Credit Default Swaps as Indicators of Bank Financial Distress

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Abstract

We examine the ability of CDS contracts written on individual banks to provide market discipline. Changes in CDS spreads are found to represent a robust signal of bank failure, thus providing 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 for various cohorts, for excess and 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

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Thomas Conlon and John Cotter would like to acknowledge the financial support of Science Foundation Ireland under Grant Number 08/SRC/FM1389.

1. Introduction

In contrast to many other industries, banks, and financial institutions more generally, are subject to high levels of non-market regulatory oversight. Various justifications for such regulation are proposed, linked to the specific characteristics of banks such as asymmetric information, liquidity creation and concerns about depositors. Furthermore, banks are prone to systemic risks, with considerable evidence for this apparent during the global financial crisis (Eichengreen *et al.*, 2012). According to Flannery (2001), market forces may encourage banking discipline in two primary ways. 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. While a number of previous studies have considered the ability of equity and bond markets to limit bank risk taking, this is the first paper to test empirically the possibility that firm level credit default swaps (CDS) might serve to exert market discipline on banks.

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. However, one argument against this view is that equity investors may condone increased risk taking, as they are 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. However, in practice, 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).

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 contracts 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). Finally, CDS markets are more liquid than corporate debt markets (Longstaff *et al.*, 2005) and CDS spreads tend to lead bond markets in price discovery (Blanco *et al.*, 2005).

In this paper we investigate the capacity of CDS contracts on individual banks to provide market discipline, acting 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 to distinguish between safe and troubled banks during the 2004-2012 period. 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 focusses on CDS contracts associated with both senior and subordinated debt of individual institutions.

Empirical findings indicate that changes in CDS spreads provide a strong signal of 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 a 15% increase in the probability of bank failure. Moreover, our results indicate that CDS spreads incorporate information about the condition of banks which is above and beyond that available from equity market returns. In doing so, CDS contracts may induce bank market discipline, as they signal increasing borrowing costs for distressed firms. Moreover, both senior and subordinated debt are examined, with each found to distinguish between weak and strong banks. Findings are shown to be robust to alternative dependent variables (both rating downgrades and accounting variables), to hold for various cohorts, and for excess and idiosyncratic changes in CDS.

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. Relevant 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 by means of two channels; through 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 should be related to changes in measures of risk (Gorton and Santomero, 1990). On this basis, empirical evidence for market discipline has been missed. 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 predict 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 financial instruments such as CDS provides a fresh opportunity to test for market discipline through these novel securities.

There is considerable evidence to suggest that equity markets display efficiency in processing information and, so, should act as a strong indication 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) and Cannata and Quagliariello (2005) 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 metric, suggested as a complement to bond information in signalling 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. In this study, we again assess whether equity markets have an ability to forecast bank distress 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 firm condition information. However, evidence for the effectiveness of debt markets is mixed. Krishnan *et al.* (2005) show that credit spread levels are associated with risk taking behaviour but that changes in spread levels are not. Gorton and Santomero (1990) and Avery *et al.* (1988) find little support for the ability of subordinated debt to limit bank risk taking following the expansion of the government safety 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 contrast, various studies have documented evidence that debt markets reflect the riskiness of financial institutions (see, for example, Gropp *et al.*, 2006; Sironi, 2003; Flannery and Sorescu, 1996). Moreover, models of market discipline through subordinated debt have arrived at differing 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 was the first to start reporting CDS notionals since 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).[1] CDS have a variety of features which

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

may make them a better proxy (than bonds) for determining the ability of debt markets to discipline banks. Oehmke and Zawadowski (2014) suggest that speculative trading volume concentrates in the CDS rather than bond markets. Moreover, CDS spreads are less affected by illiquidity than credit 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).

Interest in bank CDS has increased markedly since the global financial crisis. Alter and Schüler (2012) 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. The determinants of bank CDS spreads are evaluated by Chiaramonte and Casu (2013) and shown to vary strongly over time. Considering the case of a single distressed institution, Northern Rock, Hamalainen *et al.* (2012) determine that equity markets provide a stronger signal than debt or CDS markets of impending problems. Finally, a number of studies have used aggregate CDS spreads and CDS indices to examine bank fragility, (Ballester Miquel *et al.*, 2012; 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 banks 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 how the sample of banks with available CDS was selected. The accounting-based and market-related variables employed as inputs to the default predictability models are also described. Theory and mathematical representation of the logit model used to predict bank failure is further detailed.

3.1. Data

In order to test the predictive power of CDS for bank failure, 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. In order to restrict our main focus to banks, we 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 our set of control variables 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.[2] Appendix A lists the names of the set of banks included in our sample.

We select the 2004-2012 period because (i) we are interested in assessing the signalling power of CDS before crisis periods (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.[3] 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.

The set of cross-sectional bank CDS spreads are then used to investigate the signalling power of single-name CDS for bank financial distress. We use the yearly change in the log CDS spread (ΔCDS) as the main variable to forecast bank default. Furthermore, we examine the forecasting power of the log of the CDS spread (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).[4]

[2] 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 Setion 4.4, we investigate the forecasting power of subordinated spreads for a subsample of banks with available data. Results are qualitatively similar.

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

[4] iTraxx Europe is an equally weighted index which comprises 125 highly liquid, invest-

In order to calculate the idiosyncratic component, we first regress daily CDS spread changes on a constant and either CDS index changes (for US firms) or iTraxx index changes (for European firms). The idiosyncratic risk is then formed using the standard deviation of the residual from the market model for each bank. CDX and iTraxx index spreads are obtained from Bloomberg.

The set of 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*, *ROAA*, *LADEPST* and *SIZE*. Accounting-based variables are obtained from 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 (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; Cannata

ment 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.

and Quagliariello, 2005). The return on average assets, $ROAA$, measures earnings quality and is expected to have a negative relationship with bank failure (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.

In this paper, the marginal ability of CDS spreads to forecast bank failure relative to equity-derived measures is further studied. Individual equity prices are obtained from Thomson Datastream. Market related variables are represented by $STOCK$, $STOCKVOL$ and $STOCK_{orth}$. $STOCK$ is the log stock return, calculated on an annual basis. $STOCKVOL$ is the annualised standard deviation of daily returns over the 3 months prior to portfolio formation. $STOCK_{orth}$ is the orthogonalised log stock return and is computed as the residual on the last day of each year (expressed on an annual basis) obtained from a regression of daily log stock returns on a constant and daily changes in log CDS spreads.

We next define some of 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 banking 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. 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 B we present the full list of variables used in our study and their mnemonics.

Table 1 gives 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.

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.[5] 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. Some of the banks in our sample are unlisted and, for this reason, the number of observations for the stock market variables (namely, $STOCK$, $STOCKVOL$ and $STOCK_{orth}$) are reduced relative to the other variables. A similar argument applies to the variables that have been estimated from daily data when a continuous time series was available for most of the estimation period (namely, $\Delta IDCDS$, CDS_{orth}[6], $CDSVOL$, $STOCK_{orth}$ and $STOCKVOL$). 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 ΔCDS and $CDSVOL$ (0.63), CDS and $STOCKVOL$ (0.61), $T1RC$ and $LADEPST$ (0.51), CDS and ΔCDS (0.53), CDS and $ROAA$ (-0.51).

[5] Note that we exclude year 2012 from this table because our sample period ends in 2012. This would be our final year for which we can predict bank failures. In order to do that, we would be using our explanatory variables up until year 2011.

[6] CDS_{orth} is the orthogonalised CDS change and is computed as the residual on the last day of each year (expressed on an annual basis) obtained from a regression of daily changes in log CDS spreads on a constant and daily log stock returns.

3.2. Methodology

In order to investigate the predictive 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. They are estimated via maximum likelihood. A higher value of $\alpha + \beta X_{i,t}$ indicates a higher probability of failure.

Common to most studies incorporating both market and accounting variables as failure predictors, 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 31^{st} 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.[7]

[7] The majority of banks in our sample do not report interim results with sufficient

The coefficients from a model based upon a logistic function do not have any direct intuitive interpretation. However, they 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 predictive power of CDS spread changes for a variety of forecasting horizons. We then assess whether this predictive power is affected by (i) introducing various accounting and market variables and (ii) selecting a shorter sample period which only includes the subprime crisis. The forecasting ability of CDS spread levels and the volatility of CDS spread changes are then examined. Subsequently, we test the sensitivity of our results to

granularity, so, in this study, we use annual accounting data to forecast failure over the following year.

the use of different measures of CDS spread changes. The robustness of the CDS predictive power with respect to alternative measures of bank failure for our dependent variable is further detailed. Finally, the predictive 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 as predictors of 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 the log changes in the CDS spreads during 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 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 predictive performance 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. The last column of Table 3 reports the logit estimation when 1-year log stock returns are instead used as the only predictor.[8] The estimated coefficient is negative (as expected) but not statistically significant.

In order to explore further the marginal predictive ability of CDS spread changes relative to stock returns, we run various logit models including different versions of both explanatory variables. In particular, we consider the log changes of the two variables and the orthogonalised log changes. Estimated coefficients are reported in Table 4. They have the expected sign and are all significant at the 10% significance level. CDS spread changes and orthogonalised CDS changes display the highest z-statistics in all specifications. Strong evidence for marginal predictive ability of CDS relative to equity returns is evident across all specifications, including those using orthogonalised returns. This complementary predictability 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 predict 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

[8] 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.

end, various accounting variables, previously proposed as drivers of banking risk, (described in Section 3.1) in addition to stock returns and the volatility of stock returns 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 5. 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 volatility of stock returns is significant at the 10% level and is positive. In contrast to the findings in table 4, stock returns are not found to be significant once we control for other aspects of banking risk. While previous research has found mixed predictive performance for bank bond yields, these findings suggest that CDS spreads have strong forecasting ability, even relative to equity market returns.[9]

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 is examined using Equation 2. In each case, we assume an initial mean value of the predictor variables. For instance, if we consider the sixth specification in Table 5 (M6), a one-standard-deviation increase in the CDS spread change would increase the probability of failure by 15% of its initial value.

Next, we evaluate the predictive power of CDS spread changes during

[9]We also exclude the US banks from our sample and run the same logit regressions as in Table 5. We obtain very similar results that are available on request.

the shorter sample 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 6 reports the coefficient estimates for the various model specifications. With the exception of the last model specification (M9), the coefficients on the CDS spread change are highly significant, despite the substantial reduction in the number of observations. In model M9, when stock volatility is included, the explanatory power of CDS spread changes is mitigated. This suggests that similar information relating to failure may have been incorporated in these two varied markets during the height of the financial crisis. The level of tier 1 capital is also found to be a significant predictor of risk. Finally, in contrast to the analysis over the entire sample, bank size is found to be a significant predictor of 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 5, suggesting that logit models would have better predicted failures during the height of the financial crisis. Other major differences with the logit estimation for the whole sample includes the *LLPTA*, *ROAA* and *STOCK* variables, which flip sign but not significance. With hindsight, it is not surprising to observe such changes in the signs of these variables: it is well known that the banks with large stock returns in 2006 were the banks whose stock suffered the largest losses during the crisis (Beltratti and Stulz, 2012). Likewise, banks with high historic ROAA may have adopted a strategy of taking on higher risk loans, leaving them susceptible to failure. Finally, it is worth noting that while stock returns are not significant, the volatility of stock returns is highly significant and has better predictive power than in Table 5.

Next, we determine whether the forecasting ability of CDS for bank failure is confined to returns. Specifically, we examine the predictive power of both CDS spread levels and the volatility of CDS spread changes. The estimations of the logit models are reported in Table 7. The results from univariate regressions show that the two explanatory variables are significant at the 1% level and are positively related to the failure indicator. Even after controlling for the accounting and market variables, both variables remain significant at the 5% level. Both measures also demonstrate predictability while controlling for stock returns and volatility, suggesting that they reflect a different facet of banking risk.

4.2. CDS Excess Returns and Idiosyncratic Risk

In the previous section we examined the role of total CDS spread changes in the prediction of bank failure. Next, we examine the sensitivity of our results to two related measures. The first, $\Delta EXCDS$, 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 our analysis, important in a cross-sectional analysis. The second is $\Delta IDCDS$, the idiosyncratic component of the log change in the CDS spread, computed as the standard deviation of the residuals obtained from running each year a regression of daily CDS spread changes on a constant and CDX index spread changes (for US financial firms) or iTraxx index spread changes (for European financial firms).

Table 8 and Table 9 report the logit estimation results when $\Delta EXCDS$ and $\Delta IDCDS$ are used, respectively. From these Tables, we can clearly confirm our previous findings: both measures of excess CDS spread changes are found to have a positive and highly significant relationship with bank failure in all model specifications. The findings on idiosyncratic changes in CDS are 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 CDS point to the vital role of market-derived company-specific information in forecasting bank failure.

Similar to the results obtained in the previous section, we find that, for M6, a one-standard-deviation increase in either $\Delta EXCDS$ or $\Delta IDCDS$ would increase the probability of failure by 9% and 10% of their initial value, respectively.

4.3. Forecasting ability of CDS for alternative measures of failure

In the absence of bank failures, which tend to cluster in time, previous researchers have adopted alternative measures of banking distress such as rating agency downgrades as the dependent variable (Miller *et al.*, 2015; Distinguin *et al.*, 2006; Gropp *et al.*, 2006). We test the robustness of our findings to the use of 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 and Poor's) and zero otherwise. Downgraded banks are excluded from the sample in the years following the downgrade. Results, detailed in Table 10, are supportive of the ability of CDS spread changes to predict 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 mitigating such failures. Early intervention in trouble institutions might, however, help to mitigate 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, namely the Z-score and the ROAA volatility. Considering Z-score first, 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. While changes in CDS spreads are not found to be significant for all specifications when ROAA volatility is used as dependent variable, they have the correct sign. In summary, these results reinforce our main finding: CDS spread changes represent useful warning signals which are able to predict a bank's deteriorating solvency conditions.

4.4. Subordinated CDS spread changes and bank default predictability

Previous studies which investigated the predictive role of subordinated debt have found a variation in 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 provide predictive power for bank failure. To this end, a set of subordinated debt spreads is gathered from the Markit database, resulting in a total of 36 firms with available data. Table 12 reports the estimation output of logit models for the nine different specifications, incorporating each of the accounting variables in turn. 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 predicting bank failure, a question we leave for further research.

In order to get an idea of the economic significance of these estimates we can again 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 8% of its initial value. This effect is slightly lower but still similar in magnitude to the 15% increase in probability predicted for a one-standard-deviation increase in senior CDS spread changes. This reduced sensitivity relative to senior may be a consequence of subordinated debt investors condoning bank risk taking, as a gamble for redemption during times of financial distress.

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 issued 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 limit bank risk taking.

This study is the first to examine whether CDS instruments can exert effective market discipline on banks. In particular, we examine whether single-name CDS contracts act as a signal of bank failure, thus providing 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 suggests that relative changes in firm-level CDS spreads are a strong and significant predictor of 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 by 15% of its initial value.

We undertake several steps to check the robustness of our main result. First, we use alternative measures for CDS spread changes that neutralise 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). Finally, we test whether subordinated CDS spread changes have a similar predictive power for bank distress during our sample period. In each case, we find that changes in CDS spreads are able to forecast bank failure.

Overall, the analyses detailed impart an important message for both policy makers and regulatory bodies: CDS spreads play a fundamental role in forecasting banks' financial distress. Hence, they can be used as early warning signals for forthcoming problems within banks. Moreover, we establish that CDS instruments can exert effective market discipline on banking institutions over and above stock market indicators.

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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 log of the CDS spread (CDS), 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 orthogonalized log change in the CDS spread (ΔCDS_{orth}), the annualized standard deviation of daily log changes in the CDS spread over the 3 months prior to portfolio formation (CDSVOL), 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 assets (ROAA), 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 orthogonalised log stock return ($STOCK_{orth}$), the annualised standard deviation of daily returns for the 3 months prior to portfolio formation (STOCKVOL). Panel C shows the Pearson correlation coefficient between pairs of the main variables used in the empirical analysis. CDS levels and 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**					
CDS	3.951	4.142	1.372	1.216	8.117	289	3.460	3.105	1.355	1.335	8.112	103
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
ΔCDS_{orth}	0.460	0.201	0.955	-1.528	2.581	163	0.518	0.006	1.042	-1.528	2.581	70
CDSVOL	62.868	46.799	38.394	4.391	216.861	246	67.501	48.915	41.029	19.296	216.861	87
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
ROAA	0.588	0.561	0.485	-1.430	2.000	308	0.673	0.698	0.499	-1.02	1.76	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
$STOCK_{orth}$	8.781	12.168	35.408	-114.759	72.410	157	13.022	13.473	30.180	-114.759	72.410	70
STOCKVOL	34.414	25.248	28.851	6.527	200.390	210	35.753	23.767	34.416	8.386	200.390	81

Panel C: Correlations

	CDS	ΔCDS	*CDSVOL*	*T1RC*	*LLPTA*	*CI*	*ROAA*	*LADEPST*	*SIZE*	*STOCK*	*STOCKVOL*
CDS	1										
ΔCDS	0.53	1									
CDSVOL	0.23	0.63	1								
T1RC	0.22	-0.11	-0.23	1							
LLPTA	0.50	0.07	0.01	-0.09	1						
CI	0.12	0.14	0.23	0.08	-0.19	1					
ROAA	-0.51	-0.12	-0.02	-0.08	-0.19	-0.50	1				
LADEPST	-0.17	-0.09	-0.08	0.51	-0.36	0.31	-0.05	1			
SIZE	-0.11	-0.00	0.15	0.21	-0.11	0.17	-0.07	0.44	1		
STOCK	-0.37	0.10	-0.08	0.01	-0.41	-0.18	0.37	0.08	0.08	1	
STOCKVOL	0.61	0.39	0.45	0.07	0.23	0.39	-0.50	0.01	0.01	-0.33	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 (not failed) 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 5 different specifications of the logit regressions (M1 to M5). 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
$\Delta CDS3M$	2.65 (3.22)***				
$\Delta CDS6M$		1.49 (5.41)***			
$\Delta CDS9M$			1.38 (5.25)***		
ΔCDS				1.59 (5.54)***	
$STOCK$					-0.56 (-1.13)
$Constant$	-2.59 (-8.62)***	-2.99 (-9.43)***	-3.03 (-8.83)***	-3.62 (-8.20)***	-2.15 (-9.51)***
$Pseudo\ R^2$	0.136	0.186	0.185	0.243	0.006
$Nobs$	280	271	268	278	210

Table 4: **Logit Regressions of Failure Indicator on CDS Changes and Stock Returns**

This table summarizes results of binary logit regressions of the failure indicator on CDS log changes and log stock returns from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (not failed) during the subsequent 12 months. ΔCDS *is the log change in the CDS spread. STOCK is the log stock return.* ΔCDS_{orth} *is the orthogonalized log change in the CDS spread.* $STOCK_{orth}$ *is the orthogonalised 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 4 different specifications of the logit regressions (M1 to M4). For instance, M1 regresses the failure indicator on a constant, the log stock return and the log change in the CDS spread.*

	M1	M2	M3	M4
ΔCDS	2.09 (5.77)***	2.32 (5.37)***		
$STOCK$	-1.94 (-2.24)**		-4.50 (-3.26)***	
ΔCDS_{orth}			2.32 (5.24)***	2.31 (5.36)***
$STOCK_{orth}$		-2.27 (-2.18)**		-3.12 (-2.61)***
$Constant$	-4.41 (-7.00)***	-4.07 (-7.12)***	-4.57 (-5.99)***	-3.86 (-7.70)***
$Pseudo\ R^2$	0.312	0.332	0.324	0.222
$Nobs$	193	157	157	157

Table 5: **Logit Regressions of Failure Indicator on Predicting Variables**

This table summarizes results of binary logit regressions of the failure indicator on predicting variables from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (not failed) 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. ROAA is the return on average assets. 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. STOCKVOL is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation.* $Pseudo\ R^2$ *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	1.37	1.37	1.35	2.81	3.06
	(5.54)***	(4.48)***	(4.27)***	(3.85)***	(3.68)***	(3.72)***	(3.70)***	(4.13)***	(3.19)***
$T1RC$		-0.30	-0.30	-0.43	-0.44	-0.47	-0.48	-0.87	-0.99
		(-2.33)**	(-2.26)**	(-2.71)***	(-2.82)***	(-2.86)***	(-2.85)***	(-2.96)***	(-3.29)***
$LLPTA$			84.34	112.66	91.40	116.57	115.75	360.16	378.19
			(0.82)	(1.07)	(0.88)	(1.01)	(1.01)	(2.34)**	(2.61)***
CI				0.02	0.02	0.02	0.02	0.01	0.01
				(2.19)**	(1.53)	(1.21)	(1.24)	(0.89)	(1.14)
$ROAA$					-0.46	-0.46	-0.48	-1.06	-0.83
					(-0.78)	(-0.75)	(-0.80)	(-1.62)	(-1.19)
$LADEPST$						0.02	0.01	0.06	0.05
						(0.61)	(0.43)	(2.14)**	(1.35)
$SIZE$							0.08	0.05	0.15
							(0.33)	(0.17)	(0.52)
$STOCK$								-0.81	-0.31
								(-0.68)	(-0.23)
$STOCKVOL$									2.07
									(1.99)**
$Constant$	-3.62	-1.05	-1.35	-1.72	-1.15	-1.21	-2.68	-2.61	-4.98
	(-8.20)***	(-0.97)	(-1.18)	(-1.24)	(-0.72)	(-0.73)	(-0.58)	(-0.42)	(-0.85)
$Pseudo\ R^2$	0.243	0.238	0.244	0.300	0.304	0.308	0.309	0.496	0.523
$Nobs$	278	249	249	249	249	249	249	175	175

Table 6: **Logit Regressions of Failure Indicator on Predicting Variables During the Period 2005-2008**

This table summarizes results of binary logit regressions of the failure indicator on predicting variables from 2005 to 2008. The failure indicator is 1 (0) if the firm failed (not failed) 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. ROAA is the return on average assets. 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. STOCKVOL is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation.* $Pseudo\ R^2$ *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	2.48	2.60	2.39	3.35	0.43
	(5.25)***	(3.53)***	(3.67)***	(3.62)***	(3.60)***	(3.83)***	(4.20)***	(1.98)**	(0.57)
$T1RC$		-0.33	-0.37	-0.43	-0.47	-0.52	-0.53	-0.57	-1.02
		(-1.93)*	(-1.93)*	(-1.95)*	(-2.04)**	(-2.16)**	(-1.98)**	(-1.87)*	(-1.76)*
$LLPTA$			-123.75	-122.09	-149.06	-134.23	-182.96	20.14	-228.68
			(-0.62)	(-0.58)	(-0.76)	(-0.71)	(-1.05)	(0.09)	(-0.72)
CI				0.02	0.04	0.03	0.03	0.00	0.12
				(1.22)	(1.39)	(1.27)	(0.88)	(0.13)	(2.29)**
$ROAA$					0.75	0.91	0.82	0.05	4.60
					(0.64)	(0.69)	(0.61)	(0.03)	(1.46)
$LADEPST$						0.02	-0.02	0.01	0.01
						(0.53)	(-0.32)	(0.11)	(0.22)
$SIZE$							0.76	1.08	2.41
							(1.95)*	(2.60)***	(2.22)**
$STOCK$								1.62	1.46
								(0.32)	(0.11)
$STOCKVOL$									32.29
									(2.93)***
$Constant$	-4.56	-2.64	-2.25	-3.09	-4.26	-4.51	-17.68	-24.98	-63.79
	(-6.31)***	(-1.67)*	(-1.30)	(-1.62)	(-1.69)*	(-1.66)*	(-2.31)**	(-2.95)***	(-2.84)***
$Pseudo\ R^2$	0.414	0.416	0.423	0.433	0.437	0.442	0.482	0.556	0.730
$Nobs$	150	126	126	126	126	126	126	97	97

Table 7: **Logit Regressions of Failure Indicator on the CDS Spread Level, the CDS Spread Volatility and Other Predicting Variables**

This table summarizes results of binary logit regressions of the failure indicator on the level of the CDS spread and the other predicting variables (M1 and M2) as well as the volatility of the CDS spreads and the other predicting variables (M3 and M4). The sample period is from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (not failed) during the subsequent 12 months. CDS is the log of the CDS spread. CDSVOL is the annualized standard deviation of daily log changes in the CDS spread over the 3 months prior to portfolio formation. 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. ROAA is the return on average assets. 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. STOCKVOL is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation. $Pseudo\ R^2$ *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	M4
CDS	0.46	1.17		
	(4.21)***	(3.11)***		
CDSVOL			2.18	0.98
			(2.73)***	(2.09)**
T1RC		-1.16		-0.93
		(-4.32)***		(-4.03)***
LLPTA		106.20		229.91
		(0.69)		(1.26)
CI		0.02		0.01
		(1.89)*		(0.78)
ROAA		0.54		-0.46
		(0.62)		(-0.55)
LADEPST		0.05		0.05
		(1.54)		(1.56)
SIZE		0.45		0.20
		(1.50)		(0.67)
STOCK		1.60		1.00
		(2.29)**		(1.59)
STOCKVOL		1.31		2.78
		(1.39)		(2.93)***
Constant	-4.07	-10.10	-3.76	-2.87
	(-7.72)***	(-1.70)*	(-5.68)***	(-0.53)
$Pseudo\ R^2$	0.052	0.329	0.113	0.336
Nobs	289	181	253	164

Table 8: **Logit Regressions of Failure Indicator on Predicting Variables Using the Excess CDS Change**

This table summarizes results of binary logit regressions of the failure indicator on predicting variables from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (not failed) during the subsequent 12 months. $\Delta EXCDS$ *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). 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. ROAA is the return on average assets. 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. STOCKVOL is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation.* $Pseudo\ R^2$ *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 excess log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
$\Delta EXCDS$	1.54	1.31	1.27	1.45	1.48	1.47	1.44	2.13	2.49
	(3.66)***	(2.90)***	(2.62)***	(3.30)***	(3.23)***	(3.21)***	(3.18)***	(3.78)***	(3.71)***
$T1RC$		-0.36	-0.38	-0.56	-0.57	-0.58	-0.60	-1.09	-1.27
		(-2.51)**	(-2.41)**	(-2.80)***	(-2.92)***	(-2.91)***	(-2.88)***	(-3.24)***	(-3.87)***
$LLPTA$			60.40	103.09	79.87	90.13	91.46	356.71	351.10
			(0.59)	(1.00)	(0.78)	(0.78)	(0.80)	(2.09)**	(2.35)**
CI				0.03	0.02	0.02	0.02	0.02	0.02
				(2.39)**	(1.85)*	(1.67)*	(1.80)*	(2.61)***	(2.62)***
$ROAA$					-0.50	-0.50	-0.53	-0.96	-0.39
					(-0.79)	(-0.76)	(-0.87)	(-1.64)	(-0.59)
$LADEPST$						0.01	-0.00	0.05	0.03
						(0.24)	(-0.03)	(1.42)	(0.70)
$SIZE$							0.19	0.23	0.39
							(0.68)	(0.81)	(1.34)
$STOCK$								0.36	0.41
								(0.49)	(0.61)
$STOCKVOL$									3.78
									(4.07)***
$Constant$	-2.79	0.18	0.12	-0.55	0.14	0.10	-3.25	-2.69	-6.14
	(-8.35)***	(0.15)	(0.10)	(-0.33)	(0.07)	(0.05)	(-0.65)	(-0.49)	(-1.02)
$Pseudo\ R^2$	0.121	0.155	0.158	0.252	0.257	0.258	0.262	0.392	0.478
$Nobs$	278	249	249	249	249	249	249	175	175

Table 9: **Logit Regressions of Failure Indicator on Predicting Variables Using the Idiosyncratic CDS Change**

*This table summarizes results of binary logit regressions of the failure indicator on predicting variables from 2005 to 2012. The failure indicator is 1 (0) if the firm failed (not failed) during the subsequent 12 months. $\Delta IDCDS$ is the idiosyncratic component of 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. ROAA is the return on average assets. 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. STOCKVOL is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation. $Pseudo\ R^2$ 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 idiosyncratic log change in the CDS spread.*

	M1	M2	M3	M4	M5	M6	M7	M8	M9
$\Delta IDCDS$	1.67	1.43	1.43	1.62	1.62	1.62	1.60	2.33	2.99
	(4.61)***	(3.63)***	(3.52)***	(3.94)***	(3.84)***	(3.83)***	(3.79)***	(4.61)***	(3.66)***
$T1RC$		-0.47	-0.48	-0.71	-0.71	-0.71	-0.78	-0.97	-1.10
		(-2.30)**	(-2.27)**	(-2.91)***	(-2.94)***	(-2.92)***	(-3.20)***	(-3.05)***	(-3.11)***
$LLPTA$			58.45	95.98	84.47	85.33	89.56	189.49	235.72
			(0.47)	(0.72)	(0.65)	(0.58)	(0.58)	(1.02)	(1.25)
CI				0.03	0.03	0.03	0.03	0.01	-0.00
				(3.05)***	(2.17)**	(1.94)*	(2.43)**	(1.05)	(-0.03)
$ROAA$					-0.23	-0.23	-0.30	-0.87	-0.43
					(-0.27)	(-0.27)	(-0.40)	(-1.13)	(-0.52)
$LADEPST$						0.00	-0.03	0.03	0.06
						(0.01)	(-0.69)	(0.61)	(1.14)
$SIZE$							0.56	0.39	0.14
							(1.55)	(0.97)	(0.31)
$STOCK$								-1.47	-1.74
								(-1.32)	(-1.42)
$STOCKVOL$									5.03
									(2.71)***
$Constant$	-2.99	0.92	0.76	0.24	0.50	0.50	-9.54	-5.42	-2.84
	(-7.55)***	(0.56)	(0.46)	(0.12)	(0.22)	(0.22)	(-1.36)	(-0.66)	(-0.32)
$Pseudo\ R^2$	0.212	0.259	0.262	0.367	0.368	0.368	0.391	0.467	0.539
$Nobs$	212	184	184	184	184	184	184	139	139

Table 10: **Logit Regressions of Downgrade Indicator on Predicting Variables**

This table summarizes results of binary logit regressions of the downgrade indicator on predicting variables from 2005 to 2012. 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.* $ROAA$ *is the return on average assets.* $LADEPST$ *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.* $STOCKVOL$ *is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation.* $Pseudo\ R^2$ *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 3 different specifications of the logit regressions (M1 to M3). For instance, M1 regresses the downgrade indicator on a constant and the log change in the CDS spread.*

	M1	M2	M3
ΔCDS	0.88 (4.64)***	1.05 (4.52)***	1.01 (3.00)***
$T1RC$		0.08 (0.85)	-0.03 (-0.17)
$LLPTA$		338.15 (2.24)**	143.58 (0.79)
CI		-0.02 (-0.85)	-0.00 (-0.00)
$ROAA$		-1.81 (-2.41)**	-0.19 (-0.17)
$LADEPST$		0.01 (0.53)	0.03 (1.33)
$SIZE$		0.25 (1.21)	0.39 (1.59)
$STOCK$			-2.99 (-1.78)*
$STOCKVOL$			1.19 (0.83)
$Constant$	-1.49 (-6.80)***	-5.73 (-1.49)	-10.68 (-2.04)**
$Pseudo\ R^2$	0.114	0.263	0.290
$Nobs$	188	164	118

Table 11: **OLS Regressions of ROAA Volatility and Z-score on Predicting Variables**

*This table summarizes results of OLS regressions of ROAA volatility on predicting variables (M1, M2 and M3) as well as OLS regressions of Z-score on predicting variables (M4, M5 and M6). 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. 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. ROAA is the return on average assets. 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. STOCKVOL is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation. Adj R^2 is the value of the adjusted R-squared. Nobs is the number of observations. We report the t-statistics in parentheses. *, ** and *** denote significance at the 10%, 5% and 1%, respectively.*

	M1	M2	M3	M4	M5	M6
ΔCDS	0.10	0.05	0.09	-18.45	-20.01	-23.31
	(1.52)	(1.03)	(4.26)***	(-4.78)***	(-4.62)***	(-3.74)***
$T1RC$		0.01	-0.00		1.24	1.22
		(0.71)	(-0.54)		(0.92)	(0.51)
$LLPTA$		50.90	26.47		-627.72	-2370.09
		(9.72)***	(3.47)***		(-1.41)	(-1.09)
CI		-0.00	0.00		-0.21	-0.08
		(-1.84)*	(1.41)		(-1.60)	(-0.35)
$ROAA$		-0.28	-0.07		1.47	12.86
		(-7.27)***	(-1.65)		(0.45)	(1.09)
$LADEPST$		0.00	0.00		-0.78	-1.00
		(1.33)	(2.22)**		(-2.82)***	(-2.42)**
$SIZE$		-0.08	-0.00		2.63	8.27
		(-1.95)*	(-0.27)		(0.80)	(1.79)*
$STOCK$			0.05			-8.73
			(0.93)			(-0.53)
$STOCKVOL$			-0.06			-4.38
			(-0.76)			(-0.20)
$Constant$	0.38	1.67	0.18	58.06	32.63	-77.07
	(5.72)***	(2.29)**	(0.59)	(15.65)***	(0.53)	(-0.86)
Adj R^2	0.004	0.600	0.196	0.057	0.097	0.119
$Nobs$	366	328	175	361	325	174

Table 12: **Logit Regressions of Failure Indicator on Predicting Variables for Firms with Subordinated CDS**

This table summarizes results of binary logit regressions of the failure indicator on predicting variables from 2005 to 2012 for the firms for which subordinated CDS are also available. The failure indicator is 1 (0) if the firm failed (not failed) 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. ROAA is the return on average assets. 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. STOCKVOL is the annualised standard deviation of daily returns for the 3 months prior to portfolio formation.* $Pseudo\ R^2$ *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	1.06	1.06	1.05	1.42	1.35
	(3.34)***	(3.08)***	(3.14)***	(2.93)***	(2.90)***	(2.91)***	(2.85)***	(3.94)***	(3.37)***
$T1RC$		-0.35	-0.35	-0.51	-0.51	-0.51	-0.56	-0.80	-0.85
		(-2.19)**	(-2.10)**	(-2.77)***	(-2.78)***	(-2.67)***	(-2.47)**	(-2.88)***	(-3.07)***
$LLPTA$			94.60	119.67	104.32	109.97	114.23	156.43	161.12
			(0.70)	(0.83)	(0.76)	(0.71)	(0.77)	(0.80)	(0.85)
CI				0.02	0.02	0.02	0.02	-0.01	-0.01
				(2.36)**	(1.75)*	(1.50)	(1.64)	(-0.41)	(-0.82)
$ROAA$					-0.25	-0.26	-0.25	-1.13	-1.08
					(-0.36)	(-0.36)	(-0.35)	(-1.29)	(-1.34)
$LADEPST$						0.00	-0.01	0.05	0.07
						(0.10)	(-0.23)	(1.44)	(1.61)
$SIZE$							0.24	0.04	-0.15
							(0.65)	(0.10)	(-0.33)
$STOCK$								-0.90	-0.18
								(-0.72)	(-0.13)
$STOCKVOL$									2.05
									(1.50)
$Constant$	-3.37	-0.28	-0.61	-0.85	-0.55	-0.58	-4.85	0.83	3.88
	(-6.65)***	(-0.22)	(-0.45)	(-0.62)	(-0.34)	(-0.35)	(-0.72)	(0.11)	(0.49)
$Pseudo\ R^2$	0.147	0.188	0.196	0.252	0.253	0.254	0.259	0.358	0.373
$Nobs$	175	165	165	165	165	165	165	127	127

Appendices

A. List of Banks

1) Allied Irish Banks PLC
2) Banca Monte dei Paschi di Siena Spa
3) Banca Nazionale del Lavoro Spa
4) Banca Popolare di Milano Scarl
5) Banco Bilbao Vizcaya Argentaria SA
6) Banco Comercial Portugues SA
7) Banco de Sabadell SA
8) Banco Popolare SC
9) Banco Popular Espanol SA
10) Banco Santander SA
11) Bank of America Corp
12) Bank of Ireland
13) Bankinter SA
14) Barclays Bank PLC
15) Bear Stearns Cos LLC
16) Caixa Geral de Depositos SA
17) Caja de Ahorros y Monte de Piedad de Madrid
18) Citigroup Inc
19) Commerzbank AG
20) Cooperatieve Centrale Raiffeisen - Boerenleenbank BA

21) Credit Agricole SA

22) Credit Suisse Group AG

23) Danske Bank A/S

24) Deutsche Bank AG

25) DNB Bank ASA

26) Fundacion Bancaria Caixa d'Estalvis y Pensions de Barcelona

27) Goldman Sachs Group Inc

28) HSBC Bank PLC

29) ING Bank NV

30) Intesa Sanpaolo Spa

31) Irish Bank Resolution Corp Ltd

32) JPMorgan Chase & Co

33) Lehman Brothers Holdings Inc

34) Lloyds Bank PLC

35) Mediobanca Spa

36) Merrill Lynch & Co Inc

37) Morgan Stanley

38) Nationwide Building Society

39) Natixis SA

40) NIBC Bank NV

41) Norddeutsche Landesbank Girozentrale

42) Nordea Bank AB

43) Novo Banco SA

44) Permanent TSB Group Holdings PLC

45) Royal Bank of Scotland NV

46) Royal Bank of Scotland PLC

47) Santander UK PLC

48) Skandinaviska Enskilda Banken AB

49) SNS Bank NV

50) Standard Chartered PLC

51) Svenska Handelsbanken AB

52) UBS AG

53) Unicredit Bank AG

54) Unicredit Bank Austria AG

55) Unicredit Spa

56) Unione di Banche Italiane Scpa

57) Wachovia Corp

58) Washington Mutual Inc

59) Wells Fargo & Co

60) Yorkshire Building Society

B. Definitions of Variables

Variables	**Mnemonics**
Dependent variables	
Binary	
Failure indicator	
Downgrade indicator	
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 assets	*ROAA*
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*
Orthogonalized yearly log change in senior CDS spread	ΔCDS_{orth}
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	$STOCK$
Volatility of daily log stock returns over the past 3 months	*STOCKVOL*
Orthogonalized yearly log stock return	$STOCK_{orth}$