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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 market-based structural models and accounting-based bank fundamentals to price global bank credit risk. First, we find that variables predicted by structural models are significantly associated with bank CDS spreads. Second, some CAMELS indicators contain incremental information for bank CDS prices. We find no evidence in favor of one model over the other, while the combined structural and CAMELS model performs better than each individual model. 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, fewer entry barriers, and/or more financial conglomerate restrictions tend to have lower credit risk. Deposit insurance appears to have an adverse effect on bank CDS spreads, indicating a moral hazard problem.

Keywords: Credit default swaps, · Structural models, · CAMELS, · Global banks, · Bank regulation

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

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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 market-based variables predicted by the structural models, which usually apply to *nonfinancial* firms, also relevant for pricing bank CDS? Do accounting-based financial-soundness indicators (CAMELS ratings, in particular) have incremental explanatory power for bank CDS spreads? Are the structural model and the CAMELS model complementary in pricing bank credit risk? 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 for corporations. Specifically, leverage, volatility, and risk-free rates are significant determinants of the levels of and changes in corporate bond yield spreads (Duffee 1998; Collin-Dufresne et al. 2001, etc.). Benkert (2004) shows that the structural model can also apply to CDS pricing. Ericsson et al. (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). Das et al. (2009) find that a combined model of accounting metrics (e.g. Altman (1968) and its extensions) and market-based model (e.g. Merton (1974) and its extensions) performs better than either of the two models in pricing the corporate CDS spread.[1]

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 et al. 2006; Berger et al. 1995; Brewer et al. 2008; Diamond and Rajan 2000; Flannery 1994; Tian et al. 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

[1] Augustin et al. (2014) provide a survey on issues related to CDS spread pricing. However, the referenced papers mainly focus on pricing of corporate CDS spreads, while the research on pricing of bank CDS spreads is limited.

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 (e.g., Collin-Dufresne et al. 2001), and we examine whether structural variables can explain CDS spreads for financial firms. We find that leverage and equity return volatility are statistically and economically significant for bank CDS spreads and robust to our model specifications. To be specific, a standard deviation increase in the market leverage is associated with widening of CDS spreads by 110 bp, and a standard deviation increase in equity-return volatility is associated with an increase in raw CDS spread of 175 bps. However, the variables predicted by the structural model without controlling for time and bank fixed effects can explain only about 22 % 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. CAMELS stands for Capital adequacy, Asset quality, Management quality, Earnings potential, Liquidity, and Sensitivity to market risk. 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 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.[3]

With a large sample of 161 large, medium, and small banks in 23 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 all CAMELS indicators are significantly associated with bank CDS spreads with the adjusted R-squares of roughly 20 %. We use the Vuong test (Vuong 1989) to compare the structural model and the CAMELS model, and find no evidence in favor of one over the other.

Including both structural variables and CAMELS in the combined model improves the model fit from 20 % to 30 %. We use the F-test to compare the model fit of each individual model with the combined model. The results show that the combined model performs better than either of the Structural model/CAMEL model on its own, suggesting that structural variables and CAMELS indicators contain complementary information about bank credit risk. Our results are similar to those in Das et al. (2009) and Ericsson et al. (2009) in that leverage and volatility are found important determinants for both corporate and bank CDS spreads. However, our finding differs

[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.

[3] A growing literature analyzes the usefulness of accounting information in pricing corporate CDS spreads, e.g., Arora et al. (2014); Callen et al. (2009); Das et al. (2009); Shivakumar et al. (2011), and Zhang and Zhang (2013). See Augustin et al. (2014) for a survey of relevant studies. Also see, Peltonen et al. (2014) on the determinants of the CDS market.

from Das et al. (2009) in terms of most accounting-based explanatory variables that reflect different industry characteristics of corporations versus banks. Das et al. (2009) find that firm size and inventory to cost of goods sold are significant determinants of corporate CDS spreads. In comparison, we find that asset quality, management quality, and costs of funds are important in pricing bank credit risk. Earnings reduce both corporate and bank CDS spreads.

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 curve slope, country governance, banking concentration, financial conglomerate 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 (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.[4]

We find that banks in a country with more stringent financial conglomerate restriction have higher CDS spreads. This finding is consistent with Beltratti and Stulz (2012) which suggest that large banks from countries with more restrictions on bank activities perform better and cut back on lending less during the recent crisis. In addition, fewer entry barriers in a country are associated with narrower bank CDS spreads, suggesting that competition helps to reduce bank credit risk. 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.

Several tests are conducted for robustness. We use the stepwise selection method to keep the most important determinants, and the model fit does not suffer from the selection approach. We also replace Z-score with Tier 1 and Tier 2 capital ratios to proxy for capital adequacy, and find similar results. In addition, we test whether the combined model performs well in explaining CDS spreads of other maturities. Similar results hold for 3-year, 7-year and 10-year CDS contracts. Interestingly, the model fit is even higher for less liquid contracts, indicating that liquidity factor is not a main driver of bank CDS spreads. Furthermore, the out-of-sample prediction following the approach used by Das et al. (2009) confirms the applicability of structural models and CAMELS indicators to predict bank credit risk. Finally, we construct cumulative accuracy profile (CAP) curves and the associated accuracy ratio (AR) statistics to test rank-order predictability. Results support our earlier findings that comprehensive model performs better than the individual models. Our study suggests that CDS spreads are more difficult to model than corporate CDS spreads. This could be due to limited variation in leverage and financing patterns, or different regulatory norms for banks than corporations.

[4] 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.

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 mostly 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 CAMELS indicators that are widely used in the banking industry, to examine whether they provide incremental information to price bank credit risk beyond structural variables. We confirm that the combined structural and CAMELS model performs better than each individual model. 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 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 provides robustness check. Section 6 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 Peña 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 23 bp in 2011 from 115 bp to 138 bp. 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. Campbell and Taksler (2003) use the structural approach to identify the theoretical determinants of levels of corporate bond credit spreads. They use historical equity return volatility to proxy for assets volatility and conclude that firm-specific equity volatility is an important determinant of the corporate bond spread and that the economic effects of volatility are large. Similarly, Ericsson et al. (2009) also use historical equity return volatility as proxy for the assets volatility in estimating the relationship between theoretical determinants of default risk and corporate CDS spread. They find that volatility has substantial explanatory power for credit default swap premia. We construct volatility 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 volatility, which increases the default likelihood.

The government bond yield is used to proxy for risk-free rate (Ericsson et al. 2009). Since we use the five-year CDS spread as the dependent variable, we use the 5-year government bond yield to proxy for risk-free rate.[5] 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 et al. (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.

[5] We also use 2-year and 10-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 et al. 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 potential, 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. We follow Otker-Robe and Podpiera (2010) and Chiaramonte and Casu (2013) to select accounting ratios to proxy for the CAMELS indicators. 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.[6]

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 et al. 2013). Thus, capital adequacy should be a critical determinant of bank credit risk. Capital adequacy could be measured by Tier 1 capital, Tier 2 capital and Z-score (Otker-Robe and Podpiera 2010). We use *Log*(*Z-score*) to measure capital adequacy in the baseline analysis, Tier 1 and Tier 2 capital ratios as alternative measures in the robustness check.[7] Z-score is a derivative measure of bank capitalization, that is, whether banks have enough capital to deal with potential loss. It gauges available funds for loss absorption and measures a bank's distance from insolvency (Laeven and Levine 2009, 2010; Otker-Robe and Podpiera 2010). It is calculated as the return on asset plus the capital-asset ratio divided by the standard deviation of asset returns. A higher value of Z-score indicates a greater level of capital adequacy and higher resistance to shocks. We take the natural logarithm of this measure

[6] 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 and Tier 2 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.

[7] We use Z-score in the baseline analysis because there are many missing observations for Tier 1 and Tier 2 capital. In the robustness check, we use Tier 1 and Tier 2 capital ratios to replace Z-score as a measure of capital adequacy and results are similar. For a related study, see, Barakova (2014).

because Z-score is highly skewed. 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 provision ratio*, measured as 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, support growth, and sustain and increase capital. Therefore, a bank with higher return on its assets or 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 *Liquidity ratio*, measured as liquid assets to total assets, to proxy for bank liquidity. Presumably, a higher liquid asset ratio should be negatively related to CDS spread.

The last element of the CAMELS system is sensitivity to market risk, which is the sensitivity of all loans and deposits to relatively abrupt and unexpected shifts in interest rates. *Cost of fund*, measured as the ratio of interest expense to total liabilities, captures a bank's liability funding costs. Therefore, it is used 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 higher capital adequacy, asset quality, management quality, earnings potential, liquidity position, and lower sensitivity to market risk should have lower CDS spreads.

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 et al. 2004; La Porta et al. 1998). Therefore, we control for economic-development and market-condition differences across countries using the natural log of *GDP* per capita, *Country governance*, *Stock market volatility*, and *Yield curve 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). The information on the quality of country governance is from the Worldwide Governance Indicators (www.govindicators.org). We create an aggregated index, *Country governance*, by averaging six dimensions of governance, including voice and accountability, political stability and the absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption. A higher value of the index corresponds to higher quality of governance. 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 daily stock index return in a particular year. Lower stock market volatility indicates less economic uncertainty, lower default risk, and credit risk premia (Tang and Yan 2010). *Yield curve slope* 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 concentration* as the fraction of bank assets held by the five largest commercial banks in the country. We compute this using the Bankscope database.[8] Banks would earn monopoly rents in more concentrated banking systems and thus are less likely to default (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 conglomerate 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 regulatory restrictions.

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 and higher risk taking. Our information on deposit insurance is collected from the "Comprehensive Deposit Insurance 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 relationship between explicit deposit insurance adoption and bank CDS spread is ambiguous.

[8] 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.

3 Data

Our bank CDS spread data is from MarkIt, which provides comprehensive coverage for over 3000 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. To maintain uniformity in contracts, we only keep CDS quotations for senior unsecured debt with a modified restructuring (MR) clause. For each day, reference entities in our dataset could have several CDS spread quotations that are denominated in different major currencies, e.g., USD, EUR, JPY, GBP, etc. Since the quotation in USD usually has the longest history, to keep the uniformity and time-series consistency of data, we do the filtering of data based on whether the currency is USD.[9]

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.[10] 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.[11] 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 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. 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.

Panel A of Table 2 presents summary statistics for key variables in the regressions. In our sample, the average of 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

[9] We appreciate the editor's comments regarding currency risk.

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

[11] 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.

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

	Main sample		Expanded sample	
Panel A: Sample distribution by year				
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				
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				
Bank Specialization	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 %

when banks' credit risk was negligible and the crisis period when banks' credit risk skyrocketed. We also calculate the mean (median) of CDS spreads over each year as alternative measures. The

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.	P5	P95
CDS Spread_Year End (basis point)	707	194.50	74.50	510.07	12.99	620.82
CDS Spread_Mean (basis point)	707	175.41	81.22	500.92	16.73	534.48
CDS Spread_Median (basis point)	707	146.15	67.91	309.83	11.11	502.28
Structural model determinants						
Market leverage (%)	707	89.96	90.11	6.74	78.09	98.02
Equity volatility (%)	707	2.69	2.14	1.83	0.86	6.68
Government bond yield (5-year)	707	2.99	3.03	1.80	0.61	5.69
Bank CAMELS indicators						
Capital Adequacy						
Log(Z-score)	707	2.49	2.50	1.08	0.80	4.14
Tier 1 capital ratio (%)	557	10.19	9.40	3.97	6.50	16.00
Tier 2 capital ratio (%)	557	3.13	3.30	1.90	0.70	5.10
Quality of Bank Assets						
Loan loss provision ratio (%)	707	1.83	0.62	3.79	0.00	7.90
Nonperforming loan ratio (%)	630	3.70	2.22	5.03	0.22	11.28
Quality of Management						
Cost efficiency (%)	707	63.12	60.20	29.91	31.65	96.42
Trading income ratio (%)	467	0.63	0.13	4.91	−1.01	2.28
Earnings Potential						
ROE (Return on equity) (%)	707	3.77	10.15	68.81	−23.44	22.39
ROA (Return on assets) (%)	707	0.36	0.62	2.89	−1.27	2.48
Liquidity/Funding Position						
Liquidity (%)	707	15.26	10.61	13.48	2.43	42.60
Wholesale funding ratio (%)	703	21.07	14.18	20.52	1.36	68.51
Sensitivity to Market Risk						
Cost of funds (%)	707	2.33	2.03	1.54	0.36	4.94

Table 2 (continued)

Key country factors								
Log(GDP per capita)	707	10.38	10.60	0.80	8.21	10.81		
Stock market volatility (%)	707	1.89	1.78	0.71	0.92	3.04		
Yield curve slope	707	0.24	1.15	0.87	−0.11	2.70		
Country governance	707	1.09	1.19	0.81	−0.41	2.16		
Bank concentration (%)	707	47.62	44.44	24.00	17.54	97.82		
Financial conglomerate restriction	707	4.88	5.00	0.80	3.00	6.00		
Entry barrier	707	5.36	2.19	13.95	0.00	25.00		
Explicit	707	0.92	1.00	0.27	0.00	1.00		
Panel B: Correlation table								
	Market leverage	Equity volatility	Government bond yield	Log(Z-score)	Loan loss provision ratio	Cost efficiency	ROE	Liquidity ratio
Equity volatility	0.213***	1.000						
	0.000							
Government bond yield	−0.100***	−0.217***	1.000					
	0.008	0.000						
Log(Z-score)	−0.130***	−0.386***	0.229***	1.000				
	0.001	0.000	0.000					
Loan loss provision ratio	−0.161	0.261***	−0.234***	−0.270***	1.000			
	0.000***	0.000	0.000	0.000				
Cost efficiency	0.178	0.188***	−0.009	−0.157***	−0.139***	1.000		
	0.000***	0.000	0.821	0.000	0.000			
ROE	−0.094**	−0.188***	0.058	0.254***	−0.256***	−0.081**	1.000	
	0.012	0.000	0.127	0.000	0.000	0.031		
Liquidity ratio	0.190***	−0.090**	−0.027	0.028	−0.139***	0.218***	0.051	1.000
	0.000	0.017	0.475	0.461	0.000	0.000	0.178	
Cost of funds	−0.016	0.080**	0.457***	0.038	−0.048	−0.003	−0.004	−0.060
	0.664	0.034	0.000	0.314	0.203	0.932	0.923	0.111

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

statistics of Cook's D suggest that there are no highly influential data points for CDS spread worth checking for validity. The average bank market leverage is 90 %. The daily equity-return volatility has an average of 2.69 %. The average 5-year government bond yield is 3.62 %.

In terms of bank CAMELS indicators, we find that, on average, a sample bank has a Log (Z-score) of 2.48, loan-loss provisions to total loans of 1.8 %, cost efficiency of 63.1 %, ROE of 3.8 %, and liquid assets to total assets of 15.3 %. The average cost of funds is 2.3 %.

The table also shows great variation in terms of bank characteristics, key country economic and governance indicators, bank concentration structure, regulation and restriction variables. All these values are comparable with prior studies (e.g., Laeven and Levine 2010; Houston et al. 2010; Beltratti and Stulz 2012).

Panel B presents a correlation matrix of structural variables and CAMELS indicators. Among the significant correlation relationships, *Market leverage* is negatively correlated with *Government bond yield*, *Log(Z-score)*, *Loan loss provision ratio and ROE* and positively related to *Equity volatility*, *Cost efficiency*, and *Liquidity ratio*. *Equity volatility* is negatively correlated with *Government bond yield*, *Log(Z-score)*, *ROE*, and *Liquidity ratio*, and is positively correlated with *Loan loss provision ratio*, *Cost efficiency*, and *Cost of funds*. *Government bond yield* has a positive correlation with *Log(Z-score)* and *Cost of funds*, and negative correlation with *Loan loss provision ratio*. Among CAMELS indicators, *Log(Z-score)* is negatively related to *Loan loss provision ratio* and *Cost efficiency*, and positively related to *ROE*. *Loan loss provision ratio* is negatively related to *Cost efficiency*, *ROE*, and *Liquidity ratio*. Finally, *Cost efficiency* has negative correlation with *ROE* and a positive correlation with *Liquidity ratio*. We test the potential issue of multicollinearity problems in our regressions, but find the Variance Inflation Factors (VIF) are all below ten.[12] Thus, we include both structural variables and CAMELS indicators in our specifications.

Empirical methods and results

We conduct a multivariate panel data regression with the natural logarithm of CDS spread as the dependent variable, which is stationary using the unit-root test. For robustness, we use three measures of CDS spreads, i.e., the end-of-year CDS spreads, the average, and the median of CDS spreads over each year. Independent variables include bank structural variables, CAMELS indicators, and country economic and regulation variables as control variables. The model is as follows:

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

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. In all our regression models, we use country-clustered, heteroskedasticity-robust standard errors. If there are unobservable common country components, CDSs in a given country cannot be treated independently. The residuals are correlated and OLS standard errors may be biased. Therefore, it is important to adjust standard errors to account for the within-country correlations (see 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. We use the Vuong

[12] Neter et al. (1985) (page 392) stated that the rule-of-thumb cutoff value for the VIF is ten for multiple regression models. The VIF values in our models are substantially below the cutoff value, so providing evidence that multicollinearity problems are not present.

test (Vuong 1989) for non-nested models to statistically examine whether one model performs better than the other model. Then we test whether the combined structural and CAMELS model is an improvement over the individual model. Finally, we include country-level variables to account for variation across countries.

3.1 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, in Model 2 and 3, the coefficient is 0.029 (t = 3.92) and 0.033 (t = 4.10) when the dependent variable is the average and the median of CDS spreads over a year, respectively.

Models 4–6 control for year and bank fixed effect. We use bank fixed effect to account for unobserved time-invariant bank characteristics and time fixed effect to account for unobserved time-varying factors. Leverage remains positively related to all three measures of CDS spreads. While banks have a narrower leverage distribution than corporate firms, leverage appears a significant determinant of CDS spreads.[13] 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. After controlling for the time and bank fixed effect, the adjusted R-squared increases to over 60 %. We perform the Wald test to confirm that the increase in the model fit with fixed effects is significant. As shown at the end of the table, the F-test shows that the corresponding increases of the model fit (e.g., Model 4 vs. Model 1; Model 5 vs. Model 2, and Model 6 vs. Model 3) are all significant at the 1 % level.

Next, we investigate all three variables predicted by structural models in Panel B. *Market leverage* is positive and significant in Models 1–6. In terms of economic magnitude, a standard deviation increase in *Market leverage* is associated with an increase in CDS spread of 110 bps (=the exponential of 0.014 × 6.74) in Model 1. The coefficients for *Equity 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 volatility* is associated with an increase in CDS spread of 175 bps (=the exponential of 0.306 × 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 4–6 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

[13] 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.

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 within country clustering

Variables	(1) Log (Spread)	(2) Log (Spread_Mean)	(3) Log (Spread_Median)	(4) Log (Spread)	(5) Log (Spread_Mean)	(6) Log (Spread_Median)
Panel A: Regression using leverage only						
Market leverage	0.031***	0.029***	0.033***	0.028***	0.025**	0.019**
	(3.220)	(3.915)	(4.104)	(3.664)	(2.629)	(2.120)
Constant	1.593*	1.773***	1.249*	1.807***	2.108**	2.395***
	(1.818)	(2.638)	(1.712)	(2.896)	(2.483)	(2.993)
Country clustering	Y	Y	Y	Y	Y	Y
Year and bank fixed effect	N	N	N	Y	Y	Y
N. of obs./countries	707/23	707/23	707/23	707/23	707/23	707/23
Adjusted R-squared	0.028	0.030	0.035	0.615	0.774	0.805
OLS vs. Fixed effect F-test				(4) vs (1) $F = 7.64$	(5) vs (2) $F = 14.64$	(6) vs (3) $F = 16.50$
				$Prob > F = 0.000$	$Prob > F = 0.000$	$Prob > F = 0.000$
Panel B : Regression using structural variables						
Market leverage	0.014*	0.011*	0.014**	0.022**	0.018*	0.019*
	(1.679)	(1.746)	(2.045)	(2.683)	(1.836)	(1.830)
Equity volatility	0.306***	0.331***	0.334***	0.086***	0.111***	0.109***
	(9.239)	(11.776)	(11.285)	(2.879)	(4.386)	(3.633)
Government bond yield	0.009	0.048	−0.001	0.128***	0.110***	0.087***
	(0.238)	(1.592)	(−0.016)	(3.927)	(3.268)	(2.990)
Constant	2.307***	2.337***	2.083***	1.594**	3.036***	2.879***
	(3.137)	(4.124)	(3.418)	(2.154)	(3.321)	(3.082)
Country clustering	Y	Y	Y	Y	Y	Y
Year and bank fixed effect	N	N	N	Y	Y	Y

Table 3 (continued)

Variables	(1) Log (Spread)	(2) Log (Spread_Mean)	(3) Log (Spread_Median)	(4) Log (Spread)	(5) Log (Spread_Mean)	(6) Log (Spread_Median)
Country clustering	Y	Y	Y	Y	Y	Y
N. of obs./countries	707/23	707/23	707/23	707/23	707/23	707/23
Adjusted R-squared	0.222	0.306	0.294	0.631	0.796	0.806
OLS vs. Fixed effect F-test				(4) vs (1) F = 4.92	(5) vs (2) F = 9.63	(6) vs (3) F = 11.24
				Prob > F = 0.000	Prob > F = 0.000	Prob > F = 0.000

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

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-squareds range from 63 % to 81 %. We conduct the F-test to examine whether the fixed effect model improves the model fit. The last row shows that the increases in model fit in fixed effect models (Model 4–6) are all statistically significant at the 1 % level. Therefore, incorporating time-varying factors and cross-sectional variations should help to resolve the credit-spread puzzle.

3.2 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 1–6 are based on the main sample and Models 7–9 are based on the expanded sample.

The coefficients on *Loan loss provision 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 ratio is not significantly related to CDS spreads when the bank and time fixed effects are accounted for. The adjusted R-squared of Models 1–3 using the six CAMELS indicators are about 20 %, comparable to the explanatory power of three structural variables in Table 3 (Model 1). The model fit increases to a range of 63 % to 83 % when the year and bank fixed effect is controlled for. For the expanded sample, bank CDS spreads are significantly associated with *Loan loss provision ratio* and *Cost of funds.*

Given that both structural variables and CAMELS indicators are useful determinants of bank CDS spreads, does one model perform better than the other? We conduct a Vuong (1989) test for non-nested models to compare Model 1 in Table 3 and Model 1 in Table 4. The Vuong Z-statistic is 0.5687 (p-value = 0.5696). Hence, we cannot reject the null hypothesis that two models are equally distant from the true model. Therefore, the CAMELS model performs comparably to the structural model.

3.3 Models with both structural variables and CAMELS indicators

To show whether the market-based and accounting-based models are complementary in pricing bank CDS spreads, we include both structural variables and CAMELS indicators in a combined model as shown in Table 5. Several observations are noted.

First, *Market leverage* and *Equity volatility* are positive and significant in Model 1 to 6, which is robust to model specification. *Government bond yield* is positive and significant when the time and bank fixed effects are controlled for, consistent with the Table 3 result. Second, among CAMELS variables, the impact of *Loan loss provision ratio* is positive and significant across all models. *Cost efficiency*, *ROE* and *Cost of funds* have the expected sign and are significant after controlling for time and bank fixed effects.

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 within country clustering

	Main sample						Expanded sample		
Variables	(1) Log (Spread)	(2) Log (Spread _Mean)	(3) Log(Sprea _Median)	(4) Log (Spread)	(5) Log(Spread _Mean)	(6) Log(Spread _Median)	(7) Log (Spread)	(8) Log (Spread _Mean)	(9) Log (Spread _Median)
Log(Z-score)	−0.243***	−0.263***	−0.275***	−0.042	−0.087**	−0.077**	−0.046	−0.083**	−0.073**
	(−5.118)	(−6.097)	(−6.117)	(−1.069)	(−2.262)	(−2.137)	(−1.557)	(−2.422)	(−2.266)
Loan loss provision ratio	0.076***	0.067***	0.062***	0.052**	0.042*	0.040**	0.058***	0.045**	0.044**
	(4.466)	(3.574)	(3.284)	(2.443)	(1.999)	(2.290)	(2.963)	(2.475)	(2.653)
Cost efficiency	0.005***	0.005***	0.005***	0.003***	0.003***	0.003***	0.001	0.002**	0.003***
	(3.123)	(4.055)	(4.274)	(2.897)	(3.588)	(3.499)	(1.127)	(2.671)	(2.877)
ROE	−0.0012**	−0.0007	−0.0008	−0.0006***	−0.0003**	−0.0004**	−0.0004	−0.0002**	−0.0002*
	(−2.408)	(−1.516)	(−1.539)	(−4.104)	(−2.783)	(−2.218)	(−1.257)	(−2.319)	(−1.742)
Liquidity ratio	−0.010***	−0.011***	−0.012***	0.011	−0.002	−0.003	0.006	−0.001	−0.003
	(−3.124)	(−3.577)	(−3.836)	(1.213)	(−0.488)	(−0.796)	(1.091)	(−0.165)	(−0.855)
Cost of funds	0.138***	0.069**	0.062*	0.123***	0.132***	0.122***	0.101***	0.124***	0.123***
	(4.478)	(2.295)	(1.969)	(3.127)	(4.740)	(4.423)	(2.933)	(4.565)	(6.023)
Constant	4.406***	4.613***	4.500***	3.523***	3.902***	3.644***	3.778***	3.836***	3.587***
	(21.636)	(23.730)	(21.882)	(27.443)	(27.616)	(17.978)	(25.108)	(25.153)	(18.039)
Country clustering	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year and bank fixed effect	N	N	N	Y	Y	Y	Y	Y	Y
N. of obs./countries	707/23	707/23	707/23	707/23	707/23	707/23	968/26	968/26	968/26
Adjusted R-squared	0.198	0.201	0.189	0.634	0.794	0.825	0.658	0.803	0.825
OLS vs. Fixed effect F-test				(4) vs (1) F = 6.15	(5) vs (2) F = 12.32	(6) vs (3) F = 14.37			
				Prob > F = 0.00	Prob > F = 0.00	Prob > F = 0.00			

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

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 heteroskedasticity and within country clustering

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Log(Spread)	Log(Spread_Mean)	Log(Spread_Median)	Log(Spread)	Log(Spread_Mean)	Log(Spread_Median)
Structural Model Determinants						
Market leverage	0.025***	0.019***	0.023***	0.016**	0.017**	0.016**
	(3.298)	(2.918)	(3.187)	(2.324)	(2.100)	(2.001)
Equity volatility	0.208***	0.252***	0.259***	0.064**	0.082***	0.073**
	(6.449)	(8.394)	(8.057)	(2.242)	(3.310)	(2.299)
Government bond yield	−0.008	0.023	0.016	0.112***	0.087***	0.067**
	(−0.191)	(0.719)	(0.440)	(5.053)	(3.067)	(1.987)
Bank CAMELS Variables						
Log(Z-score)	−0.114***	−0.125***	−0.128***	−0.031	−0.058*	−0.079**
	(−2.644)	(−3.123)	(−3.179)	(−0.828)	(−1.897)	(−2.444)
Loan loss provision ratio	0.065***	0.053***	0.048***	0.040***	0.027**	0.030*
	(4.561)	(3.667)	(3.390)	(2.821)	(2.474)	(1.783)
Cost efficiency	0.002	0.002	0.002	0.002*	0.002*	0.003***
	(1.136)	(1.434)	(1.538)	(1.703)	(1.885)	(3.013)
ROE	−0.0007***	−0.0002	−0.0002	−0.0006**	−0.0003**	−0.0004*
	(−2.862)	(−0.815)	(−1.079)	(−2.762)	(−2.720)	(−1.932)
Liquidity ratio	−0.010***	−0.009***	−0.011***	0.013	−0.002	−0.002
	(−3.001)	(−3.307)	(−3.572)	(1.323)	(−0.424)	(−0.305)
Cost of funds	0.119***	0.030	0.025	0.103**	0.115***	0.084***
	(3.106)	(0.898)	(0.738)	(2.242)	(3.698)	(3.024)
Constant	1.569**	2.066***	1.649**	1.540**	3.033***	3.037***
	(2.356)	(3.454)	(2.546)	(2.196)	(4.004)	(3.931)
Country clustering	Y	Y	Y	Y	Y	Y

Table 5 (continued)

Variables	(1) Log(Spread)	(2) Log(Spread_Mean)	(3) Log(Spread_Median)	(4) Log(Spread)	(5) Log(Spread_Mean)	(6) Log(Spread_Median)
Year and bank fixed effect	N	N	N	Y	Y	Y
N. of obs./countries	707/23	707/23	707/23	707/23	707/23	707/23
Adjusted R-squared	0.304	0.358	0.346	0.646	0.809	0.820
OLS vs. Fixed effect F-test				(4) vs (1) F = 4.28	(5) vs (2) F = 8.87	(6) vs (3) F = 10.59
				Prob > F = 0.00	Prob > F = 0.00	Prob > F = 0.00

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

Third, for the panel regressions with no fixed effects, the adjusted R-squares are in the range of 30 % to 36 %, respectively, which are about 50 % higher than when only structural variables or only CAMELS elements are used. To test whether the combined model is a significant improvement over each individual model, we perform the F-test to compare the individual model and the combined model (no fixed effect). The F-test for the comparison between the model fit of structural model and the combined model is 27.00 with Prob > F = 0.000, suggesting that the collective contribution of these structure variables is statistically significant. The F-test to compare the model fit of CAMELS model and the combined model is 17.64 with Prob > F = 0.000, showing that the collective contribution of these CAMELS variables is also statistically significant. Taken together, the bank CDS pricing model performs better by incorporating both the market information impounded in Structural model variables and some accounting-based bank fundamentals.[14]

In terms of explanatory variables, our finding is similar to Das et al. (2009) and Ericsson et al. (2009) in that leverage and volatility are important determinants for both corporate and bank CDS spreads. However, accounting-based explanatory variables reflect differences between corporations and banks. While earnings reduce both corporate and bank CDS spreads, Das et al. (2009) find that firm size and inventory to cost of goods sold are also significant determinants of corporate CDS spreads. Our results suggest that asset quality, management quality, and costs of funds are important in pricing bank credit risk.

3.4 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 regulations proxied by financial conglomerate restriction and entry barriers, and the adoption of explicit deposit insurance.

To investigate the explanatory power of the comprehensive model with country factors, we conduct regression without controlling for year and bank fixed effect in Model 1 for the main sample. Leverage, equity volatility and all CAMELS indictors are significant and have the expected signs. Several country-level factors also affect bank CDS spreads. The R-squared shows an improvement from 30 % in Model 1 of Table 5 to 40 % in Model 1 of Table 6. The F-test statistic used to compare the two models is 13.07 (Prob >F = 0.0000), confirming the importance of country-level factors.

Model 2 controls for the year and bank fixed effects. We find that the three structural variables are significant after controlling country and bank regulation factors. *Loan loss provision ratio* and *Cost efficiency* are two CAMELS indicators that remain important. 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 restriction, more entry barrier, and explicit deposit insurance scheme. The significant effect of the country's stock market volatility provides cross-country evidence that systematic risk and

[14] Similar comparison is conducted to compare the structural model with the combined model using the Vuong test for nested models. The Z-statistic is −4.9443 (Prob > F = 0.000), rejecting the null hypothesis in favor of the combined model. A similar test is conducted to examine whether the combined model performs better than the CAMELS model. The Z-statistic is −4.0284 with the *p*-value of 0.0001, showing that the combined model performs better than the CAMELS. So both F-test and the Vuong test yield consistent results.

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 that adjust for heteroskedasticity and within country clustering. Year and bank fixed effects are controlled

	Main sample		Expanded sample
	(1)	(2)	(3)
Variables	Log(Spread)	Log(Spread)	Log(Spread)
Market leverage	0.012*	0.018**	
	(1.797)	(2.639)	
Equity volatility	0.094**	0.056*	
	(2.578)	(2.051)	
Government bond yield	−0.049	0.125***	0.146***
	(−0.629)	(4.107)	(4.880)
Log(Z-score)	−0.102***	−0.023	−0.041
	(−2.960)	(−0.685)	(−1.507)
Loan loss provision ratio	0.073***	0.043**	0.057**
	(6.817)	(2.572)	(2.612)
Cost efficiency	0.004***	0.002*	0.001
	(4.048)	(1.792)	(1.191)
ROE	−0.0007***	−0.0002	−0.0001
	(−4.580)	(−0.635)	(−0.289)
Liquidity ratio	−0.009**	0.013	0.010
	(−2.479)	(1.290)	(1.644)
Cost of funds	0.135*	0.091	0.059
	(1.741)	(1.110)	(1.602)
Log(GDP per capital)	0.046	0.288	0.237
	(0.229)	(0.550)	(0.669)
Stock market volatility	0.532***	0.293**	0.279***
	(3.961)	(2.638)	(2.975)
Yield curve slope	−0.052	0.171	0.169**
	(−0.508)	(1.633)	(2.324)
Country governance	−0.290**	−0.204	−0.109
	(−2.541)	(−0.570)	(−0.416)
Bank concentration	0.014***	−0.004	−0.006
	(3.671)	(−0.377)	(−0.800)
Financial conglomerate restriction	−0.211*	−0.497**	−0.680***
	(−1.779)	(−2.785)	(−3.475)
Entry barrier	−0.005	0.102*	0.022***
	(−0.463)	(1.837)	(3.311)
Explicit	0.075	0.587***	0.354**
	(0.240)	(3.307)	(2.219)
Constant	0.063	−0.288	3.661
	(0.032)	(−0.054)	(0.952)
Country clustering	Y	Y	Y
Year and bank fixed effect	N	Y	Y
N. of obs./countries	707/23	707/23	968/26
Adjusted R-squared	0.400	0.652	0.675

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

risk premia in a country is important for credit risk pricing of global banks. Banks in countries with greater financial conglomerate 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 positive and significant coefficient of entry barrier suggests that more restrictions on bank entry are likely to limit bank competition and lead to higher monopoly power, hence increasing their default probabilities. The coefficient on the 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.[15] The positive sign of *Explicit* suggests that the adverse impact from moral hazard dominates its intended positive impact of promoting financial stability.

In Model 3 for the expanded sample, government bond yield and bank *Loan loss provision ratio* remain significant and robust determinants of bank CDS spread. The coefficients on the country-level factors, *Stock market volatility*, *Yield curve slope*, *Financial conglomerate restriction* and *Explicit* are both economically and statistically significant. Using the average and median CDS spread as dependent variables yield very similar results. We do not report to save space.

Finally, we use the stepwise selection approach to select the crucial determinants of CDS spreads at the 10 % level.[16] Results are reported in Table 7. For the main sample, the selection procedure keeps a set of important determinants of CDS spreads, including the three structural variables, loan loss provision, cost efficiency, country-level stock market volatility, country governance, financial conglomerate restriction, entry barrier and the explicit deposit insurance dummy. The adjusted R-squared is at 68.7 %, which is slightly better than the full model (Model 1 in Table 6). Results are quite similar for the expanded sample with the adjusted R-squared at 67.7 %. Overall, the results suggest that the model fit does not suffer from the stepwise selection.

3.5 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 variables by subtracting the mean from the raw value before constructing the interaction terms. The results are presented in Table 8.

In Model 1 for the main sample, the coefficient on the banking *Crisis* variable is positive and significant (1.283, $t = 2.604$), confirming that the bank CDS spread is significantly higher since the onset of the financial crisis. The coefficient on the interaction term between *Market leverage* and *Crisis* is positive and significant (0.014, $t = 2.114$), 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

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

[16] We thank the referee for suggesting using the stepwise approach to select crucial determinants.

Table 7 Stepwise tests. This table presents results for stepwise tests, which perform a backward-selection search for the regression model on the structural variables, CAMELS indicators, country-level economic indicators, bank industry structure, and bank regulations. Model (1) and (3) do not control for the year and bank fixed effects. Model (2) and (4) control for the year and bank fixed effect. If the significance of the control variable is larger than 10 %, the variable will be automatically removed from the full model. Banks in the expanded sample have no stock return data available. Reported in parentheses are t-statistics based on robust standard errors that adjust for heteroscedasticity and within country clustering

	Main sample	Expanded sample
	(1)	(2)
Variables	Log(Spread)	Log(Spread)
Leverage	0.026***	
	(4.897)	
Volatility	0.070***	
	(3.193)	
Government bond yield	0.111***	0.096***
	(5.681)	(4.900)
Log(Z-score)		
Loan loss provisions	0.047***	0.050***
	(4.278)	(4.620)
Cost efficiency	0.002*	0.002**
	(1.778)	(2.319)
ROE		
Liquidity		
Cost of funds		
Log(GDP per capital)		
Stock market volatility	0.322***	0.385***
	(4.186)	(5.565)
Yield curve slope		
Country governance	−0.295***	
	(−4.992)	
Bank concentration		−0.005**
		(−2.369)
Financial conglomerate restriction	−0.206***	−0.154***
	(−4.252)	(−3.052)
Entry barrier	0.011***	0.008***
	(2.716)	(3.360)
Explicit	0.584***	0.351**
	(3.207)	(2.214)
Constant	2.120***	3.606***
	(3.559)	(10.217)
Country clustering	Y	Y
Year and bank fixed effect	Y	Y
N. of obs./countries	707/23	968/26
Adjusted R-squared	0.687	0.677

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

Table 8 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 the sample year is 2007 and 2008, 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 that adjust for heteroscedasticity and within country clustering. Year and bank fixed effects are controlled

	Main Sample	Expanded Sample
	(1)	(2)
Variables	Log(Spread)	Log(Spread)
Market leverage*Crisis	0.014**	
	(2.114)	
Equity volatility*Crisis	−0.081	
	(−0.671)	
Government bond yield*Crisis	−0.062	−0.005
	(−0.773)	(−0.107)
Log(Z-score)*Crisis	0.021	0.035
	(0.407)	(0.871)
Loan loss provision ratio*Crisis	0.090***	0.071***
	(4.174)	(2.957)
Cost efficiency*Crisis	0.002	0.001
	(0.976)	(0.682)
ROE*Crisis	0.0005	−0.0005
	(0.187)	(−0.467)
Liquidity ratio*Crisis	0.003	0.001
	(0.553)	(0.327)
Cost of funds*Crisis	0.097	0.050
	(1.025)	(0.872)
Crisis	1.283**	1.338***
	(2.604)	(3.167)
Market Leverage	0.017	
	(1.445)	
Equity volatility	0.085*	
	(1.811)	
Government bond yield	0.159**	0.153***
	(2.727)	(3.724)
Log(Z-score)	−0.019	−0.040
	(−0.604)	(−1.609)
Loan loss provision ratio	0.021	0.039
	(0.791)	(1.362)
Cost efficiency	0.002	0.001
	(1.704)	(0.902)
ROE	−0.0003	0.0002
	(−0.248)	(0.289)
Liquidity ratio	0.012	0.009
	(1.331)	(1.635)
Cost of funds	0.052	0.035
	(0.966)	(0.850)

Table 8 (continued)

Variables	Main Sample (1) Log(Spread)	Expanded Sample (2) Log(Spread)
Log(GDP per capital)	0.344	0.382
	(0.621)	(1.064)
Stock market volatility	0.360***	0.311***
	(2.949)	(2.994)
Yield curve slope	0.236**	0.209***
	(2.527)	(2.976)
Country governance	−0.102	−0.142
	(−0.238)	(−0.493)
Bank concentration	−0.006	−0.007
	(−0.512)	(−0.794)
Financial conglomerate restriction	−0.634**	−0.711***
	(−2.269)	(−3.054)
Entry barrier	0.126	0.028
	(1.659)	(0.394)
Explicit	0.834***	0.433**
	(2.921)	(2.321)
Constant	2.571	3.260
	(0.437)	(0.853)
Country clustering	Y	Y
Year and bank fixed effect	Y	Y
N. of obs./countries	707/23	968/26
Adjusted R-squared	0.663	0.681

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

financial crisis. We also find that the coefficient on the interaction term between *Loan loss provision ratio* and *Crisis* is positive and strongly significant (0.090, t = 4.174). 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.

4 Robustness

In this section, we conduct additional robustness checks. First we use Tier 1 and Tier 2 capital ratios rather than Z-score as our measure of capital adequacy. We repeat the analysis for the combined structural and CAMELS model and the comprehensive model with country factors. Results are presented in Panel A of Table 9. The use of alternative capital adequacy measures does not impact the effect of structure variables, other accounting variables and country-level variables.

Second, we investigate how well the combined model performs in explaining CDS spreads of other maturities. In particular, we use the 3-year, 7-year and 10-year CDS

Table 9 Robustness tests. This table presents results for the robustness checks. In Panel A, we use Tier 1 and Tier 2 capital ratios rather than Z-score as our measure of capital adequacy. In Panel B, we test the model fit for the 3-year, 7-year and 10-year CDS spreads. The sample is smaller due to the requirement of complete CDS spreads for different maturities. Reported in parentheses are t-statistics based on robust standard errors that adjust for heteroscedasticity and within country clustering. Year and bank fixed effects are controlled

Panel A: Alternative accounting variables

	(1)	(2)	(3)	(4)
Variables	Log(Spread)	Log(Spread)	Log(Spread)	Log(Spread)
Market leverage	0.018**	0.019**	0.016**	0.018***
	(2.138)	(2.399)	(2.432)	(2.867)
Equity volatility	0.067*	0.060*	0.068**	0.058*
	(2.044)	(1.927)	(2.200)	(1.989)
Government bond yield	0.113***	0.126***	0.116***	0.127***
	(4.763)	(4.054)	(4.600)	(4.217)
Tier 1 capital ratio	1.503	1.572		
	(1.010)	(0.865)		
Tier 2 capital ratio			4.902	5.546
			(1.494)	(1.518)
Loan loss provision ratio	0.041***	0.044**	0.042***	0.044**
	(3.005)	(2.664)	(2.977)	(2.549)
Cost efficiency	0.002	0.002*	0.002	0.002
	(1.683)	(1.751)	(1.561)	(1.619)
ROE	−0.0008***	−0.0003	−0.0006***	−0.0002
	(−4.876)	(−1.260)	(−3.132)	(−0.579)
Liquidity ratio	0.013	0.013	0.012	0.012
	(1.307)	(1.299)	(1.288)	(1.268)
Cost of funds	0.107**	0.094**	0.103**	0.092**
	(2.293)	(2.195)	(2.213)	(2.230)
Log(GDP per capital)		0.342		0.156
		(0.627)		(0.278)
Stock market		0.287**		0.304**
		(2.487)		(2.621)
Yield curve slope		0.178		0.163
		(1.655)		(1.491)
Country governance		−0.245		−0.232
		(−0.650)		(−0.626)
Bank concentration		−0.003		−0.003
		(−0.271)		(−0.302)
Financial conglomerate restriction		−0.482**		−0.470**
		(−2.730)		(−2.572)
Entry barrier		0.096		0.102*
		(1.613)		(1.794)
Explicit		0.593***		0.549**
		(3.152)		(2.794)
Constant	1.227	−1.185	1.337*	0.732
	(1.424)	(−0.207)	(2.046)	(0.129)
Country clustering	Y	Y	Y	Y
Year and bank fixed effect	Y	Y	Y	Y
N. of obs./countries	557/22	557/22	557/22	557/22
Adjusted R-squared	0.647	0.653	0.647	0.654

Table 9 (continued)

Panel B: CDS spreads of different maturities

Variables	(1) Log(Spread) 5-year	(2) Log(Spread) 3-year	(3) Log(Spread) 7-year	(4) Log(Spread) 10-year
Market leverage	0.021***	0.023***	0.017**	0.015**
	(3.025)	(2.921)	(2.259)	(2.085)
Equity volatility	0.075**	0.103***	0.074**	0.069**
	(2.574)	(3.144)	(2.772)	(2.764)
Government bond yield	0.119***	0.129***	0.102***	0.096***
	(4.570)	(3.547)	(3.076)	(3.047)
Log(Z-score)	−0.010	0.011	−0.005	−0.010
	(−0.252)	(0.444)	(−0.215)	(−0.511)
Loan loss provision ratio	0.044**	0.053***	0.047***	0.044***
	(2.569)	(3.413)	(3.991)	(3.808)
Cost efficiency	0.003	0.004	0.003	0.003
	(1.309)	(1.428)	(1.519)	(1.499)
ROE	−0.021	−0.059**	−0.053***	−0.050***
	(−0.788)	(−2.639)	(−2.941)	(−2.839)
Liquidity ratio	0.013	0.001	0.002	0.002
	(1.222)	(0.216)	(0.339)	(0.361)
Cost of funds	0.079	0.107**	0.070**	0.062*
	(1.628)	(2.770)	(2.206)	(1.918)
Log(GDP per capital)	0.041	−1.133*	−0.871*	−0.778*
	(0.071)	(−2.030)	(−2.000)	(−1.789)
Stock market historical volatility	0.237**	0.145	0.143	0.159
	(2.085)	(1.090)	(1.188)	(1.397)
Yield curve slope	0.199*	0.114	0.051	0.047
	(1.986)	(1.062)	(0.511)	(0.493)
Country governance	−0.168	−0.023	−0.027	−0.039
	(−0.394)	(−0.061)	(−0.091)	(−0.135)
Bank concentration	−0.580	−1.004	−0.900	−0.842
	(−0.459)	(−0.941)	(−1.068)	(−1.062)
Financial conglomerate restriction	−0.259	−0.395**	−0.470***	−0.530***
	(−1.479)	(−2.097)	(−3.045)	(−3.787)
Entry barrier	0.085	0.084	0.093*	0.101**
	(1.275)	(1.455)	(2.044)	(2.398)
Explicit	0.338*	0.587**	0.652**	0.551**
	(2.006)	(2.285)	(2.697)	(2.246)
Constant	1.816	13.871**	13.008***	12.625***
	(0.313)	(2.547)	(3.138)	(3.040)
Country clustering	Y	Y	Y	Y
Year and bank fixed effect	Y	Y	Y	Y
N. of obs./countries	576/23	576/23	576/23	576/23
Adjusted R-squared	0.678	0.863	0.859	0.852

The superscripts ***, **, and * indicate significance at 1 %, 5 %, and 10 % levels, respectively

spreads as dependent variables. To ensure the sample is the same, we require the sample to have complete data for CDS spreads for all the above three maturities and the 5-year maturities. Results are presented in Panel B of Table 9. Several observations are noted. First, leverage is positively related to CDS spreads of all maturities. The magnitude of coefficient declines as the maturity increases, suggesting that leverage plays a stronger role to explain imminent credit risk. Similar pattern exists for equity return volatility. Second, loan-loss provision ratio, ROE and cost of funds are significant accounting variables for the 3-year, 7-year and 10-year CDS spreads, in a way similar to the 5-year CDS spreads. Third, it is interesting to observe that the model fit is about 85 % for the 3-year, 7-year and 10-year CDS spreads, in comparison with R-square of 68 % for the 5-year CDS spreads, the most liquid contract among all maturities. The higher model fit for the less liquid contracts indicates that liquidity factor is not a dominating factor for bank credit risk in the CDS market.

Third, we test the out-of-sample performance of our models following Das et al. (2009). We randomly split our sample of CDS spreads into two sub-samples, an in-sample and an out-of-sample. The subsamples roughly have equal sizes, with the in-sample of 355 and out-of-sample of 352 observations, respectively. We use the in-sample data to estimate structural model, CAMELS model, the combined structural and CAMELS model, and the comprehensive model with country factors to get coefficients, and then calculate the predicted values for the out-of-sample. Fig. 1 shows the regression results of actual versus predicted values for all four models. The null hypothesis is that the slope is one and the intercept is zero. The F-statistics and its p-values are reported. For example, the out-of-sample test for the structural model shows that the F-statistic is 0.52 (prob > F = 0.5950). So the null hypothesis cannot be rejected at the 10 % level. The R-squared are 21 % and 20 % for the

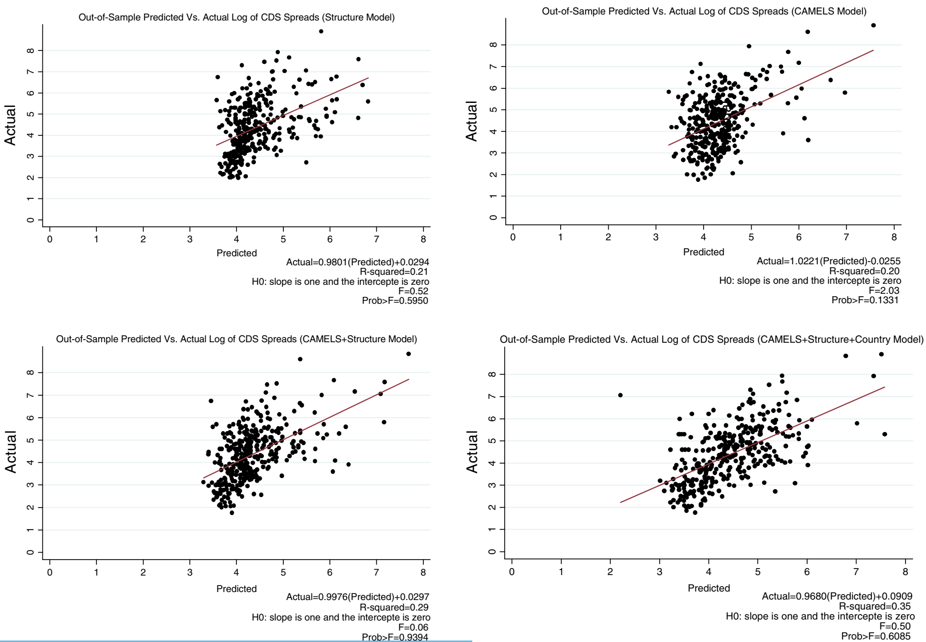

Fig. 1 Out-of-sample tests

structural model and CAMELS model, respectively. For the combined model and the comprehensive model, the fit is stronger with R-squared of 29 % and 35 %, respectively. The joint hypothesis that the slope is one and the intercept is zero also fails to be rejected in all four models, suggesting that the out-of-sample prediction performs well.

Finally, we compare the models in terms of rank-order predictability by constructing cumulative accuracy profile (CAP) curves and the associated accuracy ratio (AR) statistics. The relative ranking complements the approach of point estimates and provides an alternative way to compare models. Fig. 2 presents the cumulative accuracy profile for four models and their corresponding accuracy ratios. Following Das et al. (2009), we first rank the predicted values of log(Spread), then we create 100 bins for the predicted value group and assign the top 1 % of all predicted values to the first bin, the top 2 % of all predicted values to the second bin and so on and so forth. We then do the same for the actual value group. For each bin, we calculate how many predicted values have their actual values in that same bin. The percentage is plotted as the cumulative accuracy profile of our model.

The accuracy ratios are 31 % and 30 % for the structural model and CAMELS model, respectively. For the combined model and the comprehensive model, the accuracy ratios improved significantly to 50 % and 55 %, respectively, lower than the accuracy ratio of 61.6 % for the comprehensive model in Das et al. (2009). This suggests that bank CDS spreads are more difficult to model than corporate CDS spreads. This could reflect limited variation in leverage and financing patterns, or different regulatory norms for banks than corporations.

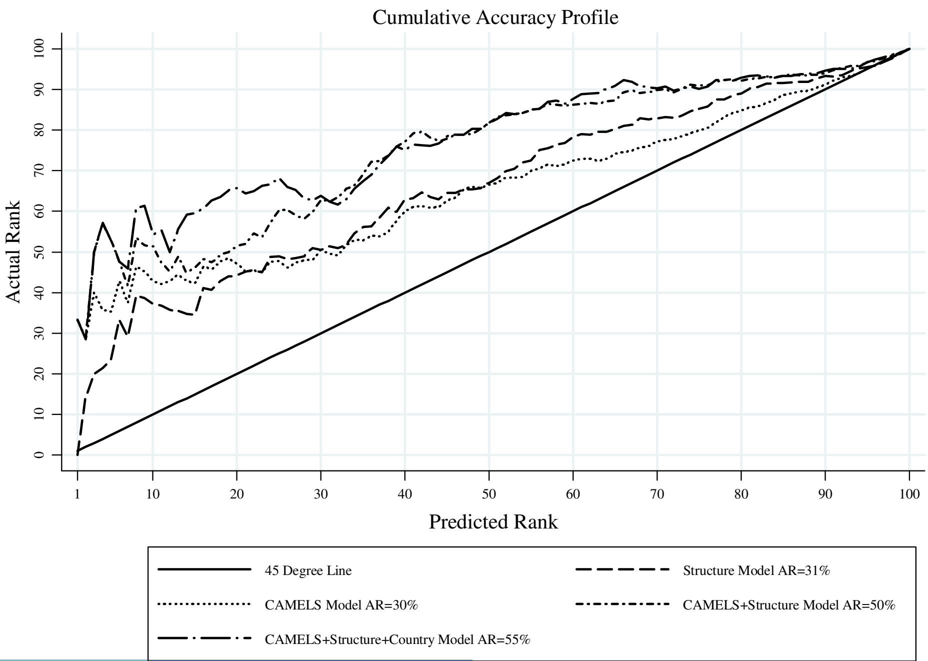

Fig. 2 Cumulative accuracy profile and accuracy ratio (AR) statistics

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 Model variables and CAMELS indicators 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 23 countries, we find that the market-value based leverage measures and equity return volatility are significant determinants of bank credit risk. This provides 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 and cost efficiency appear the most significant determinants among CAMELS indicators 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. This finding supports the regulators' concern on the potential risks of allowing banking-commerce integration due to conflicts of interest and difficulties to discipline. Entry barrier is positively related to the 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 market 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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Appendix

Table 10 Variable definitions and data sources

Variable	Definition	Sources
CDS Spread Variables		
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.	MarkIt
CDS Spread_mean	The average of the daily CDS spread over a year.	MarkIt
CDS Spread_median	The median of the daily CDS spread over a year.	MarkIt
Structural Model Variables		
Market leverage	Book value of liabilities to the sum of book value of liabilities and market value of equity.	Bankscope, Global Compustat
Equity volatility	The historical standard deviation of bank's daily equity returns in a particular year.	Bloomberg
Government bond yield	The 5-year government bond yield.	Bloomberg
Bank CAMELS Variables		
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
Loan loss provision ratio	The ratio of loan loss provisions to total loans.	Bankscope
Cost efficiency	The ratio of operating costs to revenues.	Bankscope
ROE	Net income divided by total common equity.	Bankscope
Liquidity ratio	The ratio of liquid assets to total assets.	Bankscope
Cost of funds	The ratio of interest expense to total liabilities.	Bankscope
Alternative Measures		
Tier 1 capital ratio	The ratio of Tier 1 capital to total risk-adjusted assets.	Bankscope
Tier 2 capital ratio	The ratio of Tier 2 capital to total risk-adjusted assets.	Bankscope
Nonperforming loan ratio	The ratio of nonperforming loans to total loans.	Bankscope
Trading income ratio	The ratio of trading income to revenues.	Bankscope
ROA	Net income divided by total assets.	Bankscope
Wholesale funding ratio	The ratio of wholesale funds to total liabilities.	Bankscope
Country Variables		
Log(GDP per capital)	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
Yield curve slope	The return on ten-year government bonds minus return on two-year government bonds.	Global insights
Country governance	The country governance indicator.	Worldwide Governance Indicators

Table 10 (continued)

Variable	Definition	Sources
Bank concentration	The fraction of bank assets held by the five largest commercial banks in the country.	Bankscope
Financial conglomerate 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 0 otherwise.	World Bank and the 2010 annual survey results of International Association of Deposit Insurers

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