Noth, Felix; Tonzer, Lena

Working Paper

Bank Risk Proxies and the Crisis of 2007/09: A Comparison

IWH Discussion Papers, No. 13/2015

Provided in Cooperation with:
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Suggested Citation: Noth, Felix; Tonzer, Lena (2015) : Bank Risk Proxies and the Crisis of 2007/09: A Comparison, IWH Discussion Papers, No. 13/2015

This Version is available at:
http://hdl.handle.net/10419/119324

Terms of use:
Documents in EconStor may be saved and copied for your personal and scholarly purposes. You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public. If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.
Bank Risk Proxies and the Crisis of 2007/09: A Comparison

Felix Noth
Lena Tonzer

September 2015

IWH DISCUSSION PAPERS
Authors:  
*Felix Noth*  
Halle Institute for Economic Research (IWH)  
Department of Financial Markets  
E-mail: Felix.Noth@iwh-halle.de  
Phone: +49 345 7753 702

Otto-von-Guericke University Magdeburg  
E-mail: felix.noth@ovgu.de

*Lena Tonzer*  
Halle Institute for Economic Research (IWH)  
Department of Financial Markets  
E-mail: Lena.Tonzer@iwh-halle.de  
Phone: +49 345 7753 835

The responsibility for discussion papers lies solely with the individual authors. The views expressed herein do not necessarily represent those of the IWH. The papers represent preliminary work and are circulated to encourage discussion with the authors. Citation of the discussion papers should account for their provisional character; a revised version may be available directly from the authors.

Comments and suggestions on the methods and results presented are welcome.

IWH Discussion Papers are indexed in RePEc-EconPapers and in ECONIS.

Editor:  
**Halle Institute for Economic Research (IWH) – Member of the Leibniz Association**  
Address:  
Kleine Maerkerstrasse 8, D-06108 Halle (Saale), Germany  
Postal Address:  
P.O. Box 11 03 61, D-06017 Halle (Saale), Germany  
Phone:  
+49 345 7753 60  
Fax:  
+49 345 7753 820  
Internet:  
www.iwh-halle.de

ISSN  
1860-5303 (Print)  
ISSN  
2194-2188 (Online)
Bank Risk Proxies and the Crisis of 2007/09: 
A Comparison*

Abstract

Motivated by the variety of bank risk proxies, our analysis reveals that nonperforming assets are a well-suited complement to the Z-score in studies of bank risk.

Keywords: banking, financial institutions, risk proxies

JEL Classification: G21, G28, G32

* All errors are our own.
1. Introduction

The financial crisis of 2007/09 has anew brought the issue of bank risk at the heart of the academic discussion. A review of the literature shows that different proxies that come from balance sheet and profit and loss information of banks are used to measure bank risk. However, there is no consensus which measure fits best to gauge bank risk. This becomes crucial, if the measures capture different aspects of bank risk, which then leads to different interpretations of results conditional on the risk proxy. We aim to provide an overview by comparing the most commonly used measures for bank risk for the population of U.S. commercial banks between 1995 and 2013.

We employ four risk proxies. First, we use the Z-score which indicates banks’ distance to default by calculating the difference between banks’ profitability and the equity ratio of banks, scaled by the volatility of bank profitability (Laeven and Levine 2009; Berger et al. 2009; Anginer et al. 2013 2014; Klomp 2014; Gropp et al. 2014). Second, non-performing assets which include loans past due 30 or 90 days, nonaccrual loans and other real estate owned indicating bank asset risk are used by, e.g., Barth et al. (2004), Berger et al. (2009), Gropp et al. (2010), Cole and White (2012) or Jiménez et al. (2013). Third, loan loss provisions are an estimate of future losses that reduce the operating income for the current period (Ahmed et al. 1999; Cebenoyan and Strahan 2004; Laeven and Majnoni 2003). Fourth, loan loss reserves (allowances) are a contra asset that reflect the amount of loan provisions on banks’ balance sheets and reduce the book value of loans (Elliott et al. 1991; Hasan and Wall 2004; Ng and Roychowdhury 2014).

According to Carbo et al. (2009) who investigate various proxies for bank competition, we do three things in this study. First, we use data for U.S. commercial banks between 1995 and 2013 and calculate four common proxies for bank risk (Section 2). In Section 3 we then analyse correlations and explanatory power between these variables and test whether the measures are useful in predicting bank failures (Cole and White 2012; Dam and Koetter 2012; Lepetit and Strobel 2015; Ng and Roychowdhury 2014; Shaffer 2012a,b; Wheelock and Wilson 2000). We give a short conclusion in Section 4.

2. Data

We use balance sheet and profit and loss data for all U.S. commercial banks between q4:1992 and q4:2013 provided by the Federal Deposit Insurance Corporation (FDIC). We append information on bank failures for the same period from the FDIC Failed Bank List. The FDIC provides quarterly data. We require for the banks to have consecutive quarters only which results in a maximum number of 10,332 banks in 1995 decreasing to 6,055 banks in 2013. We exploit the quarterly observations and calculate a 12-quarter rolling standard deviation ($SD(RoA)$) of banks’ return on assets ($RoA$) for each bank $i$. Some only use non-performing loans. 2FDIC item roa.
which limits the observation period to 1995-2013. We then collapse the data on a bank-year \((i,t)\) level.

We calculate a Z-score for each bank and year with

\[
Z\text{-score}_{it} = \frac{EQ_{it} + \text{RoA}_{it}}{SD(\text{RoA})_{it}}
\]  

(1)

EQ is the ratio of bank equity over total assets\(^3\). The Z-score indicates a bank’s loss absorbing capacity (Laeven and Levine 2009), i.e., if the Z-score is lower, the bank is less stable. Z-scores are often skewed, therefore it is common to take the natural logarithm (Laeven and Levine 2009) which we also do (hereafter Z-score). Also Lepetit and Strobel (2015) show that the log of the Z-score performs well to capture insolvency risk. We multiply the Z-score by \(-1\) so that more negative values indicate more stable banks.

Next, we calculate the ratio of non-performing assets (NPA)\(^4\) over total assets\(^5\) according to Cole and White (2012) which includes loans past due 30 and 90 days, nonaccrual loans and other real estate owned. We further calculate banks’ loan loss reserves\(^6\) over total assets (LLR) which reflects banks’ contra asset items that reduce the loan volume from the balance sheet. The equivalent item from the profit and loss statement is loan loss provisions\(^7\) which should reflect a reasonable estimate of coming losses from loans.\(^8\)

We again standardize by total assets (LLP). Figure 1 provides mean values for NPA, LLR, LLP and the Z-score over time. All four risk proxies indicate an increase in risks during the recent crisis.

Figure 1: Risk proxies for U.S. banks over time

---

\(^3\)FDIC item eqv.

\(^4\)FDIC items: p3asset, p9asset, naasset and ore.

\(^5\)FDIC item asset.

\(^6\)Allowances is equivalent. The FDIC item lnatres.

\(^7\)FDIC item elnatr.

\(^8\)We winsorize one massive outlier value (-12018) to the next value of the distribution.
3. Results

Table 1 shows correlations between all four risk proxies for the period 1995-2013. Banks’ Z-score, NPA and LLR are reasonably and significantly correlated whereas the correlation of NPA with the other two variables is highest. In each case, movements in one variable are mirrored less than 50% in the other variables. Correlations with LLP are very weak and not significant which might indicate that loan loss provisions do not capture asset bank risk adequately.

<table>
<thead>
<tr>
<th></th>
<th>Z-score</th>
<th>NPA</th>
<th>LLR</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPA</td>
<td>0.4341</td>
<td>0.4864</td>
<td></td>
</tr>
<tr>
<td>LLR</td>
<td>0.3194</td>
<td>0.4864</td>
<td>0.4864</td>
</tr>
<tr>
<td>LLP</td>
<td>-0.0060</td>
<td>0.0018</td>
<td>0.0036</td>
</tr>
</tbody>
</table>

Correlation coefficients with p-values in parentheses.

Figure 2 shows R-squared values from regressions in which we explain one risk proxy \( k = 1, \ldots, 4 \) with the remaining \( j \) proxies.

\[
Risk_{kit} = x_{j \neq k, it}^\prime \beta + \epsilon_{it}
\]

Figure 2(a) thereby considers the full sample period while Figure 2(b) provides results from regressions based on cross sections for each year between 1995 and 2013. For the full period, we find that 13.36% of the variation of banks’ Z-score is explained by NPA, LLR and LLP. Contrary, the variation in NPA explained by Z-score, LLR and LLP is the highest among the four proxies showing a value of 28.21%. This indicates that NPA contains relevant information as concerns the other three variables. Figure 2(b) shows that the variation in LLR and LLP explained by the other risk proxies is sensible to crisis periods. Comparing the pattern over time for the explained variation in the Z-score and NPA, we find again a higher R-squared for NPA.

The ultimate signal for bank risk is a default of a financial institution. We use a probability model explaining the occurrence of a bank failure (0/1) with the four risk proxies (lagged by one year).

\[
Pr(\text{Failure} = 1) = F(x_{it-1}^\prime \beta)
\]

Table 2 shows marginal effects for probit regressions of Equation (3). We find that lagged Z-scores and NPAs explain bank failures by roughly 40%. In line with previous results, NPA shows the highest explanatory power. In comparison, LLP and LLR only explain roughly 12% and 16% of the variation in

\[\text{Hasan and Wall (2004)}\] also find that NPA is a good proxy for LLR.
4. Conclusion

We investigate four proxies for bank risk that are frequently used in the literature. Our analysis shows that non-performing assets are a good proxy for bank risk for two reasons. First, non-performing assets nest the alternative proxies as shown by the high share of variation in non-performing assets explained by the Z-score, loan loss reserves and loan loss provisions. Second, non-performing assets are well-suited to explain bank failures one year ahead. The latter point also holds for the Z-score whereby the information content of the Z-score seems to differ from the other variables. We conclude that non-performing assets are a well-suited complement to the Z-score, which may come with calculation issues regarding the volatility of profitability, in studies of bank risk.
References


