11] All these values are comparable with prior studies (e.g., Laeven and Levine, 2010; Houston et. al., 2010; Beltratti and Stulz, 2012).

[Insert Table 2 here]

Panel B presents a correlation matrix of structural variables and CAMELS indicators. Among the significant correlation relationships, *leverage* is negatively correlated with *loan-loss provisions to total loans* and positively related to *equity-return volatility*, *cost efficiency*, and *liquid assets to total assets*. *Equity-return volatility* is negatively correlated with *government bond yield, Z-score, ROE, liquid assets to total assets*, and it is positively correlated with *loan-loss provisions to total loans, cost efficiency*, and *cost of funds*. *Government bond yield* has a positive correlation with *Z-score* and *cost of funds*, and negative correlation with loan-loss

[11] Australia, China, South Africa, and Thailand do not have explicit deposit insurance.

provisions and ROE. Among CAMELS indicators, Z-score is negatively related to *loan-loss provisions to total loans* and *cost efficiency*, but its correlation with *ROE* is positive. *Loan-loss provisions to total loans* is negatively related to *cost efficiency*, *ROE*, and *liquid assets to total assets*. Finally, *cost efficiency* has negative correlation with *ROE* and a positive correlation with *liquid assets to total assets*. We test the potential issue of multicollinearity problems in our regressions, but find the Variance Inflation Factors (VIF) are all below 8. Thus, we include both structural variables and CAMELS indicators in our specifications.

4. Empirical Methods and Results

We conduct a multivariate panel data regression with the natural log of CDS spread as the dependent variable, which is stationary using the unit-root test. Independent variables include bank structural variables, CAMELS indicators, and country economic and regulation variables as control variables. The model is as follows:

$$CDS_{i,t} = \alpha + \beta X_{i,t} + \gamma Y_{i,t} + \lambda Z_t + \varepsilon_{i,t} \qquad (1)$$

where *CDS* is the natural log of *CDS spread* for bank *i* at year *t*; *X* represents the structural variables predicted by theory, leverage, volatility, and risk-free rate for bank *i* at year *t*; *Y* represents the CAMELS indicators for bank *i* at year *t*; and *Z* represents country-level economic and governance indicators, bank industry concentration level, and bank regulation variables at year *t*. Our data is a pooled time series and cross-sectional unbalanced panel data. We use bank fixed effect to account for unobserved time-invariant bank characteristics and time fixed effect to account for unobserved time-varying factors. Moreover, CDS spreads for a given country are likely correlated over time; hence, we adjust for country clustering effect, following Petersen (2009).

Our analysis proceeds in step wise approach. We start with the model with structural variables only, then move to the model with CAMELS indicators only. Then we test the model with both structural variables and CAMELS variables. Finally, we include country-level variables to account for variation across countries.

4.1. Models with Structural Variables Only

The structural model (Merton, 1974) links the prices of credit-risky instruments directly to the economic determinants of the likelihood of default (i.e., financial leverage, volatility, and the risk-free term structure). To examine the explanatory power of the structural variables, we also report a panel regression without the time and bank fixed effects.

Panel A of Table 3 reports the regression results for leverage only. In Model 1 in which the dependent variable is the year-end CDS spreads and no fixed effects are controlled, the coefficient on the market value based leverage measure is 0.031 (t=3.22), consistent with the prediction by structural model. Similarly, the coefficient is 0.029 (t=2.73) when the dependent variable is the average of CDS spreads over a year. Models 3-4 control for year and bank fixed effect, in which leverage remains positively related to the log of year-end CDS spread and the log of year-average CDS spread. While banks have a narrower leverage distribution than corporate firms, leverage appears a significant determinant of CDS spreads.[12] Thus our initial evidence suggests that a bank with higher leverage is associated with greater credit risk, and leverage is useful to price credit risk not only for industrial firms, but also for financial institutions.

[12] As shown in Table 2, the average of leverage ratio for our sample banks is 0.90, with standard deviation of 0.09. The 1st and 99th percentile values are 0.56 and 0.99. This is in contrast to the wide leverage-ratio distribution for corporate entities. For example, Ericsson et al. (2009) report that the average leverage for the corporations in their sample is 0.52. Their 5th and 95th percentile values are 0.23 and 0.80, respectively.

Next, we investigate all three variables predicted by structural models in Panel B. *Leverage* is positive and significant in Models 1-4. In terms of economic magnitude, a standard deviation increase in *leverage* is associated with an increase in CDS spread of 110bps (=the exponential of (0.014×6.74)) in Model 1. The coefficients for *equity-return volatility* are positive and strongly significant across the four models, confirming that banks with higher volatility have higher CDS spreads. The economic magnitude is also significant. For example, a standard deviation increase in *equity-return volatility* is associated with an increase in CDS spread of 175bps (=the exponential of 0.308×1.83) in Model 1.

Although Ericsson et al. (2009) find a negative coefficient for the government bond yield for a sample of U.S. industrial firms, we find positive coefficients in Models 3-4 in which time and bank effects are controlled for. Note that Ericsson et al. (2009) consider only U.S. firms, so the coefficient should capture the time-series variation in the U.S. bond yield. In contrast, our sample covers a wide range of countries, so the coefficient on the bond yield should capture cross-sectional variation after the model accounts for the time effect. Banks in countries with higher government yields, and thus higher cost of funds, are likely to have higher CDS spreads. An alternative explanation is that there is a spillover effect from sovereign bonds to bank bonds.

In terms of model fit, the structural variables per se explain approximately 22% of the variation in the log of year-end CDS spreads in model 1, corroborating earlier evidence that structural models can only explain a limited percentage of spread variation. In comparison, the structural model explains 52%-66% of corporate CDS spreads in Ericsson et al. (2009). This suggests that the credit-yield puzzle is more pronounced for banks than for industrial corporations. After controlling for the time and bank fixed effect, the adjusted R-squared increases to 60%. Therefore, incorporating time-varying factors and cross-sectional variations should help to resolve the credit-spread puzzle.

[Insert Table 3 here]

4.2. Models with CAMELS Indicators Only

Next, we investigate whether bank CDS spreads can timely reflect CAMELS indicators. We expect that banks with higher capital adequacy, asset quality, management quality, earnings potential, and liquidity have lower CDS spreads, and that banks with greater sensitivity to market risk have higher CDS spreads. Table 4 presents the results. Models 1-4 are based on the main sample and Models 5-6 are based on the expanded sample.

The coefficients on *loan-loss provisions to total loans ratio*, *cost efficiency*, and *cost of funds* are all positive and significant across most models. *ROE* is negatively related to log of the CDS spread. Liquidity is not significantly related to CDS spreads when the bank and time fixed effects are accounted for. The adjusted R-squareds of Models 1 and 2 using the six CAMELS indicators are about 20%, comparable to the explanatory power of three structural variables in Table 3 (Model 1). For the expanded sample, bank CDS spreads are significantly associated with *loan-loss provisions to total loans ratio* and *cost of funds.*

[Insert Table 4 here]

4.3. Models with Both Structural Variables and CAMELS Indicators

To show whether the accounting variables provide incremental explanatory power in addition to the structural variables, we include both structural variables and CAMELS indicators in the regressions as shown in Table 5. Several observations are noted.

First, *leverage* and *volatility* are positive and significant, which is robust to model specification. *Government bond yield* is positive and significant when the time effect is controlled for, consistent with the Table 3 result. Second, among accounting variables, the impact of *loan-loss provisions* is positive and significant across all models. Using the year-end CDS spreads and year-average CDS spreads provide similar results. Third, for the panel regression with no fixed effects in Models 1 and 2, the adjusted R-squareds are 0.30 and 0.36, respectively, which are about 50% higher than when only structural variables or only CAMELS elements are used. Therefore, we could improve the model fit by incorporating both the market information impounded in structural variables and the bank fundamentals, especially asset quality.

[Insert Table 5 here]

4.4. Models Controlling for Cross-Country Variation in Economic Factors, Bank Concentrations, and Regulations

Because our sample is based on 161 banks across 23 countries in different regions, we need to control for the impact of country-level factors. Key country economic indicators in our analysis include log of GDP per capita, country-level stock market volatility, country governance, slope of bond yield, bank concentration, bank regulation proxied by financial conglomerate restriction and entry barriers, and the adoption of explicit deposit insurance.

In Model 1 for the main sample, we find that the results on three structural variables hold after controlling country and bank regulation factors. In addition, some country-level variables affect bank CDS spreads. Banks generally have higher CDS spreads in a country with greater stock market volatility, fewer financial conglomerate restrictions, and explicit deposit insurance scheme. Our results provide cross-country evidence that systematic risk and risk premia in a country, as proxied by stock market volatility, is important for credit risk pricing for global banks.

In terms of bank regulation, we find that banks in countries with greater restrictions face lower default risk, consistent with the findings of Beltratti and Stulz (2012) that banks in countries with more restrictions on bank activities perform better and decrease loans less during the recent crisis. The coefficient on *explicit deposit insurance dummy* is positive and significant at the 1% level. Deposit insurance is generally intended to protect the country's banks by avoiding bank runs. However, it may also lead to moral-hazard problems. Because banks have limited downside risk and unlimited upside potential with the protection of deposit insurance, they may take greater risks and reduce the capital available to generate more profits.[13] The positive sign of *explicit deposit insurance dummy* suggests that the adverse impact from moral hazard dominates its intended positive impact of promoting financial stability.

We include CAMELS variables in model 2. Among CAMELS, Loan loss provisions, cost efficiency, and cost of funds are significant and have the expected sign.

In Model 3 for the expanded sample, government bond yield, bank loan-loss provisions, and cost of funds remain significant determinants of bank CDS spreads. The coefficients on the three country-level factors, *stock market volatility*, *financial conglomerates restriction* and *explicit* are both economically and statistically significant.

[Insert Table 6 here]

4.5. The Impact of Crisis

To investigate the impact of the financial crisis on determinants of bank CDS spreads, we add a dummy variable, *crisis*, and the interaction terms in our model. *Crisis* equals 1 if the sample year is 2007 or after; it equals 0 otherwise. The structural variables and CAMELS indicators are interacted with *crisis*. To avoid multicollinearity problems, we demean main

[13] Beltratti and Stulz (2012) find that the banks in countries with a formal deposit insurance regime have higher idiosyncratic risk.

variables by subtracting the mean from the raw value before constructing the interaction terms. The results are presented in Table 7.

[Insert Table 7 here]

In Model 1 for the main sample, the coefficient on the banking *crisis* variable is positive and significant (1.216, t=2.404), confirming that the bank CDS spread is significantly higher since the onset of the financial crisis. The coefficient on the interaction term between *leverage* and *crisis* is positive and significant (0.015, t=2.339), suggesting that the adverse impact of leverage on CDS spreads during the crisis is stronger than the pre-crisis period. So there is an additional widening of CDS spreads for banks with high leverage during the financial crisis. We also find that the coefficient on the interaction term between *loan-loss provisions* and *crisis* is positive and strongly significant. So the impact of asset quality plays a substantially more important role with the onset of the recent financial crisis, which also holds for the expanded sample as shown in Model 2.

5. Conclusion

Global banks experienced a relatively stable period over the first half of the 2000-2010 decade, though turmoil of course eventually ensued. For this reason, credit default spreads for banks, which are excellent measures of default risk and early warning signals, deserve more research efforts.

Existing studies investigate the determinants of U.S. corporate bond-yield spreads and CDS spreads. However, banks differ from corporations in their business models and risk-taking behaviors and regulations, among other things. It is not clear, therefore, whether structural models apply to financial firms. Prior studies that focus on bank CDSs in a country, region, or certain period likely involve samples with very little variation in bank fundamentals and market environments.

Our study evaluates the effects of both structural variables and balance-sheet ratios on bank CDS spreads, while controlling for business, market conditions, and regulation environment over time and across countries. Based on a panel data of 161 bank CDS spreads across 22 countries, we find that the market-value based leverage measures, equity return volatility, and government bond yield are all significant determinants of bank credit risk. This lends support to the applicability of structural models for financial institutions. However, the low model fit with structural variables of about 20% suggests that the credit spread-puzzle is more pronounced for financial firms than industrial firms. CAMELS indicators provide incremental explanatory power beyond structural models. A model fit with both structural variables and CAMELS indicators reaches 30%. Asset quality is the most significant determinant of bank CDS spreads after controlling for time and bank fixed effect.

In addition, stock market volatility is positively and significantly associated with bank CDS spreads, which provides cross-country evidence that systematic risk and risk aversion are important in pricing bank credit risk. Financial conglomerate restriction is negatively related to bank CDS spreads, implying that competition helps to reduce bank credit risk. Banks in countries with deposit insurance tend to have higher CDS spreads. This is likely due to more risk-taking behaviors. With time and bank fixed effects, our model fit increases to 60-80%. So cross-bank variations in systematic risk and some unobserved time-varying factors have important explanatory power for bank CDS spreads. Furthermore, we investigate the impact of the recent financial crisis on bank credit risk. The impacts of leverage and asset quality on CDS spreads are much stronger for banks during the crisis.

Taken together, our study sheds light on the applicability of structural models and bank fundamentals to price global bank credit risk. This study should help policymakers around the world develop early warning systems and associated supervisory norms for financial institutions.

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Table 1. Sample Distribution

The sample is from 2001 to 2011 and includes 161 banks (707 bank-year observations) in the main sample; it includes 222 banks (968 bank-year observations) in the expanded sample. Banks in the expanded sample have no stock return data available.

Panel A: Sample Distribution by Year

	Main Sample		Expanded Sample	
Year	**N. of Bank-year Obs.**	**Percentage**	**N. of Bank-year Obs.**	**Percentage**
2001	20	2.83%	24	2.48%
2002	25	3.54%	33	3.41%
2003	39	5.52%	55	5.68%
2004	46	6.51%	58	5.99%
2005	62	8.77%	86	8.88%
2006	84	11.88%	116	11.98%
2007	100	14.14%	140	14.46%
2008	100	14.14%	139	14.36%
2009	92	13.01%	130	13.43%
2010	85	12.02%	118	12.19%
2011	54	7.64%	69	7.13%
Total	707	100.00%	968	100.00%

Panel B: Distribution by Region

	Main Sample		Expanded Sample	
Region	**N. of Bank-year Obs.**	**N. of Banks**	**N. of Bank-year Obs.**	**N. of Banks**
Africa	2	1	2	1
Asia Pacific	50	17	58	20
Australia	34	11	59	13
EU	206	53	322	84
East Europe	24	5	36	10
Japan	111	23	138	27
Latin America			2	2
USA/Canada	280	51	351	65
Global	707	161	968	222

Panel C: Distribution by Bank Specialization				
	Main Sample		Expanded Sample	
Calendar Year	**N. of Banks**	**% of Banks**	**N. of Banks**	**% of Banks**
Commercial banks	79	49.07%	105	47.30%
Banking holding companies	45	27.95%	50	22.52%
Finance companies	11	6.83%	16	7.21%
Cooperative banks	8	4.97%	12	5.41%
Investment banks	7	4.35%	10	4.50%
Real estate & mortgage banks	5	3.11%	10	4.50%
Specialized government credit institutions	2	1.24%	11	4.95%
Savings banks	2	1.24%	4	1.80%
Securities firms	2	1.24%	3	1.35%
Investment & trust			1	0.45%
Total	161	100.00%	222	100.00%

Table 2. Summary Statistics

This table presents summary statistics for CDS five-year spreads; structural variables; CAMELS indicators; and country economic, governance, and regulation variables in Panel A. Panel B presents a correlation matrix for the main variables. Variable definitions and data sources are in the appendix.

Panel A: Summary Statistics

Variable	N	Mean	Median	Std.dev.	P1	P99
CDS Spread_Year End (basis point)	707	194.50	74.50	510.07	7.75	1979.25
CDS Spread_Mean (basis point)	707	175.41	81.22	500.92	11.27	1328.67
Bank assets($mil)	707	428,998	132,351	616,327	1,239	2,542,739
Commercial bank dummy	707	0.41	0.00	0.49	0.00	1.00
Structural Model Determinants						
Leverage (%)	707	89.96	90.11	6.74	66.29	99.18
Equity volatility	707	2.69	2.14	1.83	0.36	9.24
Government bond 10-year yield	707	3.62	3.84	1.62	1.13	8.21
Bank CAMELS Indicators						
Capital Adequacy						
Log(Z-score)	707	2.48	2.50	1.02	0.01	5.15
Tier 1 capital ratio	557	0.10	0.09	0.04	0.05	0.31
Quality of Bank Assets						
Loan-loss provisions to total loans	707	0.02	0.01	5.03	0.05	25.45
Share of nonperforming loans to total loans	630	3.70	2.22	5.03	0.05	25.45
Quality of Management						
Cost efficiency (ratio of operating costs to revenues)	707	63.12	60.20	29.91	7.84	167.93
Trading income to total revenue ratio	467	0.63	0.13	4.91	-3.08	8.67
Earnings Potential						
ROE (Return on equity)	707	0.04	0.10	0.69	-1.03	0.36
ROA (Return on assets)	707	0.36	0.62	2.89	-15.44	3.71
Liquidity/Funding Position						
Liquid assets to total assets	707	0.15	0.11	0.13	0.01	0.60
Wholesale funds to total liabilities	703	21.07	14.18	20.52	0.00	92.24
Sensitivity to Market Risk						
Cost of funds	707	2.33	2.03	1.54	0.17	6.49
Key Country Factors						
Slope of the yield curve	707	0.24	1.15	0.87	-0.28	2.70
Log(GDP per capita)	707	10.38	10.60	0.79	6.99	11.03
Stock market volatility	707	1.89	1.77	0.71	0.84	4.06
Country governance indicator	707	1.09	1.19	0.81	-1.01	2.33
Bank industry concentration	707	0.48	0.44	0.24	0.18	1.00
Financial conglomerates restriction	707	4.88	5.00	0.80	3.00	6.00
Entry barrier	707	5.36	2.19	13.94	0.00	80.00
Explicit deposit insurance dummy	707	0.92	1.00	0.27	0.00	1.00

Panel B: Correlation Matrix of Main Regression Variables

	Leverage	Equity-Return Volatility	Government Bond Yield	Log (Z-score)	Loan-Loss Provisions to Total Loans	Cost Efficiency	Liquid Assets to Total Assets
Equity-return volatility	0.1619***	1.0000					
	0.0000						
Government bond yield	0.0551	-0.1241**	1.0000				
	0.1431	0.0009					
Capital adequacy:	-0.0495	-0.3861***	0.1750***	1.0000			
Log(Z-score)	0.1886	0.0000	0.0000				
Asset quality: Loan-loss	-0.3456***	0.2611***	-0.2192***	-0.2701***	1.0000		
provisions to total loans	0.0000	0.0000	0.0000	0.0000			
Management quality:	0.2354***	0.1877***	0.0125	-0.1568***	-0.1392***	1.0000	
Cost efficiency	0.0000	0.0000	0.7402	0.0000	0.0002		
Earnings potential: ROE	-0.0582	-0.1881***	-0.0628*	0.2537***	-0.2560***	-0.0812**	1.0000
	0.1221	0.0000	0.0955	0.0000	0.0000	0.0309	
Liquidity:	0.2247***	-0.0899**	-0.0229	0.0277	-0.1393***	0.2179***	0.0507
Liquid assets to total assets	0.0000	0.0168	0.5430	0.4614	0.0002	0.0000	0.1780
Sensitivity to market risk:	0.0360	0.0797**	0.4414***	0.0379	-0.0480	-0.0032	-0.0037
Cost of funds	0.3385	0.0341	0.0000	0.3141	0.2026	0.9320	0.9225

Table 3. Determinants of CDS spreads Based on Structural Model Predictions

This table presents results for regressions using the three explanatory variables suggested by structural models: leverage, volatility, and the riskless interest rate. We report robust t-statistics that adjust for heteroskedasticity and country-level clustering. The superscripts ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Regression using Leverage only

Model	**(1)**	**(2)**	**(3)**	**(4)**
VARIABLES	**Log(Spread)**	**Log(Spread_Mean)**	**Log(Spread)**	**Log(Spread_Mean)**
Structural Model Determinants				
Leverage	0.031***	0.029**	0.028***	0.025**
	(3.220)	(2.737)	(3.664)	(2.629)
Constant	1.593*	1.773*	1.807***	2.108**
	(1.818)	(1.880)	(2.896)	(2.483)
Year and bank fixed effect	N	N	Y	Y
N. of obs./banks	707/23	707/23	707/23	707/23
Adjusted R-squares	0.029	0.030	0.615	0.774

Panel B : Regression using Structural Variables

Model	**(1)**	**(2)**	**(3)**	**(4)**
VARIABLES	**Log(Spread)**	**Log(Spread_Mean)**	**Log(Spread)**	**Log(Spread_Mean)**
Structural Model Determinants				
Leverage	0.014*	0.011*	0.023**	0.017*
	(1.687)	(1.654)	(2.574)	(1.731)
Equity return volatility	0.308***	0.331***	0.079***	0.105***
	(9.378)	(7.914)	(2.897)	(4.137)
Government bond yield (10 year)	0.033	0.048	0.168***	0.155***
	(0.840)	(1.113)	(4.583)	(4.387)
Constant	2.182**	2.337***	1.295	1.808*
	(2.862)	(3.572)	(1.569)	(1.791)
Year and bank fixed effect	N	N	Y	Y
N. of obs./countries	707/23	707/23	707/23	707/23
Adjusted R-squares	0.224	0.306	0.634	0.8

Table 4. Determinants of CDS Spreads Based on CAMELS Indicators

This table presents results for regressions using bank fundamental CAMELS indicators, including measures of capital adequacy, asset quality, management quality, earnings potential, liquidity, and sensitivity to market risk. Banks in the expanded sample have no stock return data available. In all of the regressions we report robust t-statistics that adjust for heteroscedasticity and country-level clustering. The superscripts ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Main Sample				**Expanded Sample**	
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
VARIABLES	**Log(Spread)**	**Log(Spread _Mean)**	**Log(Spread)**	**Log(Spread _Mean)**	**Log(Spread)**	**Log(Spread _Mean)**
Capital Adequacy: Log(Z-score)	-0.243***	-0.263***	-0.042	-0.087**	-0.046	-0.083**
	(-3.939)	(-5.665)	(-1.069)	(-2.262)	(-1.557)	(-2.422)
Asset Quality: Loan-loss provisions to total loans	0.076***	0.067***	0.052**	0.042*	0.058***	0.045**
	(8.256)	(3.463)	(2.443)	(1.999)	(2.963)	(2.475)
Management Quality: Cost efficiency	0.005***	0.005***	0.003***	0.003***	0.001	0.002**
	(3.481)	(4.253)	(2.897)	(3.588)	(1.127)	(2.671)
Earnings Potential: ROE	-0.123**	-0.068	-0.063***	-0.030**	-0.038	-0.024**
	(-2.577)	(-1.551)	(-4.104)	(-2.783)	(-1.257)	(-2.319)
Liquidity: Liquid assets to total assets	-0.010***	-0.011***	0.011	-0.002	0.006	-0.001
	(-5.025)	(-4.538)	(1.213)	(-0.488)	(1.091)	(-0.165)
Sensitivity to Market Risk: Cost of funds	0.138***	0.069	0.123***	0.132***	0.101***	0.124***
	(3.401)	(1.502)	(3.127)	(4.740)	(2.933)	(4.565)
Constant	4.406***	4.613***	3.523***	3.902***	3.778***	3.836***
	(34.090)	(24.442)	(27.443)	(27.616)	(25.108)	(25.153)
Year and bank fixed effect	N	N	Y	Y	Y	Y
N. of obs./countries	707/23	707/23	707/23	707/23	968/26	968/26
Adjusted R-squares	0.198	0.201	0.634	0.794	0.658	0.803

Table 5. Determinants of CDS Spreads Based on Structural Variables and CAMELS Indicators

This table presents results for regressions using the three structural variables and six CAMELS indicators. In all of the regressions we report robust t-statistics that adjust for heteroscedasticity and country-level clustering. The superscripts ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Model	**(1)**	**(2)**	**(3)**	**(4)**
VARIABLES	**Log(Spread)**	**Log(Spread_Mean)**	**Log(Spread)**	**Log(Spread_Mean)**
Structural Model Determinants				
Leverage	0.025**	0.021**	0.017**	0.016*
	(2.457)	(2.623)	(2.373)	(1.685)
Volatility	0.211***	0.254***	0.059**	0.081***
	(4.144)	(5.402)	(2.207)	(3.482)
Government bond yield	0.024	0.082	0.144***	0.126***
	(0.287)	(1.601)	(5.905)	(4.819)
Bank CAMELS Variables				
Log (Z-score)	-0.119**	-0.134***	-0.028	-0.067**
	(-2.693)	(-3.394)	(-0.761)	(-2.384)
Loan-loss provisions to total loans	0.068***	0.058***	0.041***	0.030**
	(6.706)	(5.865)	(3.181)	(2.351)
Cost efficiency	0.002	0.002**	0.002*	0.002*
	(1.527)	(2.156)	(1.733)	(1.985)
ROE	-0.063*	0.013	-0.024	0.005
	(-1.898)	(0.611)	(-1.102)	(0.345)
Liquid assets to total assets	-0.010***	-0.009***	0.013	-0.000
	(-3.393)	(-4.118)	(1.361)	(-0.089)
Cost of funds	0.104	0.004	0.102**	0.115***
	(1.500)	(0.089)	(2.210)	(3.767)
Constant	1.434	1.782**	1.248	1.759*
	(1.643)	(2.265)	(1.696)	(2.031)
Year and bank fixed effect	N	N	Y	Y
N. of obs./countries	707/23	707/23	707/23	707/23
Adjusted R-squares	0.305	0.368	0.648	0.813

Table 6. Determinants of CDS Spreads Controlling for Country Factors

This table presents results for regressions using the three structural variables and six CAMELS indicators, controlling for country-level economic indicators, bank industry structure, and bank regulations. Banks in the expanded sample have no stock return data available. Reported in parentheses are t-statistics based on robust standard errors adjusted for clustering by countries. Year and bank fixed effects are controlled. The superscripts ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Main Sample	**Main Sample**	**Expanded Sample**
Model	**(1)**	**(2)**	**(3)**
VARIABLES	**Log(Spread)**	**Log(Spread)**	**Log(Spread)**
Structural Model Determinants			
Leverage	0.024***	0.018***	
	(3.079)	(2.823)	
Volatility	0.077***	0.057**	
	(2.899)	(2.073)	
Government bond yield	0.140***	0.129***	0.149***
	(3.896)	(3.843)	(4.025)
Bank CAMELS Variables			
Log (Z-score)		-0.022	-0.040
		(-0.663)	(-1.469)
Loan-loss provisions to total loans		0.045***	0.059***
		(2.747)	(2.736)
Cost efficiency		0.002*	0.001
		(1.849)	(1.217)
ROE		0.007	0.017
		(0.198)	(0.519)
Liquid assets to total assets		0.012	0.009
		(1.273)	(1.591)
Cost of funds		0.091**	0.061*
		(2.097)	(1.662)
Key Country Factors			
Log(GDP per capita)	0.382	0.287	0.218
	(0.685)	(0.542)	(0.602)
Stock market volatility	0.298**	0.290**	0.276***
	(2.494)	(2.676)	(2.972)
Slope	0.097	0.102	0.084
	(0.941)	(1.049)	(1.296)
Country governance	-0.289	-0.202	-0.099
	(-0.671)	(-0.558)	(-0.376)
Bank industry concentration	-0.197	-0.337	-0.596
	(-0.169)	(-0.325)	(-0.743)
Financial conglomerates restriction	-0.381**	-0.461**	-0.637***
	(-2.597)	(-2.515)	(-3.253)
Entry barrier	0.081	0.099*	0.021
	(1.361)	(1.742)	(0.298)
Explicit	0.479***	0.565***	0.322**
	(2.767)	(3.176)	(2.043)
Constant	-1.609	6.331***	3.656
	(-0.303)	(4.712)	(0.930)
Year and Bank Fixed Effects	Y	Y	Y
N. of obs./countries	707/23	707/23	968/26
Adjusted R-squares (%)	0.639	0.652	0.674

Table 7. The Impact of Financial Crisis on Determinants of CDS Spreads

This table presents regression results for the impact of financial crisis. Model 1 presents the coefficients and t-statistics for the variables and interaction terms between main variables and the crisis dummy, which is defined as 1 if year is after 2007 and 0 otherwise. To avoid multicollinearity problems, we demean main variables by subtracting the mean from the raw value before constructing the interaction terms. Reported in parentheses are t-statistics based on robust standard errors adjusted for clustering by banks. Year and bank fixed effects are controlled. The superscripts ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Main Sample	**Expanded Sample**	***Cont. from left panel***	**Main Sample**	**Expanded Sample**
Model	**(1)**	**(2)**	**Model**	**(1)**	**(2)**
VARIABLES	**Log(Spread)**	**Log(Spread)**	**VARIABLES**	**Log(Spread)**	**Log(Spread)**
Leverage	0.017*		Leverage*Crisis	0.015**	
	(1.736)			(2.339)	
Volatility	0.085*		Volatility*Crisis	-0.081	
	(1.833)			(-0.669)	
Government bond yield	0.161**	0.152***	Government bond yield*Crisis	-0.061	0.002
	(2.383)	(3.072)		(-0.644)	(0.026)
Log (Z-score)	-0.018	-0.040	Log (Z-score)*Crisis	0.021	0.035
	(-0.570)	(-1.558)		(0.400)	(0.865)
Loan-loss provisions to total loans	0.022	0.041	Loan-loss provisions to total loans*Crisis	0.091***	0.071***
	(0.833)	(1.422)		(4.266)	(2.956)
Cost efficiency	0.002*	0.001	Cost efficiency*Crisis	0.002	0.001
	(1.720)	(0.903)		(1.066)	(0.768)
ROE	-0.026	0.033	ROE*Crisis	0.084	-0.026
	(-0.189)	(0.522)		(0.313)	(-0.242)
Liquid assets to total assets	1.201	0.819	Liquid assets to total assets*Crisis	0.261	0.090
	(1.325)	(1.582)		(0.509)	(0.326)
Cost of funds	0.050	0.035	Cost of funds*Crisis	0.100	0.053
	(0.895)	(0.842)		(1.011)	(0.901)
Log(GDP per capita)	0.355	0.362	Banking crisis	1.216**	1.296***
	(0.622)	(1.011)		(2.404)	(2.963)
Stock market volatility	0.357***	0.308***	Constant	0.655**	0.794***
	(2.964)	(2.956)		(2.380)	(4.397)
Slope	0.153	0.116*	Year and bank fixed effect	Y	Y
	(1.702)	(1.743)	N. of obs./countries	707/23	968/26
Country governance	-0.099	-0.138	Adjusted R-squares (%)	0.662	0.681
	(-0.226)	(-0.470)			
Bank industry concentration	-0.556	-0.623			
	(-0.454)	(-0.726)			
Financial conglomerates restriction	-0.611*	-0.662**			
	(-1.914)	(-2.732)			
Entry barrier	0.124	0.027			
	(1.567)	(0.387)			
Explicit	0.803**	0.389*			
	(2.604)	(1.969)			

Appendix: Variable Definitions and Data Sources

Variable	Definition	Sources
CDS Spread	The 5-year CDS spreads in basis points. To maintain uniformity in contracts, we only keep CDS quotations for senior unsecured debt with a modified restructuring clause. *CDS spread* is the year-end CDS quote, and *CDS spread_mean* is the average of the daily CDS spread over a year.	MarkIt
Bank Assets	The book value of a bank borrower's total assets, in millions of U.S. dollars.	Bankscope
Log(Z-score)	Z-score equals the return on assets plus the capital-asset ratio, divided by the standard deviation of asset returns. Because the Z-score is highly skewed, we use the natural logarithm of the Z-score as the risk measure (following Laeven and Levine, 2007).	Bankscope
Leverage	Book value of liabilities to the sum of book value of liabilities and market value of equity.	Bankscope, Bloomberg
Volatility	The historical standard deviation of bank's daily equity returns in a particular year.	Bloomberg
Government bond yield	The 10-year government bond yield.	Global insights
Tier 1 capital	The ratio of capital (shareholders capital, reserves, and hybrid capital to certain limits) divided by risk-weighted assets. This is reported by each bank.	Bankscope
Loan-loss provisions to total loans	The ratio of loan-loss provisions to total loans.	Bankscope
Share of nonperforming loans to total loans	The ratio of nonperforming loans to total loans.	Bankscope
Cost efficiency	The ratio of operating costs to revenues.	Bankscope
Trading income to total revenue ratio	The ratio of trading income to revenues.	Bankscope
ROE	Net income divided by total common equity.	Bankscope
ROA	Net income divided by total assets.	Bankscope
Liquid assets to total assets	The ratio of liquid assets to total assets.	Bankscope
Wholesale funds to total liabilities	The ratio of wholesale funds to total liabilities.	Bankscope
Cost of funds	The ratio of interest expense to total liabilities.	Bankscope
Log(GDP per capita)	The natural log of GDP per capita.	WDI
Stock market volatility	The historical standard deviation of a country's stock index in a particular year.	Bloomberg
Slope	The return on 10-year government bonds minus return on two-year government bonds.	Global insights
Country governance	The country governance indicator.	Worldwide Governance Indicators
Bank industry Concentration	The fraction of bank assets held by the five largest commercial banks in the country.	Bankscope
Financial conglomerates restriction	An indicator measuring the extent to which banks may own and control nonfinancial firms, the extent to which nonfinancial firms may own and control banks, and the extent to which nonbank financial firms may own and control banks.	Barth et al. (2006, 2008)
Entry Barrier	The fraction of bank entry applications denied.	Barth et al. (2006, 2008)
Explicit	A dummy variable that equals 1 if the borrower's country has an explicit deposit insurance system; it equals and 0 otherwise.	World Bank, and the 2010 annual survey results of International Association of Deposit Insurers

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