Brunel University London

Department of
Economics and Finance

Economics and Finance Working Paper Series

Working Paper No. 17-23

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EVALUATING CONCENTRATION AND DISTRIBUTION MEASURES OF IMF FINANCIAL SOUNDNESS INDICATORS

December 2017

http://www.brunel.ac.uk/economics

22nd November 2017

EVALUATING CONCENTRATION AND DISTRIBUTION MEASURES OF IMF FINANCIAL SOUNDNESS INDICATORS

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Abstract: This paper is a first approach to assessing the analytical usefulness of Concentration and Distribution Measures (CDMs) of IMF Financial Soundness Indicators (FSIs) in financial surveillance, using an experimental data collection of the IMF from 36 countries for up to 8 years (2007-2014). Besides illustrating the use made of CDMs in recent policy and academic work, we show econometrically annually over 2008-14 that a range of these CDMs can help to predict system wide vulnerabilities, with appropriate control variables to reduce omitted variable bias. Overall, the exercise lends support to the IMF's intention to collect CDM data on a regular basis, and supports the argument made in IMF (2013) that CDMs would "allow policy makers and Fund staff to better identify potential build-up of systemic risks, thus providing additional inputs for macro-financial management."

Keywords: Concentration and distribution measures, financial soundness indicators, financial surveillance, financial stability, banking sector Z-Score, Non-performing loans, panel estimation.

JEL classification: G01, G21

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1 Introduction

In IMF (2013), in the context of a review and update of ongoing collection of data on financial soundness indicators (FSIs), it was suggested that “the global financial crisis revealed the need to develop indicators that could identify and monitor the build-up of systemic risks in a forward-looking manner. FSIs for a sector as a whole act more as contemporaneous indicators and may hide variations within the population of financial institutions that may eventually put in danger the whole financial system”. As contemporaneous indicators, they would also pose difficulties if there are delays in data collection.

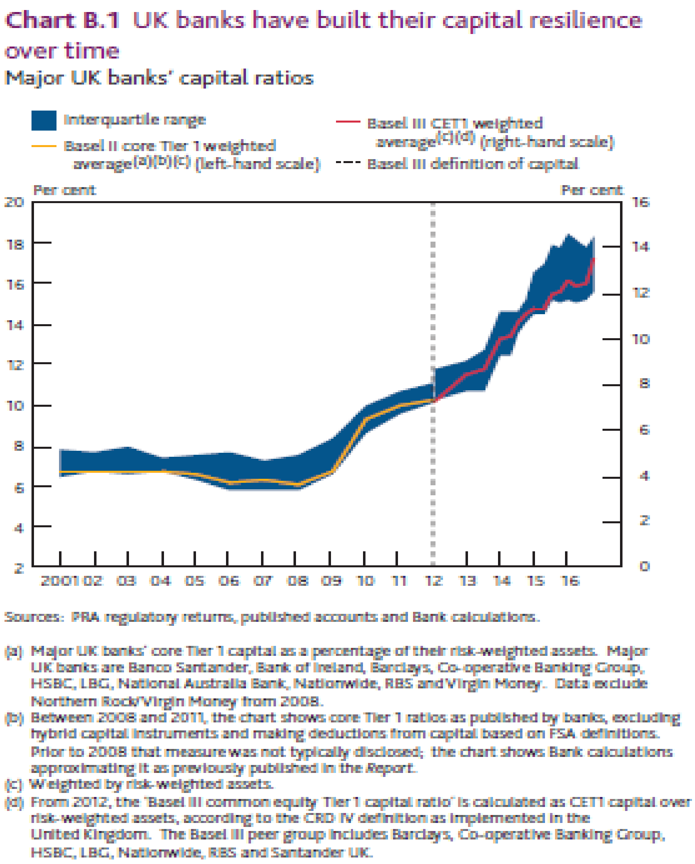
Accordingly, data collection was undertaken for a variety of concentration and distribution measures (CDMs) of key financial soundness indicators (FSIs), and Crowley et al (2016) highlighted the main features of this experimental data collection on CDMs, from 36 countries for up to 8 years (2007-2014). The initial paper did not present statistical tests of the usefulness of CDMs for financial stability analysis. However, the fact central banks, international organisations and academics routinely use CDMs for illustration and analysis is promising.

This article seeks to deepen knowledge of the usefulness of CDMs by assessing their potential for helping predict vulnerabilities at a national level. We show some recent examples of figures using CDMs from key macroprudential reports from the IMF, ECB and Bank of England, then we note some recent academic work that relates to CDMs. We then go on to our own analytical work which is centred on panel estimates of the relation of lagged CDMs to key indicators of financial instability, with appropriate control variables to avoid omitted variables bias. We also present some preliminary results using quantile approaches. We then conclude with a summary and suggestions for extensions to the analytical work.

2 Practice of policy institutions

A first motivation for the use of CDMs is their growing use in policy analysis by institutions at the cutting edge of financial stability analysis. So for example the Bank of England, FSR (2016) (Figure 1) shows here the varying distribution of bank capital adequacy across the interquartile range, as the mean increased in the wake of tighter regulation, recapitalisation and the approach of Basel III, with the aggregate common equity Tier 1 (CET1) ratio of major UK banks being 13.5% of risk-weighted assets in September 2016.

Figure 1: UK banks’ capital ratios



Similarly the ECB, FSR (2016) shows in Figure 2 how the evolution of capital adequacy varied according to the measure used in early 2016, but was generally increasing, as shown by the median, the interquartile range and 90-10 percentile range. Their comment was that "Euro area significant institutions' fully loaded common equity Tier 1 (CET1) ratio increased further in the first two quarters of 2016, with the median ratio rising by around 30 basis points to 13.4%".

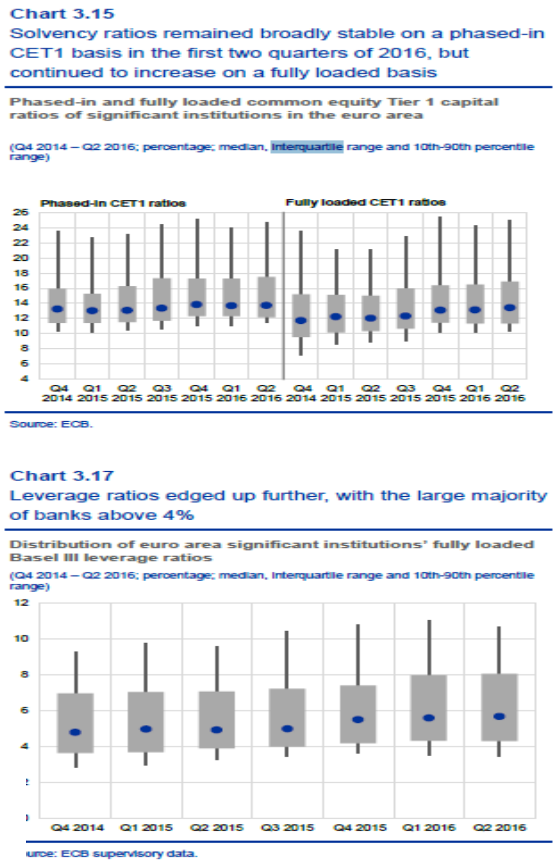


Figure 2: Euro area banks' capital ratios

Finally, the IMF in its Global Financial Stability Report (2016) shows in Figure 3 on the left the distribution of equity to assets, total assets and debt to assets for the range of financial sectors (commercial banks, investment banks, life insurance, nonlife insurance, finance companies) representing 368 listed firms across the following countries, namely Austria, Belgium, Brazil, Canada, Germany, Finland, Ireland, Italy, Japan, Korea, Mexico, the Netherlands, Portugal, Spain, Sweden, and the United States. These were used in turn for analysis on the firm-level responses of financial intermediaries to monetary policy changes

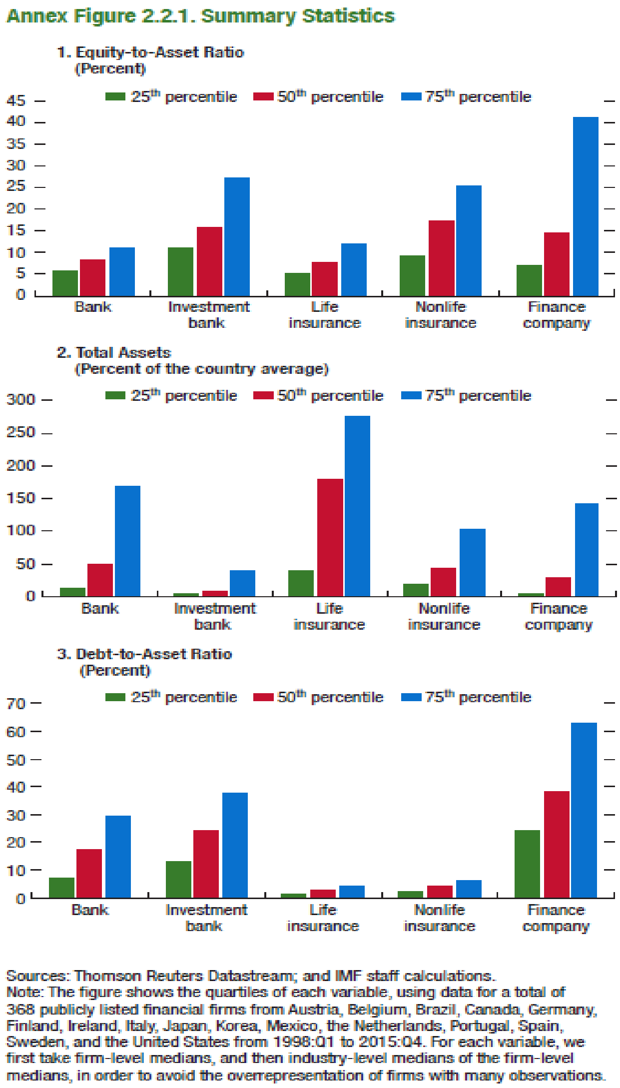


Figure 3: Summary statistics on financial institution sectors

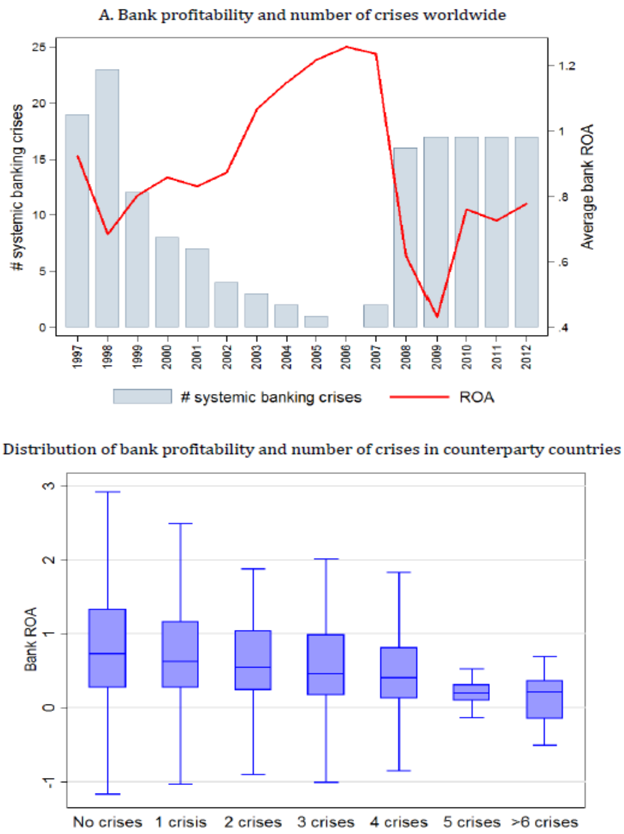
3 Academic work

We cite here three recent articles that utilise CDMs, while noting that the literature on their use is fairly sparse, although in principal calculation is fairly straightforward using individual bank data.

Figure 4: Bank performance and systemic banking crises (Source: Hale et al (2014))

Hale et al (2014) showed that interconnected financial systems are prone to shock transmission, and network position matters for bank performance. In that context they show in the charts on the right (Figure 4), first an inverse relationship between average bank ROA and the number of systemic banking crises that occurred during 1997-2012 and, second, that the entire ROA distribution shifts downwards as median profitability declines, monotonically, with the number of crises in counterparty countries (while its dispersion measured by the interquartile range remains relatively stable).

Figure 5: Bank performance and systemic banking crises, 1997-2012



Notes: The bars in Panel B boxplot show the interquartile range of ROA with the median indicated by a horizontal line; the bars extend from the minimum to the maximum value of the ratio. Counterparty countries are the countries vis-à-vis whose banks a bank has direct exposures. Source: Authors' calculations based on Bankscope and Laeven and Valencia (2013).

Using data for 69 countries over 1980-1997, Beck et al (2006) found crises are less likely in economies with more concentrated banking systems (measured as the share of assets of the three largest banks in total banking system assets, and in one regression breaking concentration into quintiles), controlling for differences in bank regulatory policies, national institutions affecting competition, macroeconomic conditions, and shocks to the economy. Regulatory policies and institutions that limit competition are related with greater banking system fragility.

Finally, Fahlenbrach et al (2016) showed that U.S. banks with loan growth in the top quartile of banks over a three-year period between 1973-2014 underperform the common stock of banks with loan growth in the bottom quartile over the next three years, as growth slows and provisions increase. They link this in turn to overoptimism on loans made in fast growth period.

4 Econometric analysis

In order to further elucidate the usefulness of CDMs. we undertook panel estimation using CDMs for the IMF sample of up to 36 countries over a period up to 2007-2014, comparing the CDMs in each case with the predictive power of the traditional mean for up to six financial soundness indicators calculated economy-wide for the banking sector. These are the leverage ratio, liquidity ratio return on equity (ROE), return on assets (ROA), Tier 1/risk adjusted assets ratio and the non-performing loans (NPL)/total loans ratio.

The countries in the sample are as follows (Crowley et al 2016): Armenia, Republic of, Macedonia, FYR, Bosnia and Herzegovina, Malta, Brazil, Mauritius, Canada, Namibia, Chile, Netherlands, China, P.R.: Macao, Nigeria, Costa Rica, Norway, Cyprus, Panama, Czech Republic, Paraguay, Dominican Republic, Romania, El Salvador, Slovak Republic, France, South Africa, Georgia, Sri Lanka, Germany, Turkey, India, Uganda, Ireland, Ukraine, Israel, Zambia and Italy. In terms of income level, 37% are higher income, 34% upper-middle income, 23% lower middle income, and 6% lower income.

Three dependent variables of macroprudential relevance were drawn from the World Bank Global Financial Development Database (GFDD) (Cihak et al (2012), World Bank (2017)): First, the Z-Score[2] captures the probability of default of a country's commercial banking system. Z-score compares the buffer of a country's commercial banking system (capitalization and returns) with the volatility of those returns. Hence Z-Score = (ROA+(Capital/Assets))/SD(ROA)).[3] Second, we use the NPL/loans ratio[4] which is often used as a proxy for asset quality and may show problems with asset quality in the loan portfolio across the banking sector as a whole. It is defined as the ratio of defaulting loans (payments of interest and principal past due by 90 days or more) to total gross loans (total value of loan portfolio). The loan amount recorded as nonperforming includes the gross value of the loan as recorded on the balance sheet, not just the amount that is overdue.[5] Third, the Provisions/NPL ratio[6] is an indicator of how well protected a banking sector is against future losses. Again, nonperforming loans are defined as loans for which the contractual payments are delinquent, usually defined as being overdue for more than a certain number of days (e.g., usually more than 90 days).

Control variables (lagged) were similar to Beck et al (2013) and Davis and Karim (2013), namely NONINTSH (share of noninterest income)[7]; CREDASSET (ratio of bank loans of deposit money banks to assets for deposit money banks)[8]; PROVNPL (provisions/NPL ratio) or NPLLOAN (NPL/loan ratio);

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[2] This is GFDD series GFDD.SI.01.

[3] Note that this is quite distinct from standard statistical definition of Z-Score which indicates how many standard deviations an element is from the mean.

[4] This is GFDD series GFDD.SI.02.

[5] What NPL data typically do not record is whether the loans are recoverable and have been collateralized. Hence the impact on banks' balance sheet may vary. This implies write offs and uncollateralized NPL may be measures to look at as well.

[6] This is GFDD series GFDD.SI.07.

[7] The noninterest income share is bank's income that has been generated by noninterest related activities as a percentage of total income (net-interest income plus noninterest income). Noninterest related income includes net gains on trading and derivatives, net gains on other securities, net fees and commissions and other operating income. This is GFDD series GFDD.EI.03.

[8] Loans are seen as the financial resources provided to the private sector by domestic money banks, while assets held by deposit money banks include claims on the domestic real nonfinancial sector which includes central, state and local governments, nonfinancial public enterprises and private sector enterprises. Deposit

COMPLERNER (Lerner index for bank competition)[9] and DEPASSET (ratio of deposits of deposit money banks to total assets of deposit money banks), which shows the dependence of banks on deposits for their funding[10]. We also used time dummies. Controls for the NPL/loan ratio were as for Z-Score, while for Provisions/NPL ratio, we replace provisions/NPL with NPL/loans

We present below the statistical data for the dependent variables over the 2007-14 period from the GFDD. Note that the Z-Score is at times negative, leaving two options for presentation, first the raw data and second a log form of ln (1 + (Z-Score/100)), which allows the ratio to go below zero without taking the log of a negative number. As noted by Lui et al (2013) it is appropriate to log the Z score as the level is highly skewed, while the log is normally distributed (see Table 1). We present results for the latter in results below and the former for comparison in the Appendix.

Table 1: Statistical data for dependent variables (common sample)

	Z-Score	Ln (1+(Z-Score/100)	NPL/loans	Provisions/NPL
Mean	10.7	0.099	5.6	68.1
Median	9.6	0.091	3.6	59
Maximum	31.0	0.27	44.9	209.8
Minimum	-12.0	-0.13	0.1	7
Std. Dev.	6.9	0.062	6.1	36.4
Skewness	0.6	0.39	3.1	1.3
Kurtosis	3.3	3.3	15.6	4.9
Jarque-Bera	14.0	6.96	1954.11	104.9
Probability	0.0009	0.031	0	0
Sum	2546.1	23.7	1345.2	16265.6
Sum Sq. Dev.	11470.2	0.91	8993.53	315868
Observations	239	239	239	239

Source: GFDD

As noted, Financial Soundness variables tested for predictive power of their CDMs in this respect as national banking sector financial stability indicators are: Leverage (unweighted capital/assets); Liquidity (liquid assets/short term liabilities); ROA (return on assets); ROE (return on equity); Tier 1 ratio (Tier 1 equity capital/risk weighted assets) and the NPL ratio (non performing loans/gross loans). Separate regressions were run for the following: Mean plus controls (benchmark); Skewness and Standard Deviation plus controls; Quartiles 1, 2, 3 and 4 plus controls; Maximum, Median and Minimum plus controls; and Interquartile range (Quartile 1 minus Quartile 4) plus controls.

money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. This is calculated as the ratio of GFDD series GFDD.DI.01 to GFDD.DI.02

[9] The Lerner Index is a measure of market power in the banking market. It compares output pricing and marginal costs (that is, mark-up). An increase in the Lerner index indicates a deterioration of the competitive conduct of financial intermediaries. For recent work assessing the link for individual banks of competition as measured by the Lerner index to risk as measured by the Z-Score, see Beck et al (2013) and Davis and Karim (2013). This is GFDD series GFDD.OI.04.

[10] This is the ratio of GFDD series GFDD OI.02 to GFDD DI.02.

There remain some statistical issues. Firstly there are outliers, notably in the maxima, which raises the question whether they also distort other CDMs. One option is to Winsorize (i.e. remove the top and bottom 1% or 5% of observations) if necessary, but we have chosen not to do that in the current work. Second, there are no observations in advance of the global financial crisis so we cannot do crisis prediction. The post crisis period covered by the sample is of course subject to high risk aversion by banks and authorities. Third, as noted there are some negative values requiring linear and not log linear calculations, although this is fairly standard other than for the Z-Score as noted above. Fourth, there is a short time series and large number of countries. We have chosen to enter the variables as levels rather than differences to maximise information and also given that in a large sample all of the variables are by nature stationary, being ratios. This again is common to papers such as Beck et al (2013) and Davis and Karim (2013) using individual bank data, and we contend the same argument is applicable to financial systems.

We present below a typical regression for the Z-Score. Note that there are considerably fewer observations than the full sample would allow, as many countries reported short samples. Also we use only 26 countries for similar data reasons. In this particular regression, all variables are significant or nearly so except the noninterest share.

Table 2: Typical regression for log (1+(Z-Score/100))

Variable	**Coefficient**	**t-Statistic**
C	-0.0926	(-1.7)
MEAN LEVERAGE(-1)	-0.484	(-3.2)
NONINTSH(-1)	-0.000646	(-1.1)
CREDASSET(-1)	0.255	(5.0)
PROVNPL(-1)	0.000358	(2.4)
COMPLERNER (-1)	0.216	(3.9)
DEPASSET(-1)	-0.0361	(-1.6)
Panel OLS regression		
Period fixed dummy variables		
Sample (adjusted):	2008-2014	
Periods included:	7	
Cross-sections included:	26	
Observations:	99	
R-squared	0.398	
Adjusted R-squared	0.314	
S.E. of regression	0.0464	
Sum of squared residuals	0.185	

We show in Tables 3-5 our main results for the coefficient and significance of the mean and CDM variables (lagged to enable indicator properties to be evaluated), being in mind the controls are always included. It can be seen that a wide range of CDMs show significance in this dataset, and often increase the R-bar-squared and reduce the residual sum of squares compared with the mean equation.

Table 3: Results for log(1+(Z-Score/100)) as dependent variable

	Leverage ratio	Liquid assets /Short term liabilities	ROE	ROA	Tier1 capital /risk weighted assets	NPL/total loans
Equation (1) mean only						
Mean	-0.48*** (3.2)	0.0009 (0.8)	0.059* (1.9)	0.386 (0.9)	-0.449** (2.4)	-0.494*** (4.4)
R-bar-sq RSS	0.314 0.185	0.295 0.186	0.251 0.204	0.227 0.211	0.274 0.183	0.376 0.16
Equation (2) skewness and standard deviation						
Skew	-0.0018 (1.2)	-0.0003 (1.2)	0.00002 (0.0)	0.0009 (1.1)	0.0007 (1.1)	-0.0017* (1.9)
Stdev	-0.514*** (3.8)	0.00002 (0.5)	-0.023** (2.3)	-1.04*** (3.4)	-0.306*** (3.8)	-0.644*** (4.7)
R-bar-sq RSS	0.335 0.178	0.295 0.184	0.257 0.2	0.342 0.177	0.338 0.164	0.409 0.149
Equation (3) Four quartiles of the distribution						
Q1	-0.126** (2.6)	0.00008 (0.4)	-0.073 (1.6)	0.633 (1.3)	-0.093*** (2.9)	-0.576 (1.1)
Q2	0.28 (1.1)	0.045** (2.6)	-0.137 (1.0)	-2.97** (2.3)	-0.241 (1.5)	-0.661 (1.4)
Q3	-0.799** (2.3)	0.0036 (0.1)	0.429** (2.7)	1.73 (1.1)	0.396 (1.1)	0.435 (1.6)
Q4	0.319** (2.7)	-0.095*** (3.2)	0.03 (1.6)	1.11*** (4.8)	-0.023 (0.2)	-0.177** (2.6)
R-bar-sq RSS	0.387 0.155	0.419 0.144	0.411 0.151	0.492 0.13	0.417 0.136	0.444 0.133
Equation (4) Maximum, median and minimum						
Max	-0.014 (0.9)	0.00001 (0.1)	-0.0009 (0.6)	0.071 (0.9)	-0.0006 (0.2)	-0.059*** (3.1)
Med	-0.515*** (3.6)	0.041*** (3.5)	0.154** (2.2)	0.131 (0.2)	-0.647*** (3.3)	-0.293* (1.7)
Min	0.0086 (1.0)	-0.066*** (2.8)	0.0018 (1.5)	0.037** (2.5)	0,031 (1.6)	-0.611 (1.0)
R-bar-sq RSS	0.345 0.175	0.37 0.162	0.279 0.192	0.263 0.197	0,348 0.169	0.401 0.158
Equation (5) interquartile range (q1-q4)						
IQ range	-0.129*** (3.5)	0.0002 (0.7)	- 0.057*** (3.8)	-0.95*** (5.3)	-0.112*** (4.9)	0,21*** (4.2)
R-bar-sq RSS	0.351 0.171	0.313 0.176	0.346 0.174	0.422 0.154	0.421 0.141	0.38 0.154

Notes: Separate regressions (1)-(5) include control variables as shown in Table 2. T-values are shown in parentheses. * indicates significance at 90%, ** at 95% and *** at 99%.

Table4: Results for NPL/loans as dependent variable

	Leverage ratio	Liquid assets /Short term liabilities	ROE	ROA	Tier1 capital /risk weighted assets
Equation (1) mean only					
Mean	33.8** (2.5)	-0.,146 (1.4)	-16.5*** (7.2)	-200.1*** (6.4)	32.8** (2.0)
R-bar-sq RSS	0.291 1582	0.25 1583	0.51 1109	0.46 1210	0.25 1497
Equation (2) skewness and standard deviation					
Skew	-0.24* (1.7)	0.025 (1.1)	-0.075 (0.8)	-0.17** (2.5)	-0.054 (0.9)
Stdev	12.0 (0.9)	-0.0045 (1.2)	2.25** (2.6)	89.8*** (3.4)	18.9** (2.5)
R-bar-sq RSS	0.277 1596	0,247 1571	0.28 1609	0.39 1349	0.26 1452
Equation (3) Four quartiles of the distribution					
Q1	0.93 (0.2)	-0.028 (1.3)	-7.4** (2.2)	-19.7 (0.5)	2.5 (0.8)
Q2	5.6 (0.2)	-2.4 (1.4)	13.5 (1.4)	-42.7 (0.4)	34.4** (2.1)
Q3	28.6 (0.8)	0.78 (0.3)	-34.4*** (3.1)	-110.9 (0.9)	-45.3 (1.3)
Q4	-12.2 (1.0)	3.2 (1.1)	-5.56*** (4.1)	-90.3*** (4.8)	11.3 (1.0)
R-bar-sq RSS	0.256 1585	0.256 1503	0.651 755	0.584 903	0.288 1355
Equation (4) Maximum, median and minimum					
Max	-1.2 (0.8)	-0.0002 (1.2)	0.118 (1.1)	-25.1*** (4.8)	0.075 (0.3)
Med	22.2* (1.7)	-1.18 (1.0)	-35.4*** (6.9)	-295.7*** (6.4)	24.9 (1.5)
Min	-1.47 (1.7)	0.62 (0.3)	-0.195 (2.2)	-3.9*** (3.9)	-2.6 (1.4)
R-bar-sq RSS	0.265 1623	0.241 1562	0.543 1008	0,598 889	0.271 1517
Equation (5) interquartile range (q1-q4)					
IQ range	4.33 (1.2)	-0.03 (1.4)	4.77*** (3.4)	60.6*** (3.5)	5.57** (2.4)
R-bar-sq RSS	0.251 1661	0.25 1573	0.316 1537	0.318 1533	0.264 1459

Notes: Separate regressions (1)-(5) include control variables as shown in Table 2. T-values are shown in parentheses.* indicates significance at 90%, ** at 95% and *** at 99%.

Table 5: Results for Provisions/NPL as dependent variable

	Leverage ratio	Liquid assets /Short term liabilities	ROE	ROA	Tier1 capita /risk weighted assets
Equation (1) mean only					
Mean	-27.9 (0.3)	2.18*** (2.9)	45.5* (1.7)	473.8 (1.5)	-253.2** (2.1)
R-bar-sq RSS	0.06 99394	0.155 87783	0.09 98077	0.08 98757	0.14 87934
Equation (2) skewness and standard deviation					
Skew	0.77 (0.7)	0.116 (0.7)	-1.26* (1.9)	-0.22 (0.4)	0.96** (2.0)
Stdev	217.4** (2.2)	0.062** (2.2)	-4.42 (0.6)	-143.9 (0.6)	14.9 (0.2)
R-bar-sq RSS	0.102 94088	0.117 90732	0.088 97133	0.055 100670	0.134 87428
Equation (3) Four quartiles of the distribution					
Q1	77.3** (2.4)	0.42*** (3.3)	27.2 (0.7)	31.1 (0.1)	65.2*** (3.0)
Q2	-171.8 (1.0)	-9.3 (0.9)	134.9 (1.3)	1572.9 (1.5)	-235.3** (2.0)
Q3	446.1* (1.9)	40.7** (2.5)	-215.9* (1.7)	-1664.8 (1.3)	583.9** (2.4)
Q4	-226.6** (2.7)	0.65 (0.1)	16.5 (1.0)	151.3 (0.7)	-216.6*** (2.9)
R-bar-sq RSS	0.218 75338	0.4 56516	0.086 89807	0.082 90147	0.245 69816
Equation (4) Maximum, median and minimum					
Max	8.88 (0.8)	0.002** (2.0)	-01.7 (0.2)	67.9 (1.1)	2.42 (1.2)
Med	238.6** (2.4)	32.9*** (4.8)	-46.2 (0.8)	305.9 (0.6)	172.3 (1.3)
Min	1.97 (0.3)	-28.0* (1.9)	-0.03 (0.1)	3.54 (0.3)	-31.9** (2.2)
R-bar-sq RSS	0.119 92801	0.345 66499	0.046 100480	0.056 99494	0.157 86521
Equation (5) interquartile range (q1-q4)					
IQ range	84.5*** (3.7)	0.45*** (3.0)	2.57 (0.2)	96.7 (0.6)	55.8*** (3.4)
R-bar-sq RSS	0.202 79705	0.181 80146	0.07 94556	0.07 94153	0.217 75446

Notes: Separate regressions (1)-(5) include control variables as shown in Table 2. T-values are shown in parentheses.* indicates significance at 90%, ** at 95% and *** at 99%.

Note that the only concentration measure available was for the Tier 1 ratio. This was significant for a log Z-Score regression with coefficient and t value being 0.278 (3.3)***. It was not significant for NPL/loans or Provisions/NPL.

Tables 6 and 7 provide a summary of the significant variables and significant CDMs, where it can be seen that the performance is variable but many of the variables and CDMs show promise for helping to predict system wide vulnerabilities.

Table 6: Number of significant variables (at 90% or more)

Dependent:	log (1+(Z-Score/100)	NPL/loans	Provisions/NPL	Total
Leverage	7	3	6	16
Liquidity	4	0	8	12
ROE	5	6	3	14
ROA	5	8	0	13
Tier1/risk weighted assets	5	4	8	17
NPL/loans	7	Na	Na	(7)

Table 7: Significant variables by CDM (at 90% or more)

	log (1+(Z-Score/100)	NPL/loans	Provisions/NPL	Total
Mean	4	4	3	11
Skew	1	2	2	5
Stdev	5	3	2	10
Q1	2	1	3	6
Q2	2	1	1	4
Q3	2	1	4	7
Q4	4	2	2	8
Max	1	1	1	3
Med	5	3	2	10
Min	2	1	2	5
IQ range	5	3	3	11

In sum, it can be seen that the CDMs are widely significant for helping predict the chosen indicators of systemic vulnerability, often more so than the traditional means. We highlight in particular the usefulness of the interquartile range, which is often significant and also often retains significance in more restricted samples (see below). The standard deviation, median, minimum and fourth quartile also show promise. Capital adequacy measures, both risk weighted and non-risk weighted are somewhat more commonly significant than the other FSIs.

We proceeded to test further for the example of the log Z score and the two capital adequacy measures whether the CDM variables “add value” when we retain the mean in the equation. This is shown in Tables 8 and 9 below. It is evident that there is a great deal of improvement in the indicator properties of the equations when we add the CDMs to the mean as shown by the t values, the R-bar-squared and Residual Sum of Squares improvement in explanatory power. The mean retains significance, however, in all but one case.

Table 8: Adding CDM variables for leverage to mean leverage, Dependent variable: log (1+(Z Score/100))

	(1)	(2)	(3)	(4)	(5)
Mean	-0.485*** (3.8)	-0.551*** (3.8)	-0.908** (2.6)	-0.23 (0.8)	-0.467*** (3.3)
Skew		-0.003** (2.3)			
Stdev		-0.529*** (4.1)			
Q1			-0.146*** (3.1)		
Q2			0.179 (0.7)		
Q3			0.145 (0.3)		
Q4			0.282** (2.4)		
Max				-0.024 (1.4)	
Med				-0.29 (1.1)	
Min				0.009 (1.0)	
IQ range					-0.13*** (3.8)
R-bar-sq	0.314	0.424	0.429	0.35	0.419
RSS	0.185	0.151	0.143	0.169	0.151

Notes: Separate regressions (1)-(5) include control variables as shown in Table 2. T-values are shown in parentheses.* indicates significance at 90%, ** at 95% and *** at 99%.

Table 9: Adding CDM variables for Tier 1 ratio to mean Tier 1 ratio, Dependent variable: log (1+(Z Score/100))

	(1)	(2)	(3)	(4)	(5)
Mean	-0.448** (2.4)	-0.529*** (3.1)	-0.739*** (2.8)	-0.609** (2.0)	-0.41** (2.4)
Skew		0.001** (2.4)			
Stdev		-0.33*** (4.3)			
Q1			-0.091*** (3.0)		
Q2			-0.136 (0.8)		
Q3			0.592* (1.7)		
Q4			0.035 (0.3)		
Max				-0.00002 (0.1)	
Med				-0.2 (0.7)	
Min				0.068** (2.5)	
IQ range					-0.11*** (5.1)
R-bar-sq	0.274	0.404	0.469	0.365	0.456
RSS	0.183	0.146	0.122	0.153	0.131

Notes: Separate regressions (1)-(5) include control variables as shown in Table 2. T-values are shown in parentheses.* indicates significance at 90%, ** at 95% and *** at 99%.

Further robustness checks (below) show broad stability of effects across income levels and time periods. Table 10 shows, in particular, that excluding income levels leaves many of the key results unchanged and highly significant. The right hand column shows also that the inclusion of income level dummies, capturing the average level of the dependent variable by income level, does not affect the results.

Table 10: Robustness check for interquartile range (1) Excluding income levels (dependent: log (1+(Z-Score/100))

Excluding:	High income	Upper middle Income	Lower middle Income	Total	Memo: with Income level dummies
IQ range leverage	-0.149*** (3.4)	-0.153*** (3.4)	-0.075 (1.4)	-0.13*** (3.5)	-0.133*** (3.7)
IQ range Liquidity	0.0002 (0.8)	0.0005** (2.2)	0.0002 (0.9)	0.0002 (0.7)	0.0002 (0.7)
IQ range ROE	-0.046** (2.6)	-0.062** (3.8)	-0.06* (1.9)	-0.057*** (3.8)	-0.058*** (3.8)
IQ range ROA	-0.926*** (3.7)	-1.05*** (4.9)	-0.77** (2.7)	-0.95*** (5.3)	-0.975*** (4.8)
IQ range Tier1/RWA	-0.125*** (4.9)	-0.084** (2.6)	-0.116** (2.5)	-0.112*** (4.9)	-0.111*** (4.9)
IQ range NPL/loans	0.287*** (5.6)	0.112 (1.4)	0.23*** (3.2)	0.21*** (4.2)	0.209*** (4.2)

Notes: Regressions include control variables as shown in Table 2. T-values are shown in parentheses.* indicates significance at 90%, ** at 95% and *** at 99%.

Table 11 shows that individual income levels' results are more variable, partly because of fewer observations for high income and lower middle income countries, but still a number of variables are significant or virtually so, and the effects for upper middle income countries are highly robust.

Table 11: Robustness check for interquartile range (2) Individual income levels (dependent: log (1+(Z-Score/100))

Region:	High income	Upper middle income	Lower middle Income	Total
IQ range leverage	0.126 (0.6)	-0.142** (2.0)	-0.072 (1.4)	-0.13*** (3.5)
IQ range Liquidity	0.004 (0.7)	0.0002 (0.7)	0.0005 (0.3)	0.0002 (0.7)
IQ range ROE	0.067 (1.2)	-0.177*** (3.1)	-0.019 (1.4)	-0.057*** (3.8)
IQ range ROA	0.35 (0.4)	-1.1** (2.0)	-0.53*** (2.9)	-0.95*** (5.3)
IQ range Tier1/RWA	0.087 (1.2)	-0.144*** (4.5)	-0.072 (1.6)	-0.112*** (4.9)
IQ range NPL/loans	0.093 (1.5)	0.57*** (6.2)	0.11 (1.4)	0.21*** (4.2)

Notes: Regressions include control variables as shown in Table 2. T-values are shown in parentheses.* indicates significance at 90%, ** at 95% and *** at 99%.

Finally, Table 12 shows remarkable stability of effects across two separate time periods, 2007-11 and 2012-14.

Table 12: Robustness check (3) Sub-periods (dependent: log (1+(Z-Score/100))

Subperiod	2007-2011	2012-2014	Memo: 2007-2014
IQ range leverage	-0.119** (2.2)	-0.134** (2.6)	-0.13*** (3.5)
IQ range Liquidity	0.0005 (1.5)	0.00007 (0.3)	0.0002 (0.7)
IQ range ROE	-0.043** (2.4)	-0.101*** (2.8)	-0.057*** (3.8)
IQ range ROA	-0.96*** (3.6)	-0.85*** (3.2)	-0.95*** (5.3)
IQ range Tier1/RWA	-0.116*** (4.2)	-0.123** (2.4)	-0.112*** (4.9)
IQ range NPL/loans	0.26*** (3.7)	0.154** (2.0)	0.21*** (4.2)

Notes: Regressions include control variables as shown in Table 2. T-values are shown in parentheses.* indicates significance at 90%, ** at 95% and *** at 99%.

5 Quantile estimates

As a further indication of the potential for the CDM variables, we show here results of some preliminary quantile regressions for the log Z-Score. While our main regressions above, in common with most other econometric work, analyse determinants of the conditional mean of a dependent variable, there is also interest in methods of modelling other aspects of the conditional distribution.

As originally proposed by Koenker and Bassett (1978), quantile regression provides estimates of the linear relationship between regressors and a specified quantile of the dependent variable . It can be argued that quantile regression permits a more complete description of the conditional distribution than conditional mean analysis alone, allowing us, for example, to describe how the median, or specific percentiles of the response variable, are affected by regressor variables. Moreover, since the quantile regression approach does not require strong distributional assumptions, it offers a robust method of modelling these relationships.

Extant work using quantile regressions for assessing determinants of bank risk include for example Klomp and de Haan (2012), who examine the impact of bank regulation and supervision on banking risk using quantile regressions with data for more than 200 banks from 21 OECD countries for the period 2002–2008. They used factor analysis to derive measures of bank risk, and found banking regulation and supervision has an effect on the risks of high-risk banks but does not have a significant effect on low-risk banks. Meanwhile, Kohler (2013), analyzes the impact of banks' non-interest income share on risk (including the Z-Score) in the German banking sector for the period between 2002 and 2010. Using linear and quantile regression estimators, they found that the impact of non-interest income on risk depends on the business model of a bank.

It is important to note that quantile regressions as presented here are in a pool and not a panel. Accordingly, they do not provide information relevant for national financial surveillance but may be helpful for pinpointing risks in a multilateral surveillance framework. Thus, we estimated quantile regressions using the same controls as in the main paper for the median, 90th percentile and 10th percentile of the distribution of the Z-Score, before focusing on the 10th percentile in more detail.

The latter can be seen as a rough form of tail risk modelling, since it is giving a broad idea of risk as measured by a low Z-Score for the banking system as a whole.

As shown in Table 13 below, the mean and interquartile range are able in several cases to predict the median and 90th percentile, while the interquartile range of the Tier 1 ratio is significant for the 10th percentile. Furthermore, Table 14 shows that the CDMs are able in a number of cases to help to predict the 10th percentile across our sample.

Table 13: Quantile regression coefficients for the median, 90th and 10th percentiles of the log (1+(Z-Score/100)) distribution

Independent variable	Quantile Regression	Coefficient/t-value
Tier 1 mean	Median	-1.0*** (3.6)
	90th percentile	-0.59 (1.5)
	10th percentile	-0.28 (1.6)
Tier 1 interquartile	Median	-0.096*** (3.9)
	90th percentile	-0.104** (2.0)
	10th percentile	-0.064 (1.4)
Leverage mean	Median	-0.74*** (3.8)
	90th percentile	-0.48** (2.5)
	10th percentile	-0.26 (1.3)
Leverage interquartile	Median	-0.151*** (2.8)
	90th percentile	-0.143*** (2.8)
	10th percentile	-0.068* (1.7)

Note: Includes also control variables from Table 2. We use Huber Sandwich Standard Errors & Covariance; Sparsity method: Kernel (Epanechnikov) using residuals; Bandwidth method: Hall-Sheather.

Table 14: Quantile regression coefficients for the 10th percentile of the log (1+(Z-Score/100)) distribution

CDM/FSI	Leverage	Tier 1 ratio
Equation (1) mean only		
Mean	-0.26 (1.3)	-0.28 (1.6)
Equation (2) skewness and standard deviation		
Skewness	0.009 (0,9)	0.001 (0.9)
Standard deviation	-0.208 (2.1)	-0.28 (0.7)
Equation (3) Four quartiles of the distribution		
Q1	-0.057 (0.8)	-0.045 (1.4)
Q2	-0.166 (1.5)	-0.169** (2.1)
Q3	-0.174 (1.0)	-0.125 (0.8)
Q4	0.085 (1.1)	0.024 (0.3)
Equation (4) Maximum, median and minimum		
Maximum	-0.029 (0.8)	-0.001 (0.1)
Median	-0.34** (2.1)	-0.444** (2.7)
Minimum	0.004 (0.8)	0.027* (1.9)
Equation (5) interquartile range (q1-q4)		
Interquartile range	-0.068* (1.7)	-0.064 (1.4)

Note: Includes also control variables from Table 2. We use Huber Sandwich Standard Errors & Covariance; Sparsity method: Kernel (Epanechnikov) using residuals; Bandwidth method: Hall-Sheather.

6 Conclusions

Our empirical work follows the preparation of CDMs, as highlighted in Crowley et al (2016), and common use of CDMs in official and academic publications. In this statistical exercise with the new CDM dataset, we have shown that a range of CDMs can help to predict system wide vulnerabilities, with appropriate control variables to reduce omitted variable bias.

Overall, the exercise lends support to the IMFs' intention to collect CDM data on a regular basis, and supports the argument made in IMF (2013) that CDMs would "allow policy makers and Fund staff to better identify potential build-up of systemic risks, thus providing additional inputs for macro-financial management."

We suggest that it would be desirable to collect data from earlier dates, ideally back to 2000, to allow the prediction of the global financial crisis to be evaluated, and also to limit outliers. A full range of countries would allow more systematic analysis of country groups at different income levels.

Further empirical work could use additional controls (e.g. for financial regulation) and also alternative estimation methods; use of quarterly data for prediction could also be helpful. To show potential in this regard, we included results of simple quantile regressions, showing CDMs can help predict the lower tail of the distribution of Z-Scores for a pool of countries, that may be helpful in multilateral surveillance.

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APPENDIX: ALTERNATIVE RESULTS SET

In this Appendix, we show results presented at the STA conference (Davis 2017), which were amended in the light of comments received. In particular, we used here the level rather than the log of the Z-Score as one of the dependent variables, and also we included here the variable LIQLIASSET (ratio of liquid liabilities to total assets) rather than DEPASSET as one of the controls. We decided that the former was less satisfactory than the latter, since liquid liabilities, the numerator, is defined as M3 while the denominator is deposit money bank assets. Hence, the numerator has wider sectoral coverage than the denominator. In contrast, DEPASSET refers to the deposit money bank sector for both the numerator and the denominator. That said, we highlight the consistency of the results shown here with those in Tables 3-5 of the main paper (the different coefficients for the Z-Score reflect the level and not log scale of the dependent variable). Note that insignificant variables are included in the regressions but the coefficients are not reported in Tables A1.1-A.1.3.

Table A1.1: Results for Z-Score (significant coefficients only). Dependent variable: Z-Score

	Leverage ratio	Liquid assets/Short term liabilities	ROE	ROA	Tier1 capita/risk weighted assets	NPL/total loans
Mean	-50.4 (2.9)				-50.2 (2.3)	-52.4 (4.1)
Skew						-0.23 (2.2)
Stdev	-57.2 (3.7)		-2.5 (2.3)	-113.1 (3.2)		-71.4 (4.7)
Q1	-11.5 (2.1)				-8.5 (2.5)	
Q2		4.1 (2.1)		-320.7 (2.2)	-33.0 (1.8)	
Q3			47.3 (2.6)			
Q4	27.0 (2.0)	-9.3 (2.8)		125.2 (4,7)		
Max						-7.2 (3.2)
Med	-53.7 (3.3)	4.5 (3.3)	16.5 (2.0)		-71.7 (3.2)	
Min		-7.0 (2.7)		4.1 (2.4)		
IQ range	-14.1 (3.4)		-6.4 (3.9)	-108.9 (5.2)	-11.0 (4.5)	23.2 (4.0)

Source: Davis (2017). Includes also control variables from Table 2 except with LIQLIASSET (-1) as defined above instead of DEPASSET (-1). Insignificant variables are included in the regressions but the coefficients are not reported in the table.

Table A1.2: Results for NPL/loans (significant coefficients only). Dependent variable: Z-Score

	Leverage ratio	Liquid assets/Short term liabilities	ROE	ROA	Tier1 capita/risk weighted assets
Mean	27.4 (2.0)		-15.5 (6,5)	-191.3 (6.2)	31.3 (1.9)
Skew	-0.26 (1.9)			-0.2 (2.9)	
Stdev			2.15 (2.5)	77.6 (3.0)	16.0 (2.2)
Q1					
Q2					37.9 (2.3)
Q3			-35.8 (3.2)		
Q4			-5.0 (3.6)	-86.2 (4.7)	
Max				-26.2 (5.0)	
Med			-34.9 (6.8)	-248.7 (6.4)	
Min	-1.45 (1.7)		-0.18 (2.1)	-3.4 (3.5)	
IQ range			4.9 (3.7)	53.3 (3.0)	3.8 (1.7)

Source: Davis (2017). Includes also control variables from Table 2 except with LIQLIASSET (-1) as defined above instead of DEPASSET (-1). Insignificant variables are included in the regressions but the coefficients are not reported in the table.

Table A1.3: Results for Provisions/NPLs (significant coefficients only). Dependent variable: Z-Score

	Leverage ratio	Liquid assets/Short term liabilities	ROE	ROA	Tier1 capita/risk weighted assets
Mean		2.2 (2.9)			-263.5 (2.1)
Skew			-1.3 (1.9)		0.99 (2.1)
Stdev	213.3 (2.2)	0.06 (2.1)			
Q1	64.0 (2.1)	0.4 (3.3)			54.7 (2.7)
Q2					-216 (1.8)
Q3		36.0 (2.3)	-209.6 (1.7)		593.5 (2.4)
Q4	-170.1 (2.0)				-207.4 (2.8)
Max		-0.002 (2.0)			
Med	235.2 (2.4)	35.4 (5.2)			
Min		-30.9 (2.2)			-28.2 (1.9)
IQ range	81.7 (3.7)	0.45 (3.1)			48.0 (3.2)

Source: Davis (2017). Includes also control variables from Table 2 except with LIQLIASSET (-1) as defined above instead of DEPASSET (-1). Insignificant variables are included in the regressions but the coefficients are not reported in the table.