UCD GEARY INSTITUTE FOR PUBLIC POLICY
DISCUSSION PAPER SERIES

Credit Default Swaps as Indicators of Bank financial Distress

Davide Avino,
Management School,
University of Liverpool

Thomas Conlon,
Smurfit Graduate Business School,
University College Dublin

John Cotter,
Smurfit Graduate Business School and Geary Institute for Public Policy,
University College Dublin

Geary WP2016/01
Jan 7, 2016
(Updated May 22, 2019)

Credit Default Swaps as Indicators of Bank Financial Distress

Davide E. Avino[a], Thomas Conlon[b,*], John Cotter[b]

[a]*Management School, University of Liverpool, Liverpool, L69 7ZH, United Kingdom.*
[b]*Smurfit Graduate Business School, University College Dublin, Ireland*

Abstract

We examine whether CDS contracts written on individual banks are effective leading indicators of bank financial distress during a period of systemic bank crisis. Changes in CDS spreads are found to yield a robust signal of failure across a set of European and US banks, in keeping with indirect market discipline. Furthermore, changes in CDS spreads provide information about the condition of banks which supplements that available from equity markets and contained in accounting metrics. Consistent results are detailed for both senior and subordinated CDS spreads. Our results hold out-of-sample, for logit and proportional hazards models, for various cohorts, for idiosyncratic changes in CDS and are robust to the use of alternative measures of bank distress, including rating downgrades and accounting risk.

Keywords: Bank Failure, Market Discipline, Credit Default Swap, CDS

---

*Corresponding Author

Email addresses: `Email: d.avino@liverpool.ac.uk` (Davide E. Avino), `Email: conlon.thomas@ucd.ie, Tel: +353-1-7168909` (Thomas Conlon), `Email: john.cotter@ucd.ie, Tel: +353-1-7168900` (John Cotter)

The authors would like to thank Barbara Casu, Claudia Giradone, Xing Huan, Stefanie Kleimeier, Jose Linares-Zegarra, David Mayes, Linh Nguyen, Antonio Parbonetti, Amedeo Pugliese, John Wilson and participants at the British Accounting and Finance 2016 Conference, the 2016 INFINITI Conference on International Finance, the 2016 International Finance and Banking Conference, the 2016 Workshop on European Banking Union and Financial Distress and seminar participants at the University of Padua and the University of Warwick for helpful comments and suggestions. This publication has emanated from research conducted with the financial support of Science Foundation Ireland under Grant Number 16/SPP/3347 and 17/SP/5447.

1. Introduction

In contrast to many other industries, banks, and financial institutions more generally, are subject to high levels of regulatory oversight. Regulatory supervision may also be supplemented by market forces in two primary ways (Flannery, 2001). First, changes in market prices may be linked to increased funding costs, limiting risk taking and inducing direct market discipline. Second, market prices may act as a signal to investors, policy makers and supervisors regarding the condition of individual financial institutions, leading to indirect market discipline. Moreover, such market signals may be employed as inputs to early warning models of bank financial distress. Previous studies have indicated mixed success in using market-based information to distinguish between safe and distressed banks, in particular for bond markets. Firm-level credit default swaps (CDS) present many advantages over bond markets in terms of price discovery, liquidity and standardization. In light of these benefits, we address the following research question: Do firm-level CDS contracts act as effective and distinct leading indicators of bank vulnerability to distress?

For banks with actively traded securities, changes in prices of equity and debt act as a source of market information regarding the market's perception of their financial condition. Equity investors appear well placed to provide market discipline, given their status as residual claimants in the event of default. One argument against this view is that equity investors may condone increased risk taking, being the primary beneficiaries from any upside gains (Gropp *et al.*, 2006). For this reason, bond markets and, in particular, subordinated debt have been considered as a means to promote market discipline. If debt markets accurately reflect bank risks, banks may be discouraged from adopting riskier strategies to ward off potential increases in funding costs. In practice, however, the use of debt markets to monitor banks is beset by implementation problems, such as differing yields for bond issues from a single institution, and illiquidity (Gropp *et al.*, 2006; Chen *et al.*, 2007).

We examine whether single-name CDS can distinguish between safe and distressed banks using a sample encompassing the global financial crisis. A CDS is a protection or insurance agreement between two parties, whereby the protection seller undertakes, in exchange for a premium paid by the protection buyer, to make a payment if a specified credit event occurs (Chiaramonte and

Casu, 2013). As a signal of bank condition, CDS offer a number of differences and potential benefits relative to corporate debt markets. First, the CDS market is attractive due to smaller trading frictions compared to the underlying bond (Oehmke and Zawadowski, 2014). Second, CDS market prices are standardized with constant maturity, whereas bond yields of a given maturity can only be obtained by interpolating yields between bonds of different maturities (Blanco *et al.*, 2005). Third, CDS markets are more liquid than corporate debt markets (Longstaff *et al.*, 2005). Finally, CDS spreads tend to lead bond markets in price discovery (Blanco *et al.*, 2005). Related to this, Acharya and Johnson (2007) have also shown that CDS markets may be able to reveal information in advance of the equity market. Given these strong relative benefits, CDS contracts seem well placed to act as an indicator of bank distress, thus providing indirect market discipline.

In this paper we provide the first analysis of the capacity of CDS contracts on individual banks to act as a signal of a bank's financial condition. Relative to accounting and equity information, we investigate the marginal contribution of changes in CDS spreads in forecasting bank distress during the years 2004-2012, a period of systemic banking crisis during which many banks failed. Previous literature has considered the propensity of aggregate CDS spreads (based on broad CDS indices) to act as a signal of bank distress (Knaup and Wagner, 2012), investigated the drivers of bank CDS spreads during the global financial crisis (Chiaramonte and Casu, 2013) and the interdependence of sovereign and bank CDS during times of market turbulence (Alter and Schüler, 2012). In contrast, this paper focuses on single-name CDS contracts associated with both senior and subordinated debt of individual institutions.[1]

Empirical findings indicate that changes in CDS spreads help to explain forthcoming distress in banks, whilst controlling for alternative drivers. The economic significance is substantial: a one standard deviation increase in CDS spread changes is found to be associated with an increase in the probability of bank failure which ranges from 7% to 14%. Moreover, our results indicate that CDS spreads incorporate information about the condition of banks which is above and beyond

[1] Single-name or firm-level CDS contracts are a derivative where the underlying instrument is a bond of a particular company.

that available from both equity market indicators and accounting metrics, the latter forming the backbone of many early-warning models. This is in keeping with indirect market discipline, as CDS contracts signal increasing borrowing costs for distressed firms. Moreover, both senior and subordinated debt are examined, with CDS spread increases found to be associated with future bank distress. Findings are shown to be robust to an alternative estimation method (a proportional hazards model), alternative dependent variables available throughout the sample period (rating downgrades and accounting risk), excluding US banks, for various cohorts, and for excess and idiosyncratic changes in CDS. While our findings are constrained by a small data sample of banks having traded CDS, the evidence presented points to the potential for CDS to contribute to indirect market discipline.

In the following section we describe literature relevant to this study. Data and methodology are detailed in Section 3. Empirical results and robustness analysis are provided in Section 4. Section 5 discusses our findings and concludes.

2. Related Literature

Corporate governance of financial institutions is constrained by many factors, not least the problem that small depositors may not be able to distinguish between safe and risky institutions, the opaque nature of banking assets, and the dangers of contagion from a single distressed institution (Flannery, 1998). Thus, government oversight aims to promote stability in the banking sector, protecting depositors through provision of deposit insurance and acting as a lender of last resort to mitigate contagion due to illiquidity. Market discipline, as provided for in the Basel II accord, aspires to complement regulatory oversight. This may be achieved through two channels: by means of direct influence on management risk taking and, indirectly, through market monitoring of banks' financial position (Flannery, 2001). If market discipline exists, then changes in the prices of liabilities or equities, both absolute and relative to competitors, should be related to changes in measures of risk (Mayes, 2004; Gorton and Santomero, 1990). On this basis, empirical evidence for market discipline has been mixed. Flannery (1998) suggests that market investors could provide further market discipline for large, traded U.S. banks, but that this may be impeded by government oversight and the potential for state intervention in distressed institutions.

The failure and near-failure of many systemically important banks during the global financial crisis and subsequent European sovereign debt crisis, has again brought banking regulation to the forefront. The considerable underperformance of many banks during this period has been variously attributed to a dependence on short-term funding, high leverage, lack of diversification, credit expansion and higher share of volatile non-interest income (Demirguc-Kunt *et al.*, 2013; Beltratti and Stulz, 2012; Altunbas *et al.*, 2011). Moreover, factors common to previous crises, including historical bank equity performance, have been shown to explain distress for individual institutions during the global financial crisis (Cole and White, 2012; Fahlenbrach *et al.*, 2012). In this study, we build on previous analyses of bank failure during the global financial crisis. The abundance of distressed banks during the period encompassing the global financial crisis and the introduction of novel financial instruments such as CDS provide a fresh opportunity to determine whether financial markets are helpful in explaining the failure of financial institutions.

There is considerable evidence to suggest that equity markets display efficiency in processing information and, so, should act as a strong indicator of a firm's financial position (Gropp *et al.*, 2006). Considering the potential of equity markets to act as a signal of bank fragility, Distinguin *et al.* (2006) identify a number of equity-derived indicators which complement traditional accounting data. Furthermore, Curry *et al.* (2008) present evidence that one-quarter lagged equity market data adds forecasting ability to a model of bank holding company risk ratings. In contrast, Krainer (2004) finds little additional ability to forecast changes in supervisor ratings from equity market information relative to supervisory factors. Gropp *et al.* (2006) use equity market data to develop a distance-to-default (*DD*) metric, suggested as a complement to bond information in signaling bank fragility. Bliss and Flannery (2002) investigate the ability of equity market discipline to influence managerial actions but do not find strong evidence for this. More recently, Milne (2014) used the *DD* measure as a market signal of bank risk, finding poor forecasting performance prior to the onset of the subprime crisis. In this study, we again assess whether equity markets help in distinguishing between safe and distressed banks and provide a comparison to the contribution of CDS markets.

Debt markets provide a further source of information regarding a bank's financial condition. Changes in bond credit spreads should reflect changes in bank risk, if firms are to furnish information on firm condition. However, evidence for the effectiveness of debt markets is mixed. Krishnan *et al.* (2005) show that credit spread levels are associated with risk taking behavior but that changes in spread levels are not. Gorton and Santomero (1990) find little support for the ability of subordinated debt to limit bank risk taking following the expansion of the government safety net in the early 1980s. Similarly, Evanoff and Wall (2001) suggest that market information embedded in subordinated debt yield spreads is too noisy to serve as a trigger for corrective action. Considering the recent global financial crisis, Miller *et al.* (2015) find no evidence that subordinated note yields act as a reliable signal of bank distress, attributed to distortion by banks deemed too-big-to-fail. In sharp contrast, a variety of studies have documented evidence that debt markets reflect the riskiness of financial institutions (see, for example, Gropp *et al.*, 2006; Sironi, 2003).

Models examining the potential of subordinated debt to provide market discipline have also arrived at disparate conclusions (Chen and Hasan, 2011; Niu, 2008; Blum, 2002). The differential results reported in empirical studies may potentially be a consequence of the various difficulties associated with the implementation of debt securities as an early warning signal. For example, firms may issue bonds with varying maturities making cross-comparison difficult, there may be difficulties in estimating an appropriate risk-free rate, and different bonds issued by the same bank may result in distinct implied yields (Gropp *et al.*, 2006). The application of information from CDS markets in early warning models of bank distress may help to overcome many of these issues.

Credit default swaps have been actively traded since the early parts of the 2000s, with liquidity and availability generally increasing over the decade: the Bank for International Settlements began reporting CDS notionals in 2004. CDS notionals doubled each year from 2004 ($6.4 trillion) until 2007 ($58.2 trillion) before being hit by the outbreak of the financial crisis in 2008 (where notionals traded declined to $42 trillion). By the end of 2012, the size of the CDS market was similar to the period preceding the subprime crisis of 2007 (still representing a sizeable market worth $25 trillion of traded notionals).[2] CDS have a variety of features which may make them a better proxy than bonds in providing market discipline for banks. Oehmke and Zawadowski (2014) suggest that speculative credit trading volume concentrates in the CDS rather than bond markets. Moreover, CDS spreads are less affected by illiquidity than bond spreads: Longstaff et al. (2005) find that the nondefault component of corporate bonds (computed as the difference between the credit spread and the CDS spread) is strongly related to bond-specific illiquidity measures (such as the bid-ask spread) as well as aggregate bond market liquidity measures (such as the flows into money market mutual funds). Huang and Huang (2012) and Elton *et al.* (2001) also find that credit risk typically accounts for less than 20 percent of the corporate-Treasury yield spreads. Blanco *et al.* (2005) documents a higher price discovery for CDS spreads relative to corporate bonds. Finally, evidence of faster information processing ability in the CDS market is also shown relative to the equity market by Acharya and Johnson (2007) and Berndt and Ostrovnaya (2014). The authors find that CDS markets reveal information in advance of the equity market for entities that experience (or are likely to experience) adverse credit events.

Interest in bank CDS has increased markedly since the global financial crisis. Stânga (2014) and Avino and Cotter (2014) examine the relationship between bank and sovereign CDS spreads from the onset of the global financial crisis. Analyzing the potential for market discipline in the CDS market, Völz and Wedow (2011) point to the influence of bank size on CDS prices. Chiaramonte and Casu (2013) evaluate the determinants of bank CDS spreads and demonstrate a tendency for considerable time variation. Hasan *et al.* (2016) also find a significant contemporaneous relationship between CDS spreads and structural variables, and a weaker link with CAMELS indicators. Considering the case of a single distressed institution, Northern Rock, Hamalainen *et al.* (2012) determine that equity markets provide a stronger signal of impending problems than debt or CDS markets. Finally, a number of studies have used aggregate CDS spreads and CDS indices to

[2]See www.bis.org and www.dtcc.com for more information on notional amounts traded on both single-name and index CDS contracts.

examine bank fragility (Ballester *et al.*, 2016; Calice *et al.*, 2012). In particular, Knaup and Wagner (2012) illustrate that information contained in aggregate CDS indices can be used to develop a credit risk indicator representing the quality of a bank's credit portfolios. Building on the extant literature considering banks and CDS contracts, the present study assesses the cross-sectional ability of single-name bank CDS contracts to perform a disciplining role on banks.

3. Data and Methodology

We now describe our sample of bank CDS, in addition to the accounting-based and market-related variables employed as inputs to the bank distress models. Theory and mathematical representation of the logit model used to explain bank failure is further detailed.

3.1. Data

In order to test the ability of CDS to distinguish between safe and distressed banks, we obtain single-name five year CDS spreads from Markit. Markit provides consensus CDS prices after aggregating contributions from various dealers on a daily basis. The initial data set contains 538 financial firms with senior CDS data. We restrict our main focus to banks and start by applying data filters, including "Banks", "Diversified Banks" and "Financial Services" sectors. After filtering the data, we are left with 259 firms. Banks whose headquarters are not in the US or Europe are then removed, resulting in 142 firms. Next, firms with missing values for their accounting ratios are taken out of the sample. This results in a final sample of 60 firms with CDS data available over the sample period 2004-2012.[3] The size of the final sample, while potentially smaller than might be available for an analogous study considering equities, is larger than available for previous studies considering cross-sectional properties of bank CDS, such as Ballester *et al.* (2016), Yang and Zhou (2013), Annaert *et al.* (2013) and Eichengreen *et al.* (2012).

[3]Following a similar filtering procedure for subordinated CDS spreads, we end up having a much smaller sample of banks. For this reason, we base our primary analysis on senior CDS spreads. However, in Section 4.6, we investigate whether subordinated spreads act as a leading indicator for a subsample of banks with available data. Results are qualitatively similar.

We select the 2004-2012 period because (i) we are interested in assessing the explanatory power of CDS before and around periods of crisis (in particular, the financial crisis of 2007-2009 and the subsequent European sovereign debt crisis beginning from 2010); (ii) the CDS market is well developed and mature during this cohort.[4] These choices help to ensure that our empirical study is focused on a liquid, actively traded security during a period of significant instability for the banking industry. Furthermore, we focus primarily on annual data as fundamental accounting data is not available on a more regular basis, especially for European banks. More granular data, at 3, 6, 9 and 12-month intervals, is considered for our variable of interest, changes in CDS spreads.

The set of cross-sectional bank CDS spreads are then used to investigate whether single-name CDS help in explaining bank financial distress. We use the yearly change in the log CDS spread (ΔCDS) as the main variable to explain bank default. Furthermore, we examine the forecasting power of the mean, 5^{th} and 95^{th} percentile of monthly changes in CDS. In Section 4.2, we also use the yearly change in excess CDS spreads ($\Delta EXCDS$) as well as the idiosyncratic CDS change ($\Delta IDCDS$). The former is the difference between the 1-year log change in the CDS spread and the 1-year log change in the CDX index spread (for US financial firms) or the iTraxx index spread (for European financial firms).[5] In order to calculate the idiosyncratic component, we first regress daily CDS spread changes on a constant and either CDX index changes (for US firms) or iTraxx index changes (for European firms). The idiosyncratic CDS change, for each bank, is the residual from the market model on the last day of each year (expressed on an annual basis). CDX and iTraxx index spreads are obtained from Bloomberg.

The control variables employed to control for various facets of banking risk are described next. They consist of both accounting and market variables. Accounting variables employed include *T1RC*, *LLPTA*, *CI*, *ROAE*, *LADEPST* and *SIZE*. Accounting-based variables are obtained from

[4]CDS data on traded notional amounts started to be published in 2004 by the Bank for International Settlements through the semiannual OTC derivatives statistics.

[5]iTraxx Europe is an equally weighted index which comprises 125 highly liquid, investment grade European entities with traded single-name CDS. Similarly, CDX is composed of 125 of the most liquid North American entities with investment grade credit ratings that trade in the CDS market. Both indices are owned, managed, compiled and published by Markit, a leading provider of financial information services.

Bureau Van Dijk's BankScope database. *T1RC* is the tier 1 regulatory capital ratio which is a measure of capital adequacy and is computed as the ratio between the tier 1 capital and risk weighted assets. Banks with greater levels of tier 1 capital should be better able to absorb losses and are expected to have a smaller probability of distress (Demirguc-Kunt *et al.*, 2013; Beltratti and Stulz, 2012; Altunbas *et al.*, 2011). *LLPTA* is the ratio between loan loss provisions and the book value of total assets and captures the quality of assets held by a bank. This is expected to have a positive relationship with bank failure (Poghosyan and Čihak, 2011; Curry *et al.*, 2008; Distinguin *et al.*, 2006). Management quality is represented by the ratio of operating costs to operating income, *CI*, and has a positive expected relationship with risk (Cole and White, 2012; Männasoo and Mayes, 2009). The return on average equity, *ROAE*, measures earnings quality and is expected to have a negative relationship with bank failure (Poghosyan and Čihak, 2011; Arena, 2008). *LADEPST* is the liquidity ratio between liquid assets and the sum of total deposits and short-term borrowing. Higher quantities of liquid assets are expected to reduce the probability of distress (Beltratti and Stulz, 2012). *SIZE* is the log of total assets and captures the potential of large banks to take advantage of their too-big-to-fail status (Molyneux *et al.*, 2014). Larger banks are expected to be less prone to financial distress (Curry *et al.*, 2008).

In this paper, the marginal ability of CDS spreads to explain bank failure relative to equity-derived measures is further studied. Individual equity prices are obtained from Thomson Datastream. Market related variables are represented by *STOCK* and *DD*. *STOCK* is the log stock return, calculated on an annual basis. *DD* is the market-based distance-to-default measure which is computed for each time period t using equity market volatility as in Gropp *et al.* (2006)[6]. This approach allows us to discern whether CDS contracts have additional information on bank condition, in excess of that inherent in equity market signals.

[6]In particular, two nonlinear simultaneous equations are solved for the asset value and asset volatility by using the generalised reduced gradient method. The necessary inputs for the computation of the *DD* measure include: the equity market capitalisation and total debt liabilities (obtained from BankScope), the equity volatility (estimated as the annualised standard deviation of daily returns over the 3 months prior to portfolio formation), the debt maturity (set equal to one year) and the risk-free rate (assumed constant and equal to 3%). Further details on this iterative method can be found in Gropp *et al.* (2006).

We next define the measures of bank distress and bank failure employed in the paper. During the global financial crisis and subsequent sovereign debt crisis, a large number of European and US banks suffered financial distress of one form or another. A bank is defined as having failed if it was nationalized or recapitalized, using either ordinary or preferred share capital, by the state. Data regarding the failure status of each bank was gathered from a variety of sources (Conlon and Cotter, 2014; Altunbas *et al.*, 2011; Goddard *et al.*, 2009; Petrovic and Tutsch, 2009). A broader measure of financial distress is also considered in Section 4.3, which captures the point at which a bank was first downgraded by a major rating agency (Fitch, Moody's or Standard and Poor's). Both measures defined are binary, taking a value of one when a bank is categorised as failed or downgraded, and a value of zero otherwise. Two continuous accounting-based measures of bank insolvency risk are also considered, namely the volatility of bank return on average assets (ROAA) calculated over a rolling three year window and the Z-score. The latter is calculated as $Z = (ROAA + EA)/\sigma(ROAA)$, where EA is the ratio of equity to assets (Abedifar *et al.*, 2013; Beltratti and Stulz, 2012). While continuous variables do not capture the extreme financial risk of a binary failure indicator, they have the advantage of allowing cross-sectional analysis during both periods of financial stress and more normal times. In Appendix A we present the full list of variables used in our study and their mnemonics.

Table 1 provides a summary of the main properties of our primary failure indicator during the period 2005-2012. A large proportion of the failures occur in 2008 with the outbreak of the subprime crisis: 20 banks from a total of 60 failed and the failure rate is highest at 33.3%. During the sample period, a total of 31 banks are deemed to have been either nationalized or recapitalized and regarded as having failed. From a total of 60 banks, we have 11 US institutions which failed by the end of 2009. While the US was the epicenter of the global financial crisis, the number of failed large banks was small relative to Europe. The analysis of 11 failed US institutions is in keeping with Beck *et al.* (2013), where the sample consisted of 12 failed US and 43 failed European banks. Furthermore, Ballester *et al.* (2016) document only 5 US banks with available CDS, compared to 50 European banks over a similar time period.

In Table 2 we show the summary statistics for all the explanatory variables used in the empirical analysis for both the whole sample of banks (Panel A) and the sample of failed banks (Panel B) during the period 2005-2011.[7] The mean and standard deviation of the change in log CDS spreads is higher for the sample of failed banks than for the entire sample. Similar differences can be observed for most of the remaining variables. Failed banks have less capital, higher cost to income, a higher return on average assets and are larger than the average. In our sample 17 banks are unlisted and, for this reason, the number of observations for the stock market variables (namely, *STOCK* and *DD*) are reduced relative to the other variables. A similar argument applies to other variables that have been estimated from daily data when a continuous time series was available for most of the estimation period (namely, $\Delta IDCDS$ and *CDSVOL*). Panel C of Table 2 reports the Pearson correlation coefficient between pairs of the main variables used in the empirical analysis. They are generally low. The highest correlations are between *T1RC* and *LADEPST* (0.51), *CI* and *ROAE* (-0.49), ΔCDS and *DD* (-0.47), *ROAE* and *DD* (0.46).

3.2. Methodology

In order to investigate the explanatory power of CDS spreads for banking failure, we follow Shumway (2001) and Chava and Jarrow (2004) and estimate the probabilities of failure over the next period using a logit model. In particular, we assume that the marginal probability of failure over the next period follows a logistic distribution and is given by:

$$P_{i,t}\left(Y_{i,t+1} = 1\right) = \frac{1}{1 + e^{-\alpha-\beta X_{i,t}}} \tag{1}$$

where $P_{i,t}$ is the probability at time t that bank i will fail in the next time period. $Y_{i,t+1}$ is a dummy variable taking on the value of 1 (0) if the bank failed (did not fail) in period $t + 1$. $X_{i,t}$ is the vector of n explanatory variables known at the end of period t. α and β represent the constant and slope parameters characterizing the logistic function, respectively and are estimated via maximum

[7] Note that we exclude year 2012 from this table because our sample period ends in 2012. Thus, for banks which failed in 2012, we would be using explanatory variables up until year 2011.

likelihood. A higher value of $\alpha + \beta X_{i,t}$ indicates a higher probability of failure. The model is formed such that only information available at time t is employed to understand the probability of failure of an individual bank during the subsequent period $t + 1$.

Common to most studies incorporating both market and accounting variables in explaining failure, we face the issue that they are not available at the same frequencies. Following Arena (2008) and Distinguin *et al.* (2006), we use accounting-based information measured yearly on December 31st of each year. Similarly, market-based information related to CDS and equity are also measured on a yearly basis on the final trading day of each year.[8]

The coefficients from a model based upon a logistic function can be used to quantify the marginal effect of a change in any of the explanatory variables on the probability of failure. The marginal effect of each variable X on P can be determined as follows:

$$\frac{\partial P}{\partial X} = \frac{dP}{d(\alpha + \beta X)} \times \frac{\partial(\alpha + \beta X)}{\partial X} = \frac{e^{-\alpha-\beta X}}{\left(1 + e^{-\alpha-\beta X}\right)^2} \times \beta. \tag{2}$$

The marginal effect is not constant because it depends on the specific values taken on by the explanatory variables X. A common procedure, adopted in this study, is to evaluate the marginal effect for the sample means of the explanatory variables.

4. Empirical Results

This section presents our main empirical results. The initial analysis considers the univariate explanatory power of CDS spread changes for a variety of forecasting horizons. We then assess whether this explanatory power is affected by (i) introducing various accounting and market variables and (ii) selecting a shorter sample period which only includes the subprime crisis. Subsequently, we test the sensitivity of our results to the use of different measures of CDS spread changes. To confirm the robustness of the CDS explanatory power we estimate a proportional haz-

[8]The majority of banks in our sample do not report interim results with sufficient granularity, so, in this study, we use annual accounting data to forecast failure over the following year.

ard model and also examine findings with respect to alternative measures of bank failure for our dependent variable. We also show how including CDS changes in logit models increases the out-of-sample predictions of the models. Finally, the explanatory power of subordinated CDS spread changes is investigated for those banks in our sample for which this data is available.

4.1. CDS spread changes and bank failure

We first empirically establish whether variations in single-name CDS spreads can be used as early warning signals of bank financial distress. In particular, we want to examine whether the use of CDS spread changes can improve the performance of bank failure models over and above models that only use accounting and/or stock market indicators.

We start our empirical analysis by estimating a logit model with the CDS spread change as our only explanatory variable. We consider log changes in the CDS spreads for the 3, 6, 9 and 12 months before the forecasting interval. In a strongly efficient market, CDS spreads would be expected to incorporate information relating to bank distress over a short period, motivating the examination of different lead-times. The results in Table 3 demonstrate a highly significant positive coefficient for all measures of CDS spread change. We observe that, for these univariate regressions, the highest value of the McFadden R-squared is obtained for the 1-year log change in CDS spread and is equal to 0.243. The improvement in explanatory power for longer lead-times is in keeping with previous findings for equity market related forecasts of financial distress (Gropp *et al.*, 2006). Given this higher explanatory power, we use the 1-year CDS spread change in our following analysis.

Model M5 of Table 3 reports the logit estimation when 1-year log stock returns are instead used as the only explanatory variable.[9] The estimated coefficient is negative (as expected) but not statistically significant. To explore further the marginal explanatory ability of CDS spread changes relative to stock returns, the last column of Table 3 includes both the log change in the CDS spread and the log stock return as explanatory variables of the logit regression. Estimated coefficients have

[9]Stock returns over various intervals were also tested for the models detailed throughout the paper, but with no qualitative alteration to results. Details available from the authors upon request.

the expected sign and are significant at the 10% significance level confirming strong evidence for marginal explanatory power of CDS relative to equity returns. This complementary explanatory power suggests that CDS markets impound additional information over and above equity markets, relevant to policy makers and regulators.

Having ascertained that CDS spread changes significantly explain bank failure (even after accounting for another aspect of market information using stock returns), we next control for various facets of banking risk. To this end, various accounting variables previously proposed as drivers of banking risk (described in Section 3.1), in addition to stock returns and the DD measure, are incrementally incorporated in the logit regressions. We assess the individual impact of each variable by estimating 9 different logit models as shown in Table 4. The coefficient estimates for the CDS spread change remain positive and highly significant (at the 1% level) after controlling for these additional variables. The tier 1 regulatory capital ratio is also highly significant and negative. The DD measure is significant at the 5% level and is negative. Stock returns are not found to be significant once we control for other aspects of banking risk. While previous research has found mixed explanatory power associated with bank bond yields, these findings suggest that CDS spreads have strong ability to discriminate between safe and distressed banks, even relative to equity market indicators.[10]

In order to get an idea of the relative impact of these variables, the marginal impact on failure probability from a one-standard-deviation increase in each explanatory variable is examined using Equation 2. In each case, we assume an initial mean value of the explanatory variables. For instance, if we consider the sixth specification in Table 4 (M6), a one-standard-deviation increase in the CDS spread change would increase the probability of failure by 14% of its initial value. Similarly, if we focus on the seventh specification (M7), a one-standard-deviation increase in the CDS spread change determines an increase in the failure probability of 12% of its initial value.

Next, we evaluate the explanatory power of CDS spread changes during the shorter sample

[10]We also exclude the US banks from our sample and run the same logit regressions as in Table 4. We obtain very similar results that are available on request.

period 2005-2008. This analysis is of particular interest in light of the fact that the majority of the failed banks in our sample period failed in 2008. Table 5 reports the coefficient estimates for the various model specifications. The coefficients on the CDS spread change remain significant, despite a reduction in the number of observations. Moreover, during this period both equity market returns and the DD measure were not found to indicate financial distress in keeping with Milne (2014). In contrast, CDS are found to have been significant indicators of banking failure. The level of tier 1 capital is only significant at the 10% level. Finally, diverging from the analysis over the entire sample, bank size is found to be significantly associated with future bank failure, possibly linked to the too-big-to-fail problem with large banks. In other words, governments were more likely to bail-out large banks quickly, due to the dangers of systemic and economic risk if they were left to default.

The observed pseudo R-squared values are found to be about 1.5 times higher than in Table 4, suggesting that logit models would have had better explanatory power during the height of the financial crisis. Other major differences with the logit estimation for the whole sample includes the *ROAE* and *STOCK* variables, which flip sign but not significance. *LLPTA* is always insignificant in Table 5, whereas it is highly significant in specifications M8 and M9 of Table 4. With hindsight, it is not surprising to observe changes in the signs of these variables: it is well known that banks with large stock returns in 2006 were the same banks whose stock suffered the largest losses during the crisis (Beltratti and Stulz, 2012). Likewise, banks with high historic *ROAE* may have adopted a strategy of taking on higher risk loans, leaving them susceptible to failure.

Finally, we establish whether the explanatory power of CDS spread changes varies with a bank's business model. Table 6 shows logit regressions which include slope dummy variables in order to capture the differential impact of CDS spread changes for different bank types (and listing status) and the probability of failure. While no incremental explanatory power is observed for cooperative banks and listed banks, we note that the explanatory power of CDS spread changes is higher for investment banks as confirmed from the high significance. Hence, CDS spreads constitute a significant indicator of bank distress, and this is especially so for the group of investment banks.[11]

4.2. Additional Measures of CDS Spread Change: Idiosyncratic, Average and 5^th^-95^th^ Percentiles

In the previous section we examined the role of total CDS spread changes in distinguishing between failed and surviving banks. Next, we examine the sensitivity of our results for a number of related measures. The first, excess CDS change ($\Delta EXCDS$), is the difference between the 1-year log change in the CDS spread and the 1-year log change in the CDX index spread (for US financial firms) or the iTraxx index spread (for European financial firms). This allows us to control for the prevailing conditions in the CDS market, important in a longitudinal analysis.[12] The second is the idiosyncratic component of the log change in the CDS spread after removing market influences ($\Delta IDCDS$), computed as the residual, at year end, obtained from running each year a regression of daily CDS spread changes on a constant and CDX index spread changes (for US banks) or iTraxx index spread changes (for European banks). We also examine whether extreme changes in CDS act as indicators of bank financial distress.

Table 7 reports our findings. Models M1 and M2 correspond to excess CDS spread changes, while M3 and M4 outline findings for idiosyncratic spread changes. In all specifications, CDS spread changes are found to have a positive and highly significant relationship with bank failure, reinforcing our earlier findings for total CDS changes. The findings on idiosyncratic changes in CDS are especially noteworthy. While previous studies considering the role of CDS in the prediction of bank failure have largely considered market-wide information (Knaup and Wagner, 2012), the significance of idiosyncratic changes in single-name CDS point to the vital role of market-derived company-specific information in explaining bank failure. Similar to the results obtained in the previous section, we find that a one-standard-deviation increase in either $\Delta EXCDS$

[11] In untabulated results, we also examined the explanatory power of both CDS spread levels and the volatility of CDS spread changes. While both measures are significant when considered on their own, they become insignificant when a full model specification is used which includes the DD measure. Furthermore, we consider the role of country-level characteristics on the forecasting ability of CDS changes for bank failure. We find that CDS spread changes remain highly significant indicators of bank distress even after controlling for these macroeconomic covariates. Full results are available from the authors on request.

[12] Market-wide factors have previously been shown to dominate in explaining risk exposures in the case of US and European bank equities (Bessler *et al.*, 2015; Bessler and Kurmann, 2014).

or $\Delta IDCDS$ increases the probability of failure by 13% and 7% of their initial value, respectively.

We also re-estimate the logit models to determine whether extreme changes in CDS spreads, both to the downside and upside, act as indicators of financial distress. In models M5 and M6 changes in the 5^{th} percentile of daily spreads are examined. While the CDS metric is insignificant in model M5, a negative coefficient is observed in model M6. This suggests that banks with small changes in their CDS spread are less likely to fail in the next period. In contrast, models M7 and M8 consider the 95^{th} percentile of the distribution and confirm that banks with high spread changes (or greatest downside risk) have a greater propensity to fail. Finally, models M9 and M10 again confirm our findings, demonstrating that banks with the highest average changes in CDS are most likely to fail.

4.3. Forecasting ability of CDS for alternative measures of failure

In the absence of bank failures, which tend to cluster in time and reveal less about any latent risks within banks, previous researchers have adopted alternative measures of banking distress as the dependent variable (Miller *et al.*, 2015; Distinguin *et al.*, 2006; Gropp *et al.*, 2006). This gives us further clues as to the drivers of bank performance and risk during both good and bad periods. We test the robustness of our findings to the use of two alternative proxies for bank failure and risk. First, we examine the use of another binary variable which takes on the value of one if the bank is first downgraded by any of the major rating agencies (Fitch, Moody's or Standard & Poor's) and zero otherwise. Downgraded banks are excluded from the sample in the years following the downgrade. With the exception of the ninth specification (M9) which includes the DD measure, the results of models M7 and M8 in Table 8 are supportive of the ability of CDS spread changes to explain downgrades. CDS spread changes have a positive and highly significant relationship with bank rating downgrades whether considered individually or with other control variables. These findings are in keeping with previous studies which suggest that market-based information can be employed to forecast downgrades (Miller *et al.*, 2015; Distinguin *et al.*, 2006; Gropp *et al.*, 2006).

Due to the hefty costs and dangers of systemic risk associated with bank failure, regulators and policy makers might mainly be concerned with avoiding such failures. Early intervention in trouble institutions might, however, help to mitigating the costs of banking failure, requiring an understanding of the characteristics of risky banks during both periods of crisis and more normal times. To this end, we also consider two continuous variables which capture the insolvency risk of a bank throughout the cycle, namely the Z-score and the ROAA volatility, defined in section 3.1. Considering the Z-score first, in models M4, M5 and M6 of Table 8 we detail a strong significant relationship between changes in CDS spreads and risk. This finding is robust to the inclusion of additional variables controlling for bank risk and the inclusion of equity market information. The same significance patterns can be observed when ROAA volatility is used as dependent variable in models M1, M2 and M3 of the same Table. However, in this case, changes in CDS spreads are not significant in univariate regressions but have the correct sign. Equity market derived measures of risk are not found to be significantly associated with forthcoming risk for the continuous variables. In summary, these results reinforce our main finding: CDS spread changes represent useful warning signals which are able to explain a bank's deteriorating solvency conditions.

4.4. Hazard model estimation

In addition to logit regression estimations, we also employ a Cox proportional hazards model as an alternative method to analyse the forecasting power of CDS spread changes for bank failure.[13] Table 9 contains the estimation results of various Cox proportional hazards models. Model 1 (M1) is a univariate model which explains time-to-default with the CDS spread change. Model 2 (M2), Model 3 (M3) and Model 4 (M4) augment Model 1 by adding accounting metrics, stock returns and the DD measure as additional covariates, respectively. All models confirm that CDS spread changes are significantly associated with default, in line with results obtained from the logit regressions.

4.5. Testing for the predictive ability of failure models

In this subsection, we conduct tests of out-of-sample predictive ability of several logit models of forthcoming bank failure. The clustering of bank failures in our sample in year 2008 (20 banks

[13]More details on hazard model estimation can be found in Shumway (2001) and Chava and Jarrow (2004).

failed in 2008 out of a total of 31 failures spread over the entire sample period), leads us to focus on the 2005-2008 period and estimate model parameters with a starting estimation sample which uses the 2005-2007 observations. The estimated coefficients are then employed to compute the ex-ante bank default probabilities for year 2008.

Various studies have investigated the out-of-sample performance of bankruptcy prediction models (Bauer and Agarwal, 2014; Betz *et al.*, 2014; Agarwal and Taffler, 2008). In a similar vein, we employ a Receiver Operating Characteristics (ROC) curve to analyze out-of-sample performance.[14] In order to determine the ability of CDS changes to distinguish between failed and surviving banks out-of-sample, we adopt a simulation approach. In addition to testing our approach on data unused in determining model parameters, this has the added benefits of facilitating analysis of the importance of sample size on results. For each logit model, we run 1000 simulations of the ROC curve area. For each simulation, model parameters are estimated during the 2005-2007 period using 50 banks randomly selected. The estimated model coefficients are then used to predict default probabilities for the remaining 10 banks which were not used in building the model.[15]

As shown in the first column of Table 10, we focus on eleven different logit models. We have four simple models, each considering a single representation of banking risk (based on ΔCDS, *STOCK*, *Accounting* and *DD*). The *Accounting* model only uses accounting variables (namely, *T1RC*, *LLPTA*, *CI*, *ROAE*, *LADEPST*, *SIZE*) as covariates to predict failure. We then run five bivariate models that combine the variables used in the univariate models. Finally, we run two trivariate models, incorporating three sets of risk predictors.

The area under the ROC curve (AUC) is computed using the trapezoidal rule and its simulated mean value is reported in column 2 of Table 10 for each logit model. Column 3 shows the simulated mean standard error for the AUC based on the unbiased estimator of Hanley and McNeil (1982). Column 4 shows the test statistic for the null hypothesis that the AUC is equal to 0.5.

[14] The receiver operating characteristic measures the trade-off between correctly predicted failure and incorrectly predicted non-failures. An ROC area under the curve of 1 would indicate complete forecasting accuracy. An ROC less than 0.50 suggests that random selection would better predict failure out-of-sample than the prediction model.

[15] As a robustness, we also estimate the models using randomly chosen 30 banks to generate default probabilities for the remaining 30 banks and obtain analogous results.

Column 5 reports the simulated mean accuracy ratio (AR = 2 * (AUC - 0.5)) based on Engelmann *et al.* (2003). Column 6 reports the *t*-statistic of a two-sample one-tailed *t*-test for the null of equality between the simulated mean AUC of a univariate logit based on ΔCDS and that obtained from any of the remaining ten logit models. When considered alone, ΔCDS has an AUC of 0.64, significantly different from the accuracy obtained from random sampling. Combining ΔCDS with accounting or stock returns results in a decrease in AUC, in keeping with the finding that information from the stock market or accounting information adds little additional information relative to CDS. Combining ΔCDS with DD, we get a AUC of 0.70, greater than that obtained from ΔCDS alone. This predictive analysis further confirms that CDS market information can be employed to generate useful predictive signals of bank distress.

4.6. Subordinated CDS spread changes and bank distress

Previous studies which investigated the predictive role of subordinated debt have reported varied results, linking this to the specific characteristics of markets in subordinated debt (Gropp *et al.*, 2006) or to noise inherent in market information (Evanoff and Wall, 2001). We next explore whether subordinated CDS spreads have explanatory power for bank failure. To this end, we start from our initial sample of 60 banks and collect data on subordinated CDS spreads from Markit when they are available. The resulting sample includes 36 firms with available data. Table 11 reports the estimation output of logit models for nine different specifications, incorporating each of the accounting variables in turn as well as the equity-based indicators. In all cases we find a positive and highly significant relationship between spread changes and the probability of bank failure. These findings imply that subordinated CDS may not suffer from the same obstacles as their respective bonds in explaining bank failure, a question we leave for further research.

To garner an idea of the economic significance of these estimates we compute the marginal effects. If we focus our attention on the sixth specification (M6) similarly to what we did in Section 4.1, a one-standard-deviation increase in the subordinated CDS spread change would increase the probability of failure by 7% of its initial value. Similarly, if we focus on the seventh specification (M7), a one-standard-deviation increase in the CDS spread change determines an increase in the failure probability of 6% of its initial value. These effects are consistent with the 7%-14% range of increase in probability estimated for a one-standard-deviation increase in senior CDS spread changes.

5. Summary and Conclusions

Banks were at the centre of the financial turmoil of recent years and, thus, have become a focal point of discussions among politicians, policy makers, regulatory authorities, academics, investors and the general public. Many jurisdictions have introduced new regulatory requirements, while banks have introduced new securities such as contingent convertibles (Sundaresan and Wang, 2015). While such securities may help to exert market discipline, there is still a need to assess the ability of market prices of actively traded financial instruments to provide market discipline.

This study is the first to examine whether single-name CDS contracts help to explain bank failure, in keeping with the premise of indirect market discipline. The period 2005-2012 is ideal to test this research hypothesis as it includes two periods of high distress in the economy: the financial crisis started in mid-2007 and the subsequent sovereign debt crisis began in 2010.

For a sample of 60 banks, we examine whether increases in CDS spread changes are associated with a greater probability of failure. Furthermore, we control for a range of alternative market and accounting measures capturing capital adequacy, asset quality, management quality, earnings quality, asset liquidity, stock market returns and volatility.

The primary finding of the paper is that relative changes in firm-level CDS spreads are strongly and significantly associated with future bank failure. This finding is found to hold when we control for alternative equity market information and for accounting drivers of risk. The economic significance of CDS spread changes is remarkable: a one-standard-deviation increase in CDS spread changes is associated with an increase in the probability of bank failure ranging from 7% to 14% of its initial value. Thus, monitoring changes in CDS market prices could assist regulators and supervisors in forecasting future distress in individual banks, thus providing indirect market discipline.

We undertake numerous steps to validate the robustness of our main result. First, we use alternative measures for CDS spread changes that neutralize the effect of general market conditions. Second, we employ alternative measures for our dependent variable: in particular, we use a binary downgrade indicator and two additional continuous variables (ROAA volatility and the Z-score). Third, we employ a Cox proportional hazard model as an alternative estimation approach. Fourth, we investigate the out-of-sample performance of various logit models including CDS spread changes. Finally, we test whether subordinated CDS spread changes have a similar explanatory power for bank distress during our sample period. In all cases, we find that changes in CDS spreads are strongly associated with bank failure.

Overall, while our results are based upon a small sample of banks, our analyses impart an important message for both policy makers and regulatory bodies: single-name CDS provide information valuable in monitoring the financial conditional of banks during a period of systemic banking crisis. Hence, they may contribute to the early warning of forthcoming problems within banks. Moreover, CDS contain relevant information regarding bank condition above and beyond that contained in equity markets and accounting metrics.

Bibliography

Abedifar, P., Molyneux, P., Tarazi, A. (2013). Risk in Islamic banking. *Review of Finance*, **17**(6), 2035–2096.

Acharya, V.V., Johnson, T.C. (2007). Insider trading in credit derivatives. *Journal of Financial Economics*, **84**(1), 110–141.

Agarwal, V., Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance*, **32**(8), 1541–1551.

Alter, A., Schüler, Y.S. (2012). Credit spread interdependencies of European states and banks during the financial crisis. *Journal of Banking and Finance*, **36**(12), 3444–3468.

Altunbas, Y., Manganelli, S., Marques-Ibanez, D. (2011). Bank risk during the financial crisis: do business models matter? *European Central Bank Working Paper*, **No. 1394**.

Annaert, J., De Ceuster, M., Van Roy, P., Vespro, C. (2013). What determines euro area bank CDS spreads? *Journal of International Money and Finance*, **32**(1), 444–461.

Arena, M. (2008). Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data. *Journal of Banking and Finance*, **32**(2), 299–310.

Avino, D., Cotter, J. (2014). Sovereign and bank CDS spreads: Two sides of the same coin? *Journal of International Financial Markets, Institutions and Money*, **32**(1), 72–85.

Ballester, L., Casu, B., Gonzalez-Urteaga, A. (2016). Bank fragility and contagion: Evidence from the bank CDS market. *Journal of Empirical Finance*, **38**, 394–416.

Bauer, J., Agarwal, V. (2014). Are hazard models superior to traditional bankruptcy prediction approaches? A comprehensive test. *Journal of Banking and Finance*, **40**(3), 432–442.

Beck, T., Todorov, R., Wagner, W. (2013). .Supervising cross-border banks: theory, evidence and policy. *Economic Policy*, **28**, 5–44.

Beltratti, A., Stulz, R. M. (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics*, **105**(1), 1–17.

Berndt, A., Ostrovnaya, A. (2014). Do equity markets favor credit market news over options market news? *Quarterly Journal of Finance*, **4**, 1450006.

Bessler, W., Kurmann, P. (2014). Bank risk factors and changing risk exposures: Capital market evidence before and during the financial crisis. *Journal of Financial Stability*, **13**, 151–166.

Bessler, W., Kurmann, P., Nohel, T. (2015). Time-varying systematic and idiosyncratic risk exposures of US bank holding companies. *Journal of International Financial Markets, Institutions and Money*, **35**, 45–68.

Betz, F., Opriča, S., Peltonen, T.A., Sarlin, P. (2014). Predicting distress in European banks. *Journal of Banking and Finance*, **45**(8), 225–241.

Blanco, R., Brennan, S., Marsh, I.W. (2005). An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps. *Journal of Finance*, **60**(5), 2255–2281.

Bliss, R.R., Flannery, M.J. (2002). Market discipline in the governance of U.S. bank holding companies: monitoring vs. influencing. *Review of Finance*, **6**(3), 361–396.

Blum, J.M. (2002). Subordinated debt, market discipline, and banks' risk taking. *Journal of Banking and Finance*, **26**(7), 1427–1441.

Calice, G., Ioannidis, C., Williams, J. (2012). Credit derivatives and the default risk of large complex financial institutions. *Journal of Financial Services Research*, **42**(1), 85–107.

Chava, S., Jarrow, R.A. (2004). Bankruptcy prediction with industry effects. *Review of Finance*, **8**(4), 537–569.

Chen, L., Lesmond, D.A., Wei, J. (2007). Corporate yield spreads and bond liquidity. *Journal of Finance*, **62**(1), 119–149.

Chen, Y., Hasan, I. (2011). Subordinated debt, market discipline, and bank risk. *Journal of Money, Credit and Banking*, **43**(6), 1043–1072.

Chiaramonte, L., Casu, B. (2013). The determinants of bank CDS spreads: evidence from the financial crisis. *European Journal of Finance*, **19**(9), 861–887.

Cole, R.A., White, L.J. (2012). Déjà Vu All Over Again: The Causes of U.S. Commercial Bank Failures This Time Around. *Journal of Financial Services Research*, **42**(1), 5–29.

Conlon, T., Cotter, J. (2014). Anatomy of a bail-in. *Journal of Financial Stability*, **15**, 257–263.

Curry, T. J., Fissel, G. S., Hanweck, G. A. (2008). Equity market information, bank holding company risk, and market discipline. *Journal of Banking and Finance*, **32**(5), 807–819.

Demirguc-Kunt, A., Detragiache, E., Merrouche, O. (2013). Bank capital: Lessons from the financial crisis. *Journal of Money, Credit and Banking*, **45**(6), 1147–1164.

Distinguin, I., Rous, P., Tarazi, A. (2006). Market discipline and the use of stock market data to predict bank financial distress. *Journal of Financial Services Research*, **30**(2), 151–176.

Eichengreen, B., Mody, A., Nedeljkovic, M., Sarno, L. (2012). How the Subprime Crisis went global: Evidence from bank credit default swap spreads. *Journal of International Money and Finance*, **31**(5), 1299–1318.

Elton, E.J., Gruber, M.J., Agrawal, D., Mann, C. (2001). Explaining the rate spread on corporate bonds. *Journal of Finance*, **56**(1), 247–277.

Engelmann, B., Hayden, E., Tasche, D. (2003). Testing rating accuracy. *Risk*, **16**, 82–86.

Evanoff, D. D., Wall, L. D. (2001). Sub-debt yield spreads as bank risk measures. *Journal of Financial Services Research*, **20**(2), 121–145.

Fahlenbrach, R., Prilmeier, R., Stulz, R.M. (2012). This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. *Journal of Finance*, **67**(6).

Flannery, M.J. (1998). Using market information in prudential bank supervision: A review of the U.S. empirical evidence. *Journal of Money, Credit and Banking*, **30**(3), 273.

Flannery, M.J. (2001). The faces of "market discipline". *Journal of Financial Services Research*, **20**(2), 107–119.

Goddard, J., Molyneux, P., Wilson, J.O.S. (2009). The financial crisis in Europe: Evolution, policy responses and lessons for the future. *Journal of Financial Regulation and Compliance*, **17**(4), 362–380.

Gorton, G., Santomero, A.M. (1990). Market discipline and bank subordinated debt. *Journal of Money, Credit and Banking*, **22**(1), 119–128.

Gropp, R., Vesala, J., Vulpes, G. (2006). Equity and bond market signals as leading indicators of bank fragility. *Journal of Money, Credit and Banking*, **38**(2), 399–428.

Hamalainen, P., Pop, A., Hall, M., Howcroft, B. (2012). Did the market signal impending problems at Northern Rock? An analysis of four financial instruments. *European Financial Management*, **18**(1), 68–87.

Hanley, J., McNeil, B. (1982). The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology*, **143**(1), 29–36.

Hasan, I., Liu, L., Zhang, G. (2016). The Determinants of Global Bank Credit-Default-Swap Spreads. *Journal of Financial Services Research*, **50**(3), 275–309.

Huang, J., Huang, M. (2012). How much of the corporate-Treasury yield spread is due to credit risk? *Review of Asset Pricing Studies*, **2**(2), 153–202.

Knaup, M., Wagner, W. (2012). A market-based measure of credit quality and bank performance during the Subprime Crisis. *Management Science*, **58**, 1423–1437.

Krainer, J. (2004). Incorporating equity market information into supervisory monitoring models. *Journal of Money, Credit and Banking*, **36**(6), 1043–1067.

Krishnan, C.N.V., Ritchken, P.H., Thomson, J.B. (2005). Monitoring and controlling bank risk: Does risky debt help? *Journal of Finance*, **60**(1), 343–378.

Longstaff, F.A., Mithal, S., Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance*, **60**(5), 2213–2253.

Männasoo, K., Mayes, D.G. (2009). Explaining bank distress in Eastern European transition economies. *Journal of Banking and Finance*, **33**(2), 244–253.

Mayes, D.G. (2004). Who pays for bank insolvency? *Journal of International Money and Finance*, **23**, 515–551.

Miller, S., Olson, E., Yeager, T.J. (2015). The relative contributions of equity and subordinated debt signals as predictors of bank distress during the financial crisis. *Journal of Financial Stability*, **16**, 118–137.

Milne, A. (2014). Distance to default and the financial crisis. *Journal of Financial Stability*, **12**, 26–36.

Molyneux, P., Schaeck, K., Zhou, T.M. (2014). 'Too systemically important to fail' in banking. *Journal of International Money and Finance*, **49**(B), 258–282.

Niu, J. (2008). Can subordinated debt constrain banks' risk taking? *Journal of Banking and Finance*, **32**(6), 1110–1119.

Oehmke, M., Zawadowski, A. (2014). The anatomy of the CDS market. *Columbia Business School Working Paper*.

Petrovic, A., Tutsch, R. (2009). National rescue measures in response to the current financial crisis. *ECB Legal Working Paper Series*, **8**.

Poghosyan, T., Čihak, M. (2011). Determinants of Bank Distress in Europe: Evidence from a New Data Set. *Journal of Financial Services Research*, **40**(3), 163–184.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business*, **74**(1), 101–124.

Sironi, A. (2003). Testing for market discipline in the European banking industry: Evidence from subordinated debt issues. *Journal of Money, Credit and Banking*, **35**(3), 443–472.

Stânga, I.M. (2014). Bank bailouts and bank-sovereign risk contagion channels. *Journal of International Money and Finance*, **48**, 17–40.

Sundaresan, S., Wang, Z. (2015). On the design of contingent capital with market trigger. *Journal of Finance*, **70**(2), 881–920.

Völz, M., Wedow, M. (2011). Market discipline and too-big-to-fail in the CDS market: Does banks' size reduce market discipline? *Journal of Empirical Finance*, **18**(2), 195–210.

Yang, J., Zhou, Y. (2013). Credit Risk Spillovers Among Financial Institutions Around the Global Credit Crisis: Firm-Level Evidence. *Management Science*, **59**(10), 2343–2359.

Table 1: **Number of Firms and Failures per Year**

This table shows the number of banks and failures for every year of our sample period. We also include a geographical breakout which lists the number of firms, whose headquarters are based in Europe (EU) or the United States of America (US). Failure rate is the number of failures divided by the number of firms.

Year	**No. of firms (EU/US)**	**No. of failures (EU/US)**	**Failure rate (%) (EU/US)**
2005	60 (49/11)	-	-
2006	60 (49/11)	-	-
2007	60 (49/11)	-	-
2008	60 (49/11)	20 (11/9)	33.33 (22.45/81.82)
2009	40 (38/2)	7 (5/2)	17.50 (13.16/100)
2010	33 (33/0)	1 (1/0)	3.03 (3.03/0)
2011	32 (32/0)	2 (2/0)	6.25 (6.25/0)
2012	30 (30/0)	1 (1/0)	3.23 (3.23/0)

Table 2: **Summary Statistics**

This table shows the summary statistics for the following variables during the period 2005-2011 for both the whole sample (Panel A) and the sample of failed banks (Panel B): the annual log change in the CDS spread (ΔCDS), the difference between the log change in the CDS spread and the log change in the CDX index spread (for US financial firms) or the iTraxx index spread for European financial firms ($\Delta EXCDS$), the idiosyncratic component of the log change in the CDS spread ($\Delta IDCDS$), the tier 1 regulatory capital ratio (T1RC), the ratio between the loan loss provisions and the book value of total assets (LLPTA), the ratio between the operating costs and the operating income (CI), the return on average equity (ROAE), the ratio between the liquid assets and the sum of the total deposits and short-term borrowing (LADEPST), the log of total assets (SIZE), the annual log stock return (STOCK), the distance-to-default measure (DD). Panel C shows the Pearson correlation coefficient between pairs of the main variables used in the empirical analysis. CDS changes are expressed in basis points. All remaining variables are in percentages.

	Mean	Median	Std	Min	Max	Obs	Mean	Median	Std	Min	Max	Obs
	Panel A: Whole Sample						**Panel B: Failed Sample**					
ΔCDS	0.450	0.203	0.927	-2.070	2.944	278	0.531	-0.050	1.064	-1.708	2.944	101
$\Delta EXCDS$	0.239	0.111	0.579	-1.254	2.109	278	0.311	0.084	0.688	-1.254	2.109	101
$\Delta IDCDS$	0.247	0.008	0.734	-1.896	2.283	212	0.307	-0.099	0.876	-1.667	2.283	85
T1RC	9.438	8.595	2.717	5.130	18.100	286	8.136	7.965	1.492	5.130	12.900	82
LLPTA	0.297	0.234	0.269	-0.128	1.425	295	0.267	0.225	0.252	-0.018	1.425	90
CI	62.080	59.235	25.676	22.292	331.128	308	66.382	62.644	24.410	22.292	230.463	102
ROAE	11.068	12.270	9.111	-44.454	34.684	308	13.076	13.207	10.064	-26.763	32.176	103
LADEPST	25.078	21.473	16.520	0.979	75.422	308	29.814	26.113	18.734	3.549	69.049	103
SIZE	19.368	19.322	1.166	16.985	21.674	308	19.452	19.718	1.172	17.237	21.674	103
STOCK	1.419	7.835	35.609	-181.577	97.004	210	5.410	8.267	36.004	-181.577	63.750	81
DD	3.591	3.26	2.353	-1.090	14.370	208	3.476	3.040	2.275	-1.090	10.500	79

Panel C: Correlations

	ΔCDS	*T1RC*	*LLPTA*	*CI*	*ROAE*	*LADEPST*	*SIZE*	*STOCK*	*DD*
ΔCDS	1								
T1RC	-0.11	1							
LLPTA	0.07	-0.09	1						
CI	0.14	0.08	-0.19	1					
ROAE	-0.17	-0.03	-0.35	-0.49	1				
LADEPST	-0.09	0.51	-0.36	0.31	0.04	1			
SIZE	-0.00	0.21	-0.11	0.17	0.09	0.44	1		
STOCK	0.10	0.01	-0.41	-0.18	0.44	0.08	0.08	1	
DD	-0.47	-0.13	-0.22	-0.25	0.46	0.04	-0.03	0.36	1

Table 3: **Logit Regressions of Failure Indicator on CDS Changes of 3, 6, 9 and 12 Months**

*This table summarizes results of binary logit regressions of the failure indicator on CDS log changes of the past 3, 6, 9 and 12 months before the portfolio formation (end of each year) from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. $\Delta CDS3M$ is the 3-month log change in the CDS spread. $\Delta CDS6M$ is the 6-month log change in the CDS spread. $\Delta CDS3M$ is the 9-month log change in the CDS spread. ΔCDS is the annual log change in the CDS spread. STOCK is the annual log stock return. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 6 different specifications of the logit regressions (M1 to M6). For instance, M1 regresses the failure indicator on a constant and the 3-month log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6
$\Delta CDS3M$	2.65 (3.22)***					
$\Delta CDS6M$		1.49 (5.41)***				
$\Delta CDS9M$			1.38 (5.25)***			
ΔCDS				1.59 (5.54)***		2.09 (5.77)***
$STOCK$					-0.56 (-1.13)	-1.94 (-2.24)**
$Constant$	-2.59 (-8.62)***	-2.99 (-9.43)***	-3.03 (-8.83)***	-3.62 (-8.20)***	-2.15 (-9.51)***	-4.41 (-7.00)***
$Pseudo\ R^2$	0.136	0.186	0.185	0.243	0.006	0.312
$Nobs$	280	271	268	278	210	193

Table 4: **Logit Regressions of Failure Indicator on CDS Changes with Control Variables.**

*This table summarizes results of binary logit regressions of the failure indicator on CDS changes with control variables from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 9 different specifications of the logit regressions (M1 to M9). For instance, M1 regresses the failure indicator on a constant and the log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS	1.59	1.33	1.35	1.35	1.35	1.35	1.33	2.66	3.35
	(5.54)***	(4.48)***	(4.27)***	(3.85)***	(3.80)***	(3.84)***	(3.83)***	(4.22)***	(3.01)***
$T1RC$		-0.30	-0.30	-0.43	-0.43	-0.46	-0.46	-0.81	-1.07
		(-2.33)**	(-2.26)**	(-2.71)***	(-2.71)***	(-2.79)***	(-2.78)***	(-2.81)***	(-3.83)***
$LLPTA$			84.34	112.66	101.32	126.02	123.59	349.97	470.95
			(0.82)	(1.07)	(0.90)	(1.04)	(1.02)	(2.15)**	(2.80)***
CI				0.02	0.02	0.02	0.02	0.01	0.01
				(2.19)**	(1.48)	(1.16)	(1.18)	(0.84)	(1.28)
$ROAE$					-0.01	-0.01	-0.01	-0.04	0.00
					(-0.23)	(-0.23)	(-0.28)	(-1.06)	(0.06)
$LADEPST$						0.02	0.01	0.06	0.05
						(0.62)	(0.45)	(2.08)**	(1.71)*
$SIZE$							0.08	0.03	0.08
							(0.31)	(0.10)	(0.23)
$STOCK$								-0.94	
								(-0.81)	
DD									-1.19
									(-2.36)**
$Constant$	-3.62	-1.05	-1.35	-1.72	-1.54	-1.59	-2.94	-2.66	-1.34
	(-8.20)***	(-0.97)	(-1.18)	(-1.24)	(-0.94)	(-0.91)	(-0.65)	(-0.43)	(-0.21)
$Pseudo\ R^2$	0.243	0.238	0.244	0.300	0.300	0.304	0.305	0.488	0.568
$Nobs$	278	249	249	249	249	249	249	175	175

Table 5: **Logit Regressions of Failure Indicator on CDS Changes with Control Variables During the Period 2005-2008**

*This table summarizes results of binary logit regressions of the failure indicator on CDS changes from 2005 to 2008. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 9 different specifications of the logit regressions (M1 to M9). For instance, M1 regresses the failure indicator on a constant and the log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS	2.17	2.30	2.44	2.37	2.39	2.47	2.28	3.25	3.90
	(5.25)***	(3.53)***	(3.67)***	(3.62)***	(3.51)***	(3.84)***	(4.10)***	(1.95)*	(2.01)**
$T1RC$		-0.33	-0.37	-0.43	-0.45	-0.49	-0.49	-0.48	-2.93
		(-1.93)*	(-1.93)*	(-1.95)*	(-1.80)*	(-1.95)*	(-1.74)*	(-1.46)	(-1.54)
$LLPTA$			-123.75	-122.09	-117.10	-100.48	-159.55	17.14	1125.49
			(-0.62)	(-0.58)	(-0.57)	(-0.48)	(-0.84)	(0.07)	(1.18)
CI				0.02	0.03	0.02	0.02	-0.00	-0.20
				(1.22)	(1.09)	(0.90)	(0.52)	(-0.07)	(-1.19)
$ROAE$					0.01	0.02	0.01	-0.03	-0.03
					(0.27)	(0.34)	(0.12)	(-0.31)	(-0.16)
$LADEPST$						0.02	-0.02	0.00	0.14
						(0.46)	(-0.41)	(0.02)	(1.20)
$SIZE$							0.76	1.07	2.95
							(1.99)**	(2.47)**	(1.87)*
$STOCK$								2.00	
								(0.37)	
DD									-7.38
									(-1.43)
$Constant$	-4.56	-2.64	-2.25	-3.09	-3.45	-3.51	-16.55	-24.25	-22.60
	(-6.31)***	(-1.67)*	(-1.30)	(-1.62)	(-1.53)	(-1.55)	(-2.36)**	(-3.10)***	(-1.96)*
$Pseudo\ R^2$	0.414	0.416	0.423	0.433	0.433	0.436	0.477	0.557	0.718
$Nobs$	150	126	126	126	126	126	126	97	97

Table 6: **Logit Regressions of Failure Indicator on CDS Spread Changes for Different Categories of Banks**

*This table summarizes results of binary logit regressions of the failure indicator on CDS spread changes of banks with different specializations and listing status. The sample period is from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS spread. COOP is a dummy variable which equals 1 for cooperative banks and zero otherwise; INVB is a dummy variable which equals 1 for investment banks and zero otherwise; LISTED is a dummy variable which equals 1 for listed banks and zero otherwise. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively.*

	M1	M2	M3
ΔCDS	1.36	1.12	1.31
	(3.88)***	(2.86)***	(2.43)**
$COOP \times \Delta CDS$	-0.53		
	(-0.73)		
$INVB \times \Delta CDS$		1.35	
		(2.59)**	
$LISTED \times \Delta CDS$			0.03
			(0.06)
$T1RC$	-0.47	-0.48	-0.46
	(-2.82)***	(-2.69)***	(-2.77)***
$LLPTA$	120.21	144.71	122.90
	(0.98)	(1.10)	(1.01)
CI	0.02	0.02	0.02
	(1.17)	(1.12)	(1.18)
$ROAE$	-0.01	0.00	-0.01
	(-0.33)	(0.12)	(-0.28)
$LADEPST$	0.01	-0.00	0.01
	(0.43)	(-0.10)	(0.45)
$SIZE$	0.04	-0.11	0.08
	(0.15)	(-0.40)	(0.31)
$Constant$	-2.04	0.76	-2.95
	(-0.45)	(0.17)	(-0.65)
$Pseudo\ R^2$	0.309	0.344	0.305
$Nobs$	249	249	249

Table 7: **Logit Regressions of Failure Indicator on Alternative CDS Metrics**

*This table summarizes results of binary logit regressions of the failure indicator on alternative CDS metrics from 2005 to 2012, using a variety of CDS derived metrics. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS is the log change in the CDS metric. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. $STOCK$ is the log stock return. DD is the distance-to-default measure. $Pseudo\ R^2$ is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. 5 sets of regressions are reported, as follows: in M1 and M2 ΔCDS corresponds to $\Delta EXCDS$, which is the difference between the 12-month log change in the CDS spread and the 12-month log change in the CDX index spread (for US financial firms) or the iTraxx index spread (for European financial firms). In M3 and M4, ΔCDS is the idiosyncratic component of the log change in the CDS spread, after controlling for market factors ($\Delta IDCDS$). M5 and M6 treat ΔCDS as the log change of the 5^{th} percentile of the daily CDS spread , M7 and M8 take ΔCDS as the log change of the 95^{th} percentile of the daily CDS spread and in M9 and M10 ΔCDS is the log change of the average daily CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
ΔCDS	2.04	2.83	2.24	2.95	0.17	-1.36	2.81	5.66	1.85	3.58
	(3.86)***	(3.09)***	(4.60)***	(3.63)***	(-0.47)	(-2.47)**	(4.47)***	(2.84)***	(4.52)***	(3.25)***
$T1RC$	-1.05	-1.30	-0.95	-1.23	-0.84	-1.10	-1.00	-1.45	-0.90	-0.96
	(-3.06)***	(-4.19)***	(-3.03)***	(-3.55)***	(-3.71)***	(-3.99)***	(-3.58)***	(-3.51)***	(-3.85)***	(-4.32)***
$LLPTA$	343.82	463.30	217.26	427.75	273.77	416.17	447.35	641.21	271.37	224.44
	(1.98)**	(3.11)***	(1.11)	(2.48)**	(1.73)*	(2.90)***	(2.89)***	(2.57)**	(1.65)*	(1.43)
CI	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.01
	(2.34)**	(2.31)**	(1.81)*	(0.64)	(1.31)	(2.26)**	(1.24)	(0.92)	(1.02)	(1.02)
$ROAE$	-0.04	0.04	-0.00	0.04	-0.04	0.03	-0.05	-0.01	-0.04	0.02
	(-1.30)	(1.22)	(-0.13)	(1.03)	(-0.86)	(0.75)	(-1.25)	(-0.49)	(-0.99)	(0.50)
$LADEPST$	0.05	0.03	0.03	0.08	0.05	0.03	0.09	0.12	0.07	0.05
	(1.42)	(0.94)	(0.61)	(1.17)	(1.36)	(0.86)	(2.46)**	(2.55)**	(2.01)**	(1.82)*
$SIZE$	0.22	0.32	0.35	0.07	0.25	0.34	-0.01	0.03	0.18	0.28
	(0.76)	(0.92)	(0.89)	(0.13)	(0.75)	(1.04)	(-0.04)	(0.09)	(0.56)	(0.94)
$STOCK$	0.32		-1.74		0.92		0.96		1.96	
	(0.41)		(-1.42)		(0.95)		(0.90)		(1.80)*	
DD		-1.71		-2.00		-1.42		-1.32		-0.79
		(-3.04)***		(-4.73)***		(-3.93)***		(-3.05)***		(-2.84)***
$Constant$	-2.74	-0.89	-5.95	3.50	-3.28	-0.36	-1.01	-1.45	-2.83	-1.36
	(-0.50)	(-0.13)	(-0.76)	(-0.30)	(-0.58)	(-0.06)	(-0.16)	(-0.20)	(-0.48)	(-0.25)
$Pseudo\ R^2$	0.385	0.562	0.456	0.613	0.242	0.468	0.472	0.577	0.358	0.402
$Nobs$	175	175	139	139	175	175	175	175	175	175

Table 8: **OLS Regressions of ROAA Volatility and Z-score and Logit Regressions of Downgrade Indicator on CDS Changes**

*This table summarizes results of OLS regressions of ROAA volatility on CDS Changes (M1, M2 and M3), OLS regressions of Z-score on CDS Changes (M4, M5 and M6) and binary logit regressions of downgrade indicator on CDS Changes (M7, M8, and M9). The sample period is from 2005 to 2012. The ROAA volatility is the standard deviation of the ROAA for each firm over the subsequent 12 months. The Z-score refers to the 12 months following portfolio formation. The downgrade indicator is 1 (0) if the firm is first downgraded (not downgraded) by any of the major rating agencies (Fitch, Moody's or Standard & Poor's) during the subsequent 12 months.ΔCDS is the log change in the CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure. R^2 is the value of the adjusted (McFadden) R-squared for OLS regressions (logit regressions). Nobs is the number of observations. In parentheses, we report the t-statistics for OLS regressions and z-statistics (adjusting standard errors using the Huber-White method) for logit regressions. *, ** and *** denote significance at the 10%, 5% and 1%, respectively.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS	0.10	0.08	0.09	-18.45	-24.27	-21.74	0.88	1.15	0.45
	(1.52)	(4.27)***	(4.22)***	(-4.78)***	(-4.26)***	(-3.42)***	(4.64)***	(3.80)***	(1.26)
$T1RC$		-0.00	-0.00		0.93	1.36		-0.06	-0.05
		(-0.56)	(-0.42)		(0.39)	(0.56)		(-0.39)	(-0.42)
$LLPTA$		23.29	20.46		-2771.12	-2554.60		200.20	360.68
		(2.86)***	(2.64)***		(-1.19)	(-1.16)		(1.27)	(2.00)**
CI		0.00	0.00		-0.21	-0.20		0.02	0.03
		(1.09)	(0.96)		(-0.87)	(-0.85)		(1.07)	(1.07)
$ROAE$		-0.00	-0.00		0.02	-0.22		0.07	0.05
		(-1.51)	(-1.36)		(0.03)	(-0.31)		(1.49)	(1.36)
$LADEPST$		0.00	0.00		-0.98	-1.00		0.02	0.03
		(2.15)**	(2.05)**		(-2.37)**	(-2.43)**		(1.21)	(1.38)
$SIZE$		0.00	0.00		8.36	8.32		0.35	0.26
		(0.03)	(0.12)		(1.79)*	(1.79)*		(1.41)	(1.00)
$STOCK$		0.06			-3.41			-4.57	
		(1.16)			(-0.21)			(-2.50)**	
DD			0.00			2.39			-0.51
			(0.48)			(0.91)			(-2.83)***
Constant	0.38	0.10	0.06	58.06	-60.35	-71.23	-1.49	-11.76	-8.50
	(5.72)***	(0.33)	(0.18)	(15.65)***	(-0.69)	(-0.81)	(-6.80)***	(-2.35)**	(-1.57)
R^2	0.004	0.198	0.193	0.057	0.116	0.119	0.114	0.300	0.304
Nobs	366	175	175	361	174	174	188	118	118

Table 9: **Hazard Model Estimation**

This table summarizes the estimates of Cox proportional hazard models with time-varying covariates. The dependent variable is the time to default (in years). The sample period is from 2005 to 2012. ΔCDS *is the log change in the CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets.* $STOCK$ *is the log stock return. DD is the distance-to-default measure. Nobs is the number of observations. We report robust standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1%, respectively.*

	M1	M2	M3	M4
ΔCDS	4.22	3.06	8.75	11.50
	(1.186)***	(1.134)***	(5.463)***	(9.077)***
$T1RC$		0.51	0.43	0.38
		(0.059)***	(0.075)***	(0.069)***
$LLPTA$		1.52	5.42	8.29
		(1.455)	(4.490)**	(6.261)***
CI		1.02	1.01	1.01
		(0.008)**	(0.006)	(0.007)**
$ROAE$		1.03	1.02	1.06
		(0.032)	(0.028)	(0.035)*
$LADEPST$		1.03	1.06	1.05
		(0.027)	(0.025)***	(0.024)*
$SIZE$		1.11	1.00	0.97
		(0.218)	(0.195)	(0.202)
$STOCK$			0.53	
			(0.425)	
DD				0.48
				(0.180)*
$Nobs$	278	249	175	175

Table 10: **ROC Curve Areas for Different Failure Models - Out of Sample Analysis**

*This table reports the results of 1000 simulations for the area under the Receiver Operating Characteristics curve obtained using several logit models that calculate ex-ante bank default probabilities for year 2008. For each model, we estimate it during the 2005-2007 period using 50 banks randomly selected. We then use the estimated coefficients to predict default probabilities of the remaining 10 banks in our sample. The models are based on the following three sets of variables (and their combinations) used as covariates to predict failure: accounting metrics, stock market variables (STOCK and DD) and ΔCDS. The accounting variables include the following: T1RC, LLPTA, CI, ROAE, LADEPST, SIZE. In column 2, we report the simulated mean area under the ROC curve (AUC) computed using the trapezoidal rule. Column 3 shows the simulated mean standard error for the AUC, column 4 reports the test statistic for the null hypothesis that the AUC is equal to 0.5, column 5 reports the simulated mean accuracy ratio (AR = 2 * (AUC - 0.5)). Finally, column 6 shows the t-statistic of a two-sample one-tailed t-test for the null hypothesis that there is equality between the simulated mean areas under the ROC curve obtained from a model using ΔCDS only and any of the other remaining models. All t-statistics are significant at the 1% level.*

Model	AUC	SE	z	AR	t-test
ΔCDS	0.64	0.0913	6.98	0.27	-
$STOCK$	0.49	0.1023	4.78	-0.02	68.94
$Accounting$	0.53	0.0990	5.33	0.06	39.70
DD	0.78	0.0847	9.41	0.55	-41.54
$\Delta CDS + STOCK$	0.60	0.1072	5.59	0.20	14.49
$\Delta CDS + DD$	0.70	0.0975	7.38	0.40	-15.34
$\Delta CDS + Accounting$	0.53	0.1058	5.03	0.06	36.24
$STOCK + Accounting$	0.52	0.1178	4.44	0.05	361.90
$DD + Accounting$	0.58	0.1172	4.98	0.16	16.11
$\Delta CDS + STOCK + Accounting$	0.52	0.1259	4.14	0.04	35.45
$\Delta CDS + Accounting + DD$	0.54	0.1258	4.28	0.08	30.16

Table 11: **Logit Regressions of Failure Indicator on Subordinated CDS Changes**

This table summarizes results of binary logit regressions of the failure indicator on subordinated CDS changes from 2005 to 2012 for the firms for which subordinated CDS are also available. The failure indicator is 1 (0) if the firm failed (did not fail) during the subsequent 12 months. ΔCDS_{SUB} *is the log change in the subordinated CDS spread. T1RC is the tier 1 regulatory capital ratio. LLPTA represents the ratio between the loan loss provisions and the book value of total assets. CI is the ratio between the operating costs and the operating income. ROAE is the return on average equity. LADEPST is the ratio between the liquid assets and the sum of the total deposits and short-term borrowing. SIZE is the log of total assets. STOCK is the log stock return. DD is the distance-to-default measure.* $Pseudo\ R^2$ *is the value of the McFadden R-squared. Nobs is the number of observations. We report the z-statistics in parentheses and adjust standard errors using the Huber-White method. *, ** and *** denote significance at the 10%, 5% and 1%, respectively. We report 9 different specifications of the logit regressions (M1 to M9). For instance, M1 regresses the failure indicator on a constant and the log change in the subordinated CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
ΔCDS_{SUB}	1.17	1.01	1.03	1.07	1.08	1.08	1.07	1.42	0.97
	(3.34)***	(3.08)***	(3.14)***	(2.93)***	(2.91)***	(2.92)***	(2.84)***	(3.84)***	(1.74)*
$T1RC$		-0.35	-0.35	-0.51	-0.52	-0.52	-0.56	-0.74	-0.86
		(-2.19)**	(-2.10)**	(-2.77)***	(-2.74)***	(-2.66)***	(-2.34)**	(-2.88)***	(-3.49)***
$LLPTA$			94.60	119.67	146.13	147.17	145.76	166.84	187.79
			(0.70)	(0.83)	(0.98)	(0.92)	(1.12)	(0.81)	(1.00)
CI				0.02	0.02	0.02	0.02	0.00	-0.01
				(2.36)**	(2.13)**	(1.91)*	(2.34)**	(0.15)	(-0.78)
$ROAE$					0.02	0.02	0.01	-0.02	0.00
					(0.48)	(0.45)	(0.40)	(-0.50)	(0.07)
$LADEPST$						0.00	-0.01	0.05	0.10
						(0.02)	(-0.35)	(1.22)	(2.13)**
$SIZE$							0.23	0.09	-0.49
							(0.66)	(0.23)	(-1.05)
$STOCK$								-1.22	
								(-0.97)	
DD									-1.24
									(-3.92)***
$Constant$	-3.37	-0.28	-0.61	-0.85	-1.19	-1.19	-5.17	-1.31	13.32
	(-6.65)***	(-0.22)	(-0.45)	(-0.62)	(-0.79)	(-0.80)	(-0.81)	(-0.19)	(1.53)
$Pseudo\ R^2$	0.147	0.188	0.196	0.252	0.255	0.255	0.259	0.342	0.455
$Nobs$	175	165	165	165	165	165	165	127	127

Appendices

A. Definitions of Variables

Variables	Mnemonics
Dependent variables - Binary	
Failure indicator	
Downgrade indicator	
Dependent variables - Continuous	
ROAA volatility	
Z-score	
Financial accounting variables	
Capital adequacy	
Tier 1 regulatory capital ratio	*T1RC*
Asset quality	
Loan loss provisions to total assets	*LLPTA*
Management quality	
Cost to income ratio	*CI*
Earnings quality	
Return on average equity	*ROAE*
Liquidity	
Liquid assets to total deposits and borrowing	*LADEPST*
Size of institution	
Natural logarithm of total assets	*SIZE*
Financial market variables	
CDS market	
Yearly log change in senior CDS spread	ΔCDS
Yearly log change in senior excess CDS spread	$\Delta EXCDS$
Yearly log change in senior idiosyncratic CDS spread	$\Delta IDCDS$
Log of senior CDS spread	*CDS*
Volatility of daily log changes in senior CDS spread over the past 3 months	*CDSVOL*
Yearly log change in subordinated CDS spread	ΔCDS_{SUB}
3-month log change in senior CDS spread	$\Delta CDS3M$
6-month log change in senior CDS spread	$\Delta CDS6M$
9-month log change in senior CDS spread	$\Delta CDS9M$
Equity market	
Yearly log stock return	*STOCK*
Distance-to-Default	*DD*