CAN CONCENTRATION AND DISTRIBUTION MEASURES (CDMs) SIGNAL VULNERABILITIES IN THE FINANCIAL SYSTEM, WHICH ARE NOT CAPTURED IN SIMPLE AVERAGES?

Presentation at the STA Workshop on “Financial Soundness Indicators, a User’s Perspective”,
IMF, Washington DC, April 26–27, 2017

E Philip Davis

Brunel University, NIESR, IMF

1 Introduction

- In IMF (2013) 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”.
- Accordingly, IMF (2016) highlighted experimental data collection on CDMs, from 36 countries for up to 8 years (2007-2014)
- 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 illustration 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 then conclude with a summary and suggestions for extensions to the analytical work.

Structure

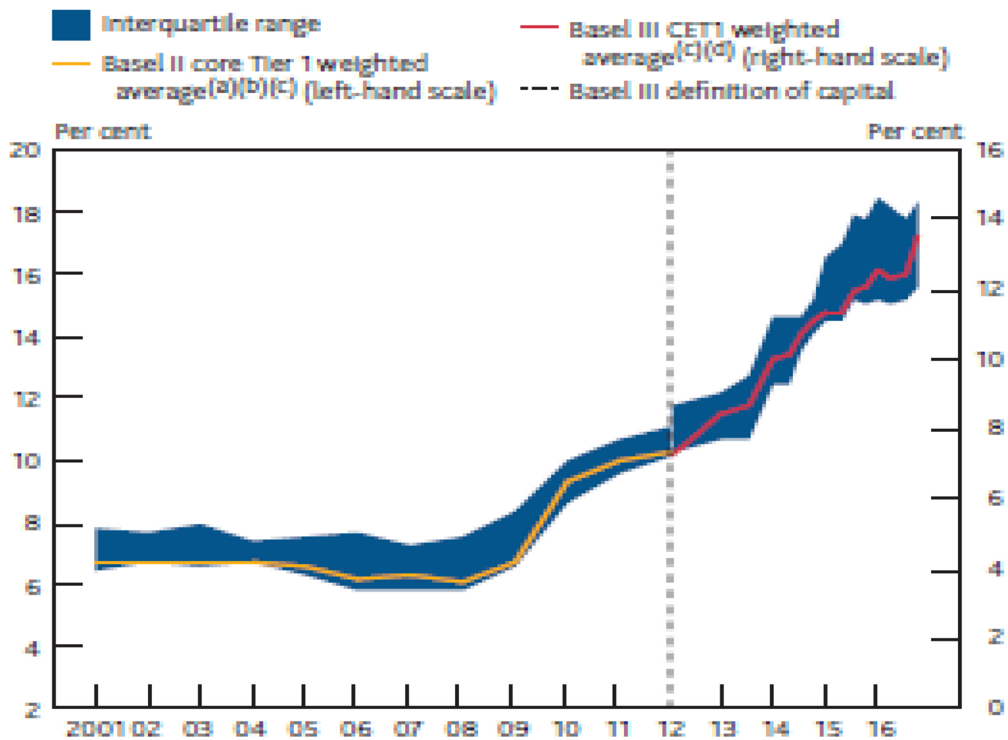
1. Introduction
2. Practice of policy institutions
3. Academic work
4. Econometric analysis
5. Conclusions

2 Practice of policy institutions

- Bank of England, FSR (2016)

Chart B.1 UK banks have built their capital resilience over time

Major UK banks' capital ratios



Sources: PRA regulatory returns, published accounts and Bank calculations.

(a) Major UK banks' core Tier 1 capital as a percentage of their risk-weighted assets. Major UK banks are Banco Santander, Bank of Ireland, Barclays, Co-operative Banking Group, HSBC, LBG, National Australia Bank, Nationwide, RBS and Virgin Money. Data exclude Northern Rock/Virgin Money from 2008.

(b) Between 2008 and 2011, the chart shows core Tier 1 ratios as published by banks, excluding hybrid capital instruments and making deductions from capital based on FSA definitions. Prior to 2008 that measure was not typically disclosed; the chart shows Bank calculations approximating it as previously published in the *Report*.

(c) Weighted by risk-weighted assets.

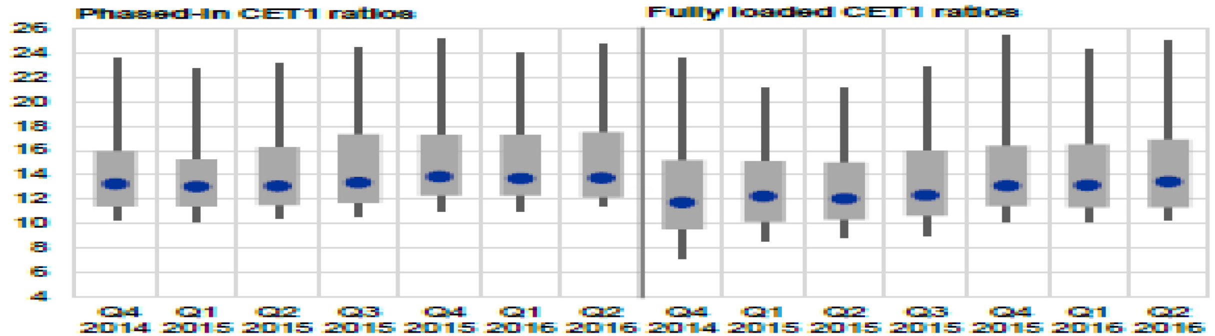
(d) From 2012, the 'Basel III common equity Tier 1 capital ratio' is calculated as CET1 capital over risk-weighted assets, according to the CRD IV definition as implemented in the United Kingdom. The Basel III peer group includes Barclays, Co-operative Banking Group, HSBC, LBG, Nationwide, RBS and Santander UK.

- ECB, FSR (2016)

Chart 3.15
Solvency ratios remained broadly stable on a phased-in CET1 basis in the first two quarters of 2016, but continued to increase on a fully loaded basis

Phased-in and fully loaded common equity Tier 1 capital ratios of significant institutions in the euro area

(Q4 2014 – Q2 2016; percentage; median, interquartile range and 10th-90th percentile range)

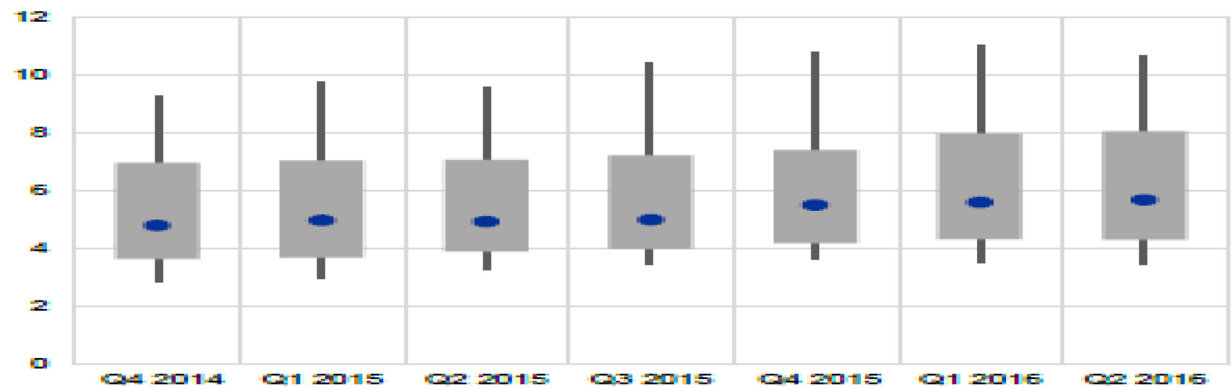


Source: ECB.

Chart 3.17
Leverage ratios edged up further, with the large majority of banks above 4%

Distribution of euro area significant institutions' fully loaded Basel III leverage ratios

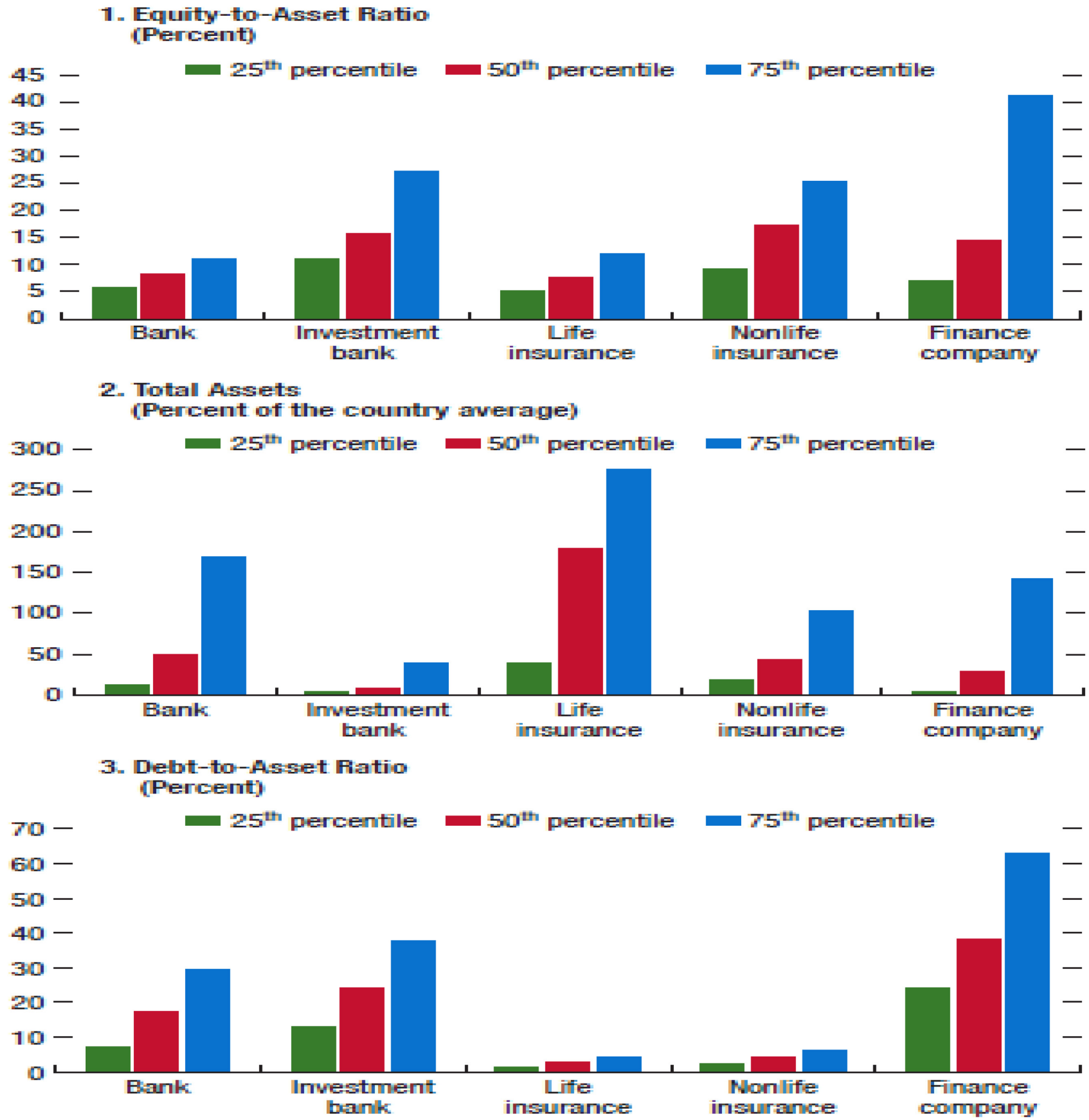
(Q4 2014 – Q2 2016; percentage; median, interquartile range and 10th-90th percentile range)



Source: ECB supervisory data.

- IMF, GFSR (2016)

Annex Figure 2.2.1. Summary Statistics

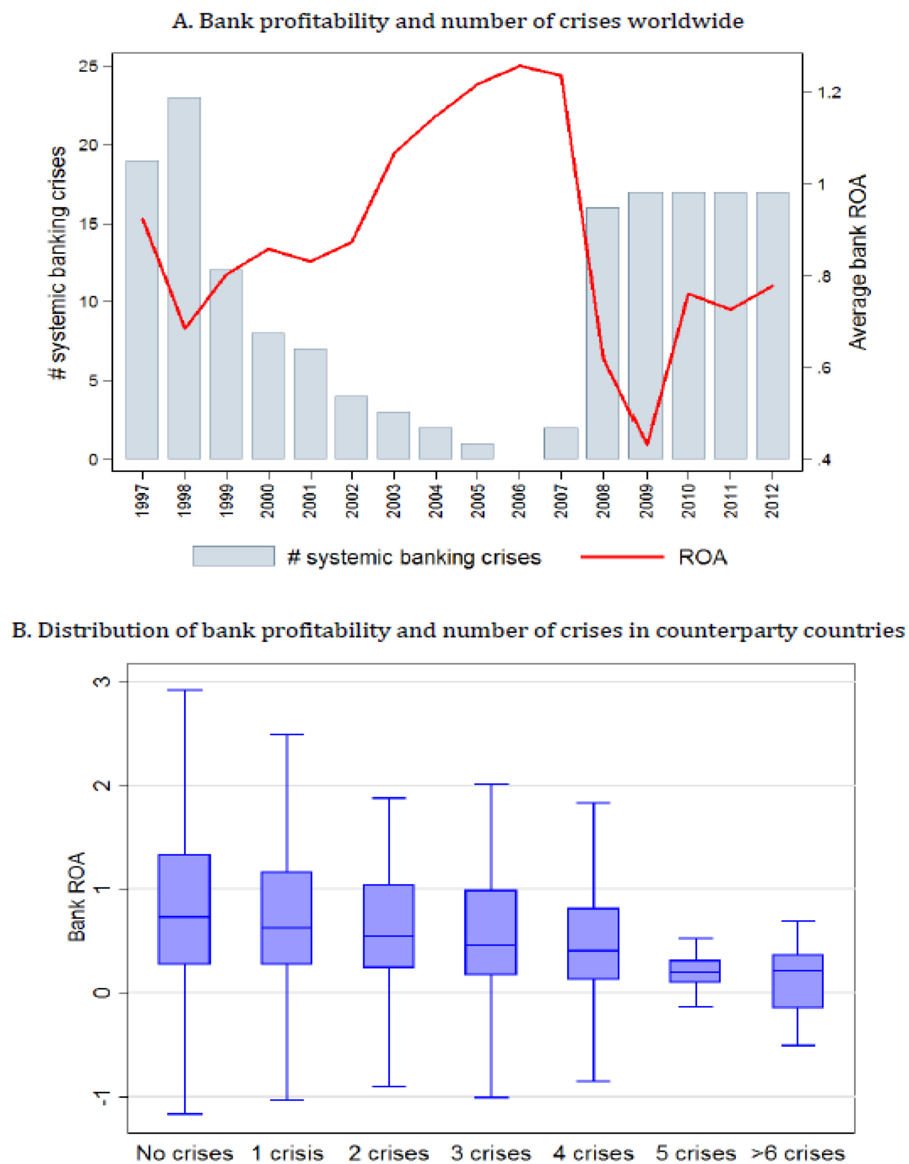


Sources: Thomson Reuters Datastream; and IMF staff calculations.
Note: The figure shows the quartiles of each variable, using data for a total of 368 publicly listed financial firms from Austria, Belgium, Brazil, Canada, Germany, Finland, Ireland, Italy, Japan, Korea, Mexico, the Netherlands, Portugal, Spain, Sweden, and the United States from 1998:Q1 to 2015:Q4. For each variable, we first take firm-level medians, and then industry-level medians of the firm-level medians, in order to avoid the overrepresentation of firms with many observations.

3 Academic work

Hale et al (2014): Interconnected systems are prone to shock transmission and network position matters for bank performance. In that context the charts show (1) inverse relationship between average bank ROA and the number of systemic banking crises that occurred during 1997-2012 and (2) 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).

- Beck et al (2006), Using data for 69 countries over 1980-1997, they found crises are less likely in economies with more concentrated banking systems, 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.
- Fahlenbrach et al (2016): U.S. banks with loan growth in the top quartile of banks over a three-year period between 1973-2014 underperforms the common stock of banks with loan growth in the bottom quartile over the next three years, as growth slows and provisions increase – link to overoptimism on loans made in fast growth period.

4 Econometric analysis

- Panel estimation of CDMs for the IMF sample
- 3 dependent variables of macroprudential relevance drawn from World Bank Global Financial Development Database:
  - Z Score for banking sector (ROA+(Capital/Assets))/SD(ROA))
  - NPL/loan ratio
  - Provisions/NPL ratio
- Control variables (lagged) similar to Beck et al (2013) and Davis and Karim (2013)
- Time dummies

Statistical data for dependent variables

	Z-Score	NPL/loans	Provisions/NPL	
Mean	10.65327	5.628452	68.0569	
Median	9.624889	3.6	59	
Maximum	30.95585	44.9	209.8	
Minimum	-12.0247	0.1	7	
Std. Dev.	6.942201	6.147189	36.43044	
Skewness	0.57824	3.068917	1.316073	
Kurtosis	3.266696	15.59189	4.90054	
Jarque-Bera	14.02703	1954.112	104.9632	
Probability	0.0009	0	0	
Sum	2546.131	1345.2	16265.6	
Sum Sq. Dev.	11470.21	8993.527	315868.1	
Observations	239	239	239	

- Variables tested for predictive power of their CDMs in this respect 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)
  - NPL ratio (non performing loans/gross loans)
- Separate regressions 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
  - Interquartile range (Quartile 1 minus Quartile 4) plus controls

Some statistical issues

- Outliers in the maxima – do they also distort other CDMs? Could Winsorise if necessary.
- There are no observations in advance of the global financial crisis so cannot do crisis prediction
- Post crisis period covered by sample subject to high risk aversion by banks and authorities
- Some negative values requiring linear and not log linear (no elasticities)
- Short time series and large number of countries

Typical regression for Z-Score

Variable	Coefficient	t-Statistic
C	-10.8	(-1.8)
CAPAMEAN(-1)	-50.4	(-2.9)
NONINTSH(-1)	-0.084	(-1.2)
CREDASSET(-1)	28.1	(4.9)
PROVNPL(-1)	0.043	(2.5)
COMPLERNER (-1)	22.2	(3.8)
LIQLIASSET(-1)	-2.73	(-1.2)

Period fixed dummy variables
Sample (adjusted): 2008 2014
Periods included: 7
Cross-sections included: 26
Observations: 99

R-squared	0.39
Adjusted R-squared	0.31
S.E. of regression	5.3

Controls for Z-Score

- NONINTSH (share of noninterest income)
- CREDASSET (share of bank loans in assets)
- PROVNPL (provisions/NPL ratio)
- COMPLERNER (Lerner index for bank competition)
- LIQLIASSET (ratio of liquid liabilities to total assets)

Controls for other regressions

- For NPL/loan ratio, as for Z-Score
- For Provisions/NPL ratio, replace provisions/NPL with NPL/loans

Results for Z-Score (significant CDM variables only)

	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)

Note: extra variable Tier 1 concentration (-1) has a coefficient of 23.5 (2.9)

Results for NPL/ loans (significant CDM variables only)

	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)

Results for Provisions /NPL (significant CDM variables only)

	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)

Number of significant variables

	Z-Score	NPL/loans	Provisions/ NPL	Total
Leverage	6	3	5	14
Liquidity	4	0	8	12
ROE	4	7	2	13
ROA	4	8	0	12
Tier1/risk weighted assets	5	4	8	17
NPL/loans	4	-	-	-

Significant variables by CDM

	Z-Score	NPL/loans	Provisions/ NPL	Total
Mean	3	4	2	9
Skew	1	2	2	5
Stdev	4	3	2	9
Q1	2	0	3	5
Q2	3	1	1	5
Q3	1	1	3	5
Q4	3	2	2	7
Max	1	1	1	3
Med	4	2	2	8
Min	2	3	2	7
IQ range	4	3	3	11

Comments

- 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 most often significant and also retains significance in more restricted samples
- 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 CDMs
- Robustness checks (Appendix) show broad stability of effects across regions and time periods.

5 Conclusion

- Our empirical work follows the preparation of CDMs 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.”

- 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.

References

- Bank of England (2016), "Financial Stability Review ,November 2016", London
- Beck T, Demirguc Kunt A and Levine R (2006) "Bank concentration, competition, and crises: First results", Journal of Banking and Finance, 30, 1581–1603
- Beck T, De Jonghe O, Schepens G (2013) "Bank competition and stability: Cross-country heterogeneity", Journal of Financial Intermediation 22 (2013) 218–244
- Crowley J, Koukpamou P, Loukoianova E, and Mialou A (2016), "Pilot Project on Concentration and Distribution Measures for a Selected Set of Financial Soundness Indicators", IMF Working Paper 16/26
- Davis E P and Karim D (2013), "Exploring The Dynamic Links From Bank Competition To Risk – Reconciling Conflicting Hypotheses?" NIESR Discussion Paper No 421
- European Central Bank (2016), "Financial Stability Review November 2016", Frankfurt
- Fahlenbrach R, Prilmeier R, and Stulz R M (2016), "Why does fast loan growth predict poor performance for banks?", NBER Working Paper No. 22089
- Hale G, Kapan T and Mioiu C (2014), "Crisis transmission in the global banking network", mimeo
- IMF (2013), "Modifications to The Current List of Financial Soundness Indicators",
- Available at: https://www.imf.org/external/np/pp/eng/2013/111313b.pdf.
- IMF (2016), "Global Financial Stability Report October 2016", Washington DC

Appendix: Robustness checks (1) Excluding regions (dependent: Z-Score)

Region excluded	High income	Upper middle income	Lower middle income	Total
IQ range leverage	-14.3 (3,1)	-22.1 (4.0)		-14.1 (3.4)
IQ range Liquidity		0.5 (2.1)		
IQ range ROE	-5.6 (2.8)	-7.5 (4.3)	-7.8 (2.3)	-6.4 (3.9)
IQ range ROA	-109.0 (4.2)	-114.6 (5.2)	-97.1 (3.4)	-108.9 (5,2)
IQ range Tier1/RWA	-12.3 (4.5)	-11.8 (3.1)	-10.4 (3.5)	-11.0 (4.5)
IQ range NPL/loans	29.3 (4.8)	23.2 (2.4)	26.6 (3.2)	23.2 (4.0)

(2) Region-by-region (dependent: Z-Score)

Region:	High income	Upper middle income	Lower middle income	Total
IQ range leverage			-30.1 (3.8)	-14.1 (3.4)
IQ range Liquidity				
IQ range ROE		-18.1 (2.9)	-4.0 (2.0)	-6.4 (3.9)
IQ range ROA		-117.2 (2.0)	-91.2 (3.8)	-108.9 (5,2)
IQ range Tier1/RWA		-12.5 (3.6)	-17.7 (3.0)	-11.0 (4.5)
IQ range NPL/loans	14.3 (1.6)	68.7 (6.1)	30.1 (3.5)	23.2 (4.0)

(3) Sub-periods (dependent: Z-Score)

Sub-period:	2007-2011	2012-2014
IQ range leverage	-13.0 (2.1)	-14.9 (2.6)
IQ range Liquidity		
IQ range ROE	-4.8 (2.4)	-10.6 (2.8)
IQ range ROA	-106.0 (3.4)	-99.4 (3.4)
IQ range Tier1/RWA	-11.6 (3.7)	-11.2 (2.1)
IQ range NPL/loans	28.8 (3.6)	17.0 (2.0)