

Common risk exposures in the Chilean banking system

Diego Avanzini Alejandro Jara
Central Bank of Chile

The opinions expressed in this presentation do not necessary represent the
Central Bank of Chile or its Board.

11 January 2013

Agenda

- 1 Introduction and motivation
- 2 A brief characterization of the Chilean banking system
- 3 The PCA approach to common exposures
- 4 Conclusions

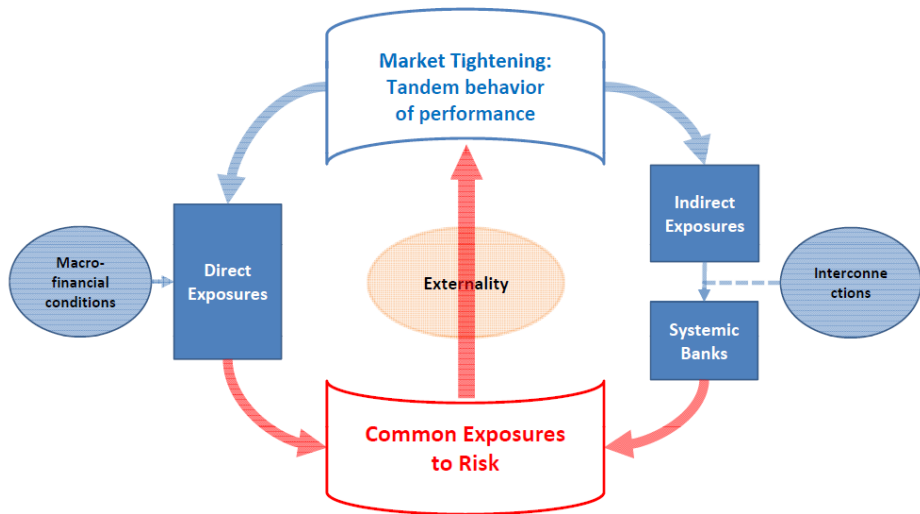
- One important lesson of the 2008-09 global financial crisis is that higher cross-correlation among financial institutions can be a source of systemic risk.
 - Tandem behavior among banks increases the exposure to common risks.
 - Even if individual risk exposures are limited, the whole financial system is relatively more sensitive to changes in the macro-financial conditions, increasing systemic risk (Borio et al., 2001).
 - In fact, a high degree of co-movement across financial institutions (i.e. tandem behavior) can be a good predictor of financial distress (Kritzman et al., 2011).
 - Therefore, understanding the degree in which banks act in tandem is fundamental for systemic risk analysis.

- The degree in which financial institutions move in tandem (i.e the degree in which they are exposed to common risks), change over time:
 - At the international level, globalization of the banking system increased the linkages across financial institutions, making them more vulnerable to changes in market conditions outside national boundaries.
 - At the local level, banking system consolidation - e.g Chile during the '90s and early 2000s - increased market concentration, resulting in a more bonded banking system.
 - In addition, changes in the macro-financial environment may favor the decision taken by banks in order to act in tandem, by increasing, for example, their lending to specific markets such as the retail sector.

Introduction and motivation

- In this paper, we study the extent to which the Chilean banking system has behaved in tandem over the past 20 years.
 - More specifically, we apply principal component analysis (PCA) and a set of measures based on it (the absorption ratio and the centrality score), in order to determine the degree to which banks are exposed to common risks and their contribution to systemic risk.
 - Since there are no market prices for a significant number of banks in Chile, we focus on the existing correlation across banks' performance (interest rate margin and total return on assets).
 - We interpret the increase in the co-movement of bank's performance as a sign of higher exposure to common risks.
 - Common risks may arise through at least two channels: (1) a direct exposure to specific markets (conditional on the macro-financial context), and (2) indirect exposure to systemic banks (conditional on the degree of interconnectedness).

Introduction and motivation

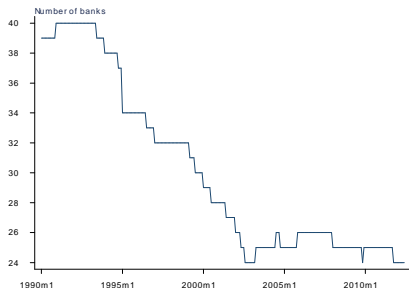


A brief characterization of the Chilean banking system

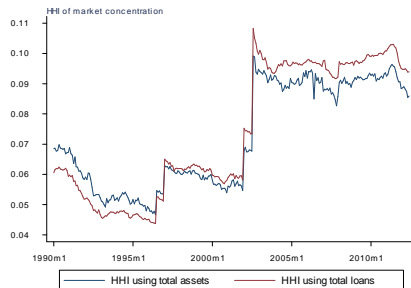
- The Chilean banking system, resembling other emerging market economies, has experienced a strong consolidation process over the past 20 years characterized by:
 - Decreasing number of banks
 - Increasing market participation of foreign banks
 - Increasing market concentration
 - Universality of the banking system (less reliance on niche banks)
- In addition, the macroeconomic stability experienced by the Chilean economy and financial system reforms undertaken in the past, have contributed to diversify the assets and liabilities of banks:
 - Higher importance of the retail sector (e.g. household lending)
 - Increasing importance of non-traditional sources of funding (e.g. bond issuing)

Chilean Banking Consolidation

Number of Banks



Market Concentration



How correlated are Chilean banks' performances?

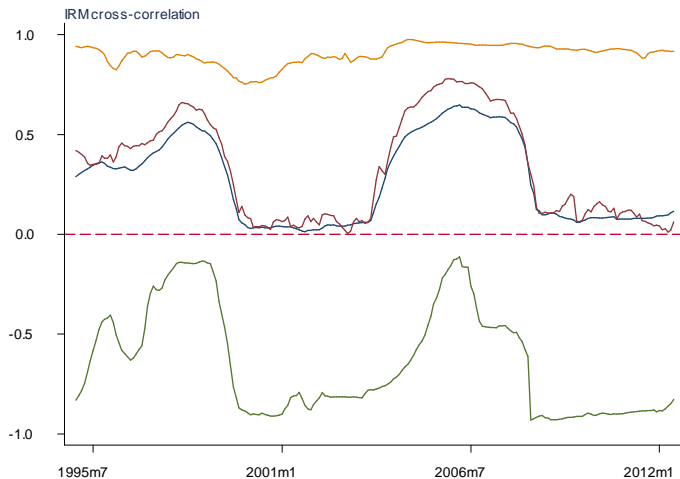
- On average, pair-wise cross-correlation of banks' performance is high and positive across several banks:
 - In particular, but not exclusively, among banks of similar size.
 - Lower correlation, and even negative correlation, occurs across some medium size banks
- Over time, average cross-correlation is not constant, reflecting changes in the degree of common exposures across banks:
 - High cross-correlation periods precede periods of financial distress
 - After periods of distress, average cross-correlation drops (almost) to zero.

IRM correlations across banks (average 1990-2012)

	Big banks					Medium banks										
	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12	b13	b14	b15	
Big banks	b1	1,00														
	b2	0,86	1,00													
	b3	0,84	0,86	1,00												
	b4	0,72	0,44	0,39	1,00											
Medium banks	b5	0,51	0,60	0,72	0,22	1,00										
	b6	0,92	0,73	0,77	0,74	0,43	1,00									
	b7	0,89	0,87	0,91	0,47	0,65	0,77	1,00								
	b8	0,76	0,55	0,63	0,80	0,53	0,79	0,62	1,00							
	b9	0,65	0,32	0,34	0,75	0,17	0,71	0,42	0,76	1,00						
	b10	0,69	0,37	0,53	0,72	0,38	0,79	0,54	0,76	0,81	1,00					
	b11	0,17	0,48	0,31	0,28	0,11	0,04	0,34	0,31	0,48	0,48	1,00				
	b12	0,43	0,53	0,08	0,35	0,64	0,56	0,35	0,03	0,20	0,50	0,57	1,00			
	b13	0,48	0,51	0,27	0,57	0,45	0,40	0,03	0,22	0,30	0,32	0,39	0,40	1,00		
	b14	0,46	0,30	0,11	0,72	0,21	0,19	0,54	0,31	0,13	0,45	0,47	0,23	0,59	1,00	
	b15	0,82	0,89	0,87	0,51	0,77	0,72	0,83	0,69	0,39	0,48	0,27	0,16	0,30	0,02	1,00

IRM: correlations across banks

(rolling window, min, max, mean and median)



A PCA approach to common exposures

- PCA is a (non-parametric) technique that reduces the dimensionality of a dataset by decomposing aggregate variance-covariance (or correlation) matrix in such a way that:
 - Few PCs contain most of the information (i.e explain most of the aggregate variance)
 - Each PC represents a linear combination of the original data.
 - PCs are ordered according to their relative importance.
- Therefore, applying PCA to banks' performance is a way to understand common exposures:
 - A tighten behavior across banks reflects in fewer PCs are needed to explained most of the variance. On the contrary, when banks are acting in a more "uncoupled" way, more PCs are needed to represent the same amount of variability.
 - PCs can be interpreted as an underlying common factor associated, for example, to macro-financial conditions, or to systemic banks.

PCA application to banks' performance

- In particular, we would like to address the following questions:
 - How unified or tighten has been the behavior of the Chilean banking system over the past 20 years?
 - During which periods banks have experienced a greater increase in their tandem behavior?
 - Which banks have contributed the most to this commonality in banks' behavior?
- Data limitations
 - Desirable data: stock returns of the banks → Not available
 - Available data: bank's accounting information → take some variables or indicators for a set of banks for a given timespan
 - Data issues:
 - Data dimensionality → ROA, IRM
 - Databases → full sample, mergers sample
 - Special weighting → Total Assets
 - Time series persistence → Exponentially Weighted Moving Average Covariance Matrix (EWMA Covar)

PCA application to banks' performance

- Absorption ratio (AR)
 - Equals the fraction of total variance of a set of assets returns explained or “absorbed” by a fixed number of eigenvectors.
 - Captures the extent to which markets are unified or tightly coupled.
- Standardized Shift of the AR (SAR)
 - Determines when changes in AR are big enough to worry about systemic risk.
 - Can be understood as a leading indicator of financial distress (Kritzman et al., 2011).
- Centrality Score (CS)
 - Look for those banks that explain a higher portion of aggregate variance
 - Rank banks according to their contribution to systemic risk during periods of high systemic risk

The Absorption Ratio (AR)

- Formally:
 - The Absorption Ratio is given by:

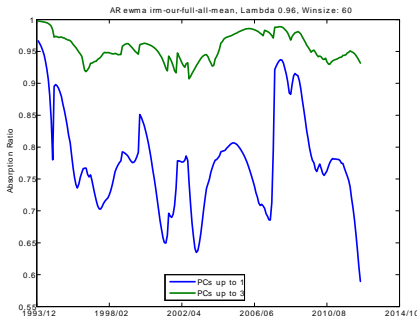
$$AR = \frac{\sum_{i=1}^n \sigma_{E_i}^2}{\sum_{j=1}^N \sigma_{A_j}^2}$$

where n is the number of eigenvectors used in calculating the AR, N is total number of assets or banks, $\sigma_{E_i}^2$ is the variance of eigenvector i , and $\sigma_{A_j}^2$ is the variance of asset j .

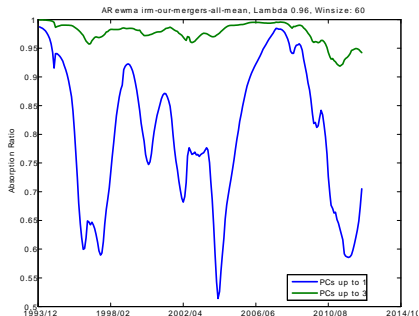
- What do we find?
 - PC1-PC3 explain most of the aggregate variance (~80%)
 - However, the degree of tightening changes over time

IRM: Absorption ratio time series for all banks

Full database



Mergers database



Standardized Shift of the AR (SAR)

- Formally:
 - Given our data availability, the ΔAR is given by:

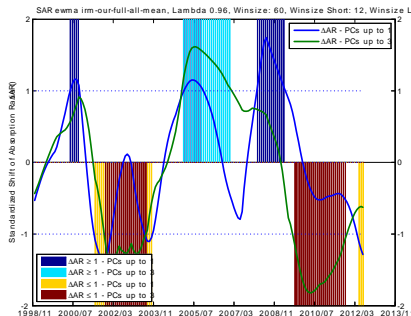
$$\Delta AR = \frac{\overline{AR}_{12-Month} - \overline{AR}_{5-Year}}{\sigma_{AR_{5-Year}}}$$

where ΔAR is the standardized AR shift, $\overline{AR}_{12-Month}$ is the 12-month moving average of AR, \overline{AR}_{5-Year} is the 5-year moving average of AR, and $\sigma_{AR_{5-Year}}$ is the standard deviation of the 1-year AR.

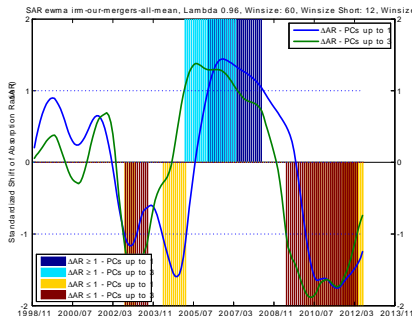
- What do we find?
 - ΔAR at least points out the distress periods.

IRM: Standardized Shift of the AR and distress periods

IRM - Full database



IRM - Mergers database



Centrality Score (CS)

- Formally,

$$CS_i = \frac{\sum_{j=1}^n AR^j \cdot \frac{|EV_i^j|}{\sum_{k=1}^N |EV_k^j|}}{\sum_{j=1}^n AR^j}$$

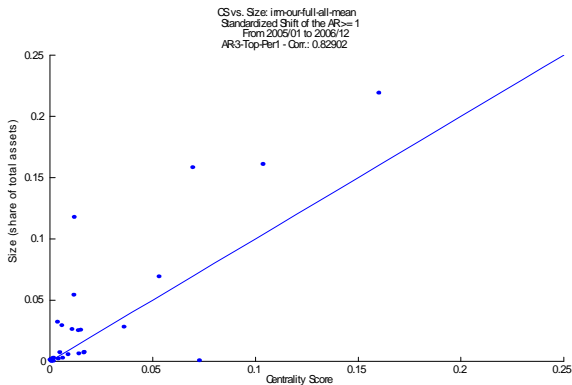
where CS_i is the asset centrality score, AR^j is the absorption ratio of the j^{th} eigenvector, EV_i^j is the absolute value of the exposure of the i^{th} asset within the j^{th} eigenvector, n is the number of eigenvectors in the numerator of the absorption ratio, and N is the total number of assets or banks.

- What do we find?
 - Heterogeneity: weights are not constant, ranking changes over time
 - A few banks top the most of the times
 - Ranks associated to size, but not always

Ranking banks' contributions to systemic risk using the CS

Full database - AR up to 3 PCs
Standardized Shift of the AR ≥ 1
From 2005/01 to 2006/12

Rank	CS	Share
1	16.00	21.93
2	10.36	16.11
3	7.27	0.09
4	6.94	15.85
5	5.31	6.94
6	3.60	2.83
7	1.67	0.78
8	1.64	0.73
9	1.49	2.58
10	1.40	0.66
11	1.38	2.55
12	1.18	11.79
13	1.16	5.45
14	1.07	2.65



- Using PCA approach to banks' performance allows to:
 - describe the dynamics of common exposure.
 - identify periods when banks' behavior becomes tighter.
 - rank banks according to their contributions to systemic risk.
- Periods of tighter behavior may be associated to systemic risk.
- Bank's size does not necessarily relate to centrality score measures of contribution to systemic risk.
- Application of PCA and related metrics can be used as a surveillance methodology to address systemic risk.