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

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We propose a new method for measuring the quality of banks' credit portfolios. This method makes use of information embedded 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). This indicator represents the perceived share of high-risk exposures in a bank's portfolio and can be used as a risk weight for computing regulatory capital requirements. We estimate CRIs for the 150 largest U.S. bank holding companies. We find that their CRIs are able to forecast bank failures and share price performances during the crisis of 2007–2009, even after controlling for a variety of traditional asset quality and general risk proxies.

Key words: credit portfolio risk; asset quality; banks; subprime crisis
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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 supervisors and regulators to monitor general trends in the financial system. They also allow them to identify weak banks and to put them under increased scrutiny. For example, many of the banking failures during the crisis of 2007–2009, and their 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, because of the variety of information required in judging the riskiness of their lending activities, there are no good measures of the quality of their loan portfolios. To obtain proxies of loan quality one typically relies on accounting data, such as, for example, the share of nonperforming loans in a bank's portfolio or the ratio of loan-loss allowances to total loans. 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, when 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.[1] 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,

[1] There 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).

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banks trade in credit derivatives, take part in complex securitizations, or grant credit lines. Many of those activities are off the balance sheet. Even if banks report them, 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 portfolio quality. Rather than using balance sheet data, this method is based on the information embedded 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 through 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. 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 investors in bank shares. It thus presents a simple market-based alternative to the risk weights currently used to compute regulatory capital requirements, which either rely on crude risk categories (standardized approach of Basel I) or assessments generated by the bank itself (advanced approach of Basel II).[2]

We believe that this measure has several attractive features. Because 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. 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.

[2] We thank an anonymous referee for suggesting this use of the CRI.

We estimate CRIs for the 150 largest U.S. bank holding companies (BHCs). We find that their CRIs display substantial variation.[3] Among the ten largest surviving BHCs, for example, Citigroup has the largest CRI, implying that it is considered to have relatively poor exposures. It should be noted that Citigroup is also the bank that has incurred the largest write-downs in the subprime crisis. 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 measures of loan riskiness, such as the share of nonperforming loans or loan-loss provisions. We also find that banks with larger leverage have significantly higher CRIs, which is consistent with the notion that risk-shifting incentives are higher at banks with more debt.

As a measure of credit risk quality, the CRI may 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 prediction using the subprime crisis. For this we first study whether the CRI can predict share price performance of banks during the subprime crisis. We regress a bank's share price change in the year following June 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. This predictive power survives when we control for a variety of other variables, such as various proxies of loan quality, share price beta, or distance-to-default. We also find that traditional measures of asset quality do not explain well banks' performance during the subprime crisis. Next, we use the CRI to dynamically predict bank failures during the subprime crisis. We find evidence that the CRI is able to predict failures at a two-quarter horizon, and to some extent also at a one-quarter horizon. By contrast, traditional measures of asset quality are not consistently related to bank failures.

2. Related Literature

In recent years there has been a growing interest in using market-based information to measure bank risk (for surveys, see Flannery 1998, 2001). 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

[3] Our preferred way of constructing the CRI is to also include information that is common to CDS and stock markets. If such information is not included, the CRI is found to be much less precisely estimated and also less informative about bank risk.

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distinguish between banks based on their exposures to certain types of risks or asset compositions. This is true for share prices (see, for instance, Flannery and James 1984b, Sachs and Huizinga 1987, Smirlock and Kaufold 1987) as well as for bond and subordinated debt spreads (see, for example, Flannery and Sorescu 1996, Morgan and Stiroh 2001, Hancock and Kwast 2001). There is also evidence that market information has predictive power for banks, be it forecasting of bank performance (Berger et al. 2000), rating changes (Evanoff and Wall 2001, Krainer and Lopez 2004, Gropp et al. 2006), or default (Gropp et al. 2006).

Spurred by the crisis of 2007–2009, there has recently been a focus on developing market-based measures of system-wide risk (see, for example, Elsinger et al. 2006, Acharya et al. 2009, Huang et al. 2009). Although our approach also captures system risk (in that we measure exposures to economy-wide credit risk), it differs from these measures in that it focuses on the asset side of banks. To our best knowledge, the CRI is the first market-based measure that quantifies asset risk at banks. The CRI also differs conceptually from these, and other market-based measures. Market-based measures of bank risk, such as the distance-to-default or CDS spreads, typically tell us the perceived proximity of a bank (or a set of banks) to default at a given point in time. By contrast, the CRI measures the *exposure* of a bank to an economic downturn in which high-risk assets perform worse than low-risk assets. It is hence particularly useful for identifying in advance banks that are vulnerable to downturns in the economy. For example, in the years prior to the crisis of 2007–2009, the risk of a downturn was perceived as low. Market-based measures of bank defaults (such as CDS spreads or the distance-to-default) consequently implied a low probability of default at the time. However, banks had already accumulated high risks at this point (and our empirical results suggest that the market may have been aware of this) and hence were indicated as vulnerable by their CRI.

In part of our analysis we relate estimated share price sensitivities to bank balance sheet variables. This approach has also been followed in the literature that studies the interest rate sensitivity of bank share prices. The typical procedure in this literature is to estimate share price sensitivities to interest rate changes, and then to relate these sensitivities to balance sheet information. For example, Flannery and James (1984b) show that interest rate sensitivities are related to proxies of maturity mismatch at banks, and Flannery and James (1984a) show that sensitivities depend on the composition of banks' balance sheets. Hirtle (1997) finds that they are also related to derivative usage at banks. Our paper follows a similar methodology and finds that default risk sensitivities of bank share prices are also related to balance sheet characteristics.

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 units of shares. The term $V(E)$ 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 is given by $\mathrm{EL} = \mathrm{PD} \cdot \mathrm{LGD}$, where PD is the probability of default and LGD is the loss given default. We assume that there are two types of loans, high-risk and low-risk loans. The outstanding amounts on each type of loan are denoted with H and L, respectively, and we have $\mathrm{EL}^H > \mathrm{EL}^L$. The value of the loan portfolio can then be expressed as

$$\begin{aligned} V(Loans) &= V(H) + V(L) \\ &= H(1 - \mathrm{EL}^H) + L(1 - \mathrm{EL}^L). \end{aligned} \quad (2)$$

We define the *credit risk indicator* (CRI) as the share of high-risk loans in the loan portfolio, expressed in terms of market values:[4]

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

We use as a proxy for the expected losses on high- and low-risk loans the spreads of two (economy-wide) CDS indices (these indices are discussed in greater detail in §4.1). CDS spreads provide a fairly clean measure of default risk because they represent the market price 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 hence approximates the expected loss. We can thus write for the CDS prices of high- and low-risk exposures

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

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.

[4] We have also estimated CRIs based on *outstanding* values (instead of market values), which yielded similar results.

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The CRI can be obtained as follows. We can first transform Equation (1) in order to obtain percentage changes in the value of equity:

$$\frac{\Delta V(E)}{V(E)} = \frac{V(S)}{V(E)} \cdot \frac{\Delta V(S)}{V(S)} + \frac{V(Loans)}{V(E)} \cdot \frac{\Delta V(Loans)}{V(Loans)}, \quad (5)$$

where Δ indicates the change from t to $t+1$ and where we have assumed constant debt.[5] We can replace $V(Loans)$ in (5) with the expression derived earlier and approximate the return on the bank's security portfolio with the return on the market index (denoted with $\Delta M/M$). We obtain for the change in the bank's share price:

$$\frac{\Delta p}{p} = \frac{V(S)}{V(E)} \frac{\Delta M}{M} - \frac{V(H)}{V(E)} \frac{\Delta CDS^H}{1-CDS^H} - \frac{V(L)}{V(E)} \frac{\Delta CDS^L}{1-CDS^L}. \quad (6)$$

We can then estimate the following relationship at the bank level:

$$\frac{\Delta p_{i,t}}{p_{i,t}} = \alpha_i + \beta_i \frac{\Delta M_t}{M_t} + \gamma_i \frac{\Delta CDS_t^H}{1-CDS_t^H} + \delta_i \frac{\Delta CDS_t^L}{1-CDS_t^L} + \phi_i \frac{\Delta \mathbf{Z}_t}{Z_t} + \varepsilon_{i,t}, \quad (7)$$

where i denotes the bank, t denotes time, and $\mathbf{Z}$ is a vector of control variables. Noting that

$$\gamma_i = -\frac{V(H_i)}{V(E_i)} \quad \text{and} \quad \delta_i = -\frac{V(L_i)}{V(E_i)},$$

the CRI $(= V(H_i)/(V(H_i)+V(L_i)))$ 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).

3.1. Discussion of the Properties of the CRI

In deriving the CRI we have presumed that a bank's credit risk comes exclusively from loans. Banks, however, also have credit risk exposures from other investments. Because 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 exposures. 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. For example, if a bank tends to sell lower-risk senior and mezzanine tranches (but retains the equity tranche), this lowers the average quality of the bank's credit exposures and increases a bank's CRI. The CRI will also reflect the effect of risk mitigation techniques, such as through collateralization of loans. If, for instance, a bank has a large number of high-risk loans, but at the same time these loans are fully collateralized, its share price should not be sensitive to news about high-risk loans. The bank's estimated CRI will then be low and hence reflect that its high-risk exposure is effectively small.

Although ideally we would like to measure share price sensitivities to a basket of exposures consisting of all credit types (e.g., commercial, real estate, consumer, etc.), CDS indices for such a basket do not (yet) exist. By contrast, CDS indices are readily available for corporate exposures, for which there also exist high- and low-risk baskets. In our empirical implementation we will thus measure sensitivities to corporate credit spreads. Credit spreads, however, tend to be correlated across exposures. For example, in an economic downturn default risks typically increase for all loan types. Hence our estimated CRI will also (at least partially) capture other credit types. Nevertheless, if broader CDS indices become available they should be used to improve estimation of the CRI.

The CRI is derived from share prices. 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 approach is that we compute CRIs from daily share price responses over a longer period of time. The impact of any noise in returns is likely to cancel out over 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 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.

Another issue is that when there is an option value of equity (such as predicted by the Merton model), there is a potentially second channel through which changes in CDS prices can affect the value of equity. For example, if the spread on high-risk credits declines, this has a direct positive effect on the value of equity. At the same time, asset risk may change as the composition of the bank's lending portfolio (measured in market values) changes. This may also influence share prices, by affecting the option value of equity. In the online appendix to this paper (available at http://lyrawww.uvt.nl/~wagner/lpq_appendix.pdf), we derive an expression for the bias that may be induced by this. Using simulations we show that the bias in the CRI is modest (9–12%) and, more importantly, it does not distort the cross-sectional variation of the CRI.

[5] Any changes in debt cannot plausibly be contemporaneously correlated with (aggregate) CDS spread changes (as there is a significant decision and implementation lag associated with debt changes). Omitting debt changes should hence not bias the CDS estimates.

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4. The Empirical Evidence

4.1. Data

We estimate CRIs for U.S. BHCs that are classified as commercial banks and listed in the United States. We exclude foreign banks (even when listed in the United States), 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 bank share prices, two CDS indices (to be discussed in more detail below), short-term and long-term interest rates, and a market return from Datastream and the Federal Reserve Economic Data database. Additionally, various balance sheet data are collected from the FR Y-9C Consolidated Financial Statements for BHCs. The sample ranges from February 1, 2006, to March 5, 2010. 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 industries. 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). 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.

Taken together, both indices cover a large part of the overall rating distribution (from AAA to B). We checked the distribution of loans by U.S. banks since 2000 using the Dealscan database (which contains syndicated loans) and found that the share of rated loans outside this range was only 2%. Thus, the two indices seem to capture a large part of the relevant risk profiles. It should be noted that the indices also contain financial institutions, which is desirable for our purpose because banks may also grant loans to other banks.[6]

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. The XO index thus should have a larger spread as it represents riskier underlyings: during our sample period its average spread was around 280 bps, compared to around 120 bps for the IG index. In addition, as typical in crises, the spread widens during the subprime crisis (from around 100 bps in the beginning of 2007 to up to 400 bps at the height of the crisis).

The indices are available for different maturities, ranging from one to ten years. We focus on the five-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. When changing between different rolls, the underlying reference entities may change as well (typically, between six and nine 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. The average CDS price change (in absolute terms) on rollover days is 9 bps for the IG-index and 28 bps for the XO index. These changes seem large and we hence include dummy variables for the rollover dates in our econometric analysis (however, our results are essentially invariant to their inclusion).

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 one-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). For the market return, we take the return on the S&P 500.

The market return and the CDS indices have a significant common component. We estimate the CRI under two different assumptions on this component. First, we estimate the CRI orthogonalizing the S&P 500 with both CDS indices. This attributes the common component to credit risk, which is consistent with structural models of credit risk (such as the Merton model).[7] Second, we estimate the CRI orthogonalizing the CDS indices with the S&P 500. This orthogonalization ensures that the CRI is constructed using only information that is unrelated to market risk. Among others, this guarantees that the CRI does not simply pick up the market exposures of banks.

[6] An alternative to using CDX indices 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 crisis of 2007–2009.

[7] Evidence for that the common component is related to credit risk is provided in Schaefer and Strebulaev (2008).

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The CDS indices themselves will also be highly correlated. We hence orthogonalize the CDS prices on each other and, specifically, include only IG-spread changes unrelated to changes in the XO index (the direction of the orthogonalization does not matter as the CRIs under both directions are nearly perfectly correlated).

4.2. The Aggregate CRI

Before turning to the estimation of the bank-specific 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:

$$\frac{\Delta p_{i,t}}{p_{i,t}} = \alpha + \beta\frac{\Delta S\&P500_t}{S\&P500_t} + \gamma\frac{\Delta CDS_t^{\mathrm{XO}}}{1-CDS_t^{\mathrm{XO}}} + \delta\frac{\Delta CDS_t^{\mathrm{IG(orth)}}}{1-CDS_t^{\mathrm{IG(orth)}}} + \phi\frac{\Delta \mathbf{Z}_t}{Z_t} + \varepsilon_{i,t}, \qquad (9)$$

where $p_{i,t}$ is a bank's share price, $S\&P500_t$ is the S&P 500 index (possibly orthogonalized with the CDS indices), CDS_t^{XO} is the XO CDS index (possibly orthogonalized with the market index), $CDS_t^{\mathrm{IG(orth)}}$ is the XO-orthogonalized IG CDS index (possibly also orthogonalized with the market index), and $\mathbf{Z}_t$ is the vector of control variables. In addition, we also include dummies for each day on which either the IG or the XO index is rolled over. We exclude day-bank observations at which a stock was not traded in order to reduce the impact of illiquidity in bank stock prices. The overall liquidity of the stocks seems reasonable: the mean daily trading volume is above four million stocks and the median volume is about 275.000.

Column (1) of Table 1 contains the regression results for the first orthogonalization method. All variables have the expected sign and are significant. In particular, the two variables of interest, ΔCDS^{XO} and $\Delta CDS^{\mathrm{IG(orth)}}$, 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 0.147. We note that the CRI is quite precisely estimated: the last row in the table shows that the 95% confidence interval for the CRI (computed using the (nonlinear) Wald test) is between 0.1406 and 0.1534.

The results for the second orthogonalization method are contained in column (2). We can see that the high-risk CDS index is now insignificant, whereas the low-risk CDS index is still negative and significant. The other control variables have the same sign and significance level as in column (2). The mean CRI is now negative (−0.066) and the confidence intervals are wide: the lower bound of the 95% confidence band is −0.1562 and the upper bound is 0.0245. This is the consequence of the fact that the standard error of the CRI is now about fourteen times than the one for the first orthogonalization. The CRI is thus imprecisely estimated.

Table 1 Aggregate CRI

	(1) Market orthogonalization	(2) CDS orthogonalization
S&P500	1.734***	1.809***
	(0.0162)	(0.0138)
CDS^{XO}	−7.633***	0.307
	(0.192)	(0.195)
$CDS^{\mathrm{IG(orth)}}$	−44.45***	−4.961***
	(0.526)	(0.604)
One-month interest rate	−1.492***	−1.492***
	(0.117)	(0.117)
10-*year interest rate*	0.0561	0.0561
	(0.326)	(0.326)
Inflation	−2.967***	−2.967***
	(0.533)	(0.533)
Constant	0.000137	−0.000567***
	(0.000137)	(0.000137)
Observations	130,834	130,834
R^2	0.170	0.170
CRI	0.147	−0.0659
95% confidence interval	0.1406 0.1534	−0.15626 0.024456

Notes. The dependent variable is the daily return in the individual bank share price. The regression in column (1) is that of Equation (9) with the orthogonalized stock market index. Column (2) reports the same regression but with the CDS indices orthogonalized. Robust standard errors are reported in parentheses.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The reduced precision under the second method surely reflects the importance of the factor that is common to the equity and CDS markets. Under the second orthogonalization method, this factor is not taken into account in the estimation of the CRI. The informational content of the CRI is hence likely to be lower in this case. In the following we will thus focus on interpreting the results for the CRI estimated using the first method, but we will report the results for the second method alongside. In doing so, it should be kept in mind that the first method potentially attributes market risk exposure to the CRI—to the extent that the common factor does not represent credit risk. The CRI may thus not solely capture information unique to credit markets but also normal stock market exposures.[8] This has potentially important implications for interpreting any forecasting ability of the CRI. In this respect, an important question will be whether the forecasting ability will disappear once we control for the stock market beta

[8] The orthogonalization method will also tend to introduce a (positive) bias in the CRI. Intuitively, this is because the high-risk CDS coefficient may pick up noncredit market risk exposure and hence inflate the CRI. The standard errors of the estimated CRIs should thus be interpreted with caution.

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Table 2 Descriptive Statistics for Individual CRIs

Variable	Observations	Mean	Median	Min	Max	SD
CRI (*Market orthogonalization*)	150	0.1677	0.1535	0.0517	0.4136	0.0613
CRI (*CDS orthogonalization*)	150	0.4046	0.0139	−10.0567	54.9068	5.1235

in these regressions. This would be indicative of the CRI's forecasting power coming through market risk and not credit risk.

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:

$$\frac{\Delta p_{i,t}}{p_{i,t}} = \alpha_i + \beta_i \frac{\Delta S\&P500_t}{S\&P500_t} + \gamma_i \frac{\Delta CDS_t^{XO}}{1 - CDS_t^{XO}} + \delta_i \frac{\Delta CDS_t^{IG(orth)}}{1 - \Delta CDS_t^{IG(orth)}} + \phi_i \frac{\Delta Z_t}{Z_t} + \varepsilon_{i,t}. \quad (10)$$

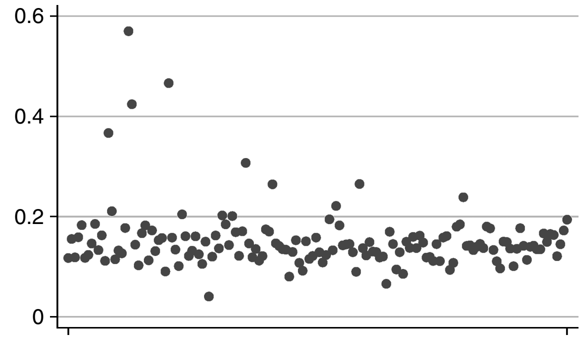
Using Equation (8), we can then compute for each bank its CRI from the estimated γ_i and δ_i.

The first row of Table 2 reports the summary statistics for our preferred orthogonalization. The mean CRI across all 150 banks is 0.168, which is a bit higher than the previously estimated aggregate CRI (0.147). The (cross-sectional) standard deviation of the CRIs is 0.061. The lowest CRI among the banks is 0.052, and the largest CRI takes the value of 0.414. Figure 1 depicts the underlying individual CRIs, ordering banks by asset size. Most banks have a CRI in the range from 0.1 and 0.2. There are outliers but only relatively few. From the 10 largest surviving BHCs, Citigroup (the last dot in the figure) has the highest CRI. Interestingly, Citigroup is also the bank with the largest accumulated write downs during the subprime crisis. It is also interesting to note that there is significant cross-sectional variation in the CRIs, suggesting that the market differentiates across banks in terms of credit risk sensitivities.[9]

The second row of Table 2 and Figure 2 contain the results for the second orthogonalization method. The mean CRI is now 0.405, which is much higher than for the first orthogonalization method. This is, by itself, not surprising because any orthogonalization will surely distort the absolute value of the CRI. However, it can also be seen that the CRIs fluctuate widely and take unreasonable values: the lowest CRI is −10.06 and the highest CRI is 54.91, which are both well outside the [0, 1] interval. The cross-sectional standard deviation is also very large (5.12).

[9] The cross-sectional correlation of the CRIs with the beta is weak and negative (−0.17), somewhat alleviating concerns that the CRI picks up market risk.

Figure 1 CRIs for Market Orthogonalization

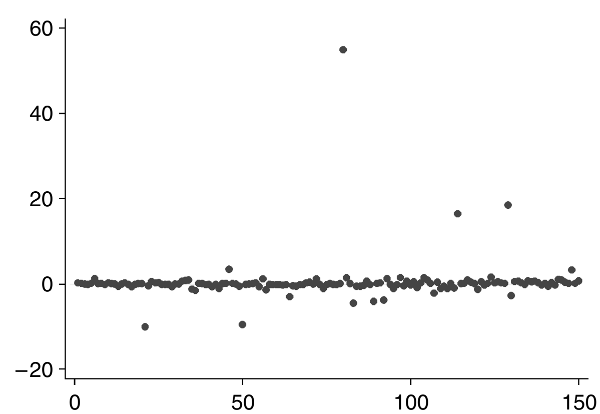


This can also be appreciated by looking at the plot of individual CRIs (Figure 2), showing that CRIs fluctuate widely and that there are a few large outliers. A potential explanation for this is that the CRIs are imprecisely estimated. Indeed, their mean standard error is about twenty times higher than for the first orthogonalization method. In fact, the majority of the estimated CRIs are not significantly different from the mean CRI obtained of the first orthogonalization method. The CRIs estimated under the second orthogonalization method thus seem to have less informational value. This confirms the results obtained for the aggregate CRI.

4.4. The CRI and Other Measures of Bank 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. Among others, this will help us understand whether the CRI contains information about general lending risk or

Figure 2 CRIs for CDS Orthogonalization



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applies only to specific segments of lending. In addition, we will also relate the CRI to some basic bank characteristics; this may inform us about whether the CRI depends on the business model of banks.

A straightforward way to study how the CRI is related to other bank variables is to look at the correlation between the estimated CRI and these variables. However, this is not an efficient procedure because information from the first step (the estimation of the CRIs itself) is not fully used in the second step (computation of the correlations). In 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 in the second step.

We instead develop a method that allows us to (efficiently) estimate the relationship in one step.[10] For this we adjust the equation for the aggregate CRI (9) in order to allow the CDS sensitivities to depend on a bank characteristic, 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:

$$\frac{\Delta p_{i,t}}{p_{i,t}} = \alpha + \beta \frac{\Delta S\&P500_t}{S\&P500_t} + (\gamma + \eta(X_i - \tilde{X})) \frac{\Delta CDS_t^{XO}}{1 - CDS_t^{XO}} + (\delta + \theta(X_i - \tilde{X})) \frac{\Delta CDS_t^{IG(orth)}}{1 - CDS_t^{IG}} + \phi \frac{\Delta Z_t}{Z_t} + \varepsilon_{i,t}. \quad (11)$$

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 gives the following equation:

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

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

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

The expression $CRI'(X)_{X=\tilde{X}}$ is the counterpart of the coefficient on X in a two-step regression where in the second step the CRIs (which have been 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, $\mathrm{CRI}'(X)_{X=\tilde{X}}$, using Equation (13). Whether the relationship is a significant one is determined by carrying out a (nonlinear) Wald test of $(\eta\delta - \theta\gamma)/(\delta + \gamma)^2 = 0$.

Table 3 shows the estimated relationships between the CRI and various balance sheet variables (which are for the purpose of this table averaged over the entire sample period). Note that Table 3 essentially reports a number of univariate relationships because we run (11) for each variable and then compute its relationship with the CRI.

The table reports first the results for the first orthogonalization method. The first four variables in the table are traditional measures of banks' loan risk: nonperforming loans, loan-loss provisions, loan-loss allowances, and net charge offs (all four scaled by total loans). Nonperforming loans and loan-loss provisions have the expected sign (positive) and are significantly related to the CRI. Loan-loss allowances and net charge offs also have a positive point estimate; however, the relationship is not significant (in the case of net charge offs the level of significance is 10%). Overall, we conclude that there is some

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

	Market orthogonalization		CDS orthogonalization	
	Coefficient	SE	Coefficient	SE
Nonperforming loans/TL	1.652**	(0.694)	27.99***	(8.800)
Loan-loss provisions/TL	3.224**	(1.579)	58.95***	(19.45)
Loan-loss allowance/TL	1.668	(1.147)	32.24**	(14.55)
Net charge offs/TL	3.671*	(2.209)	69.27**	(27.62)
Total risk weighted assets/TA	0.0406	(0.0325)	0.568	(0.462)
Loan growth	0.279	(0.193)	4.413	(2.864)
Interest from loans/TL	0.774	(0.878)	16.03	(11.69)
ROA	−2.518**	(1.248)	−28.95*	(16.47)
Debt/TA	0.332**	(0.145)	5.172**	(2.022)
Loans/TA	0.0209	(0.0316)	−0.173	(0.484)
log(*TA*)	−0.000701	(0.00237)	0.0524	(0.0443)
Real estate loans/TL	0.0193	(0.0250)	0.220	(0.345)
Dummy sec. real estate loans	0.00499	(0.00866)	0.217	(0.139)

Notes. This table reports the coefficient of the nonlinear Wald test on Equation (13). *TL*, *total loans*; *TA*, *total assets*; *sec*, *securitization*.
***, **, and * denote a significant relationship between the CRI and the corresponding variable at the 1%, 5%, and 10% levels, respectively.

[10] Note that our setup differs from the usual two-step regression problem in that the variable of interest that is estimated in the first step (the CRI) is a (nonlinear) combination of coefficients, and not simply a coefficient itself.

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evidence suggesting that banks whose balance sheet indicates that they have a lower loan quality also tend to have a higher CRI.

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, which is not significantly related to the CRI. The second variable is loan growth, which has been found to explain asset risk at banks (see Foos et al. 2010). The idea behind this proxy is that a bank that wants to expand its loan volume quickly, presumably has to do so at the cost of accepting lower quality borrowers. This would suggest a positive relationship between loan growth (computed as the average loan growth over the sample period) and the CRI. The point estimate is indeed positive, however, the relationship is not significant. The next variable is the ratio of interest income from loans to total loans. This variable has no significant relationship with the CRI. Finally, we consider a bank's return on assets (ROA). The a priori relationship of this variable with the CRI is ambiguous. On one hand, banks may charge higher rates on riskier loans. On the other hand, riskier borrowers are also more likely to default, thus reducing the ROA. In addition, banks with poor management may have simultaneously risky loans and low profitability. The table shows that there is a negative and significant relationship with the CRI. Thus, the market perceives banks with high profitability to have a relatively safe loan portfolio.

The next set of variables contains three basic characteristics of banks' balance sheets: leverage, loan-to-asset ratio, and size. First, it can be seen that 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 different risk preferences at banks: a bank that follows a high-risk strategy may jointly choose a high-risk loan portfolio and operate with high leverage. Note that because the CRI is a *relative* credit risk sensitivity, there is no mechanical relationship between the CRI and leverage that may arise from the fact that (everything else being equal) highly leveraged banks are more sensitive to changes in loan values. The same argument also applies to our next variable, the loan-to-asset ratio. This variable is found not to be significantly related to the CRI. The last of the basic balance sheet characteristics we consider is size, measured by the log of total assets. The estimates show that a bank's size is not correlated with its share of high-risk loans.

The last two variables in Table 3 are a bank's share of real estate loans and a dummy for whether the bank securitizes such loans. Both variables are motivated by the subprime crisis, which has been partly attributed to real estate securitization. However, none of these variables are significantly related to the CRI. An explanation of this is that securitization has two opposing effects on securitizing banks themselves. On one hand, securitizing real estate loans may directly reduce high-risk exposures at these banks. On the other hand, these banks may use the freed-up capital to extend new loans (for a theoretical analysis of this effect, see Wagner 2008). Such loans are presumably riskier, for example, due to the incentive problems created by the securitization business.

Given that the first orthogonalization method also allows stock market information to enter the estimation of the CRI, it is important to examine whether these relationships are due to information unique to the CRI, or whether this information is already contained in standard measures of bank risk that can be generated from the stock market index. To test this, we rerun the above regressions controlling for bank betas. The results (not shown here) are almost identical to ones in Table 3, both in terms of coefficients and significance. This suggests that the CRI captures information that is not contained in standard risk measures obtained from the market index.

The last two columns of the table contain results for the second orthogonalization method. We can see that now all four traditional measures of loan risk are positively and significantly related to the CRI (under the first orthogonalization method loan-loss allowances were not significant). The coefficients are generally lower than previously, which is to be expected because the mean CRI is lower there. The only other significant variables in Table 3 are ROA and leverage. ROA is negatively and significantly related to the CRI (but only at the 10% level) and leverage is positively and significantly related to the CRI. Again, these results parallel the results of the other method. We can thus conclude that—perhaps surprisingly given that the previous section showed large differences in precision of the CRI estimates—the determinants of the CRI do not depend on the orthogonalization method. A potential explanation for this is that in this section we can estimate relationships between the CRI and bank characteristics (efficiently) in one step and thus make use of the large number of bank-day observations. This enables us to identify the determinants of the CRI even when the CRIs itself has low informational value.

4.5. Using the CRI to Predict Bank Failures

In this section we study whether the CRI has predictive power in forecasting bank failures, controlling for other measures of bank risk. Our sample period is well suited for such an exercise as it comprises the subprime crisis during which there were many bank failures.

The first step is the identification of failed banks. We start with the failed bank list of the FDIC and take

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all failed commercial banks that belonged to one of our 150 bank holding companies. There are nine of such banks. In eight out of nine cases the commercial bank's BHC also went bankrupt following the failure of its commercial bank. We thus have eight failed BHCs. To these we add two rescue mergers (Wachovia and National City) as these two BHCs would have very likely failed if they were not taken over with the direct help (Wachovia) or indirect help (National City) of the government or the FED.[11] This gives us a total of ten BHCs for our empirical analysis. A first inspection of their CRIs shows that the CRI may be useful in identifying bank failures: the average CRI of these banks one month before failure was 0.20 (compared to a sample mean of 0.15).

The empirical analysis is carried out by means of probit regressions. In each quarter the dependent failure variable takes the value of one if a bank fails in this quarter, and surviving banks are assigned a zero. Failed banks are dropped from the sample after the quarter of failure. Failure is then (dynamically) predicted using information from quarters prior to failure. Our sample starts with the start of the subprime crisis (third quarter of 2007) and ends in the first quarter of 2010.

We estimate the following relationship:

$$F_{i,\,t+k} = p(CRI_{i,\,t}, \mathbf{Z}_{i,\,t}), \tag{14}$$

where F is the bank-specific failure indicator, $\mathbf{Z}$ denotes a set of controls, and $k = \{1, 2\}$ denotes quarters. We do not include bank fixed effects because for all surviving banks there is no variation in the dependent variable and we would thus only look at variations within the group of failing banks.

Table 4 contains results for two-quarter forecasting using various sets of control variables. Panel A focuses on the preferred orthogonalization. Column (1) reports the regression without controls (thus only including the CRI). In column (2) we include traditional measures 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. The share price beta (estimated from separate regressions with only the nonorthogonalized stock index return included) and the Z score are considered in columns (6) and (7), respectively. Finally, column (8) reports the results when all controls are included. Note that the table reports the marginal effects for the estimation coefficients.

Column (1) in panel A shows that the CRI is significant in explaining failures two quarters ahead, and is so with the expected (positive) sign. The (marginal) coefficient is 0.07, which indicates economic significance. A bank that has a CRI that is one standard deviation higher than its peers (the standard deviation of CRIs over the estimation periods in Table 4 is 0.12) has a probability of failing in two quarters that is $0.07 \times 0.12 = 0.84\%$ higher. This implies that over the entire sample period (which consists of 10 quarters), the bank has a chance of failing that is 8.4 percentage points higher. This is large given that the unconditional mean of failing in our sample is about 7%. Columns (2)–(8) show that the CRI is also significant in all other specifications (in column (4), however, only weakly so) and has the correct sign. In particular, the CRI is significant (at the 5% level) in the regression including all controls jointly (column (8)).

The CRI thus has forecasting power at the two-quarter horizon. This is probably the relevant horizon for regulators as they can then still take actions to prevent failure. We have also considered a shorter forecasting horizon (one quarter). The results are a bit weaker than for two-quarter forecasting (see the online appendix for the results). A potential explanation for this is that close to failure a bank's share price is probably more noisy, which should make a reliable estimation of the CRI difficult. We have also predicted bank failures for a wider set of banks by not requiring balance sheet data. This increases the number of bank failures to 20. The results for two- and one-quarter forecasting are similar to the ones obtained in the original data set but slightly stronger (see the online appendix).

Panel B of Table 4 reports the results for the two-quarter forecasting based on our normal bank sample for the second orthogonalization method. In all specifications the coefficient for the CRI is low and far away from significance. A potential concern with the first orthogonalization method is that it picks up beta risk and that this leads to (erroneous) forecasting power. It is thus of interest to see whether the significance of the stock beta in explaining bank failures increases when we move to the second orthogonalization method. Column (6) in panel B, which includes the beta, shows that this is not the case. The point estimates of the beta are in fact very similar and its significance even declines.

Overall, we can conclude that the CRI estimated using the preferred orthogonalization is able to forecast bank failures. However, this is no longer the case when reversing the orthogonalization. The latter is

[11] There are conceivably other BHCs that have only survived because of various government interventions during the crisis. This creates noise in our dependent variable and should make it more difficult to find forecasting power for the CRI. In addition, in September 2008 a short-sale ban on financial stocks was enacted. This possibly reduced price discovery and the informational efficiency of bank stock prices. As a result, the estimated CRI may become less informative after that date, which (again) should make it more difficult to identify a forecasting ability for the CRI.

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Table 4 Failure Prediction (Two Quarters)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Market orthogonalization				
CRI	0.0739***	0.0336***	0.0503***	0.0184*	0.0465***	0.0795***	0.0150**	0.00278**
	(0.0277)	(0.0165)	(0.0195)	(0.0158)	(0.0253)	(0.0283)	(0.00857)	(0.00388)
Nonperforming loans/ TL		−0.0414*						−0.00590*
		(0.0279)						(0.00925)
Loan-loss provisions/ TL		−0.0362						−0.00551
		(0.211)						(0.0228)
Loan-loss allowance/ TL		0.0425						0.0129
		(0.156)						(0.0333)
Net charge offs/ TL		0.367						0.0286
		(0.224)						(0.0490)
Total risk weighted assets/ TA			−0.00670					−0.000370
			(0.00949)					(0.00135)
Loan growth			−0.0705					0.00202
			(0.0651)					(0.00732)
Interest from loans/ TL			0.0510					−0.0104
			(0.0786)					(0.0137)
ROA			−0.124***					0.00252
			(0.0535)					(0.00605)
Debt/ TA				0.160***				0.00851
				(0.0615)				(0.0136)
Loans/ TA				0.0117*				0.00105
				(0.00667)				(0.00208)
log(*TA*)				0.00124**				0.000246***
				(0.000797)				(0.000407)
Real estate loans/ TL					0.0246**			0.00187**
					(0.00990)			(0.00323)
Dummy sec. real estate loans					0.000421			−0.000336
					(0.00367)			(0.000618)
Beta						0.00601***		0.000314
						(0.00245)		(0.000445)
Z score							−0.00127***	−0.000120
							(0.000593)	(0.000176)
Observations	1,453	1,453	1,453	1,453	1,453	1,453	1,453	1,453
Pseudo R^2	0.0535	0.221	0.153	0.180	0.0997	0.102	0.208	0.368
				Panel B: CDS orthogonalization				
CRI	0.000161	1.93e−05	9.16e−05	3.65e−05	9.03e−05	0.000140	7.17e−05	4.05e−06
	(0.000165)	(7.22e−05)	(0.000123)	(6.24e−05)	(0.000126)	(0.000178)	(7.77e−05)	(3.21e−05)
Nonperforming loans/ TL		−0.0440						−0.00674
		(0.0327)						(0.00958)
Loan-loss provisions/ TL		−0.0990						−0.00494
		(0.257)						(0.0256)
Loan-loss allowance/ TL		0.0731						0.0159
		(0.189)						(0.0358)
Net charge offs/ TL		0.487*						0.0294
		(0.270)						(0.0472)
Total risk weighted assets/ TA			−0.00568					−0.000361
			(0.0127)					(0.00152)
Loan growth			−0.0624					0.00372
			(0.0800)					(0.00911)
Interest from loans/ TL			0.0925					−0.00869
			(0.0997)					(0.0115)
ROA			−0.140**					0.00420
			(0.0579)					(0.00682)

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Table 4 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Debt/TA				0.173***				0.00902
				(0.0630)				(0.0144)
Loans/TA				0.0129				0.00133
				(0.00807)				(0.00239)
log(*TA*)				0.00139				0.000310
				(0.000869)				(0.000438)
Real estate loans/TL					0.0309***			0.00218
					(0.0107)			(0.00334)
Dummy sec. real estate loans					0.000236			−0.000428
					(0.00395)			(0.000658)
Beta						0.00538		0.000251
						(0.00381)		(0.000373)
Z score							−0.00144**	−0.000172
							(0.000601)	(0.000214)
Observations	1,453	1,453	1,453	1,453	1,453	1,453	1,453	1,453
Pseudo R^2	0.000337	0.193	0.102	0.157	0.0587	0.0207	0.185	0.343

Notes. The dependent variable is the bank specific failure indicator for each quarter. All regressions are based on Equation (14) and report marginal effects. Clustered standard errors (at the bank level) are reported in parentheses. *TL*, *total loans*; *TA*, *total assets*; *sec.*, *securitization*.
***, **, and * denote significance for the underlying coefficient at the 1%, 5%, and 10% levels, respectively.

ultimately not surprising given that we already established the low informational content of the CRI under the second method. One potential interpretation for the different results obtained under both methods is that the significance of the CRI under the first method is due to the CRI capturing market exposure. However, such market dependence would necessarily need to be nonlinear because we already account for linear market dependence (as the results are robust to the inclusion of the stock market beta).

4.6. The CRI and Banks' Share Price Performance During the Subprime Crisis

In this section we address the question of whether the CRI also has predictive power for the performance of banks during the subprime crisis, as measured by their share prices. The idea is the following. As discussed earlier, a high CRI is not necessarily a bad sign for bank management as long as the bank gets adequately compensated for the risk through higher interest rates. However, if there is an unexpected downturn in the economy, banks with higher CRIs should be harder hit because high-risk exposures perform relatively worse when economic conditions deteriorate. Thus, high CRI banks should see their share price decline more during the subprime crisis than low CRI banks.

In this section we thus study whether a bank's CRI prior to the crisis relates to its performance in the crisis. For this we consider again the same set of controls as in the previous section. In particular we are estimating the following cross-sectional regression:

$$perf_i = \alpha + \beta CRI_i + \gamma \mathbf{Z}_i + \varepsilon_i, \qquad (15)$$

where $perf_i$ is a bank's share price performance from June 15, 2007, until June 15, 2008; CRI_i is a bank's CRI calculated using information only up until June 15, 2007; and $\mathbf{Z}_i$ is the vector of control variables already discussed before. However, this time this vector is constrained to information before June 15, 2007.

Panel A of Table 5 reports the results using the same partitioning of controls as in Table 4 for the preferred orthogonalization. The main message is that the CRI is significantly and negatively related to subprime performance and that this result is robust to various controls. The CRI always remains significant at the 1% level. Its coefficient ranges from −4.7 to −7.6. A coefficient of −6, for example, implies that an increase in a bank's CRI by one standard deviation is associated with a share price performance that is 3% worse than its peers. This is noteworthy because the subprime crisis was not only a crisis of asset quality but was also driven by liquidity and funding issues. It also confirms the expectation that in periods of crisis (regardless of their origin) banks with lower asset quality should be significantly more affected.

Panel B reports the results for the reversed orthogonalization. It can be seen that in all regressions the CRI obtains a negative coefficient. The CRI is significant in five of the eight specifications. It becomes insignificant in the specification that includes various traditional proxies of bank risk (column (3)) and in the specification that includes general bank characteristics (column (4)) as well as in the regression that includes all controls jointly (column (8)). It should also be noted that the coefficient on the CRI is lower than in panel A, which is consistent with the fact that the CRI (which is an explanatory variable here)

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Table 5 Subprime Share Price Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Market orthogonalization								
CRI	−5.798***	−6.999***	−6.021***	−4.749***	−7.169***	−5.282***	−5.722***	−7.552***
	(1.704)	(1.556)	(2.176)	(1.662)	(1.785)	(1.920)	(1.772)	(2.213)
Nonperforming loans/TL		43.06						147.8
		(110.4)						(184.6)
Loan-loss provisions/TL		−8,981						−8,587
		(8,676)						(9,464)
Loan-loss allowance/TL		−1,024*						−1,079
		(559.4)						(666.1)
Net charge offs/TL		9,088						12,095
		(9,115)						(11,345)
Total risk weighted assets/TA			−27.71					−19.46
			(21.06)					(17.92)
Loan growth			−39.59					−3.821
			(27.72)					(35.31)
Interest from loans/TL			−337.2					−345.9
			(551.4)					(599.9)
ROA			−2,311*					−2,636
			(1,334)					(1,764)
Debt/TA				−5.479				−31.18
				(66.95)				(124.6)
Loans/TA				−44.14**				−9.285
				(17.38)				(19.57)
log(*TA*)				−4.754***				−3.777***
				(0.677)				(1.232)
Real estate loans/TL					−16.97**			−19.86**
					(8.089)			(8.528)
Dummy sec. real estate loans					−16.29**			−11.43
					(7.499)			(9.107)
Beta						3.478		−5.096
						(6.038)		(5.581)
Z score							0.672	−0.722
							(0.736)	(1.176)
Constant	−10.23***	3.510	45.33***	99.67*	5.376	−14.81**	−16.15**	177.3
	(1.968)	(6.139)	(17.14)	(55.59)	(5.291)	(7.010)	(7.533)	(121.4)
Observations	150	150	150	150	150	150	150	150
R^2	0.009	0.056	0.096	0.106	0.103	0.012	0.015	0.247
Panel B: CDS orthogonalization								
CRI	−0.940***	−1.043***	−0.488	−0.433	−0.983**	−0.978***	−0.969***	−0.507
	(0.291)	(0.303)	(0.330)	(0.302)	(0.485)	(0.269)	(0.276)	(0.406)
Nonperforming loans/TL		51.54						151.1
		(107.7)						(184.2)
Loan-loss provisions/TL		−8,983						−8,525
		(8,686)						(9,518)
Loan-loss allowance/TL		−983.1*						−1,036
		(565.2)						(674.4)
Net charge offs/TL		9,163						12,126
		(9,128)						(11,432)
Total risk weighted assets/TA			−26.96					−17.03
			(21.70)					(18.87)
Loan growth			−39.70					−3.662
			(28.11)					(35.60)
Interest from loans/TL			−278.2					−361.6
			(539.9)					(593.6)
ROA			−2,340*					−2,613
			(1,336)					(1,768)

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Table 5 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel B: CDS orthogonalization				
Debt/TA				−8.205				−35.71
				(66.97)				(126.2)
Loans/TA				−43.69**				−10.24
				(17.43)				(19.65)
log(*TA*)				−4.781***				−3.814***
				(0.688)				(1.248)
Real estate loans/TL					−16.51**			−19.46**
					(8.017)			(8.677)
Dummy sec. real estate loans					−15.91**			−10.91
					(7.481)			(9.063)
Beta						4.439		−3.736
						(5.961)		(5.385)
Z score							0.700	−0.708
							(0.733)	(1.180)
Constant	−11.90***	0.873	42.18**	100.9*	2.880	−17.54***	−18.05**	175.7
	(1.822)	(6.002)	(17.33)	(55.50)	(5.238)	(6.564)	(7.489)	(121.4)
Observations	150	150	150	150	150	150	150	150
R^2	0.005	0.050	0.088	0.101	0.095	0.010	0.012	0.235

Notes. The dependent variable is an individual bank's share price decline over the period June 15, 2007, to June 15, 2008. All regressions are based on Equation (15). Robust standard errors are reported in parentheses. *TL*, *total loans*; *TA*, *total assets*; *sec.*, *securitization*.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

has a higher mean under the second orthogonalization method. It can also be seen that the influence of the beta does not essentially change as we move from one to the other orthogonalization method (in both tables the beta is insignificant and its coefficient in column (6) changes from 3.48 to 4.44).

We conclude that there is consistent evidence that the CRI can forecast the shareprice of banks during the subprime crisis—but this evidence is weaker for the second orthogonalization method.

5. Concluding Remarks and Discussion

In this paper we have developed a new measure of the quality of banks' credit portfolios. This measure is not restricted to loans directly held by the bank, but also captures credit risks from other sources. It includes exposures arising from a variety of bank activities, such as securitizations and credit derivatives. Because it is derived from market prices, it comprises information from a wide range of sources and can, moreover, reflect new developments quickly. The CRI is arguably also an independent assessment of banks' risks because it should be difficult for banks to consistently manage their share price sensitivities. This is in contrast to other market-based measures, such as the distance-to-default, which can be more easily manipulated.

The CRI is a natural indicator of how well banks might perform in periods of worsening 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 bank supervisors, alongside other information, as a criterion for identifying potentially exposed institutions well before a downturn materializes. By contrast, once a crisis materializes other indicators (such as the distance-to-default or the bank's CDS spread) should be preferred from a conceptual perspective. The CRI could also potentially serve as an input for the computation of risk weights for regulatory capital requirements. For example, if one (for argument's sake) assigns investment grade exposures a risk weight of zero and subinvestment grade exposures a weight of 100%, the CRI simply gives the average risk weight of the banks' credit exposures. The CRI is thus an interesting alternative to the crude risk weights of the standardized approach of Basel I but also the advanced approach (where banks determine their own risk weights) as it does not rely on assessments that are at the discretion of banks themselves. The CRI may also help bank creditors in gauging the riskiness of loans, as well as being useful for bank shareholders in assessing the ability of bank managers to make high-quality investments.

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Conference 2009, the European Banking Center Financial Stability Conference 2009, the European Economic Association 2009 Meetings, the 28th SUERF Colloquium, the European Network for Training in Economic Research Jamboree 2009, the Netherlands Network of Economics Research Day 2008, the Money and Finance Research Group Changing Geography 2009, and the American Economic Association meetings 2010; and seminar participants at Tilburg University. The authors also 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 and the best paper prize at the Emerging Scholars in Banking and Finance conference.

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