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Finding the Bad Apples in the Barrel: Using the Market Value of Equity to Signal Banking Sector Vulnerabilities

by Will Kerry

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Finding the Bad Apples in the Barrel: Using the Market Value of Equity to Signal Banking Sector Vulnerabilities

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Abstract

This paper measures the performance of different metrics in assessing banking system vulnerabilities. It finds that metrics based on equity market valuations of bank capital are better than regulatory capital ratios, and other metrics, in spotting banks that failed (bad apples). This paper proposes that these market-based ratios could be used as a surveillance tool to assess vulnerabilities in the banking sector. While the measures may provide a somewhat fuzzy signal, it is better to have a strategy for identifying bad apples, even if sometimes the apples turn out to be fine, than not being able to spot any bad apples before the barrel has been spoiled.

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I. What Is the Best Way to Find Bad Apples?

There is a saying that "*one bad apple spoils the barrel*". The idea is, of course, that if there is one rotten piece of fruit, infested with mold, this could contaminate other apples and spread the decay through the entire barrel. This analogy is often used to describe the impact that one person's wayward behavior can have on others. But this idiom could also be applied to banks operating within an interconnected system. In a crisis, a failure of one bank can spillover to other banks. For example, the demise of one bank could cause wholesale or retail customers in other banks to quickly withdraw their deposits to avoid losing their money. This bank run could lead to the failure of a second bank, increasing depositor anxiety, inducing a further round of cash withdrawals, more bank failures, and so on. This paper looks for ways in which to spot problems in the banking sector before the rot starts spreading through the system.

In the period prior to the global financial crisis, one way of trying to identify problem banks was to look at regulatory ratios, such as the Tier 1 capital ratio. This represents one metric in the "C" or capital adequacy part of the CAMELS assessments that had been used by supervisors to assess individual banks, as discussed in Lopez (1999).[1] However, the experience in the crisis was that these ratios did not provide a useful signal of future bank distress. Supervision has since evolved to incorporate a more holistic assessment of banks. Nevertheless, there is still a need for regulatory capital ratios as a fundamental part of broader banking supervision, in ensuring that banks have a minimum level of capital relative to the size or riskiness of their balance sheet. The necessity of regulatory ratios is not in question. However, there is a question about the effectiveness of these regulatory ratios in flagging failing banks.

This paper was inspired by Haldane (2011) which suggests that equity market-based metrics of bank solvency could be used as a signal of problems at banks. Haldane finds that while Tier 1 capital ratios are no better than a coin toss at predicting the failure of banks, market-based capital ratios offer clear advance signals of impending bank distress well over a year ahead of the global financial crisis. This point is reiterated in Haldane (2012) which suggests that the explanatory power of a market-based capital ratio is about 10 times greater than the more complicated risk-weighted regulatory Tier 1 capital ratio.

Bulow and Klemperer (2015) state, rather more directly, that "it is now well understood that regulatory capital measures are only loosely related to solvency" as the major banks that required bailouts in the global financial crisis reported that they were well capitalized until the bitter end. For example, Bulow and Klemperer (2013) reports that RBS had the second

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[1] The CAMELS acronym stands for the different aspects of banks that are typically assessed by supervisors: (1) Capital adequacy; (2) Asset quality; (3) Management; (4) Earnings; (5) Liquidity; and (6) Sensitivity to market risk.

highest total capital ratio of the five large UK banks and the highest Tier 1 ratio, just four months before its bailout, and Bankia had a 9.9 percent core Tier 1 ratio until May 2012, when it had a bailout. A similar tack is taken by Calomiris and Herring (2011), who conclude that the market value of equity can signal problems at banks in advance of their eventual failure.

The use of equity market-based ratios draws on a seam of earlier work on the use of market signals in bank supervision. For example, Flannery (1998) proposed that oversight of banks could be improved if supervisors systematically incorporated more market information into their analysis. Gunther *et al* (2001) find that a measure of viability based on stock prices helps predict the financial condition of individual banks, beyond the information provided by past bank inspections and quarterly financial statements. Krainer and Lopez (2004) conclude that equity market indicators should be incorporated into off-site supervisory monitoring. Similarly, Curry *et al* (2004) deduce that equity market variables add important information to the identification of failed institutions beyond that contained in quarterly accounting data. Cannata and Quagliariello (2005) also find that equity markets may represent a valuable tool for acquiring data on the risk profile of banks, before supervisory statistics become available, and that this might enrich the assessment of financial stability. More recently, Friend and Levonian (2013) demonstrate that signals of bank condition based on equity prices are somewhat more accurate in predicting bank failures than regulatory ratios and are able to identify failing banks much farther in advance of failure.

There are also a number of papers that use market-based metrics to assess bank health from a surveillance standpoint, rather than as part of bank supervision. Such studies include Acharya, Engle and Richardson (2012)—who calculate the capital shortfall that banks would face in the event of a crisis—Brownlees and Engle (2017)—which presents a conditional capital shortfall estimate as a systemic risk measure—and Sarin and Summers (2016)—who find that financial market information provides little support for the view that major banks are significantly safer than they were before the crisis.

A. Regulatory and Market-Based Capital Ratios

One question that could be asked at this juncture is why are regulatory ratios so poor at predicting bank failure? One obvious answer is that regulatory ratios are only published on a quarterly basis, at best, and with a lag. This means that the information they provide is already stale when it is published. Market prices, however, are forward-looking and so should incorporate expectations about the future value of bank capital.

A second answer is that accounting rules are behind some of the wedge between book and book valuations of equity. For example, the valuation of some assets on bank balance sheets at cash values, the use of model-based valuations for opaque and illiquid (so called Level 3) assets, and the treatment of certain off-balance sheet exposures in some regulatory ratios may contribute to the underperformance of regulatory ratios.

Furthermore, banks may use accounting rules to flatter their balance sheets. Calomiris and Herring (2011) suggest that banks use regulatory and accounting arbitrage to delay recognition of losses. The assert that such behavior makes it unlikely that supervisors (and supervisory ratios) can keep-up with the actual state of bank balance sheets. Similarly, Huizinga and Laeven (2009) showed that banks use accounting discretion to overstate the value of distressed assets to the extent that balance sheets offer a distorted view of bank financial health. Furthermore, Bulow and Klemperer (2015) suggest that banks may be window dressing their reported accounts and that the reported book value of equity can be subject to manipulation.

Adrian, Boyarchenko and Shin (2016) find—in a similar vein—that banks actively smooth their book equity by adjusting the payouts that they give to shareholders. Market leverage, however, largely reflects movements in the valuation of bank (tangible and intangible) assets. This leads to the conclusion that book leverage is procyclical—it is high during booms when assets are large—but that market leverage is countercyclical, as also recorded in Adrian and Shin (2010).

Haldane (2012) suggests that complexity may be an additional dimension, arguing that “less may be more” when assessing bank solvency. The Tier 1 ratio uses risk-weighted assets in its denominator, and this is the result of “several million” calculations in a large, complex bank. Haldane suggests that this complexity increases opacity and places reliance on a large number of estimated parameters. Ultimately, complex risk-weighting may be a sub-optimal way of assessing bank health if the financial environment is uncertain. Simpler capital ratios, such as the leverage ratio, as suggested better metrics for assessing bank solvency.

This finding follows Estrella, Park and Persitiani (2000) which concludes that more simple ratios—such as the leverage ratio and the ratio of capital to gross revenue—are just as good at predicting bank failure as the risk-weighted Tier 1 capital ratio. Bulow and Klemperer (2015) also assert that there is tremendous discretion in the calculation of risk-weighted assets (the denominator in Tier 1 ratios) and this can affect the accuracy of regulatory ratios. In fact, a study by the Basel Committee on Banking Supervision (2013) found that differences in the risk weight assigned to the same hypothetical portfolio by a sample of 32 banks translates into a variation in the capital ratio across those banks of almost 4 percentage points (a 2 percentage point variation in either direction).

Of course, there are three pillars to the Basel approach to banking supervision, and regulatory ratios are only part of the first of these pillars. The second pillar is supervisory review and the third is market discipline. This last pillar has been implemented through a set of disclosure requirements that aim at enabling market participants to determine their own view of the capital adequacy of a bank. In this sense, market-based measures rely on the third pillar of the Basel framework and so work in tandem with banking regulation. They should not be considered a substitute for regulation.

Finally, market valuations of banks may include other valuable information that is not captured by regulatory ratios. Market prices may incorporate investor views about contagion risks between banks, particularly in periods of stress, and this may help them signal bank failures. In addition, there could be some endogeneity in market valuations that improve their predictive power. For example, if investors lose confidence about the solvency of a bank, the market valuation of the banks is likely to fall precipitously. At the same time, investors with deposits in the same bank might withdraw this cash. In an extreme case, this could trigger a bank run, and the eventual failure of the bank. The market valuation would have provided a good signal of a bank failure as it would have reflected the underlying loss of confidence in the solvency of the institution.

B. Using Equity Prices to Signal Distress

A second important question to ask, is why use the equity market to help signal banking distress, rather than other alternatives, such as subordinated bonds or credit default swaps? One argument in the literature is that equity markets are more liquid and though to be more efficient at processing information than many other markets (Calomiris and Herring, 2011). A second reason is that investors may view large banks as be too-big-to-fail and this could affect signals in bond and credit default swap markets more than equity markets (Krainer and Lopez, 2004). This paper tests whether credit default swap spreads perform as well as equity market measures, albeit with the caveat that credit default swap spreads are available for fewer banks than equity prices.

Using equity market indicators can also lead to the concern that prices can be driven by bank profitability, or more precisely investor expectations about discounted future dividends and cash flows, rather than the probability of bank failure. However, Vickers (2018) reminds us that a bank's obligations to depositors and bondholders are met by bank cash flows. This means that weak bank profitability is a problem, whatever the cause, and that low market valuations for banks are a real concern. Low profits also prevent banks from building the book value of their equity organically through retained earnings, and might encourage banks to take on more risks to boost earnings, as discussed in Das *et al* (2019). A low price-to-book ratio is also likely to make it more difficult for banks to raise equity in markets to bolster balance sheets (IMF, 2018).

Furthermore, Vickers (2019) argues that the market capitalization of a bank (the price-to-book ratio is of course the ratio of this measure to the book value of equity) reflects a view of the value of current assets less liabilities, *plus* the franchise value of future profits (in excess of the cost of capital) *plus* the option value arising from shareholders' limited liability and any implicit subsidy. The first of these items suggests that equity market valuations of banks will reflect information about the health of bank balance sheets (in addition to profitability).

This theoretical approach is corroborated by empirical work undertaken by Calomiris and Nissim (2012) which finds that stock market declines for banks since 2007 reflect falling values of lending and deposit taking activities, associated with changes in interest rate levels and their term structure. They also find that the effect of leverage on bank valuation changed sign during the crisis. The market had rewarded high leverage with higher market values prior to the crisis, but leverage then became associated with lower values during and after the crisis. Further work by Bogdanova *et al* (2018) and Grodzicki *et al* (2019) finds that, in addition to profitability, non-performing loans—a measure of poor assets on bank balance sheets—are an important driver of price-to-book ratios.

Another possible issue with using equity market valuations of banks is that they can be affected by the ebb and flow of investor sentiment. In other words, market-based metrics are affected by a time varying price of risk. Bank valuations could fall, along with other sectors in stock market indices, as investor sentiment deteriorates. So declines in valuations may, at first sight, appear to be driven by factors outside of the banking sector.

While future research could usefully look to see whether market-based metrics could be adjusted for the price of risk, it is also important to note that the factors driving investor sentiment are likely to also be relevant for banking sector health. For example, if sentiment is low because there are concerns about the state of the economy, then this will be relevant for banks as an economic slowdown can lead to a worsening in the quality of their assets and losses on their loans. If investor sentiment sours due to a sudden or unexpected increase in the risk-free rate, this is relevant for banks as their funding costs will likely rise. Banks may then pass on these costs to their customers through higher interest rates on their loans. Over time, this could increase debt service problems for some borrowers and—again—lead to a deterioration in asset quality, a rise in non-performing loans, and higher loan losses. Finally, a sudden worsening in investor sentiment, for any other reason, is also relevant for banks through their direct exposure to markets via their trading portfolios. The consequent fall in asset prices would engender mark-to-market losses for banks.

C. A Proposal

This paper uses a series of different regulatory, balance sheet and market-based measures to assess which metrics might be best suited to spotting problem banks (bad apples). The idea is to look at this issue from the point of view of someone tasked with assessing financial stability risks, rather than from the point of view of a banking supervisor. Although the analysis is based on individual banks, the focus is on identifying situations where there are either lots of problem banks or problems at a large bank—in other words identifying vulnerabilities in the banking system as a whole.

The approach is to test and calibrate the different metrics using the banks that failed (and survived) the global financial crisis (Section II). The out of sample performance of these metrics is then assessed (Section III) using the banks that have since run into trouble (as well as those that have continued operating). The paper also shows how the metrics can be implemented in practice and what they suggest about the risk of bank failures in the current environment (Section IV). Section V concludes.

Table 1. Sample of Banks

Region	Number of banks	of which: Failed in the GFC	of which: Failed since the GFC
Euro area (Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain)	50	4	15
Other advanced Europe (Denmark, Norway, Sweden, Switzerland, United Kingdom)	26	5	0
Advanced Asia-Pacific (Australia, Japan, Korea, Singapore)	44	0	0
North America (Canada, United States)	54	7	0
Emerging market economies (Brazil, China, India, Mexico, Poland, Russia, South Africa, Turkey)	55	0	0
Total sample	229	16	15

Source: Author.

II. Searching for Bad Apples: The Past

A. Suggested Metrics

The analysis is based on a sample of more than 220 banks that are—or have been—traded on equity markets (Table 1). The sample includes many of the largest banks in the countries included in the study. Out of this sample, there are relatively few banks that either failed in the 2008–09 global financial crisis or subsequently (2011–17).

While this means that we have few problem banks to condition the methodology on, it also reflects the reality that any metric will need to be able to effectively discern distressed banks from the large number of healthy ones. The definition of failure used for the sample banks includes a bankruptcy, a government bail-out or nationalization, or a government-backed merger of an ailing institution with a stronger partner.

The sample includes banks from advanced economies and large emerging market economies. Although there were no failures among the emerging market banks in the sample in the period studied, these banks were included so that the results of the study could be used to identify vulnerabilities in banking systems globally (and not just in advanced economies). The emerging market banks also act in a similar way to a control group in the study—if any of the metrics consistently flag problems in emerging market banks that did not fail, then they may not be reliable.

A number of different metrics are tested against their potential to predict the failure of bank (Table 2). The first is the regulatory Tier 1 ratio, given the bad press that it has received in the literature, discussed above. The second is the simpler leverage ratio, favored in Haldane (2012).

Table 2. Proposed Metrics

1. Tier 1 capital ratio	Tier 1 capital / risk-weighted assets
2. Leverage ratio	Tangible common equity / adjusted tangible assets
3. Loan-to-deposit ratio	Loans / customer deposits
4. Asset growth	Annual growth in adjusted tangible assets
5. Market capitalization ratio	Market capitalization / adjusted tangible assets
6. Market-adjusted capital ratio	*min*{Price-to-book ratio,1}*tangible common equity / adjusted tangible assets
7. Implied volatility	At the money call implied volatility
8. Credit default swap spreads	Five-year senior credit default swap spread

Note: Tangible assets are adjusted for derivatives netting at US banks.

The next two measures are additional balance sheet metrics. The first is the deposit-to-loan ratio, which is a structural indicator of a bank's funding profile. It can be thought of as a less sophisticated net stable funding ratio (NSFR), used as we do not have historical (or even current in some cases) NSFR data to use. The idea is that if deposits are a lower proportion of loans, then more wholesale funding is used. If this wholesale funding is short-term, then it can open the bank up to greater funding risks. If the wholesale funding is longer-term, this is more stable, but can also create rollover risk if a significant amount of funding matures at the same time.

The second balance sheet measure is asset growth, or more specifically a sharp deleveraging—or cut back in assets—following a period of fast expansion in assets. The idea here is that a bank which is expanding its assets much faster than usual could be taking on more risks. If this is being done by increasing lending, then a bank may have lent to more risky borrowers than it has done in the past. It may also have had less time to check the credit quality of those it is lending to. Similarly, a large expansion of a trading book or bond portfolio could result in a bank moving into markets that the bank is less familiar with and so it may not be able to assess the risks as well as in its more traditional habitat. But as a bank gets into trouble, through its riskier balance sheet, it is forced to deleverage by cutting back its assets sharply as capital is eroded or as bank managers seek to offload risk.

There are then two variants of equity market-based measures. The market capitalization ratio, proposed in Haldane (2011), and the market-adjusted capital ratio. The latter is effectively the same as the leverage ratio until a bank's price-to-book ratio falls below one, when the ratio then falls as the market value of the bank's equity declines. This measure attempts to avoid overvaluing banks' capital during an equity boom, a problem that could affect the market capitalization ratio.

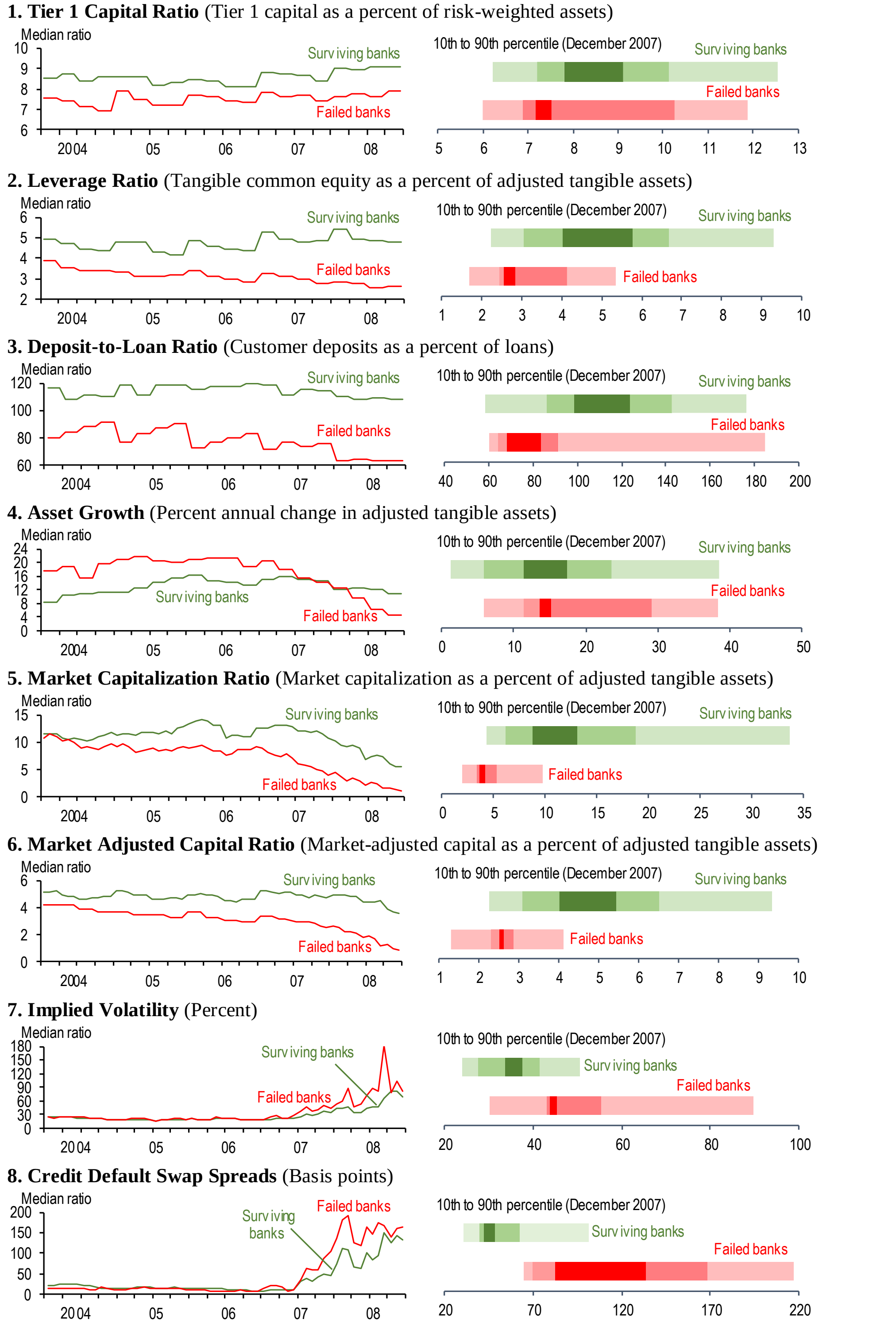
The analysis also includes bank implied volatility from equity options as an alternative equity market measure. Equity volatility is a key input into expected default frequency measures that are often based on a modified Merton model. Equity volatility is used instead of actual expected default frequencies as the former is more readily available from the data sources used here. In addition, as Munves *et al* (2010) explains, expected default frequencies were often low in advance of some bank failures during the global financial crisis, so it is better to use their value relative to other banks, rather than their face value.[2] As the methodology in this paper uses actual values against thresholds, rather than relative measures, this is another reason to favor equity volatility over expected default frequencies.

The final metric is bank credit default swap spreads. This is included to test whether measures based on other markets are useful in signaling problems at banks. Credit default swaps are contracts that compensate the buyer in the event that the reference entity (a bank in this case) defaults (or is subject to another credit event). The spread on a credit default swap is the amount a buyer must pay the seller in return for the protection against default. This means that the spread is a measure of the credit risk that is undertaken by investors in bonds issued by a bank and so, in theory, should provide a useful gauge to assess potential problem banks. Credit default swap spreads, however, are only available for a small number of banks in the sample (around 60), although this includes both failing and surviving banks.

The different metrics are plotted in Figure 1. On the left-hand side of the figure the median of the banks that failed during the crisis is shown, along with the median of the banks that survived. In most cases the median values evolved as expected. Average Tier 1 capital, leverage and deposit-to-loan ratios were lower for banks that failed. In the years in the lead-up to the global financial crisis, assets of failed banks grew at a fast pace on average, but then fell significantly as the crisis emerged and took hold. For the two market-based capital ratios, the median ratio of failed banks was not only lower than that for surviving banks, but also fell more quickly in the year before the crisis hit. While the difference in median implied volatility and credit default swap spread was almost indistinguishable for the two sets of

[2] Munves *et al* (2010) state that the expected default frequency for Lehman Brothers was 0.1 percent six months before the firm's default and 0.6 percent three months prior to the event. The paper notes that while the level of expected default was low, it was higher than some other banks at the time.

Figure 1. Proposed Metrics: Sample Medians and Distributions in the Pre-Crisis Period



Sources: Bloomberg Finance L.P.; and author calculations.

Note: In the right panels, the central band is the 40–60 percentile, and the other bands show the 10–90 percentile of the data. In panels 2, 4, 5, and 6 tangible assets are adjusted for derivatives netting at US banks. In panel 6, market adjusted capital is tangible common equity discounted by the price-to-book ratio, where the latter is below one.

banks in the years before the crisis, these diverged as the first strains emerged in 2007 and the median values for failed banks spiked higher than surviving banks.

These results are confirmed in Table 3, which shows the median values of surviving and failing banks in the months leading-up to the global financial crisis. This table also shows how different the medians of the two sub-samples are. There is a substantial difference for many of the metrics: in the case of leverage and deposit-to-loan ratios the difference is around 30–40 percent, for the market-based capital ratios it is about 40–60 percent, and for implied volatility and credit default swap spreads the difference in 2008 is 60 percent or more. There is, however, less difference between the medians of surviving and failing banks for Tier 1 capital ratios, and very little difference for asset growth until the second quarter of 2008.

Table 3. Median Value for the Proposed Metrics: Surviving and Failing Banks
(Percent)

	September 2007	December 2007	March 2008	June 2008
Tier 1 capital ratio				
Surviving bank	8.7	8.4	9.0	9.0
Failing bank	7.7	7.4	7.6	7.7
Difference (percent)	*-12*	*-11*	*-16*	*-14*
Leverage ratio				
Surviving bank	4.8	4.8	5.4	4.9
Failing bank	3.0	2.7	2.8	2.8
Difference (percent)	*-38*	*-44*	*-47*	*-44*
Deposit-to-loan ratio				
Surviving bank	115	114	110	108
Failing bank	74	76	63	64
Difference (percent)	*-36*	*-34*	*-42*	*-41*
Asset growth				
Surviving bank	15.1	14.6	12.1	12.5
Failing bank	15.5	14.3	12.5	9.6
Difference (percent)	*2*	*-2*	*3*	*-23*

	September 2007	December 2007	March 2008	June 2008
Market capitalization ratio				
Surviving bank	11.8	10.7	9.1	6.9
Failing bank	5.6	3.9	2.9	2.1
Difference (percent)	*-53*	*-63*	*-68*	*-69*
Market-adjusted capital ratio				
Surviving bank	4.7	4.8	4.9	4.4
Failing bank	3.0	2.5	2.2	1.8
Difference (percent)	*-38*	*-47*	*-55*	*-59*
Implied volatility				
Surviving bank	29	35	46	45
Failing bank	36	44	86	72
Difference (percent)	*26*	*26*	*86*	*60*
Credit default swap spread				
Surviving bank	30	45	107	101
Failing bank	59	105	192	162
Difference (percent)	*96*	*132*	*80*	*61*

Source: Author.

However, what is important here is not just the median value, but the whole distribution of the metrics for the sample of failed and surviving banks. The right-hand side of Figure 1 shows the 10^{th}–90^{th} percentiles of the two samples at December 2007 (time series of the distributions are shown in Figure 2). In many of the metrics, the distributions overlap for much of the sample, suggesting that it will be difficult to use them to identify banks that are at risk of failure. However, the market-based capital ratios and the market metrics (implied volatility and credit default swap spreads) appear to be more promising as there is less overlap between the two samples of banks.

B. Would These Metrics Have Helped Identify Problem Banks in the Pre-Crisis Period?

Having had a quick look at the data for the different metrics, a more formal assessment of their performance in signaling bank failures in the pre-crisis period (2001–2009) was conducted. The approach used was similar to Borio and Drehmann (2009) and calculates the true positive and false positive rates for the different metrics over a range of different thresholds. If a metric flagged a bank that failed at any time during the subsequent two years, this was designated as a true positive signal. The true positive rate (p) was calculated as the number of these correct signals (C) relative to the total number of failing banks (B) in the sample (this is equivalent to one minus type I errors—or one less the rate at which failing banks were missed).

$$p = \sum_{N}^{i=1} C_i \Big/ B$$

The false positive rate (f) was calculated as the number of flags issued incorrectly (I) —in other words when a signal was issued for a bank that did not fail in the following two years—relative to the total number of surviving banks in the sample (type II errors).

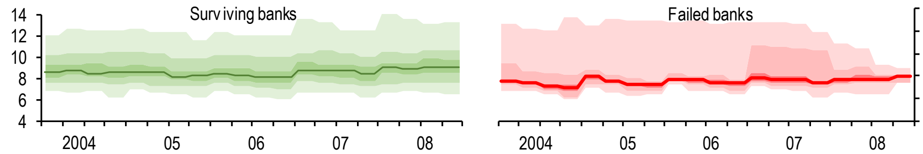
$$f = \sum_{N}^{i=1} I_i \Big/ (N - B)$$

The more formal assessment of the different metrics then follows Aldasoro *et al* (2018) and the early warning literature more generally. This uses receiver operator characteristic (ROC) curves to assess the performance of the different metrics in the pre-crisis period. These curves plot the true positive and false positive rates for a range of different thresholds of an indicator. Each point on the ROC curve shows the true and false positive rates for a particular threshold.

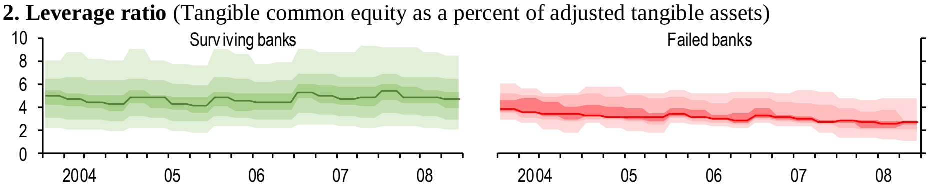
A very high threshold will lead to a high true positive rate as failing banks will fall below the threshold, but it will also have a high false positive rate as surviving banks will also come in underneath the threshold. The opposite will be true with a very low threshold, true positives will be low as only banks in the very worst shape will fall below the threshold, but the false positive rate will also be very low as surviving banks are unlikely to be captured by a low threshold. If the metric has no useful information content, then the relationship between false positives and true positives would represent a 45-degree line. A perfect metric would form a right-angled triangle with the 45-degree line, with the right angle at the top left corner of the chart (it would closely hug the y-axis until the true positive rate reached 1 and it would then follow a horizontal line until the false positive rate also reached 1).

Figure 2. Proposed Metrics: Time Series of Sample Distributions in the Pre-Crisis Period

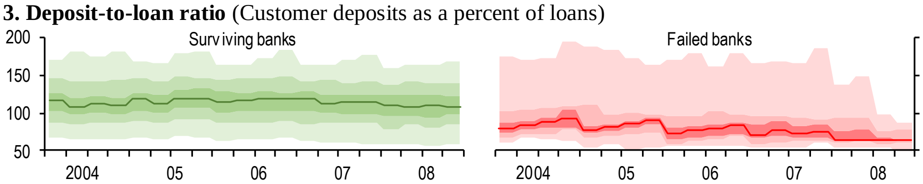
1. Tier 1 capital ratio (Tier 1 capital as a percent of risk-weighted assets)



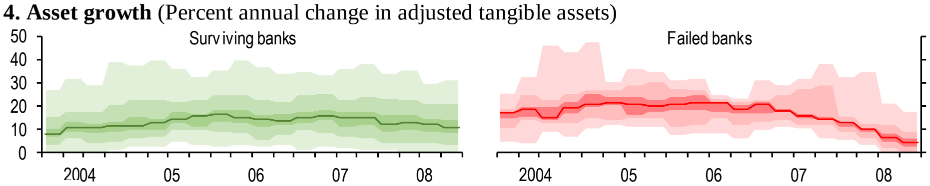
2. Leverage ratio (Tangible common equity as a percent of adjusted tangible assets)



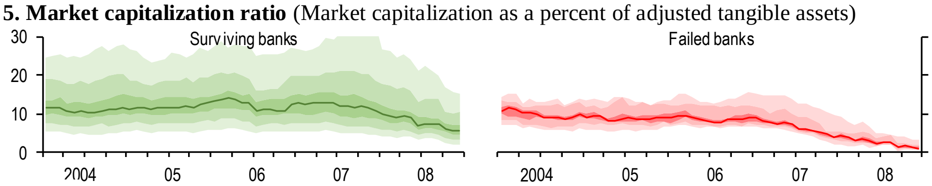
3. Deposit-to-loan ratio (Customer deposits as a percent of loans)



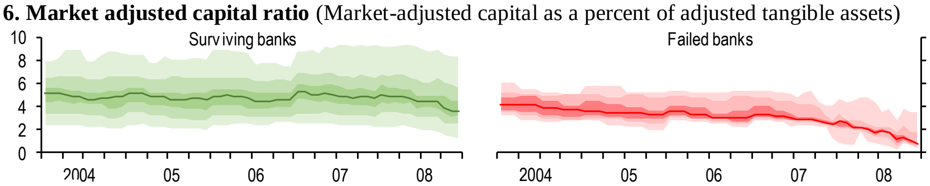
4. Asset growth (Percent annual change in adjusted tangible assets)



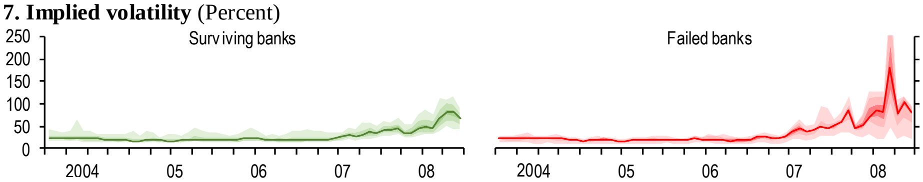
5. Market capitalization ratio (Market capitalization as a percent of adjusted tangible assets)



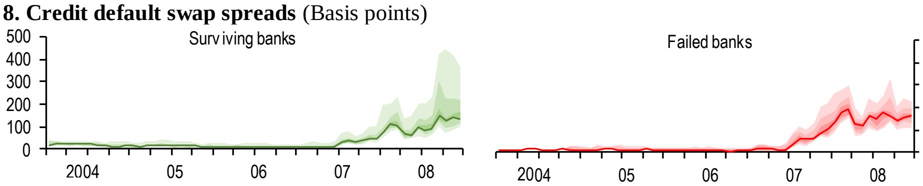
6. Market adjusted capital ratio (Market-adjusted capital as a percent of adjusted tangible assets)



7. Implied volatility (Percent)

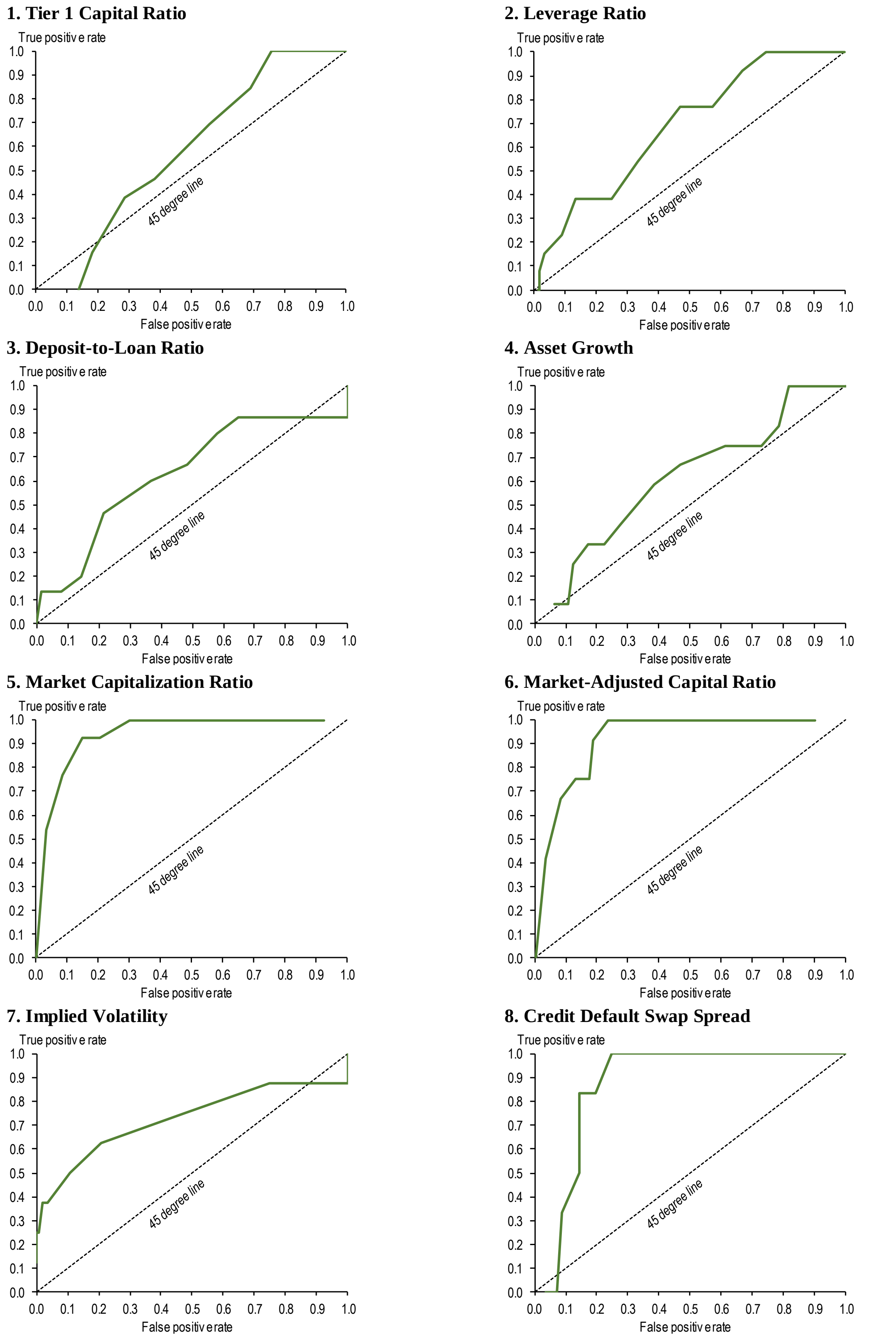


8. Credit default swap spreads (Basis points)



Sources: Bloomberg Finance L.P.; and author calculations.
Note: The line shows the median, the central band is the 40–60 percentile, and the other bands show the 10–90 percentile of the data. In panels 2, 4, 5, and 6 tangible assets are adjusted for derivatives netting at US banks. In panel 6, market adjusted capital is tangible common equity discounted by the price-to-book ratio, where the latter is below one.

Figure 3. Receiver Operator Curves for Different Metrics



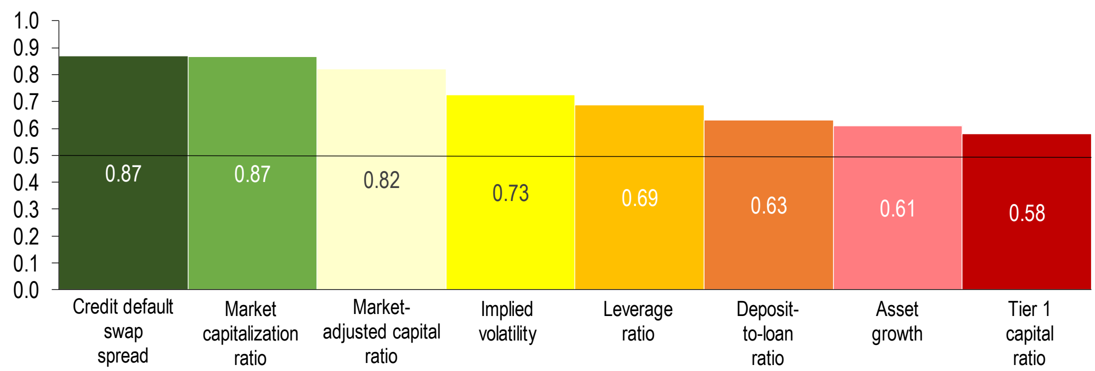
Source: Author.
Note: Each point on the line shows the true and false positive rate for a different threshold of the indicator.

A first look at the results suggest that the Tier 1 ratio performed poorly in providing a signal of bank failure in the period ahead of the global financial crisis, as the ROC curve is similar to the 45-degree line (Figure 3). The market-based capital ratios and market metrics, however, have the best ROC curves, closest to the perfect right-angled triangle. The balance sheet metrics are somewhere in between.

The ROC curves can be neatly summarized into a single statistic—which is the area under the curve. Clearly, the area under the 45-degree line would be 0.5, so for a metric to be informative it would have an area of between 0.5 and 1.0—where the higher the number the better the indicator at identifying bad apples from good.

Figure 4 shows the area under the ROC curves for the different metrics in the pre-crisis period. The Tier 1 capital ratio performs poorly on this measure as well, confirming the finding in Haldane (2011) that regulatory ratios are "no better than a coin toss" at predicting bank failure. Asset growth and the deposit-to-loan ratio do not perform much better, while the leverage ratio is the best performing balance sheet metric. At the other end of the scale, credit default swap spreads and the market-based capital ratios have the highest area under their ROC curves, following by implied volatility.

Figure 4. Area Under the Receiver Operator Curve for Different Metrics



Source: Author.

These results, however, only look at one metric at a time. Table 4 presents the area under the ROC curves for combinations of two different metrics. The true positive and false positive rates were calculated based on signals issued by either metric. If a failing bank was correctly flagged by either the first metric or the second metric, this would count towards the true positive rate, and *vice versa*.

The table shows that in many cases there are combinations of two metrics that improve the performance of the metric in isolation. For example, while the area under the curve of the Tier 1 capital ratio is only 0.58 when used alone, combining this with the market capitalization ratio raises the ROC statistic to 0.76. However, this is not always the case. Using a leverage ratio alone is better than combining it with a Tier 1 ratio. The Tier 1 ratio worsens the performance of the leverage ratio.

Table 4. Area under the Receiver Operator Curve for Different Combinations of Metrics

Metric used to predict bank failure	Tier 1 capital ratio	Leverage ratio	Deposit-to-loan ratio	Asset growth	Market capitalization ratio	Market-adjusted capital ratio	Implied volatility	Credit default swap spreads
Tier 1 capital ratio	0.58							
Leverage ratio	0.59	0.69						
Deposit-to-loan ratio	0.56	0.67	0.63					
Asset growth	0.52	0.61	0.65	0.61				
Market capitalization ratio	0.76	0.89	0.88	0.82	0.87			
Market- adjusted capital ratio	0.74	0.87	0.88	0.85	0.94	0.82		
Implied volatility	0.50	0.70	0.74	0.61	0.90	0.90	0.73	
Credit default swap spreads	0.34	0.65	0.64	0.46	0.83	0.81	0.88	0.87

Source: Author.

The best results come from combinations of metrics involving the market-based capital ratios—and the combination of the two market-based capital ratios together has the best performance of all. The other market metrics also perform well, particularly when partnered with each other or with the market-based capital ratios. The rest of this paper focuses on the most promising solo metrics or combination of metrics, those with an area under the ROC curve of 0.8 or more, as highlighted in Table 4 (in yellow if the ROC statistic is above 0.8, in light green if the ROC statistic is more than 0.85 and in dark green when it is more than 0.9). While 0.8 is a somewhat arbitrary threshold, it can be thought of as a performance that is better than the average between a random outcome (0.5) and perfect score (1)—in other words better than 0.75.

In order to operationalize the use of metrics, a threshold needs to be assigned to each of them. Here the methodology in Aldasoro *et al* (2018) is used again. The approach, which has again been used in the early warning literature more broadly, is to find the threshold (τ) that minimizes the noise-to-signal ratio (NSR). This ratio is defined as the false positive rate (f) over the (p) true positive rate. The minimization is undertaken subject to the threshold having at least a certain true positive rate. Aldasoro *et al* (2018) look to correctly identify at least two-thirds of banking crises. In this paper, where we are looking to signal stress at individual banks, and where we only have a few examples of stressed institutions, the bar will be set higher at a 90 percent true positive rate.

Table 5. Thresholds and Associated Performance Statistics for Different Metrics

Metrics used to predict bank failure: in sample testing (2001-09)

Metric #1	Market capitalization ratio						
Metric #2	-	Leverage ratio	Deposit-to-loan ratio	Asset growth	Market adjusted capital ratio	Implied volaitility	Credit default swap spread
Thresholds							
Metric #1	1.5	1.5	2.0	1.5	1.5	0.5	0.5
Metric #2	-	1.0	50	-18	1.0	100	450
Diagnostics							
False positive rate (Type II error)	0.15	0.20	0.30	0.22	0.20	0.50	0.25
True positive rate (1 - Type I error)	0.92	0.92	0.93	1.00	1.00	1.00	1.00
Noise-to-signal ratio	0.16	0.21	0.32	0.22	0.20	0.50	0.25

Metric #1	Market adjusted capital ratio					
Metric #2	-	Leverage ratio	Deposit-to-loan ratio	Asset growth	Implied volaitility	Credit default swap spread
Thresholds						
Metric #1	1.25	1.25	1.25	1.25	0.50	0.25
Metric #2	-	1.5	50	-20	100	350
Diagnostics						
False positive rate (Type II error)	0.19	0.23	0.30	0.18	0.51	0.30
True positive rate (1 - Type I error)	0.92	0.92	0.92	0.92	1.00	1.00
Noise-to-signal ratio	0.21	0.25	0.33	0.20	0.51	0.30

Metric #1	Credit default swap spread	
Metric #2	-	Implied volatility
Thresholds		
Metric #1	350	500
Metric #2	-	100
Diagnostics		
False positive rate (Type II error)	0.25	0.96
True positive rate (1 - Type I error)	1.00	1.00
Noise-to-signal ratio	0.25	0.96

Source: Author.

$$min\left\{NSR^{\tau} = \frac{f^{\tau}}{p^{\tau}}\right\} \; s.t. \;\; p \geq 0.9$$

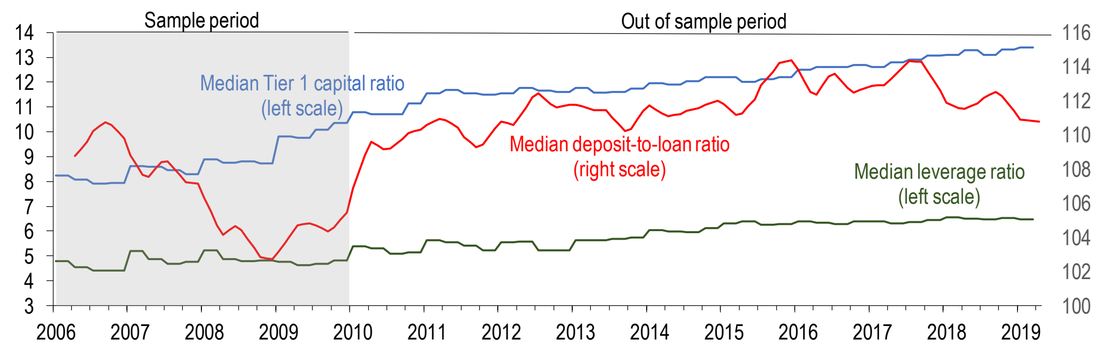
The results of this method are shown in Table 5. This reveals that—based on the noise-to-signal ratio—the performance of the two market-based capital ratios is similar when used in combination with other metrics. The cleanest signal in the pre-crisis period comes from using the market capitalization ratio alone. The noisiest signal comes from using credit default swap spreads in combination with implied volatility. In fact, other combinations of implied volatility also performed relatively poorly in the run-up to the crisis.

III. SEARCHING FOR BAD APPLES, REPRISE

Having established a set of metrics and thresholds using the pre-crisis period, it is interesting to see how well the same metrics would have performed out of sample in the years since the global financial crisis (i.e., 2010–2017). This is particularly the case given that the crisis represents somewhat of a structural break for the banking system and for bank leverage, as documented in Adrian, Boyarchenko and Shin (2016), Calomiris and Nissim (2012), and Sarin and Summers (2016).

First, substantial reforms have taken place. These have led to banks having stronger capital ratios, more liquid assets, and a greater use of deposits rather than short-term wholesale funding (Figure 5). In addition, more emphasis has been placed on the bail-in of creditors rather than the bail-out of banks and this may have affected market prices for banks. Second, the out of sample period includes the euro area crisis, which was different in nature (though arguable linked to) the global financial crisis, with more emphasis on the complex interactions between sovereign and banking vulnerabilities.

Figure 5. Bank Metrics in the Pre- and Post-Crisis Period



Sources: Bloomberg Finance L.P.; and author calculations.
Note: Months in which a bank in the sample failed is shaded in grey.

However, the structural break means that it is all the more important to assess the performance of the metrics in the out of sample period to test whether they could be useful in identifying vulnerabilities in the banking system in the future.

Table 6. Out of Sample Metric Statistics

Metrics used to predict bank failure: out of sample testing (2010-17)

Metric #1	Market capitalization ratio						
Metric #2	-	Leverage ratio	Deposit-to-loan ratio	Asset growth	Market adjusted capital ratio	Implied volaitility	Credit default swap spread
Thresholds							
Metric #1	1.5	1.5	2.0	1.5	1.5	0.5	0.5
Metric #2	-	1.0	50	-18	1.0	100	450
Diagnostics							
False positive rate (Type II error)	0.19	0.20	0.37	0.25	0.20	0.15	0.25
True positive rate (1 - Type I error)	1.00	1.00	1.00	1.00	1.00	0.82	0.83
Noise-to-signal ratio	0.19	0.20	0.37	0.25	0.20	0.30	0.30

Metric #1	Market adjusted capital ratio					
Metric #2	-	Leverage ratio	Deposit-to-loan ratio	Asset growth	Implied volaitility	Credit default swap spread
Thresholds						
Metric #1	1.25	1.25	1.25	1.25	0.50	0.25
Metric #2	-	1.5	50	-20	100	350
Diagnostics						
False positive rate (Type II error)	0.18	0.19	0.27	0.22	0.18	0.33
True positive rate (1 - Type I error)	1.00	1.00	1.00	1.00	1.00	1.00
Noise-to-signal ratio	0.18	0.19	0.27	0.22	0.18	0.33

Metric #1	Credit default swap spread	
Metric #2	-	Implied volatility
Thresholds		
Metric #1	350	500
Metric #2	-	100
Diagnostics		
False positive rate (Type II error)	0.62	0.33
True positive rate (1 - Type I error)	1.00	1.00
Noise-to-signal ratio	0.62	0.33

Source: Author.

In order to test the metrics in the out of sample period, the same method of identifying false and true positives, described above, was used. The same metrics, or combination of metrics, that were identified in Table 5, along with their associated thresholds, were used for this out of sample exercise. A new set of true and false positive rates, as well as noise-to-signal ratios, were calculated for the out of sample period.

The results are shown in Table 6, which suggests that—as before—the market-based capital ratios performed well. The market-adjusted capital ratio has the lowest noise-to-signal ratio in the out of sample period, either when used alone or in combination with implied volatility or the leverage ratio (the lowest noise-to-signal ratios are shaded in Table 6, with deeper shades denoting lower ratios). However, using the market capitalization alone has a similar noise-to-signal ratio, and the results of the two market-based capital ratios are similar when used with other metrics. Interestingly, these two ratios performed just as well—or better—when used alone than in combination with other metrics (including themselves). Credit default swap spreads, however, performed relatively poorly in the out of sample test.

While there are clearly type II errors associated with using the market-based capital ratios to signal bank failures, these are not necessarily out of line with errors in the early warning literature. For example, Aldasoro *et al* (2018) and Borio and Drehmann (2009) report type II errors in the range of 5-15 percent. While these rates are lower than those found in this paper (about 20-25 percent for the better performing metrics), they were based on an early warning of banking crises—or stress across whole banking systems—rather than spotting problems in individual banks, where one could expect that false positive signals would be more likely.

IV. SEARCHING FOR BAD APPLES: THE PRESENT

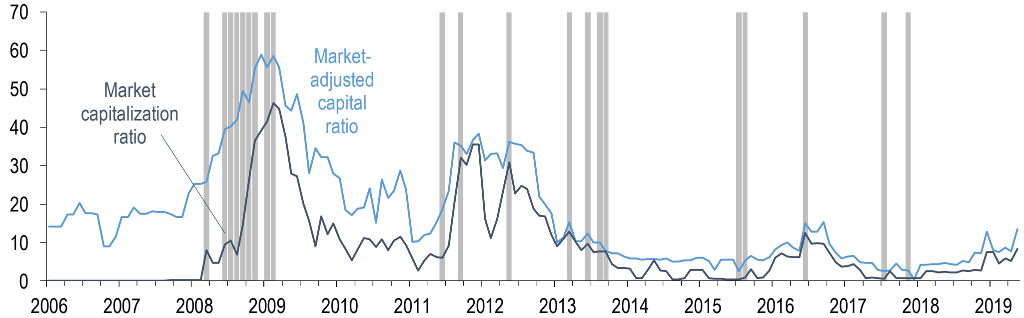
Taking the results of the in- and out-of-sample tests together, three main conclusions can be drawn. First, the two market-based capital ratios performed the best. Second, there is little difference in the performance of these two ratios. Third, little seems to be gained in terms of accuracy in combining these metrics with other indicators. The rest of this paper, therefore, focuses on the two market-based capital ratios, using the thresholds identified in Table 5 (1.5 percent for the market capitalization ratio and 1.25 percent for the market-adjusted capital ratio).

In order to assess how using these two metrics could have been used in practice to identify vulnerabilities in the banking sector, market capitalization and market-adjusted capital ratios were calculated for banks in the sample at a monthly frequency from 2006 onwards. In each month the current equity market valuation was used, along with the latest balance sheet information (i.e. adjusted tangible assets and tangible common equity) available at the time. A signal was then issued when a bank's market capitalization or market-adjusted capital ratio fell below the thresholds identified above.

The results for the sample as a whole are shown in Figure 6. As would be expected from the analysis above, signals were issued ahead of the crisis—from 2007 (for the market-adjusted capital ratio) and increasingly from early 2008 (for both market-based ratios). At least in the pre-crisis period, the market-adjusted capital ratio appears to provide a slightly earlier signal, though the two metrics are highly correlated. Looking at subsequent periods, signals of potential bank distress did rise ahead of the defaults in the wake of the euro area crisis. However, the advance warning provided by the signals varied significantly.

Figure 6. Banking Sector Distress Signals, Over Time

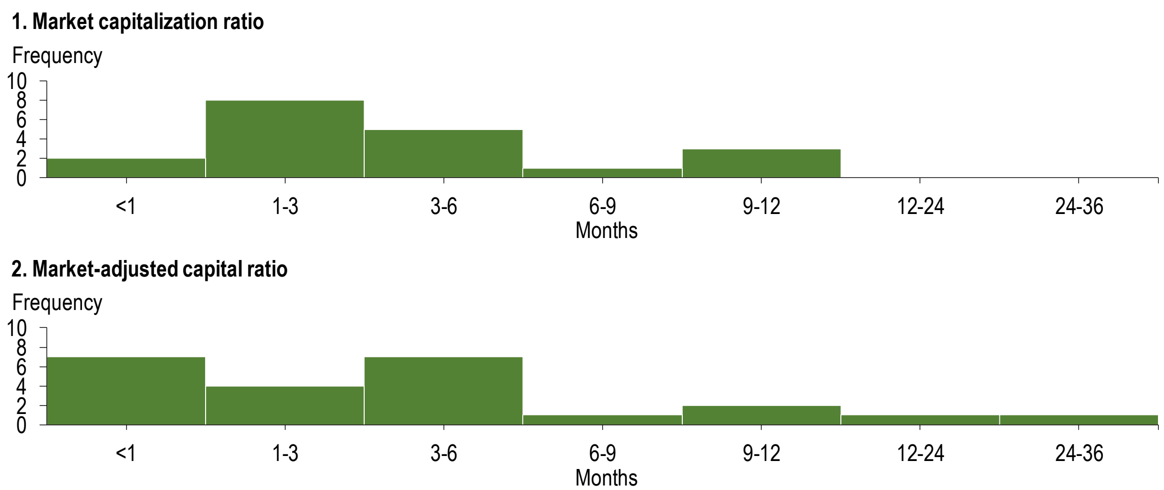
(Percent of banking assets)



Sources: Bloomberg Finance L.P.; and author calculations.
Note: Months in which a bank in the sample failed are shaded in grey.

Figure 7 calculates these advance warnings more formally on a bank-by-bank basis, using both the banks that failed in the global financial crises and those that succumbed subsequently. The distribution of advance warnings is similar for the two market-based capital ratios, ranging from less than 1 month up to 3 years. However, there are only a few cases where a signal was provided with a long time horizon and so the average advance warning provided by the two metrics was around 4 months, with the bulk of observations at a 6 month horizon or below.

Figure 7. Advance Warning Given by the Metrics



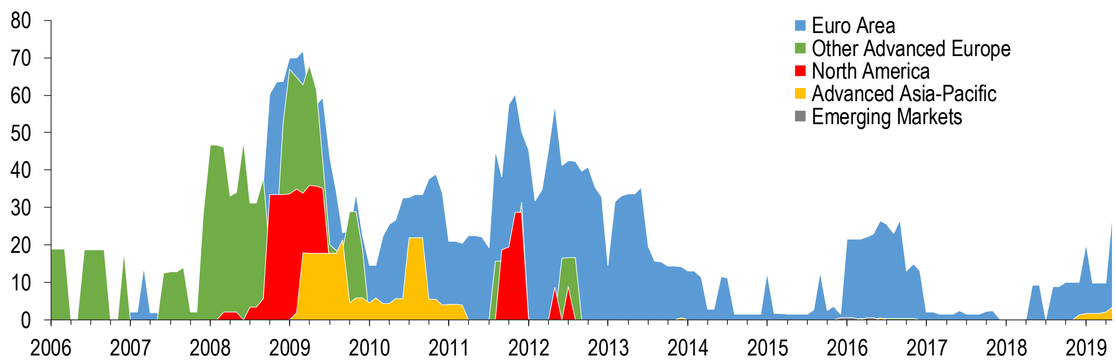
Sources: Author calculations.

As these warnings came with months rather than years of notice, and in some cases only weeks, they would have not provided enough time to alter macroprudential policy settings or comprehensively plan for a crisis. But the signals would have been issued with adequate time for authorities to register the increasing risks in the banking system and so they would have been a useful surveillance tool for assessing bank vulnerabilities.

An alternative presentation of the results is shown in Figure 8. This breaks down the signals by the region in which each bank is headquartered. The chart shows that banking sector vulnerabilities were initially centered on the North Atlantic region of North America and Europe (as discussed in Bayoumi, 2017 and Tooze, 2018) however this subsequently spilled over to Asia-Pacific banks. The chart also illustrates the morphing of the crisis to the euro area. It also suggests that problems in the euro area banking system have not been fully resolved. The metrics imply that there are still lingering concerns about the health of euro area banks many years after the onset of the global and euro area crises.

Figure 8. Banking Sector Distress Signals, by Region

(Percent of banking assets, based on the market-adjusted capital ratio)



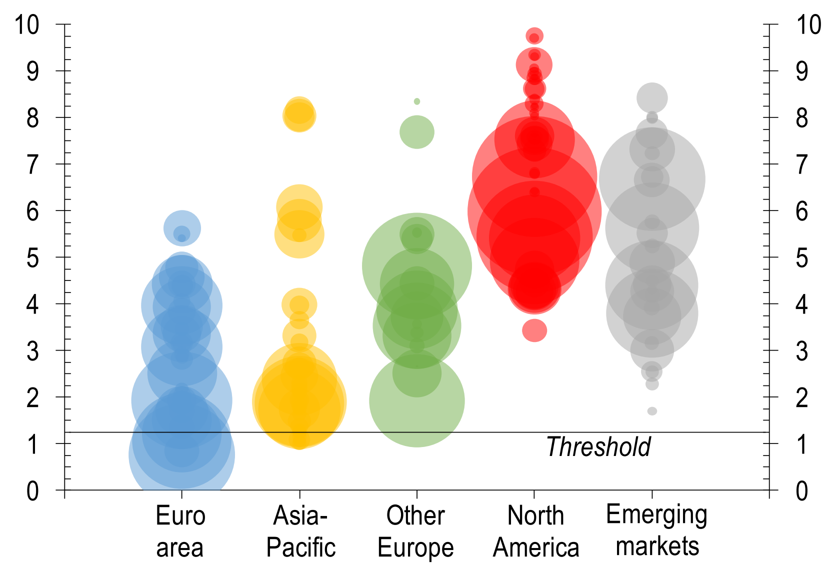
Sources: Bloomberg Finance L.P.; and author calculations.

However, Figure 8 also appears to suggest that the metrics overshot in periods of stress. For example, during the global financial crisis, a straight reading of the signals would suggest that there could be failures in around half of the sample (by assets). Thankfully, actual defaults in the financial crisis were not that severe. There is a similar pattern in the euro area crisis. While at first sight this seems to suggest that the metrics are likely to issue false alarms in periods of stress, one should also remember that huge amount of support that was provided to the banking system in these crises. Banks were recapitalized or nationalized, central banks provided liquidity support on a massive scale, and guarantees were provided to banks. This means that it is hard to assess the counterfactual scale of these crises if the support had not been provided. Indeed, Bernanke is on the record as saying that by September 2008, twelve of the thirteen most important financial institutions in the United Sates "had either failed or were at risk of failure" (United States Court of Federal Claims, 2015).

Nevertheless, the signals provided by the metrics are inevitably somewhat fuzzy and issued with different lead times. This means that the signals should be interpreted as an indicator of vulnerabilities in banking systems, rather than a foolproof predictor of individual bank failures *per se*. While this likely rules out the use of these metrics for some purposes, the metrics should still be useful in surveillance and systemic risk assessments where erring on the side of caution may be preferable to minimizing false alarms.

Finally, the results can also be shown for individual banks using the latest data available at the time of writing (May 2019). Figure 9 shows the market-adjusted capital ratios for individual banks, again organized by the region in which they are headquartered, with the size of the circles in the chart proportional to the size of the bank's assets. As discussed above, this suggests there are still vulnerabilities in euro area banks, including some large institutions. There are also some banks from the Asia-Pacific and Other Europe regions that are close to or have breached the thresholds identified in this study. The larger banks from North America and Emerging Market countries are further from the threshold. These results are qualitatively similar to the findings in Sarin and Summers (2016).

Figure 9. Market-Adjusted Capital Ratios, May 2019
(Percent)



Sources: Bloomberg Finance L.P.; and author calculations.
Note: The size of the circles is proportional to each bank's adjusted tangible assets in US dollars.

V. What Have We Learnt from the Search?

This paper has confirmed results in previous studies which suggest that equity market-based capital ratios would have been better at signaling bank distress in the run-up to the global financial crisis than regulatory capital ratios—particularly the Tier 1 capital ratio. In addition, it tests the market-based capital ratios against other market and balance sheet indicators and finds that the market-based capital ratios would have been better at predicting bank stress than these other metrics in the pre-crisis period.

The analysis goes on to show that the market-based capital ratios also performed well in the post-crisis period (i.e., out of sample). This further supports the case for using these augmented capital ratios in assessing vulnerabilities in the banking sector.

These equity market-based capital ratios suggest there are still vulnerabilities in euro area banks today, some years after the end of the euro area crisis. But there are also some banks in the Asia-Pacific and Other Europe regions that are flagged by these metrics.

These measures inevitably provide a somewhat fuzzy signal, where one can expect false alarms and perhaps overshooting in its predictions in periods of market turbulence. They also do not provide a sense of exactly when problems might arise in banks and may only provide a few months' or even weeks of advance warning of distress. They are also, obviously, only available for banks that are traded on stock markets. But these metrics are a valuable surveillance tool for financial stability authorities assessing vulnerabilities in the banking sector. It is better to have a strategy for identifying bad apples, even if sometimes the apples turn out to be fine, than not being able to spot any bad apples before the barrel has been spoiled.

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