

A Market-Based Measure of Credit Quality and Banks' Performance During the Subprime Crisis*

Martin Knaup[†] Wolf Wagner[‡]

November 18, 2009

Abstract

We propose a new method for measuring the quality of banks' credit portfolios. This method makes use of information impounded in bank share prices by exploiting differences in their sensitivity to credit default swap spreads of borrowers of varying quality. The method allows us to derive a *credit risk indicator* (CRI), which is the perceived share of high risk exposures in a bank's portfolio. We estimate CRIs for the 150 largest U.S. bank holding companies and find that they have strong predictive power for the BHCs' performance during the subprime crisis, even after controlling for a variety of traditional asset quality proxies. Interestingly, we also find that the BHCs' aggregate CRI did not deteriorate since the beginning of the subprime crisis. This suggests that the market was aware of their (average) exposure to high risk credit.

JEL classification: G21, G28

Keywords: credit risk, asset quality, banks, subprime crisis

*We thank seminar participants at Tilburg University, the NAKE Research Day 2008, and participants at the XVII Tor Vergata Conference, the ENTER Jamboree 2009, the 45th Annual Bank Structure Conference, the European Banking Center Financial Stability Conference 2009, the 3rd Banco de Portugal Conference on Financial Intermediation, the EEA 2009 Meetings, the 28th SUERF Colloquium, and the Ancona Banking Conference 2009 for comments. We would also like to thank Allen Berger, Harry Huizinga, Alfred Lehar, Lars Norden and Klaus Schaeck for comments. An earlier version of this paper won the "XVII International Tor Vergata Conference on Banking and Finance Award" for the best paper presented in the Young Economist Session.

[†]CentER, European Banking Center and Department of Economics, Tilburg University. E-mail: m.knaup@uvt.nl.

[‡]CentER, European Banking Center, TILEC, and Department of Economics, Tilburg University. E-mail: wagner@uvt.nl.

1 Introduction

It is of great value to the financial system to have informative and comprehensive indicators of the quality of banks' assets. Such indicators allow regulators to monitor general trends in the financial system. They also permit them to easily identify weak banks and to put them under increased regulatory scrutiny. For example, many of the current banking failures, and their serious systemic ramifications, could have presumably been avoided if the high-risk nature of the investments at some banks had become apparent at an earlier stage. Easily accessible information about the quality of banks' investments is also crucial for bank shareholders and debtors. It allows them to assess the performance of bank managers and to better evaluate the risks to which banks are exposed. This, in turn, enhances efficiency at banks by exposing their managers to greater market discipline.

Unfortunately, such indicators are difficult to obtain. Banks' business is complex and wide-ranging. In particular, due to the variety of information required in judging the riskiness of their lending activities, there do not exist good measures of the quality of their loan portfolios. In order to obtain proxies of loan quality one typically relies on accounting data, such as, for example, the share of non-performing loans in a bank's portfolio, or the ratio of loan-loss allowances to total loans.¹ These proxies have a range of shortcomings. For one, the scope of accounting data is limited. They miss important information (such as that contained in analyst reports or in the form of informal knowledge, e.g., a bank manager's reputation). They are also mostly backward looking in nature, while ideally one would like to have a measure of a bank's future risk. The low frequency of publication of accounting data also means that these proxies cannot reflect new information readily. The reliance on accounting-based data also suffers from the problem that loan-quality data is to a large extent at the discretion of banks themselves.² This is especially a concern if investors or supervisors base their decisions on such data. The construction of appealing indicators of asset quality is also complicated by the fact that banks nowadays undertake a variety of activities that expose them to credit risk. Beside their traditional lending business, banks trade in credit derivatives, take part in complex securitizations or grant credit lines. Many of those activities are off-balance sheet. And even if banks report them,

¹See, among others, Berger and DeYoung (1997), Wheelock and Wilson (2000), Hubbard, Kuttner and Palia (2002), DeYoung (2003) and Kwan (2003).

²There is widespread evidence that banks strategically manage the reporting of their loan loss data (see Wall and Koch (2000) for a survey of U.S. evidence and Hasan and Wall (2004) for international evidence). There is also evidence that banks delay provisioning for loans until cyclical downturns have already set in (Laeven and Majnoni (2003)) and that they overstate the value of distressed assets (Huizinga and Laeven (2009)).

and do so systematically, it is difficult to condense them into a comprehensive measure.

In this paper we develop a new method for measuring a bank's credit quality. Rather than using balance sheet data, this method is based on the information impounded in banks' share prices. The general appeal in using share prices is that they represent the market's overall assessment of a bank, and thus reflect a wide range of information. Our basic idea for how information about credit quality can be extracted from share prices is the following. Suppose that there are two types of loans in the economy, high-risk and low-risk loans, and suppose a bank's portfolio contains mostly high-risk loans. That bank's share price should then react relatively strongly to news about changes in the default risk of high-risk loans, but less so to news about low-risk loans. Thus, the bank's relative share price sensitivity to either type of news gives information about the perceived quality of its loan portfolio.

In our empirical implementation we identify default risk news as changes in the spreads of a high and a low risk credit default swap (CDS) index. For this we assign high and low risks to subinvestment grade and investment grade indices, respectively.³ The two indices can then be used to estimate share price sensitivities. From these sensitivities one can in turn derive a bank's *credit risk indicator* (CRI), which is defined as the ratio of a bank's high-risk sensitivity to its total (high-risk plus low-risk) sensitivity. Loosely speaking, the CRI thus measures the share of high risk exposures in a bank's portfolio, as perceived by the market.

We believe that this measure has several attractive features. Since it is market-based, it is forward looking and can incorporate new information quickly. It is also a comprehensive measure of a bank's credit quality. For example, for a bank's CRI it does not matter whether the bank acquired a high-risk exposure via lending to a low quality borrower, or by writing protection on a low quality underlying in the CDS market, or by buying a junior tranche of a Collateralized Loan Obligation. The CRI measures the quality of a bank's *overall* credit exposure, regardless of its source. Another advantage of the CRI is that it is based on the market's assessment of the bank, and not on the bank's assessment of itself. It is thus more difficult to manipulate. In fact, given our methodology, this would require banks to consistently influence their daily relative share price reactions to credit news in the economy.⁴

³CDS spreads have the advantage that they are considered a relatively clean and efficient measure of default risk. For example, there is evidence that a substantial part of price discovery takes place in these instruments (see Blanco, Brennan and Marsh (2005) and Norden and Weber (forthcoming)).

⁴As we argue in the paper, our methodology of computing the CRI from daily sensitivities also mitigates the influence of any noise in share prices.

We estimate CRIs for the 150 largest U.S. bank holding companies (BHCs).⁵ We find that their CRIs display substantial variation. Among the ten largest BHCs, for example, Citigroup has a much larger CRI than its peers, implying that it is considered as having relatively worse exposures.⁶ We also analyze the evolution of the BHCs' aggregate CRI over time. We find that during our sample period (February 2006 until February 2008) their aggregate CRI was relatively stable. In particular, it did not change significantly after February 2007, when problems with subprime loans first materialized in the financial system. Since the CRI measures the market's perception of credit risk, this suggests that the market seems to have been (on average) aware of the BHCs' high-risk exposures. To the extent that the decline in bank share prices during the subprime crisis was due to credit risk (and not, for example, liquidity and funding problems), it should hence be attributed to news about the default risk on high and low risk loans itself (materializing in a widening CDS spread for both subinvestment grade and investment grade exposures) and not to news about the composition of the BHCs' exposures.

We next address the question of how a bank's CRI is related to traditional measures of asset quality. We find that the CRIs are positively and significantly related to most measures of loan riskiness, such as the share of non-performing loans or loan-loss allowances. They are also positively related to factors that have been found to proxy high loan risk, such as past loan growth or the interest income on loans. We also find that banks with a higher share of real estate loans have significantly higher CRIs, which is consistent with the notion that a large part of the problem loans at banks are in the form of mortgages. We conclude from the analysis that the CRI seems to reflect a variety of information on bank risk.

The CRI may hence be a useful predictor of bank performance in downturns. This is because in a downturn the default risk of high-risk borrowers increases by more than the default risk for low-risk borrowers. Banks with a higher CRI should thus suffer relatively more. We test this relationship using the subprime crisis (during which the gap between the spread on high and low risk exposure widened). For this we first regress a banks' share price change since July 2007 (the time when problems with subprime loans became a widespread phenomenon) on its CRI estimated using information before this date. We find a significant and negative relationship between the bank's CRI and its share price performance. The relationship survives both in significance and magnitude if we control for a variety of other variables, such as various proxies of loan quality, bank leverage, share price beta and the components of the distance-to-default. We also find that the traditional measures of asset

⁵We make the CRIs available at <http://people.pwf.cam.ac.uk/ww243/CRI.xls>.

⁶Interestingly, Citigroup is up to now also the bank that has incurred the largest write-downs in the subprime crisis.

quality do not explain equally well banks' performance during the subprime crisis. Second, we compute CRIs for banks that failed during the crisis and compare them to the ones of other banks. We find that the CRI of a failed bank was about 2-3 times the average CRI in our entire sample.

The remainder of this paper is organized as follows. The next section reviews the use of market-based information on bank risk. In Section 3 we develop the methodology for measuring the CRI. The section also contains a general discussion of the CRI. Section 4 contains the empirical analysis. The final section concludes.

2 Market-Based Information on Bank Risk

In recent years there has been a growing interest in using market-based information to measure bank risk. This is on the back of evidence suggesting that the market does well in evaluating the risks at financial institutions. The existing literature suggests that investors are able to distinguish between banks based on their exposures to certain types of risks or asset compositions. This is true for share prices (see, for instance, Sachs, Huizinga and Shoven (1987) and Smirlock and Kaufold (1987)) as well as for bond and subordinated debt spreads (see, for example, Flannery and Sorescu (1996), Morgan and Stiroh (2000), and Hancock and Kwast (2001)). There is also evidence that market information has predictive power for banks, being it forecasting of bank performance (Berger, Davies and Flannery (2000)), rating changes (Evanoff and Wall (2001), Lopez and Krainer (2004), and Gropp, Vesala and Vulpes (2006)) or default (Gropp, Vesala and Vulpes (2006)).

Consequently, there now seems to be a consensus that market information does contain useful information about banks' risks (for surveys, see Flannery (1998) and Flannery (2001)). This has led to a growing interest in using market-based information for supervisory purposes. One strand of proposals advocates the use of subordinated debt spreads (e.g. U.S. Shadow Financial Regulatory Committee (2000)), in which regulators can monitor these spreads and force action if they widen too much. There are also approaches to use market information to obtain indices or measures of systemic risk. Elsinger, Lehar and Summer (2006a) propose such an index for supervisory purposes. This index gauges systemic risk from the covariances of bank asset values, as obtained from their share prices. Elsinger, Lehar and Summer (2006b) in turn develop a framework for systemic risk assessment using market data to estimate the market risk exposure. This is used to disentangle the systemic risk into risk stemming from correlated exposures and contagion risk.

Our proposed Credit Risk Indicator differs conceptually from these and other market based measures, such as the distance-to-default or CDS spreads. While these measures

focus on the *current* riskiness of a bank, the CRI measures the perceived exposure of a bank to an economic downturn (in which high risk assets presumably perform worse than low risk assets). This may be useful for regulators to identify banks vulnerable to downturns well before the downturn actually sets in. By means of example, in the years prior to the crisis credit risks were perceived as low. Market-based measures of banks such as CDS spreads or distance-to-default indicated a low probability of default at banks at the time. However, some banks had worse asset portfolios than others and were hence more vulnerable to the general deterioration in credit conditions that characterized the subprime crisis. Another difference of our measure is that it explicitly focuses on the asset side of bank risks, and is hence, to our knowledge, the first market-based measure that quantifies asset risk.

3 The Credit Risk Indicator

Consider a prototypical balance sheet of a bank. On the asset side we have securities (S) and loans ($Loans$). On the liability side we have debt (D) and equity (E), with equity being the residual claim ($E = S + Loans - D$). In terms of market values ($V(\cdot)$), we can thus write

$$V(E) = V(S) + V(Loans) - V(D). \quad (1)$$

We express all variables in unit of shares. $V(E)$ is simply given by the bank's share price. $V(D)$ can be approximated by its book value (discounted at an appropriate interest rate). For the loans, we have to take into account the risk of default. The expected loss on a loan EL is given by $EL = PD \cdot LGD$, where PD is the probability of default and LGD is the loss given default (expressed as a share of the face value). We assume that there are two types of loans, high risk and low risk loans. The amounts due on each type of loan are denoted with H and L , respectively, and we have $EL^H > EL^L$. The value of the loan portfolio can then be expressed as

$$V(Loans) = H(1 - EL^H) + L(1 - EL^L). \quad (2)$$

We define the *Credit Risk Indicator* (CRI) as the share of high risk loans in the loan portfolio

$$CRI = \frac{H}{H + L}. \quad (3)$$

We use as a proxy for the expected losses on high and low risk loans the spreads of two (economy-wide) Credit Default Swaps (CDS) indices.⁷ CDS spreads provide a fairly clean

⁷These indices are discussed in greater detail in Section 4.1.

measure of default risk since they represent the compensation the market requires for taking on credit risk. This is because the writer of the CDS has to be compensated by the buyer of protection for the expected loss on the underlying credit (consisting of the product of PD and LGD). The price of a CDS (which is expressed as a spread) hence approximates the expected loss. We can thus write for the CDS prices of high and low risk exposures

$$CDS^H = EL^H \text{ and } CDS^L = EL^L. \quad (4)$$

In our empirical work, CDS^H and CDS^L will be the prices (spreads) of a CDS-index consisting of a representative sample of subinvestment grade and investment grade exposures in the economy.

The CRI can be obtained as follows. We can first write equation (1) in terms of changes

$$\Delta V(E) = \Delta V(S) + \Delta V(Loans), \quad (5)$$

where Δ indicates the (absolute) change from $t - 1$ to t and where we have assumed constant debt. We can replace $V(Loans)$ in (5) with the expression derived earlier. We approximate the change in the value of a bank's security portfolio with the change in a market index, denoted M . Given security holdings of S , the absolute change is then given by $\Delta V(S) \approx \Delta M \frac{S}{M}$. We hence have for the change in the bank's share price:^{8,9}

$$\Delta p = \frac{S}{M} \Delta M - H \Delta CDS^H - L \Delta CDS^L. \quad (6)$$

We can then estimate the following relationship at the bank level

$$\Delta p_{i,t} = \alpha_i + \beta_i \Delta M_t + \gamma_i \Delta CDS_t^H + \delta_i \Delta CDS_t^L + \phi_i \Delta \mathbf{Z}_t + \varepsilon_{i,t}, \quad (7)$$

where i denotes the bank, t denotes time, and \mathbf{Z} is a vector of control variables. Noting that $\gamma_i = -H_i$ and $\delta_i = -L_i$, the CRI ($= \frac{H_i}{H_i + L_i}$) can be expressed as

$$CRI_i = \frac{\gamma_i}{\gamma_i + \delta_i}. \quad (8)$$

We can hence obtain the CRI by first estimating $\hat{\gamma}_i$ and $\hat{\delta}_i$, and then applying (8).¹⁰

⁸Note that the equivalent of (6) with relative changes does not hold. Dividing (6) by p we obtain (focusing on high risk loans only): $\frac{\Delta p}{p} = -H \frac{CDS^H}{p} \frac{\Delta CDS^H}{CDS^H}$. Hence, for a given loan portfolio H relative changes in the CDS spread ($\frac{\Delta CDS^H}{CDS^H}$) would only translate into relative share price changes ($\frac{\Delta p}{p}$) when $\frac{CDS^H}{p}$ is constant over time (which is unlikely to be the case).

⁹Equation (6) assumes a one-to-one relationship between the value of equity and the value of loans. Appendix A shows that our calculations are also when this is not the case, which may arise because of the option value embedded in equity or the perceived value of government bail-outs.

¹⁰The estimation of γ and δ is akin to estimating factor-loadings in the asset pricing. While in the asset

3.1 The CRI: A Discussion

In deriving the CRI we have presumed that a bank's credit risk derives exclusively from loans. Banks, however, also have credit risk exposures from other investments. Since the CRI is derived from share price sensitivities to credit risk in general (and not specifically loan-risk), it captures those as well. The CRI should hence be interpreted as a measure of the overall riskiness of a bank's credit assets. For example, a bank may have a large CRI because it has sold credit protection on a risky borrower using CDS or because it has a risky bond portfolio (consisting of, for instance, mainly subinvestment grade names). Credit exposures may also arise from banks' securitization activities, which are playing a crucial role in the current turmoil in the financial system. For example, in a Collateralized Loan Obligation (CLO) banks typically sell the lower-risk senior and mezzanine tranches, but retain the high risk equity tranche (these tranches are typically unrated but perceived to be well below investment grade). This lowers the average quality of the bank's credit exposures and increases a bank's CRI. By contrast, if a bank were to acquire AAA-rated (super-senior) tranches from securitizations, its average credit risk exposure may improve and hence its CRI would decrease.

In deriving the CRI we have assumed that banks have either high or low-risk exposures, which in our empirical implementation we take to be representative subinvestment and investment grade exposures (as given by the two respective CDS indices). Banks have, however, a variety of credit exposures, which will obviously not all fall neatly into these two categories. The CRI is thus not strictly the share of a bank's subinvestment grade exposures, but should be more generally interpreted as a measure of the average riskiness of a bank's credit exposures. Suppose, for example, that a bank has a loan portfolio that consists only of loans that have risk characteristics just between the representative investment and subinvestment grade loan. The banks' share price should then (on average) react similarly to subinvestment and investment grade CDS spread changes. Hence the bank's CRI would be $\frac{1}{2}$ (which is the same as for a bank whose loan portfolio consists of equal parts of subinvestment and investment grade exposures) even though the bank has no real subinvestment exposures at all. Moreover, since the representative investment pricing literature these factor loadings are used in a second step to predict returns (e.g., Cremer (2002)), we are here primarily interested in the cross-sectional distribution of the factor-loadings.

This regression differs from the asset pricing literature where one might use this regression as a first step to determine the factor loadings and then regress in a second step the expected returns onto these loadings to see whether the factors are priced or not. Our approach differs in that we propose to obtain the two factor loadings in order to put them into a relative measure and then use the cross-sectional variation of this measure to identify banks with bad credit risk portfolio.

and subinvestment grade exposures in the CDS index are not representing the lowest and highest possible credit risk in the economy, a bank's CRI is also not constrained to lie between zero and one. For instance, a bank that mainly has exposures of a higher quality than the representative investment grade credit in the CDS index will have a CRI smaller than zero, while banks with a portfolio quality below the representative subinvestment grade will have a CRI greater than one.

It should be emphasized that the CRI measures the *relative* sensitivities to high and low credit risk, that is, it relates to the *composition* of the bank's credit exposure. It should hence not be confused with a bank's absolute sensitivity to credit risk. The latter, besides the composition of the credit portfolio itself, will also be determined by the size of its credit portfolio and its leverage. For example, all else being equal, the share price of a highly leveraged bank will be more sensitive to changes in credit conditions than is the case for a bank with lower leverage. This emphasizes that the CRI should only be used as a measure of the quality of a bank's credit portfolio (and ideally in conjunction with other risk measures) and not as a sole measure of bank risk.¹¹

Since the CRI is derived from share prices, it represents the market's assessment of banks' credit risk. This assessment will be based on a variety of information, including for instance accounting data and analyst forecasts. However, as the current crisis is again reminding us, banks are opaque institutions.¹² Hence, it should be kept in mind that the CRI is the equivalent of the market's "best guess" of a bank's portfolio credit quality, and may hence differ from its true quality.¹³ Moreover, even though share prices may contain a wide range of useful information, they may arguably also be subject to noise. An advantage of our empirical implementation is that it computes CRIs from daily share price responses over a longer period of time (526 trading days in our sample). The impact of any noise in returns is likely to cancel out over so many observations and thus its influence on the CRI is likely to be limited. Another advantage is that the CRI relies on sensitivities, and not

¹¹A high CRI itself is also not necessarily an indication of bad management. If the bank is adequately compensated for the risk it takes on (for example, through higher interest rates), a high-CRI bank may very well be profitable in normal times. Nevertheless, we would expect such a bank to be more vulnerable to downturns.

¹²Whether banks are more opaque than other institutions remains a debated issue. Morgan (2002) finds that there are more rating disagreements for banks, suggesting higher opacity. Flannery, Kwan and Nimalendran (2004), by contrast, analyze market microstructure properties (such as bid-ask spreads) and find no evidence that banks are less transparent than similar non-financial firms.

¹³An observed change in a bank's CRI thus does not necessarily imply that the bank has actually altered its credit portfolio, but may also be due to new information that causes the market to re-evaluate the credit quality of a bank. We return to this point later in Section 4.2 when we consider the evolution of banks' CRIs.

on share price levels. If there is, for example, a bubble due to (unjustified) optimism about credit risk, this will affect the bank’s valuation, but not its responsiveness to credit risk. It should also be kept in mind that we measure *relative* share price sensitivities. Thus, even if there is some mispricing which affects the absolute response to credit risk news, it is difficult to conceive how such a mispricing might alter the relative response to high and low risk credit news. And even if it does, this should affect all banks and hence not distort the cross-section of CRIs, which is the main interest of our analysis.¹⁴

Another issue is that CDS spreads may not only reflect credit risk. This is even though CDS prices are typically considered to be a relatively clean measure of credit risk (as opposed to bond spreads, for example). In fact, recent research has suggested the existence of other pricing factors in CDS spreads, such as liquidity premia.¹⁵ If CDS prices move because of news unrelated to credit risk, this may result in the absolute share prices responsiveness to credit risk being underestimated. However, this is less of a concern in our case since this will be the case for both high and low credit risk and hence the CRI is not necessarily affected. And even if it affected the high and low risk sensitivities differently, this should consistently be the case across banks, and hence not distort the cross-sectional ranking of CRIs.

4 The Empirical Evidence

4.1 Data

We estimate CRIs for U.S. bank holding companies (BHCs) that are classified as commercial banks and listed in the U.S. (the reason why we focus on BHCs instead of the commercial bank(s) belonging to the BHCs is that it is typically the BHC which is listed). We exclude foreign banks (even when listed in the U.S.), pure investment banks and banks for which complete data was not available. Of the remaining banks, we take the 150 largest ones by asset size.

We collect daily data on banks’ share prices, two CDS indices (to be discussed in more detail below), short-term and long-term interest rates, an inflation proxy, and a market return from Datastream and the FRED database. Additionally, various balance sheet data are collected from the FR Y-9C Consolidated Financial Statements for BHCs. The sample

¹⁴The fact that the CRI measures relative sensitivities also means that any non-linearities of the value of equity with respect to the value of the bank assets will cancel out (see Appendix A for the derivations). Such non-linearities arise, for example, in the Merton-model due to the option-value embedded in equity and may particularly matter for a bank that is close to default.

¹⁵For example, Amato (2005) and Bongaerts, de Jong and Driessen (2008).

ranges from February 01, 2006 to February 08, 2008. The starting point of the sample was determined by the availability of reliable CDS data.

For the high and low risk CDS index we take the “Dow Jones CDX North America Crossover” index (“XO index”) and the “Dow Jones CDX North America Investment Grade” index (“IG index”). These indices are jointly managed by the Dow Jones Company, Markit and a consortium of market makers in the CDS market and are considered the leading CDS indices for North American underlyings. The IG index consists of 125 equally weighted U.S. reference entities with ratings ranging from BBB up to AAA. These reference entities are the most liquid entities traded in the CDS market and represent large companies in various industries¹⁶. The XO index consists of 35 equally weighted U.S. reference entities that have ratings ranging from B up to BBB (hence the term crossover, as it also represents credit risk on the border to investment grade quality).¹⁷ The reason why this index has fewer reference entities is not known to us but is likely to be due to the fact that there are less (liquid) CDS of such underlyings.

The indices are available for different maturities, ranging from one to ten years. We focus on the 5-year maturity index, which is the reference maturity for CDS contracts. The indices are rolled over twice a year (that is, the constituent’s list is checked and adjusted if necessary) and assigned a new roll number. We always use the newest roll (“on-the-run”), as this is the most liquid one.¹⁸ Both CDS indices are expressed in basis points (bps) of spreads. A higher spread implies a higher cost of hedging credit risk, and hence a higher implied default risk. Figure 1 shows the evolution of both indices over the sample period. The XO index has a larger spread since it represents riskier underlyings. We can also observe that the difference between the XO and the IG spread narrowed up to the beginning of 2007 but has widened since then. The latter is consistent with the stylized fact that in periods of crisis, the default risk of riskier borrowers increases by more than

¹⁶The IG index also contains financial institutions. This is not undesirable since a part of banks’ loan portfolios are loans to other banks. The index may also contain the institution in question itself. However, a single institution has a weight of 0.8% in the index and hence any issues arising from this are limited.

¹⁷Both indices together cover a large part of the overall rating distribution (from AAA to B). We checked the distribution of loans of U.S. banks since 2000 using the Dealscan database (which contains mainly large syndicated loans) and found that the share of loans with ratings below B was only 2%. An alternative to using the CDX index is the ABX index, which covers subprime mortgage loans. However, our aim in this paper is to estimate a general credit risk indicator, and not one that is tailored to the current crisis. Note, furthermore, that our measure captures essentially corporate credit and may miss other sources of credit risk to the extent that they are uncorrelated with the corporate CDX index.

¹⁸When changing between different rolls, the underlying reference entities may change as well (typically, between 6-9 entities are replaced from one roll to another). This may cause a jump in the index unrelated to a change in credit risk in the economy. However, it turns out that these jumps are very small in our sample, and hence our results are unlikely to be affected by them.

the one of safer borrowers. We can also observe that, even though the spreads tend to move together, they do not do so perfectly (if they were, we could not identify the CRI, which is based on relative sensitivities).

For our main regression (equation 7) we use the following variables. For the control variables \mathbf{Z}_t (which capture proxies for discount rates that might affect $V(D)$ and possibly $V(Loans)$) we include a short term and a long term interest rate (the 1-month and the 10-year Treasury Constant Maturity Rate) and an inflation-proxy (the difference between the 10-Year Treasury Constant Maturity Rate and the 10-Year Treasury Inflation-Indexed Security at Constant Maturity).¹⁹ For the market return, we take the S&P 500. We orthogonalize the S&P 500 return with both CDS indices in order to include only the part of the market movements which are unrelated to changes in credit risk (a similar approach has been followed by, for example, Longstaff (2008)).

As for the CDS-indices itself, we have seen in Figure 1 that they are highly correlated. This may result in their individual regression coefficients being not reliably estimated. We hence orthogonalize the CDS prices on each other. This effectively attributes the common component of credit risk changes to either the high or the low credit risk, depending on the chosen direction of the orthogonalization. A direct consequence of this will be that the proportion of the risk type (high or low) to which the common factor is allocated will be overestimated. This not a problem for our analysis since we are mainly interested in how CRIs differ across banks. This ranking should not be influenced by the orthogonalization since the bias it may introduce affects the CRIs of all banks. In our analysis we chose to orthogonalize the IG-spread (thus, we include only IG-spread changes unrelated to changes in the XO-index).²⁰

4.2 The Aggregate CRI

Before turning to the estimation of banks' individual CRIs, we first analyze their aggregate CRI. For this we run a pooled version of equation (7). Specifically, we estimate the following regression on daily data:

$$\Delta p_{i,t} = \alpha + \beta \Delta S\&P500_t^{(orth)} + \gamma \Delta CDS_t^{XO} + \delta \Delta CDS_t^{IG(orth)} + \phi \Delta \mathbf{Z}_t + \varepsilon_{i,t}, \quad (9)$$

¹⁹We initially considered more control variables such as the default spread (the difference between AAA and BBB rated bonds) and interest rates with even longer maturities. However, preliminary tests revealed that they had weak explanatory power for bank share prices.

²⁰The results are, however, invariant to the direction of the orthogonalization, as the correlation of the banks' CRIs across the methods of orthogonalization is nearly one ($\rho = 0.95$) and the rank-correlation is equal to one.

where $p_{i,t}$ is a bank's share price, $S\&P500_t^{(orth)}$ the orthogonalized S&P 500 index, CDS_t^{XO} the XO CDS index, $CDS_t^{IG(orth)}$ the orthogonalized IG CDS index, and \mathbf{Z}_t the vector of control variables. Note that all variables are expressed in absolute changes, consistent with the model developed in Section 3. We exclude day-bank observations at which a stock was not traded in order to reduce the impact of any illiquidity in bank stock prices.

Table 1, column 1, contains the regression results. All variables have the expected sign and are, apart from the long-term interest rate, also significant. In particular, the two variables of interest, ΔCDS^{XO} and $\Delta CDS^{IG(orth)}$, are highly significant and have the correct, that is negative, sign. The second but last row in the Table reports the implied CRI, as computed from equation (8), which is about 0.11. As discussed earlier, the absolute level of a CRI on its own is not informative since it is influenced by the orthogonalization method. We therefore do not interpret its value. We note that the CRI is quite precisely estimated. The last row in the table contains the 95% confidence interval for the CRI, computed using the (non-linear) Wald-Test. It shows that the CRI's confidence interval is between 0.10 and 0.12.

It is, however, informative to study whether the aggregate CRI has changed over time. Since underlying loan portfolios probably change very slowly, this would give us information about changes in the market's perception of the risks embedded in these portfolios. For this we split our sample into two equal parts and estimate separate CRIs for each subsample (the sample split is on February 02, 2007). The results are reported in the last two columns of Table 1.²¹ One can see that the sensitivities in each subsample are still precisely estimated, and that their values are similar across samples. Also, the implied CRIs are very similar (0.1157 versus 0.1137). They are, in particular, not significantly different from each other, as can be seen from their confidence intervals.

This suggests that market participants were (on average) aware of the BHCs' exposures to high risk investments well before the subprime crisis fully materialized. This finding is interesting given the fact that bank share prices declined significantly during the subprime crisis. It suggests that the source of their share price decline was not news about their (average) portfolio composition,²² but that the decline was due to other factors. For example, during the subprime crisis the default risks on investment and subinvestment grade exposures increased sharply (as can be seen in Figure 1, showing that CDS spreads widened). This causes a decline in banks' share prices regardless of whether there are updates about

²¹Note that the number of observations in the first and second part of the sample can differ (although the number of days is the same). This is because we only include observations where the stock of a bank is actively traded.

²²Obviously, there have been updates about individual bank's exposures. Our results only say that there is no net effect for the average bank.

banks' portfolio compositions.

We next investigate the evolution of the CRI in more detail using a rolling window analysis. Figure 2 shows the coefficient of the aggregate CRI over the sample period using a window-length of 90 days (note that in the figure, the coefficients are plotted against the last day of the window). One can see that the aggregate CRI is relatively stable over time, except for three periods: February 2007, July/August 2007 and January/February 2008. During these periods the CRI fluctuates widely but stabilizes itself afterwards at its previous level.

All three periods are associated with major turbulences in financial markets. This first period (February 2007) coincides with the time at which first warning signs about large losses connected to subprime lending emerge. For example, on February 22 HSBC fires the head of its US mortgage lending business as losses reach \$10.5bn; the largest US house builder DR Horton warns of huge losses from subprime fall-out (March 8), and shares in New Century Financial, one of the largest subprime lenders in the US, are suspended on March 12 due to fears that it might be heading for bankruptcy. The second period (August 2007) is typically considered as the time where subprime problems become apparent at a wider scale. It starts with Bear Stearns bailing out two of its funds exposed to the subprime market for \$3.2bn (June 22). Various European and American banks also revealed further large losses connected to subprime mortgages. In addition, global stock markets fall dramatically and interbank money markets dry up. The third period (January/February), where the CRI fluctuates more moderately, coincides with another wave of bad news about losses connected to subprime lending, forcing several major financial institutions to issue new capital.

One suspects that the estimations of the CRI have been obscured during these periods through the large and erratic swings in both bank stock prices and CDS prices. This is confirmed by the standard errors of the estimated of CRIs: while the median standard error of a CRI in a rolling window is about 0.0135, the standard error reaches 0.240 in the first trouble period and 0.148 in the second. The CRIs in this periods are hence not precisely estimated. We thus conclude that the rolling window analysis confirms the first impression from a simple sample split, namely that during our sample period there have apparently not been any substantial and lasting updates about the (average) exposure of the BHCs to high risk credits.

4.3 Individual CRIs

We now turn to the analysis of the BHCs individual CRIs. For this, we estimate equation (9) on the bank level. That is, we estimate for each bank the following equation

$$\Delta p_{i,t} = \alpha_i + \beta_i \Delta S\&P500_t^{(orth)} + \gamma_i \Delta CDS_t^{XO} + \delta_i \Delta CDS_t^{IG(orth)} + \phi_i \Delta Z_t + \varepsilon_{i,t}. \quad (10)$$

Using equation (8), we can then compute for each bank its CRI from the estimated γ_i and δ_i . Table 2 reports some summary statistics.²³ The mean CRI across all 150 banks is 0.1143, which is similar to the previously estimated aggregate CRI, 0.1103. The (cross-sectional) standard deviation of the CRIs is 0.0626. The lowest CRI among the banks is -0.0329, while the largest CRI takes the value of 0.4433. As discussed in Section 3, a negative CRI is not inconsistent with our model since a bank may have credit exposures that are on average of higher quality than the average entity in the investment grade CDS index.

Figure 3 depicts the individual CRIs, ordering BHCs by asset size (starting with the smallest BHC). We can see that there is in fact only one BHC with a negative CRI. There are also three positive outliers, with CRIs above 0.3. Most other banks have CRIs in the range between 0.07 and 0.17. We checked the estimation results of the four apparent outlier banks, and it turned out that their CRIs are imprecisely estimated. In fact, their standard errors are each among the five highest of all banks, and also far above the average of their peers. This suggests that these outliers are likely to be due to estimation imprecision, arising, for example, from relatively illiquid stocks²⁴. Leaving the outliers aside, no clear pattern emerges among the (asset-ranked) BHCs. An exception are perhaps the very largest banks. The top ten banks seem on average to have CRIs above the mean. Among those banks in turn, Citigroup (the rightmost dot in the Figure) has the highest CRI.

4.4 The CRI and Other Measures of Bank Risk

The CRI is a measure of credit quality that potentially captures traditional sources as well as more innovative forms of sourcing credit risk. In this section we study whether (and how) a bank's CRI is related to traditional measures of loan quality, and proxies of bank risk more generally. To analyze this, we could simply study (on the bank level) the correlation between these measures and the estimated CRIs. However, this is not efficient since information from the first step (the estimation of the CRIs itself) is then not fully

²³The complete list of the CRIs is available at <http://people.pwf.cam.ac.uk/ww243/CRI.xls>.

²⁴We calculated trading volumes for these banks and found that they are substantially lower than the average of their peers: the median volume of the outliers are 5,400, 20,900, 28,700 and 57,700 stocks per day, compared to an average median of 813,000 across all banks.

used in the second step (computation of the correlations).²⁵ It can also create a problem of generated regressors, an issue that we address in Appendix B.

Instead, we develop a method which allows us to (efficiently) estimate the relationship in one step.²⁶ For this we adjust the equation for the aggregate CRI (9) in order to allow the CDS-sensitivities to depend on a variable for bank risk, say variable X . More specifically, we include in the regression for each CDS-spread an interaction term with X , where X is expressed relative to its sample mean (\tilde{X}). We thus estimate the following regression:

$$\begin{aligned} \Delta p_{i,t} = & \alpha + \beta \Delta S\&P500_t^{(orth)} + (\gamma + \eta(X_i - \tilde{X})) \Delta CDS_t^{XO} \\ & + (\delta + \theta(X_i - \tilde{X})) \Delta CDS_t^{IG(orth)} + \phi \Delta Z_t + \varepsilon_{i,t}. \end{aligned} \quad (11)$$

Note that if the coefficients for the interaction terms are zero ($\eta = \theta = 0$), this equation is identical to equation (9). The CRI is, as before, given by the ratio of the estimated high-risk CDS-sensitivity and the total CDS sensitivity. Analogous to equation (8), this is

$$CRI(X) = \frac{\gamma + \eta(X - \tilde{X})}{\gamma + \eta(X - \tilde{X}) + \delta + \theta(X - \tilde{X})}. \quad (12)$$

Differentiating equation (12) with respect to X and evaluating at the mean ($X = \tilde{X}$) yields

$$CRI'(X)_{X=\tilde{X}} = \frac{\eta\delta - \theta\gamma}{(\delta + \gamma)^2}. \quad (13)$$

$CRI'(X)_{X=\tilde{X}}$ is the counterpart of the coefficient on X in a two-step regression where in the second step the CRIs (estimated in the first step) are regressed on X . The relationship between the CRI and a variable X can thus be estimated as follows. We first estimate (11). From the coefficients we then calculate the coefficient for X , $CRI'(X)_{X=\tilde{X}}$, using equation (13). Whether the relationship is a significant one is then determined by carrying out a (non-linear) Wald-test of $\frac{\eta\delta - \theta\gamma}{(\delta + \gamma)^2} = 0$.

Table 3 shows for various variables their estimated relationship with the CRI.²⁷ Note that these are essentially a number of univariate relationships since we run (11) for each variable and then compute its relationship with the CRI. The first two columns of the table report the relationships based on the entire sample period. The last two columns refer to regressions in which the period from June 15 to August 31, 2007 is excluded. This is the

²⁵In particular the precision with which the CRIs are estimated differs across banks and one would like to give banks with less precisely estimated CRIs a lower weight.

²⁶Note that our problem here differs from the usual two-step regression problem in that the variable of interest estimated in the first step (the CRI) is a (non-linear) combination of coefficients, and not simply a coefficient itself.

²⁷For this, the balance sheet variables are computed as the quarterly average over the period Q1 2006 to Q4 2007.

period of the most extreme fluctuations (as seen in Figures 1 and 2) in our sample. It turns out that the exclusion makes many coefficients rise (in absolute values), making several of them significant. This is probably due to the fact that this period introduces a significant amount of noise, which may in some cases obscure the overall relationship. We thus prefer to interpret the results based on an exclusion of this period.

The first four variables in the table are traditional measure of banks' loan risk: non-performing loans, loan-loss provisions, loan-loss allowances²⁸ and net charge-offs (all four scaled by total loans). They all have the expected sign (positive) and are significant at the 10% level, except for the loan loss allowances. Thus, banks whose balance sheet indicates that they have a lower loan quality also have a higher CRI, that is they are perceived by the market as having riskier exposures.

The next four variables represent common proxies of asset risk. The first variable considered is the bank's ratio of total risk-weighted assets to total assets. This measure, however, turns out to be not significantly related to a bank's CRI. Another variable which has been found to proxy asset risk is loan growth (see Foos, Norden and Weber, 2007). The idea behind this proxy is that a bank which wants to expand its loan volume quickly, presumably has to do so at the cost of accepting lower quality borrowers. Consistent with this, we find that such banks have a significantly higher CRI²⁹. The ratio of interest income from loans to total loans has a positive and significant relationship with the CRI. This is according to expectations as banks will typically charge higher rates on riskier loans, hence a high interest rate income may indicate a relatively risky loan portfolio. Finally we consider a bank's return on assets (ROA), whose a priori relationship with the CRI is ambiguous, because, on the one hand, banks may charge higher rates on riskier loans but, on the other hand, riskier borrowers are also more likely to default. The table shows that there is no significant relation with the CRI.

We conclude from these first two sets of variables that the CRI is significantly related to many alternative measures of loan and asset risk, and is so with the expected sign. The next three variables considered are basic characteristics of banks' balance sheets: leverage, loan-to-asset ratio and size. First, there is a positive and significant relationship between a bank's leverage (as measured by the debt-to-asset ratio) and its CRI. An explanation for this may be the risk preferences of banks: a bank which follows a high risk strategy may jointly choose a high-risk loan portfolio and operate with high leverage. Note that since our CRI is computed from *relative* credit risk sensitivities, there is no mechanical relationship between the CRI and leverage which may arise from the fact that, everything

²⁸Loan-loss allowances is the stock-variable that corresponds to the (flow-variable) loan-loss provisions.

²⁹The loan growth is computed as the average loan growth over the sample period.

else being equal, highly leveraged banks are more sensitive to changes in credit risk. The same argument also applies to our next variable, the banks' loan-to-asset ratio. This variable is found to be unrelated to the CRI. Previously we argued that there is weak evidence that the very largest banks have higher CRIs, but considering the entire range of asset distributions, there is no relationship between a bank's CRI and its size (as measured by log of assets). There is, however, a positive relationship between size and CRI over the entire sample period (first two columns in the Table).

The next variable we consider is a bank's share of real estate loans in its portfolio. This variable is positively, and very significantly, related to a banks' CRI. Hence banks with more real estate lending are perceived by the market as having worse credit portfolios. This result is consistent with the fact that most of the high risk subprime loans were in the form of mortgages. Subprime related problems have also been associated with securitization of real estate loans. One might argue that securitizing real estate loans off the balance sheet relieves a bank from a part of the bad credit risk, and should thus lower bank risk. However, banks may simply use the freed-up capital to extend new loans,³⁰ which are presumably riskier. Thus, the relationship between credit risk and securitization is theoretically ambiguous. Empirically, the dummy variable for securitization activities of real estate loans is (marginally) insignificant at the 10% level but becomes significant at the 5% level if the total sample period is considered. There is thus weak evidence that banks that securitize are perceived as having a higher credit risk.

In the last row of the Table we report the relationship between a bank's CRI and its share price performance during the subprime crisis. For this we take variable X to be a bank's share price performance from June 15, 2007 to the end of the sample period. In addition we restrict the estimation period to before this date. Thus, we test whether a banks' share price performance after this date is associated with its CRI estimated using information before this date.³¹ It turns out that the CRI and subprime performance are negatively related. This can be explained by the fact that the credit risk of lower-rated assets typically increases more in a downturn and hence banks with a higher share of such assets should suffer more. The relationship is also very significant. In the next section we analyze this relationship in more detail.

³⁰For a theoretical analysis of this effect, see Wagner (2007) and Wagner (2008).

³¹Note that June 15, 2007 coincides with the start of the exclusion period. This period is hence excluded by construction and we only report the regression results in the first two columns of the Table.

4.5 The CRI & Banks' Performance During the Subprime Crisis

The previous section has shown that a bank's CRI, computed using information before the subprime crisis, is related to its performance during the subprime crisis. This suggests that the CRI may be a useful indicator of how a bank can withstand adverse conditions. However, it may very well be that the information in a bank's CRI which helps to explain its subprime performance is equally contained in other, more traditional, proxies of bank risk or other market based risk measures.

To address this question we should control for such proxies when analyzing the relationship between the CRI and the subprime performance. Unfortunately, the one step-method employed in the previous section, even though preferable in terms of efficiency, cannot be used for this.³² We thus carry out the analysis using a conventional two-step regression. In the first stage, we estimate the bank-specific CRIs using equation (10) for the sample up to June 15, 2007. In the second stage, we regress a banks' share price performance after that date on these bank-specific CRIs, adding the control variables. We thus estimate in the second stage the following regression:

$$perf_i = \alpha + \beta CRI_i + \gamma \mathbf{Y}_i + \varepsilon_i, \quad (14)$$

where $perf_i$ is a bank's share price performance from June 15, 2007 to the end of the sample period, and \mathbf{Y}_i is a vector of control variables. As controls we include the various variables we considered in the previous section potentially containing information similar to the CRI. In addition, we also add other competing market based risk measures such as a bank's beta and the components of the distance to default, namely leverage and a bank's share price volatility (estimated from daily data over the sample period). This is important since the distance-to-default is a natural competing market-based measure of bank risk.

An issue that arises with estimating (14) is that CRI is a generated regressor, which may pose some econometric issues. However, as we argue in Appendix B, in our specific setting these issues are unlikely to be important.

We first consider different sets of control variables in isolation, before adding them all jointly. Table 4 reports the results. In column 1 the regression without controls is reported. In column 2 we include traditional measure of loan risk. In columns 3 and 4 the CRI is tested alongside proxies for asset quality and general bank characteristics, respectively. Column 5 controls for real estate activities, while the market based risk factors are included

³²Note that simply adding the proxies as independent variables to equation (11) does not solve the issue. This would only control the (daily) share price sensitivities to CDS-spread changes, which is very different from controlling the relationship between a bank's CRI and its subprime performance.

in column 6. Finally, column 7 reports the results when all controls are included.

The main message is that the CRI is robust to the inclusion of these various controls. The CRI is always significant at least at the 5% level, and is often so at the 1% level. Its coefficient is also relatively stable, ranging from -15 to -23. The size of the coefficient suggests that the relationship is economically relevant. A coefficient of -20, for example, implies that an increase in a bank's CRI by 0.1 is associated with a share price performance that is 8% worse than its peers.³³ This is noteworthy since the subprime crisis is not only a crisis of asset quality but crucially is also driven by liquidity and funding issues. It confirms the expectation that in periods of crises (regardless of their origin) banks with lower asset quality should be relatively more affected.

We also note that all significant control variables have the expected signs. Among the traditional loan risk measures and proxies for asset risk (column 2 and 3), the loan loss allowances, total risk weighted assets, and the interest income from loans all have a negative sign, indicating that banks with a higher share of bad credits suffered more during the subprime crisis. In column 4 we can see that banks with a higher loan-to-asset ratio experienced a higher share price decline. We can also see that larger banks performed worse as well, consistent with the notion that it was mainly those banks which engaged heavily in real estate securitization activities. This interpretation is confirmed by the results reported in column 5, which shows that banks with more real estate loans, and banks that securitize those loans, perform worse as well. Somewhat surprising is the positive coefficient for beta (column 6), suggesting that banks with a higher beta performed better during the subprime crisis. However, this effect vanishes in the full set of controls (column 7).

Column 7 also shows that, besides the CRI, only two of the fifteen control variables are significant at the 5% level. This confirms the relevance of the CRI in explaining the subprime performance. In particular, we note that all traditional loan risk proxies are insignificant. The only controls that remain significant are bank size and the share of real estate loans. These are factors that played a specific role in the current crisis but are not general measures of bank risk. This is different from the CRI, which is not construed to reflect characteristics of the crisis.

An alternative approach for studying the relation between the CRI and bank performance in a crisis is to look directly at failed banks. For this we collect share prices for all failed U.S. banks³⁴ and estimate their CRIs (none of the banks are in our original dataset of large BHCs). We end up with five banks that have complete data and liquid shares: Downey Financial, Franklin Bank, Indymac Bancorp, PFF Bancorp, and Washington Mu-

³³This number is obtained by transforming the absolute share price decline implied by a CRI change of 0.1 ($=-20 \times 0.1 = -2$) into a relative share price decline using the sample share price mean ($=30.75$).

³⁴As reported on the FDIC website <http://www.fdic.gov/bank/individual/failed/banklist.html>.

tual. For the estimation of the CRIs we use two methods. First, we estimate a bank's CRI using information up to one month before its day of failure (as identified by the FDIC). Second, we estimate it up to the date where the bank's share price dropped in anticipation of failure (as identified by visual inspection). This date is typically more than a month before the failure of the bank and using this method hence reduces the influence of share price fluctuations directly connected with the bank failure. We find that for either method each of the five bank's CRI is larger than the mean of the banks in our sample. Their average CRIs for the first and second method are 0.28 and 0.21, respectively, and hence about 2-3 times the mean CRI of banks in our sample (0.11). This substantiates our previous analysis of the CRI containing information about bank performance in crisis times.

5 Conclusions

In this paper we have developed a new measure of the quality of banks' credit portfolios. This measure is not restricted to the potential losses from defaulting loans but rather captures credit risk in general. It thus includes exposures arising from a variety of bank activities, such as securitizations and credit derivatives. Since it is derived from market prices, it comprises information from a wide range of sources and can, moreover, reflect new developments quickly. The *credit risk indicator* (CRI) is arguably also an independent assessment of banks' risks since it should be difficult for banks to consistently manage their share price sensitivities.

The CRI is a natural indicator of how well banks might perform in periods of a worsening of credit risks in the economy. Indeed, we have found that the CRI could forecast the performance of banks during the subprime crisis. The CRI may thus be used by regulators, alongside other information, as a criterion for identifying potentially exposed institutions well before a crisis materializes. It may also serve as an indicator for banks' creditors in gauging the riskiness of their loans, as well as being useful for bank shareholders in assessing the ability of bank managers to make high quality investments.

The CRI may help us in the future to better understand the factors that drive a bank's credit quality. Previous research, which has mostly focused on balance sheet data as a measure of credit quality, was constrained by the absence of comprehensive and independent measures of credit quality. We believe it may be interesting to use the CRI to study the influence of factors such as bank strategy (e.g., specialization, growth, relationship orientation), geographical location or corporate governance for credit quality. The CRI may also be of use for enhancing our understanding of how credit risk transfer activities at banks (such as securitizations or trading in credit derivatives) impact credit quality.

References

- [1] Amato, J.D. (2005), "Risk Aversion and Risk Premia in the CDS Market", *BIS Quarterly Review*, December, 55–68.
- [2] Berger, A.N. and R. DeYoung (1997), "Problem Loans and Cost Efficiency in Commercial Banks", *Journal of Banking & Finance*, 21, 849–870.
- [3] Berger, A.N., S.M. Davies and M.J. Flannery (2000), "Comparing Market and Supervisory Assessments of Bank Performance: Who Knows What When?", *Journal of Money, Credit and Banking*, 32(3), 641–67.
- [4] Blanco, R., S. Brennan and I.W. Marsh (2005), "An Empirical Analysis of the Dynamic Relationship Between Investment-Grade Bonds and Credit Default Swaps", *Journal of Finance*, 60(5), 2255–81.
- [5] Bohn, J. and P. Crosbie (2003), "Modeling default risk", Moody's KMV Company.
- [6] Bongaerts, D., F. De Jong and J. Driessen (2008), "Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market", *EFA 2007 Ljubljana Meetings Paper*.
- [7] Cremers, K.J.M. (2002), "Stock Return Predictability: A Bayesian Model Selection Perspective", *The Review of Financial Studies*, 15(4), 1223–1249.
- [8] DeYoung, R. (2003), "De Novo Bank Exit", *Journal of Money, Credit and Banking*, 35(5), 711–728.
- [9] Elsinger, H., A. Lehar and M. Summer (2006a), "Using Market Information for Banking System Risk Assessment", *International Journal of Central Banking*, 2(1), 137–65.
- [10] Elsinger, H., A. Lehar and M. Summer (2006b), "Risk Assessment for Banking Systems", *Management Science*, 52(9), 1301–1314.
- [11] Evanoff, D.D. and L.D. Wall (2001), "Sub-debt Yield Spreads as Bank Risk Measures", *Journal of Financial Services Research*, 20(2-3), 121–45.
- [12] 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), 273–305.
- [13] Flannery, M.J. (2001), "The Faces of "Market Discipline"", *Journal of Financial Services Research*, 20(2-3), 107–19.

- [14] Flannery, M.J., S.H. Kwan and M. Nimalendren (2004), "Market Evidence on the Opaqueness of Banking Firms Assets", *Journal of Financial Economics*, 71(3), 419–60.
- [15] Flannery, M.J. and S.M. Sorescu (1996), "Evidence of Bank Market Discipline in Subordinated Debenture Yields: 1983 -1991", *Journal of Finance*, 51(4), 1347–77.
- [16] Foos, D., L. Norden and M. Weber (2007). "Loan Growth and Riskiness of Banks", Working paper.
- [17] Gropp, R., J. Vesala and G. Vulpes (2006), "Equity and Bond Market Signals as Leading Indicators of Bank Fragility", *Journal of Money, Credit and Banking*, 38(2), 399–428.
- [18] Hancock, D. and M.L. Kwast (2001), "Using Subordinated Debt to Monitor Bank Holding Companies: Is It Feasible?", *Journal of Financial Services Research*, 20(2-3), 147–87.
- [19] Hasan, I. and L.D. Wall (2004), "Determinants of the Loan Loss Allowance: Some Cross-Country Comparisons", *The Financial Review*, 39, 129–52.
- [20] Hubbard, R.G., K.N. Kuttner and D.N. Palia (2002), "Are There Bank Effects in Borrowers' Costs Of Funds? Evidence From a Matched Sample Of Borrowers and Banks", *Journal of Business*, 75, 559–583.
- [21] Huizinga, H. and L. Laeven (2009), "Accounting Discretion of Banks During a Financial Crisis", IMF Working Paper WP/09/207.
- [22] Krainer, J. and J.A. Lopez (2004), "Incorporating Equity Market Information into Supervisory Monitoring Models", *Journal of Money, Credit and Banking*, 36(6), 1043–67.
- [23] Kwan, S.H. (2003), "Operating Performance of Banks among Asian Economies: An International and Time Series Comparison", *Journal of Banking & Finance*, 27, 471–489.
- [24] Laeven, L. and G. Majnoni (2003), "Loan Loss Provisioning and Economic Slowdowns: Too Much, Too Late?", *Journal of Financial Intermediation*, 12, 178–197.
- [25] Longstaff, F.A. (2008), "Train Wrecks: Asset Pricing and the Valuation of Severely Distressed Assets", Working Paper.

- [26] Morgan, D.P. (2002), "Rating Banks: Risk and Uncertainty in an Opaque Industry", *American Economic Review*, 92(4), 874–88.
- [27] Morgan, D.P. and K.J. Stiroh (2001), "Market Discipline of Banks: The Asset Test", *Journal of Financial Services Research*, 20(2-3), 195–208.
- [28] Norden, L. and M. Weber (2007), "The Co-movement of Credit Default Swap, Bond and Stock Markets: An Empirical Analysis", *European Financial Management*, forthcoming.
- [29] Pagan, A. (1984), "Econometric Issues in the Analysis of Regressions with Generated Regressors", *International Economic Review*, 25(1), 221–47.
- [30] Sachs, J., H. Huizinga and J.B. Shoven (1987), "U.S. Commercial Banks and the Developing-Country Debt Crisis", *Brookings Papers on Economic Activity*, 1987(2), 555–606.
- [31] Smirlock, M. and H. Kaufold (1987), "Bank Foreign Lending, Mandatory Disclosure Rules, and the Reaction of Bank Stock Prices to the Mexican Debt Crisis", *Journal of Business*, 60, 347–64.
- [32] US Shadow Financial Regulatory Committee (2000), "Reforming Bank Capital Regulation: A Proposal by the US Shadow Financial Regulatory Committee.", Statement No. 160, The American Enterprise Institute, Washington, DC.
- [33] Wagner, W.B. (2007), "The Liquidity of Bank Assets and Banking Stability", *Journal of Banking & Finance*, 31, 121–139.
- [34] Wagner, W.B. (2008), "The Homogenization of the Financial System and Liquidity Crises", *Journal of Financial Intermediation*, 17, 330–56.
- [35] Wall, L.D. and T.W. Koch (2000), "Bank Loan Loss Accounting: A Review of Theoretical and Empirical Evidence", *Federal Reserve Bank of Atlanta Economic Review*, 85(2), 1–19.
- [36] Wheelock, D.C. and P.W. Wilson (2000), "Why do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions", *The Review of Economics and Statistics*, 82(1), 127–138.
- [37] Wooldridge, J.M. (2002), *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

Tables

Table 1: Aggregate CRI

dep.var.: Δp	Full Sample	First Half	Second Half
$\Delta S\&P500(orth)$	0.0289*** (0.000274)	0.0348*** (0.000441)	0.0261*** (0.000350)
$\Delta CDS-XO$	-0.0123*** (0.000457)	-0.0133*** (0.000797)	-0.0126*** (0.000550)
$\Delta CDS-IG(orth)$	-0.0994*** (0.00262)	-0.102*** (0.00470)	-0.0982*** (0.00301)
$\Delta 1\text{-Month Interest Rate}$	-0.00322*** (0.000294)	-0.00387*** (0.000653)	-0.00316*** (0.000310)
$\Delta 10\text{-Year Interest Rate}$	-0.000755 (0.000621)	0.000120 (0.000870)	0.00111 (0.000849)
$\Delta Inflation$	-0.00941*** (0.00131)	-0.00504*** (0.00164)	-0.0164*** (0.00209)
Constant	-0.0174*** (0.00227)	-0.00818*** (0.00301)	-0.0260*** (0.00345)
Observations	72452	36320	36132
R^2	0.259	0.196	0.302
CRI	0.1104	0.1157	0.1137
95% Confidence Interval	0.1001 0.1209	0.1011 0.1302	0.1012 0.1261

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2 Descriptive Statistics for Individual CRIs

Variable	Observations	Mean	Median	Min	Max	St.Dev.
CRI	150	0.1143	0.1082	-0.0329	0.4433	0.0626

Table 3 The Relationship between the CRI and Other Measures of Bank Risk

	Full sample		Period 15.06. – 31.08.07 excluded	
	Coeff.	SE	Coeff.	SE
Non-Performing Loans/TL	1.72847	1.45838	4.60598**	2.08664
Loan Loss Provisions/TL	6.19080*	3.47210	16.54446***	4.58692
Loan Loss Allowance/TL	0.80538	2.15438	1.99673	2.62537
Net Charge Offs/TL	1.80995	3.55156	7.19843*	4.36488
Tot. Risk Weight. Assets/TA	-0.00626	0.05728	0.00844	0.07019
Loan Growth	0.51373**	0.25560	0.68211**	0.32522
Interest from Loans/TL	1.37607	1.26868	3.87150**	1.69372
ROA	0.49748	1.48117	-2.23820	1.79071
Debt/TA	0.34849	0.26192	0.76402**	0.31261
Loans/TA	-0.04743	0.05707	0.03401	0.07189
log(TA)	0.01499***	0.00465	-0.00056	0.00573
Real Estate Loans/TL	0.04361	0.04679	0.17752***	0.06469
Dummy Sec. Real Est. Loans	0.05155**	0.02230	0.04437	0.02704
Subprime Perform.	-0.00400***	0.00131	.	.

TL= Total Loans; TA= Total Assets; Sec. = Securitization

*** p<0.01, ** p<0.05, * p<0.1

Table 4 Subprime Performance

Dep.Var.: <i>perf</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CRI	-20.66*** (7.097)	-23.44*** (7.117)	-20.07** (8.038)	-14.05** (7.021)	-21.32*** (7.185)	-15.04** (7.219)	-16.83** (6.694)
Non-Performing Loans/TL		-2.457 (37.69)					36.40 (105.6)
Loan Loss Provisions/TL		1001 (1531)					1999 (1582)
Loan Loss Allowance/TL		-651.9** (261.9)					-451.6* (233.8)
Net Charge Offs/TL		-1352 (1711)					-1591 (1733)
Tot. Risk Weight. Assets/TA			-21.66*** (5.556)				-12.16 (9.000)
Loan Growth			-27.12 (18.72)				-14.98 (19.37)
Interest from Loans/TL			-485.8** (243.6)				-401.6 (267.6)
ROA			263.4 (454.1)				416.6 (504.8)
Debt/TA				27.19 (26.63)			4.202 (25.40)
Loans/TA				-25.91*** (5.735)			-13.39* (7.943)
log(TA)				-2.390*** (0.514)			-2.111*** (0.763)
Real Estate Loans/TL					-7.306* (3.974)		-8.825** (3.990)
Dummy Sec. Real Est. Loans					-5.593*** (1.881)		-2.542 (1.574)
Beta						5.634** (2.531)	1.170 (2.669)
Vola						-2823 (2097)	-2494 (5551)
Constant	-3.972*** (0.942)	4.282 (3.168)	19.78*** (6.055)	26.02 (26.30)	2.383 (2.977)	-11.22*** (3.721)	57.56** (27.73)
Observations	150	150	150	150	150	150	150
R^2	0.072	0.138	0.211	0.267	0.155	0.113	0.381

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figures

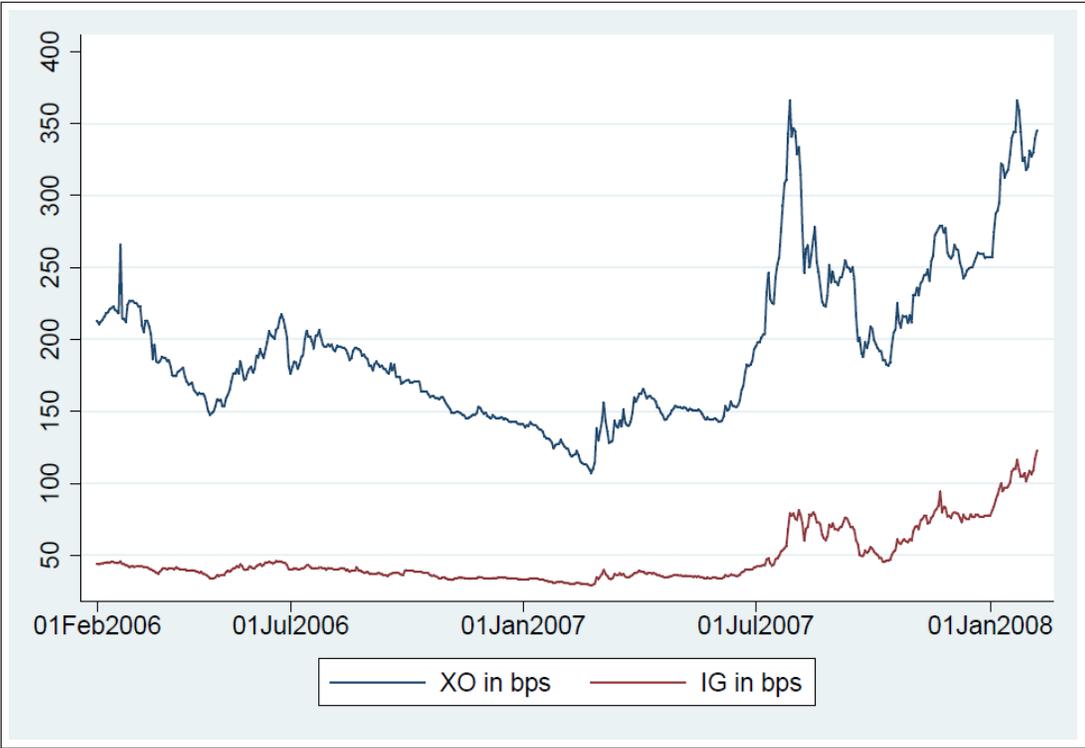


Figure 1: CDS Indices XO and IG over Time

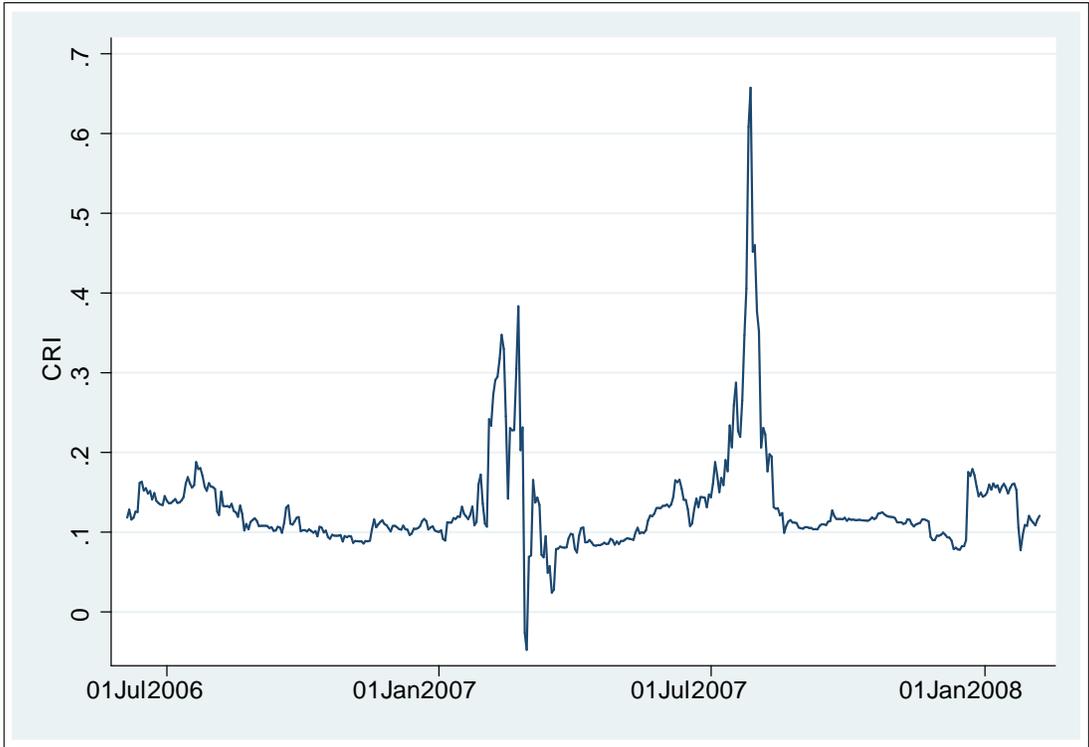


Figure 2: Rolling Window Analysis of Aggregate CRI

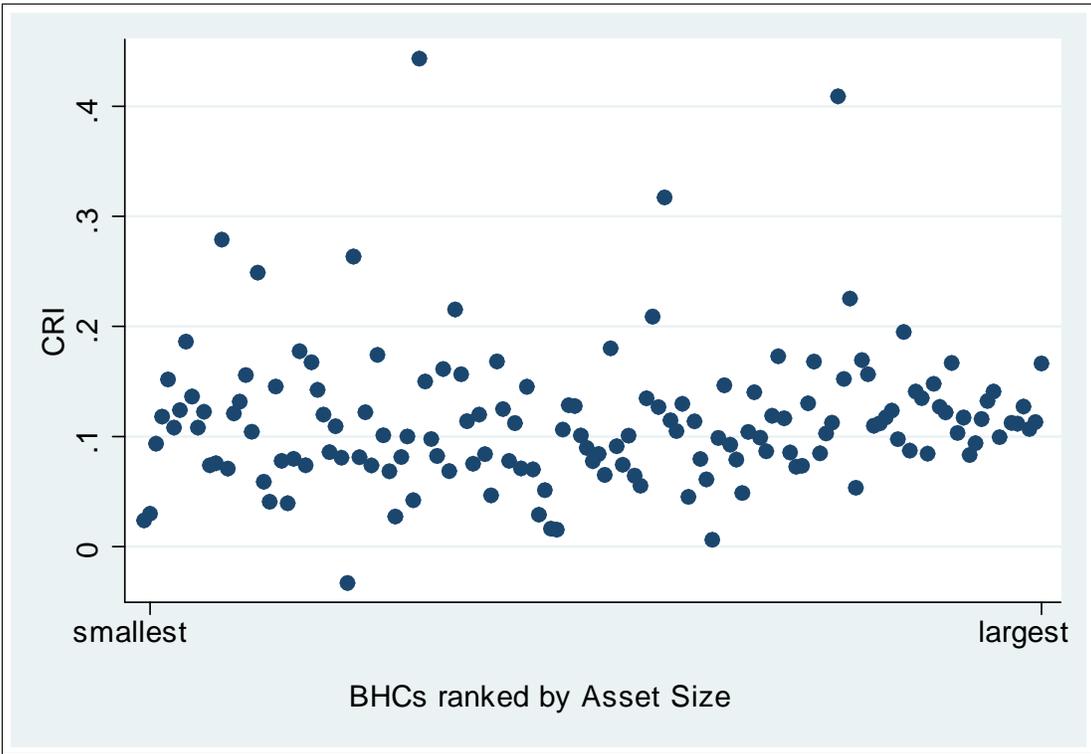


Figure 3: Scatterplot of Individual CRIs

Appendix A: Non-Linear Relationship between the Value of Loans and the Value of Bank Equity

The model in Section 3 presumes that changes in the value of a bank's loan portfolio translate one-to-one into changes in the bank's equity (in equation (5) we have $\Delta V(E) = \Delta V(Loans)$ for $\Delta V(C) = \Delta V(S) = \Delta V(D) = 0$). This may not always be the case. In particular, if a bank is close to default the one-to-one relationship may break down due to the option value of equity (as predicted by the Merton-model) or due bailout expectations. Suppose now instead that we have more generally $V(E) = f(V(Loans))$, where f is a continuous and monotonically increasing function but not constrained to be linear. The function f may also depend on other bank characteristics, such as its level of debt. Using equation (6), we can obtain a first-order approximation of Δp caused by changes in the value of loans:

$$\begin{aligned}\Delta p &\approx f'(V(Loans)) (-H \Delta CDS^H - L \Delta CDS^L) \\ &= -H_i \cdot f'(V(Loans)) \Delta CDS^H - L \cdot f'(V(Loans)) \Delta CDS^L.\end{aligned}\quad (15)$$

The γ_i and δ_i estimated from equation (7) will hence be equal to $\gamma_i = -H_i \cdot f'(V(Loans_i))$ and $\delta_i = -L_i \cdot f'(V(Loans_i))$. Thus, if we compute the CRI according to equation (8) we still obtain the share of high-risk loans:

$$CRI_i = \frac{\gamma_i}{\gamma_i + \delta_i} = \frac{-H_i \cdot f'(V(Loans_i))}{-H_i \cdot f'(V(Loans_i)) - L \cdot f'(V(Loans_i))} = \frac{H_i}{H_i + L_i}.\quad (16)$$

The reason for this result is as follows. Depending on bank characteristics, the value of equity may display different sensitivities to the value of the loan portfolio. Consequently, the sensitivities to changes in the value of high risk and low risk loans will change as well. However, these changes will change precisely in the same proportion, and since the CRI is a measure of relative sensitivities the effect cancels out.

Appendix B: Generated Regressors

Since we are using two stages in our analysis (in the first we estimate CRIs at the bank level, which we later include in the second stage as regressors), our analysis may suffer from generated regressor problems (see, for example, Pagan, 1984). While replacing a regressor with its estimate in an OLS regression causes no problems for consistency (Wooldridge, 2002, p.115), it might do so for inference. This is because the standard errors obtained are often invalid as they ignore the sampling variation of the estimated regressor. However, this problem should not apply in our setting since we use different dimensions in each stage: in the first stage we use the time dimension t (which ranges from 1 to 526) to obtain CRI estimates at the bank level, while in the second stage we use the cross-sectional dimension i (ranging from 1 to 150). Since our time dimension is large both in an absolute sense and relative to the cross-sectional dimension (more than three times larger), asymptotic theory can be applied here. Based on this theory, the CRIs estimated in the first step should be asymptotically precise so that we can draw valid statistical inferences from it when using it in the second stage of our regression.