

DOCUMENTOS DE TRABAJO

A PCA Approach to Common Risk Exposures in the Chilean Banking System

Diego Avanzini
Alejandro Jara

N.º 707 Diciembre 2013

BANCO CENTRAL DE CHILE



DOCUMENTOS DE TRABAJO

A PCA Approach to Common Risk Exposures in the Chilean Banking System

Diego Avanzini
Alejandro Jara

N.º 707 Diciembre 2013

BANCO CENTRAL DE CHILE





BANCO CENTRAL DE CHILE

CENTRAL BANK OF CHILE

La serie Documentos de Trabajo es una publicación del Banco Central de Chile que divulga los trabajos de investigación económica realizados por profesionales de esta institución o encargados por ella a terceros. El objetivo de la serie es aportar al debate temas relevantes y presentar nuevos enfoques en el análisis de los mismos. La difusión de los Documentos de Trabajo sólo intenta facilitar el intercambio de ideas y dar a conocer investigaciones, con carácter preliminar, para su discusión y comentarios.

La publicación de los Documentos de Trabajo no está sujeta a la aprobación previa de los miembros del Consejo del Banco Central de Chile. Tanto el contenido de los Documentos de Trabajo como también los análisis y conclusiones que de ellos se deriven, son de exclusiva responsabilidad de su o sus autores y no reflejan necesariamente la opinión del Banco Central de Chile o de sus Consejeros.

The Working Papers series of the Central Bank of Chile disseminates economic research conducted by Central Bank staff or third parties under the sponsorship of the Bank. The purpose of the series is to contribute to the discussion of relevant issues and develop new analytical or empirical approaches in their analyses. The only aim of the Working Papers is to disseminate preliminary research for its discussion and comments.

Publication of Working Papers is not subject to previous approval by the members of the Board of the Central Bank. The views and conclusions presented in the papers are exclusively those of the author(s) and do not necessarily reflect the position of the Central Bank of Chile or of the Board members.

Documentos de Trabajo del Banco Central de Chile
Working Papers of the Central Bank of Chile
Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 3882231

A PCA APPROACH TO COMMON RISK EXPOSURES IN THE CHILEAN BANKING SYSTEM*

Diego Avanzini
Gerencia de Investigación Financiera
Banco Central de Chile

Alejandro Jara
Gerencia de Investigación Financiera
Banco Central de Chile

Abstract

This paper studies three related aspects of the Chilean banking's systemic risk: (i) to what extent the degree of common risk exposure in the Chilean banking system has changed over the past decades, (ii) during which periods this exposure increased the most, and (iii) when this degree of commonality became a systemic concern. Additionally, it identifies systemically important financial institutions in Chile based on their contribution to the degree of common risk exposure. It finds that prior to the 2008-09 global financial crisis the degree of common risk exposure in Chile increased significantly, and that the banks that contributed the most were not necessarily the biggest ones in size, as measured by their assets share.

Resumen

Este artículo estudia tres aspectos relacionados con el riesgo sistémico de la banca en Chile: (i) ¿En qué medida el grado de exposición al riesgo común en el sistema bancario chileno ha cambiado en las últimas décadas?, (ii) ¿Durante qué períodos esta exposición se incrementó más?, y (iii) ¿Cuándo este mayor grado de co-movimiento pasó a ser una preocupación sistémica? Además, identifica las instituciones financieras de importancia sistémica en Chile sobre la base de su contribución al grado de exposición al riesgo común. Encuentra que antes de la crisis financiera global de 2008-09 el grado de exposición al riesgo común en la banca chilena aumentó significativamente y que los bancos que más contribuyeron no fueron necesariamente los de mayor tamaño, medido por la proporción de sus activos.

* Paper prepared for the Workshop "Systemically Important Financial Institutions: Identification and Regulatory Challenges" organized by the Central Bank of Chile in Santiago, Chile, January 11th 2013. We are thankful to Iman van Lelyveld, Mario Chamorro, Viral Acharya and the workshop participants for their very helpful comments and suggestions. We also have benefited from the detailed comments of an anonymous referee for the DTBC series. The usual disclaimer applies. Emails: davanzini@bcentral.cl y ajara@bcentral.cl.

1 Introduction

Policymakers concerned about systemic risk study the degree of common risk exposures in order to assess the vulnerability of the banking system. In fact, when financial institutions are exposed to common risks, the whole financial system becomes relatively more sensitive to both changes in macro-financial conditions and to those institutions that by their level of interconnectedness or size are systemically important. Moreover, common risk exposures become a systemic concern when they increase above a certain threshold or turn out to be "*abnormally high*". During those periods of excessive commonality of banks' risk exposures, the dynamics of banks' performance become highly correlated.

In this paper, we study to what extent the degree of common risk exposures in the Chilean banking system have changed over the past decades. We also address the following questions: (*i*) during which periods the degree of commonality has increased the most; and (*ii*) based on predefined thresholds, when this commonality has become systemically relevant. Additionally, we identify systemically important banks based on their contribution to common risk exposures during periods of higher systemic risk. In answering these questions we use an alternate methodology for assessing systemic risk and identifying systemically important financial institutions (SIFIs) in Chile. We claim that this technique can be used by policymakers for surveillance and supervisory purposes.

The key aspect of our approach is to measure the degree of commonality or what we call *tandem behavior* of banks. Following Kritzman et al. (2011) and Kinlaw et al. (2011), we apply principal component analysis (PCA) and a set of related measures¹ to: (*i*) assess the dynamics of common risk exposures in the banking system; (*ii*) identify those periods in which co-movements across banks' performance become particularly high and might be fostering higher systemic risk; and (*iii*) compute the contributions of each bank to the aggregate commonality, ranking banks according to their systemic risk importance.² Usually this type of analysis is based on market information. However, since the majority of banks in Chile are unlisted, we apply this methodology to performance indicators constructed from accounting data. In particular, we use two different measures of banks' performance, such as the *return on assets* (ROA) and the *interest rate margin over total assets* (IRM).

The methodology applied in this paper has at least two important advantages. First, it does not rely on the existence of a systemic event as a way to measure systemic risk or identify SIFIs. Therefore, it may be particularly suitable for those countries that have not experienced recently banking crises, which comes as an advantage compared to other approaches based on counterfactual exercises.³ Second, although using accounting data

¹V.g. the absorption ratio, the standardized shift of the absorption ratio and the centrality score.

²Our approach complements the existing measures used to identify SIFIs, such as the conditional value at risk or CoVaR (Adrian and Brunnermeir (2011)), the expected marginal shortfall or EMS (Acharya (2009); Acharya et al. (2009), Brownlees and Engle (2011)), the Shapley ratio (Gauthier et al. (2010); Tarashev et al. (2010); Drehmann and Tarashev (2011); Staum and Liu (2012)); the measures derived from network models (Chan-Lau (2010)), or from models that estimate the conditional probability of a bank's failure (Segoviano and Goodhart (2009)).

³While other approaches used to identified SIFIs use banking crises as a reference of ill-behaved periods, this is not possible in the case of Chile because the last systemic crisis took place in 1982. Moreover, our analysis is focused on the period running between 1989 and 2012.

is subject to criticism, it is a reasonable alternative for less advanced countries where market information is limited or even nonexistent. Furthermore, applying the methodology presented in this paper to the Chilean experience may be particularly interesting given the process of bank consolidation and financial integration experienced by its banking system during the 1990s and 2000s. In fact, this process may have contributed to change the degree of common exposure to risk as a result of the increasing presence of foreign banks (Ahumada and Marshall (2001)) and the deepening of financial linkages across financial institutions (Anginer and Demirguc-Kunt (2011)).

We find that the degree of common risk exposures changed over time. In particular, we are able to identify the period prior to the 2008 – 2009 global financial crisis as a period when common exposures to risk increased the most, as banks' performance became highly tighten. We also find that systemically important banks do not necessarily related to their size, as measured by their total assets share in the banking system. This is important given the broad approach taken recently by the Financial Stability Board (FSB), who looks at SIFIs beyond their size when define them as those institutions that by their "*size in terms of assets, are large enough, are highly interconnected within the financial system, or are unable to cease to exist without generating significant effects in the financial system and economic activity.*" (Financial Stability Board (2010)).

The rest of the paper is organized as follows: section 2 sets a framework that relates common risk exposures to systemic risk. Section 3 presents a brief characterization of the Chilean banking system with special attention to common risk exposures. Section 4 describes the link between principal component analysis and common exposures, as well as the set of specific measures we use throughout the paper. Section 5 presents the results of applying this methodology to the accounting data of the Chilean banking system spanning the period from January 1989 to June 2012. Finally, some concluding remarks are included in section 6.

2 A common exposure approach to systemic risk

Systemic risk has become a major concern for policymakers and supervisory authorities, in particular in the aftermath of the Global Financial Crisis. However, defining systemic risk has shown to be a difficult task. The strands of the empirical literature on the subject diverge according to the underlying concept of systemic risk. For example, Caballero (2010) associates systemic risk with the existence of financial imbalances, while Mishkin (2007) does it with problems in the generation of financial information. Rosengren (2010), on the other hand, links it to the existence of *bubbles* in financial assets, while Billio et al. (2012) take a broader perspective and define systemic risk as "*any circumstance that threatens the stability or the public confidence in the financial system*". Similarly, the European Central Bank (2010) defines systemic risk as "*the risk that financial instability is so widespread that affects the functioning of the financial system to the point of affecting economic growth and welfare.*"

Our approach highlights the idea that observing a higher degree of correlation across the performance of financial institutions implies increasing systemic risk, similar to Acharya et al. (2012). The reasoning is that systemic risk increases because a higher correlation

across financial institutions behavior makes the whole financial system more vulnerable to changes in the underlying common factors; thus, the degree of common risk exposure becomes an indicator of systemic risk. The underlying common factors can take the form of exogenous macro-financial variables, such as the level of the interest rate, or be the result of higher interconnection across financial institutions. In the latter, the common risk factors can be interpreted as one or more financial institutions (banks) that become systemically more important.

Figure 1 depicts this idea in more detail. Initially, we observe the extent to which banks *act in tandem* by looking at the degree of tightening of their performance (top of the chart). This tightness is the result of the (direct) exposures to specific markets, instruments or prices (e.g. retail sector, government securities, foreign exchange derivatives); or the consequence of the (indirect) exposures due, for example, to their level of interconnect- edness.

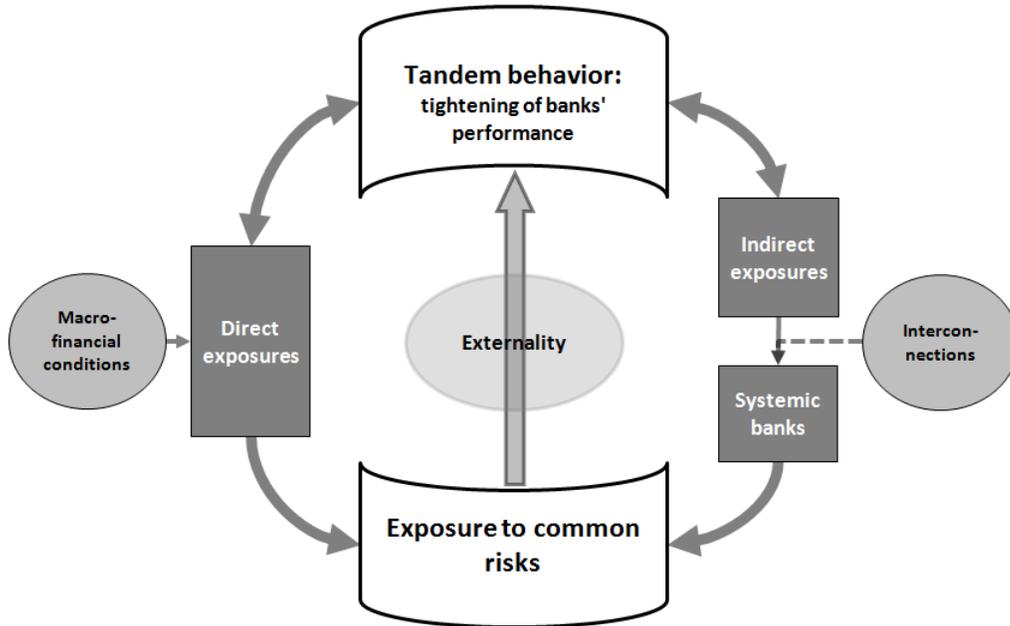
As shown in Figure 1, the direct channel increases the vulnerability of the banking system because it makes the system highly exposed to changes in the macro-financial variables, such as the phase of the economic cycle, the level of interest rates, and the exchange rates. Similarly, the vulnerability of the banking system increases due to the indirect channel, as the failure or distress of one or several (systemic) banks can be propagated more quickly and broadly throughout the entire financial system. In this case, the systemic institution becomes the underlying common risk factor that drives the degree of tightness in banks' performance. Consequently, both channels can potentially increase the exposure to common risks, as highlighted at the bottom of Figure 1.

Furthermore, information asymmetries that characterize financial markets can reinforce the importance of these channels creating an externality that end-up strengthen even more the level of market tightening (see center of Figure 1). In particular, individual banks that ignore the aggregate degree of common exposure can overreact to positive or negative news, increasing or decreasing their exposure to common risk factors.⁴

Similarly, the fact that systemically important financial institutions are usually seen by market participants as "*too big to fail*", increases moral hazard and the excessive risk-taking, resulting in banks underestimating the risks associated to their level of interconnectedness. As a result, financial institutions may overexpose themselves to systemically important financial institutions creating an externality that, indeed, increases market tightness and systemic risk.

⁴This idea is precisely what is behind the *boom/bust* behavior of financial markets known as "*risk on - risk off*" (e.g. see Lee (2012)).

Figure 1. A systemic perspective of common exposures to risk



Source: authors' own elaboration.

3 A debriefing of the Chilean banking system

Chilean banks are characterized by presenting a high degree of heterogeneity which can potentially impact their degree of common exposure to risks. This heterogeneity is explained, among other factors, because of their size, leverage, and their structure of assets and liabilities. In practice, to deal with these differences, policymakers classify banks in groups (see Central Bank of Chile (2007)). A natural way to classify banks in Chile is to group them as *commercial banks* and *treasury banks*. *Commercial banks* mainly take deposits from the public and lend to non-financial firms and households, while *treasury banks* are mostly involved in the financial business, oriented to trade finance and the holdings of financial instruments and derivative hedging, making them more vulnerable to fluctuations in financial variables, such as the interest rates and exchange rates.

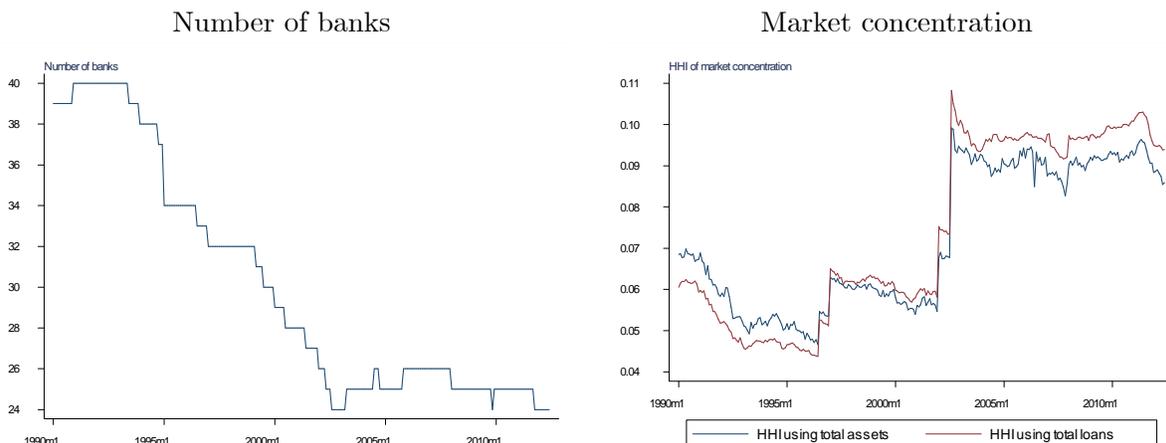
Additionally, *commercial banks* can be grouped among themselves, as they are also highly heterogeneous. For example, they can be grouped into *megabanks* and *medium-size banks*. While *megabanks* are big in terms of their market-share, they are also characterized by a relatively low level of leverage and a highly diversified assets and liabilities' structure of their balance sheets. On the other hand, *medium-size banks*, which by definition are smaller in size, are characterized by a higher leverage and a relatively lower diversification in their assets and liabilities. As a matter of fact, the latter group includes *consumer banks* which are primarily focused on consumer lending, making them particularly vulnerable to the fluctuation in macroeconomic variables, such as the unemployment rate and the output

growth.

Besides this heterogeneity, the Chilean banking system is characterized by having experienced a significant process of bank consolidation over the past 20 years. This process, undergone during the 1990s and 2000s, came together with an increasing presence of foreign banks, and the elimination of the so-called *retail financial institutions*, which became an integral part of *commercial banks*. All this might potentially change the degree of exposure to common risks in the banking system.

As a matter of fact, the Chilean banking system encompassing almost 40 institutions by the early 1990s, dropped significantly its number of banks during the second half of that decade and the early 2000s (see Figure 2, left panel). As a consequence, market concentration, as measured by the *Herfindahl–Hirschman Index* (HHI), increased significantly (see Figure 2, right panel).⁵ This results in banks becoming "structurally" more uniform and concentrated, facilitating the emergence of systemically important financial institutions.

Figure 2. Consolidation in the Chilean banking system



Source: authors' own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

Regarding foreign banks, as they became systemically more relevant (Ahumada and Marshall (2001)), they set the stage to higher risk-taking, in particular during periods when the economic growth was strong.⁶ To highlight this point, Figure 3 shows the degree of concentration of banks' balance sheets (assets and liabilities).⁷ According to the evidence,

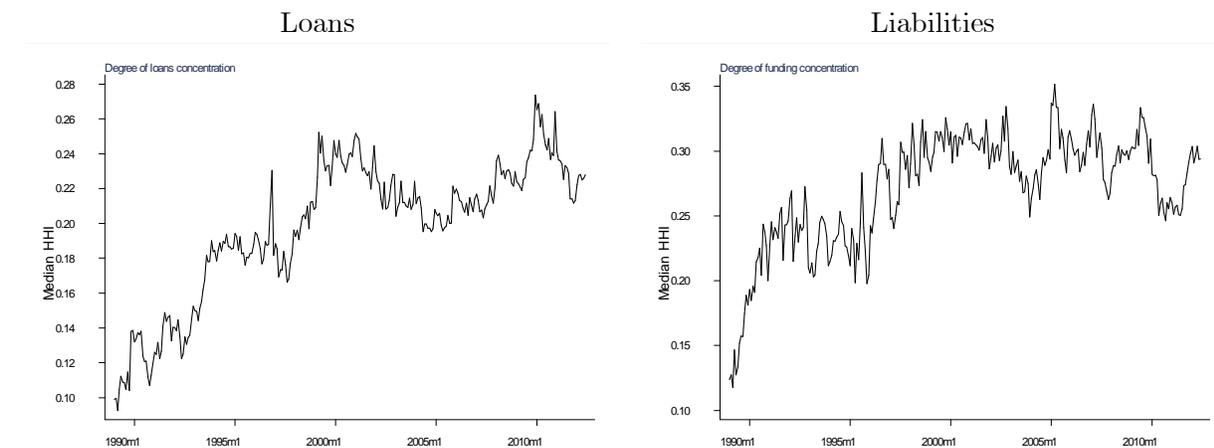
⁵The HHI_t is defined as $HHI_t = \frac{H_t - 1/N_t}{1 - 1/N_t}$ where $H_t = \sum_{i=1}^{N_t} s_{it}^2$ and s_{it} is the market share of bank i at time t in terms of total assets or total loans, and N_t is the number of banks at time t .

⁶In Chile, like in other emerging market economies, the increased presence of foreign banks contributed to reduce operational costs through technology transfer and encouraging banks to enter new credit market niches.

⁷Note that in this case the HHI_t measures the degree of concentration of assets and liabilities. From the asset side, it measures how concentrated are the different types of loans, while from the liability side, it shows the concentration of banks' sources of funding.

the average HHI for banks' loans portfolios shows a reduction in the degree of concentration during the period 2001 – 2006. However, since mid-2006 to early 2010 the concentration on specific loan types increased.⁸ Figure 3 also shows a similar result for the average HHI of banks' liabilities (right panel). In fact, the use of different sources of funding became relatively less concentrated in the mid and late 2000s, most likely due to the increasing use of non-traditional sources of funding, such as the issuance of subordinated bonds.

Figure 3. Concentration of assets and liabilities



Source: authors' own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

3.1 Cross-correlations of banks' performance

As a first step to assess the degree of *tandem behavior* in the banking system we look at the average simple pairwise correlations across banks' economic performance. Ideally, we would like to look at cross-correlations of banks' stock returns, as they better capture markets' sentiments and expectations. However, in the case of Chile this information is scarce, as only a few number of banks are publicly listed and is only available for a short period of time. Hence, we focus our analysis on a set of accounting indicators of banks' performance: (i) the *return on assets* (ROA), and (ii) the *net interest margin on assets* (IRM).⁹

Notice also that in this part of the analysis we only consider *commercial banks* (i.e. *megabanks* and *medium-size banks*), as the behavior of *treasury banks* could be particularly noisy. We make an additional effort to reflect the consolidated behavior of the banking system by constructing a dataset that considers mergers and acquisitions that occurred during the 1990 – 2012 period. We do so by taking the existing banks in June 2012, and reconstructing backward their balance sheets in such a way that mergers and acquisitions

⁸More specifically, certain types of loans have become less relevant, while banks tended to concentrate on some specific asset types.

⁹Using accounting data is certainly not free of problems, as accounting data may be subject to regulatory changes and other issues that may distort our results.

of banks are taken into account.¹⁰ As a consequence, we end-up with a dataset dubbed *mergers-dataset*, which comprises a total of 28 banks and financial institutions (see Appendix A for the list of banks being considered).¹¹

We interpret a high level of correlation across banks' performance indicators as a sign of high exposure to common risks, because the indicators used to describe the banks' performance (ROA and IRM) summarize the structural exposure to risk and the materialization of risk itself. Therefore, a high correlation across the indicators of banks' performance reflects that either the balance sheet structure across banks are becoming more alike, or that their performances are driven by a common external risk factors.¹²

When looking at average cross-correlations of banks' performance, it is worthnoticing that they are not only high and positive among banks of similar size, but also across *mega-banks* and *medium-size banks* (see Table B.1 in Appendix B). Furthermore, the dynamics of these cross-correlations are not constant over time (see Figure 4). In fact, when using a moving window of 60 months, the average pairwise cross-correlation tends to move in cycle. We interpret this result as a reflection of changes in the degree of common exposures across banks.

In particular, the average cross-correlations of the interest rate margin (see Figure 4, right panel) reach its peak during the late 1990s and the mid-2006, remaining high until mid-2007.¹³ In both cases, the average cross-correlation drops close to zero immediately after the Asian Crisis and the Global Financial Crisis.

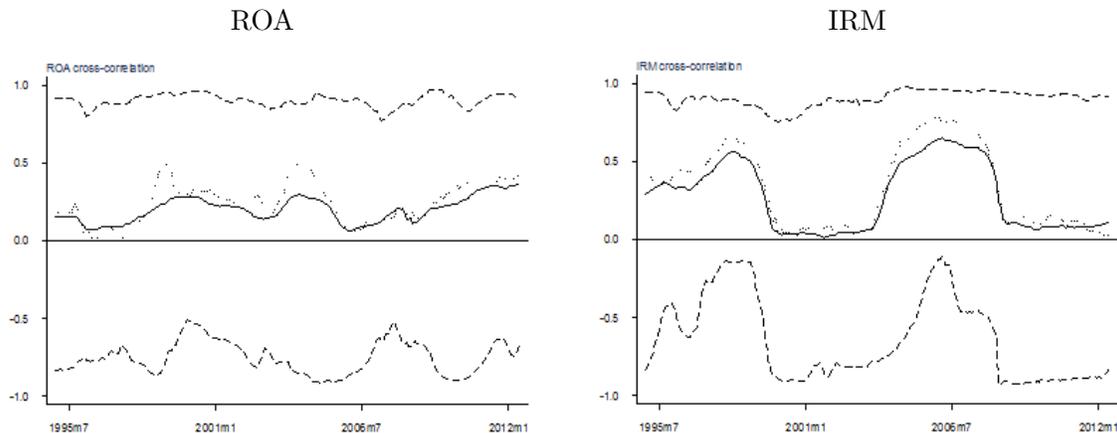
¹⁰In other words, if a currently active bank is the result of a merger or acquisition in the past, we construct a fictitious bank for the period before the merger was effective.

¹¹Alternative, the original dataset contains the complete history of banks, consisting of a total of 46 banks and financial institutions that have existed at some point in our sample. We call this the *full-dataset*.

¹²A null or negative cross-correlation, in our view, would reflect the opposite, i.e higher risk diversification within the banking system.

¹³Cross-correlations of IRM are a better measure of common risk exposure because represents a cleaner measure of banks' vulnerabilities. In fact, analysing the cross-correlations of ROA can be a misleading measure of common risk exposures because this indicator is also driven by the dynamics of "operational expenses", which fall significantly as a consequence of the efficiency gains experienced during the banking consolidation. Moreover, ROA is also affected by taxes and loan loss-provisions. While the latter is a reasonable measure of credit risk, it may be also driven by regulatory restrictions and banks' own policy towards provisioning.

Figure 4. Cross-correlations of bank performance



Note: average (solid-line), median (dotted-line), and the maximum and the minimum of cross-correlations in dashed-line.

Source: authors' own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

This analysis, though simple, is consistent with the view that in times of *booms*, financial institutions tend to *act in tandem*, increasing their exposure to common risks and consequently increasing systemic risk (*risk-on*). Once the signs of the crisis start, banks diversify their portfolio and the structure of their balance sheets, reducing their exposure to common risks. As a consequence, their performance becomes more heterogeneous, reducing the correlation across banks (*risk-off*).

4 A PCA approach to common exposures

While the cross-correlation analysis presented above represents a reasonable first approach to common risk exposures, it has certain limitations. In particular, it only considers bilateral data (pairwise correlations), which in principle is not fully informative given the hidden linkages among banks (see Pukthuanthong and Roll (2009)). Situations such as leader-follower behavior, the existence of dominant banks, high interconnection, or the fact that a group of banks is focused on a dominant economic sector, may create propagation mechanisms that favor systemic risk. Thus, pairwise correlation analysis may not be able to capture the richness of the relationship across banks.

In what follows, we describe the principal component analysis (PCA) and its application to deal with systemic risk. We claim that PCA represents a methodology that is suitable to deal with the issues described above. From a practical perspective, PCA is a non-parametric method for extracting relevant information from large datasets.¹⁴ The basic strategy embedded in PCA considers the transformation of a high dimensional dataset into

¹⁴PCA is a technique with more than a hundred years development starting with Pearson (1901) and Hotelling (1936). It has been used in several areas such as chemistry, psychology, climate studies, process control, and many other fields. For more details, see Jolliffe (2002) who nicely collects a long list of contributions that apply PCA to different fields.

a low dimensional one; the latter contains most of the information of the original dataset but with a reduced amount of data. As a result, most of the aggregate variability of the original multi-dimensional dataset can be expressed using a few principal components or PCs, constructed from a linear combination of the original data. The method also allows to know which PCs are the most important in terms of their capability to explain the aggregate variability (relative importance of each PC).

As a consequence, by applying PCA we are able to take advantage of its capacity to extract correlations among multiple instances of the observational units, largely improving the analytical capability of pairwise cross correlations.

4.1 PCA and systemic risk

Since PCA serves as a data reduction technique it can be used to disentangle the different sources explaining the commonality in banks' performance. More specifically, when we apply PCA to this data and find that a few (many) PCs are needed to explain aggregate variability, we interpret that banks' performances become tighten ("uncoupled"). Consequently, PCA can be used to understand common risk exposures because it allows us to know how much of the aggregate variability can be explained by one or more PCs, and how much of the individual variability can be explained by the common factor.

More importantly, a tighten market behavior can be related to systemic risk because when banks *act in tandem* the whole financial system becomes relatively more fragile, as shocks can propagate more quickly and broadly than when markets are loosely linked. Therefore, PCA can be used to identify periods when common exposure increases (*tighter behavior*), as well as periods when common exposure decreases or the behavior becomes more dispersed.¹⁵

In what follows, we claim that when applying PCA and a set of related tools to banks' performance information (ROA and IRM) we are able to incorporate both direct and indirect linkages across banks. In particular, we use the *absorption ratio* (AR), a measure that can be interpreted as a proxy of the degree of tightness in the financial market; the *standardized shift of the absorption ratio* (SAR or ΔAR), that helps to determine periods of abnormal change in the *absorption ratio*, which in turn can be interpreted as early warnings of forthcoming crises; and the *centrality score* (CS), representing a measure of banks' contributions to systemic risk.

4.2 The absorption ratio

The *absorption ratio* is a measure of implied tightness in financial markets developed by Kritzman et al. (2011) and applied originally to assets returns. Intuitively, the AR captures the extent to which a market is unified. Therefore, when the AR is high, it can be

¹⁵Note that alternatively we could look at *direct linkages* across banks (i.e linkages coming from the interbank market). However, this approach is subject to criticism. On the one hand, securitization, private transactions, complexity, and "creative" accounting prevent us from directly observing the many explicit linkages of financial institutions (Kritzman et al. (2011)). On the other hand, even if linkages are observed, financial institutions can be exposed to common risks indirectly. Recall Figure 1 and its explanation.

interpreted as financial institutions *acting in tandem*, increasing the risk of financial contagion. Notwithstanding, a high AR does not necessarily imply the existence of financial turbulence, but the fact that market conditions are such that risk transmission is easier.

From a technical point of view, the AR represents the fraction of the total variance of a set of assets returns that are explained or “absorbed” by a finite number of eigenvectors.¹⁶ Formally, consider a market with N banks for a time window ending in t . Then, the AR is defined as:¹⁷

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

where:

$$\begin{aligned} n &= \text{number of eigenvectors} \\ N &= \text{number of banks} \\ \sigma_{E_i}^2 &= \text{variance of eigenvector } i \\ \sigma_{A_j}^2 &= \text{variance of asset return of bank } j \end{aligned}$$

Since asset returns are highly persistent through time, in order to obtain well-behaved principal components the covariance matrix needs to be adjusted. In our case, we adjust the covariance matrix to an *exponentially weighted moving covariance matrix* (EWMCM) following JP Morgan (1996), Hawkins and Maboudou-Tchao (2008), Finch (2009), and Danielsson (2011). The EWMCM is the result of an incremental covariance matrix with each period information adjusted by an exponential factor. The exponential factor gives more importance to later observations than to earlier ones for a predefined timespan (see Appendix C for a more formal presentation of this issue). For the purpose of the empirical exercise below, the covariance matrix is adjusted using a weighting parameter λ equalling 0.96. This implies that the variances $\sigma_{E_i}^2$ and $\sigma_{A_j}^2$ are calculated assuming that the market’s memory of prior events fades away gradually as the events recede further in the past. We also set a time window of 60 months in order to calculate each AR.

4.3 The standardized shift of the absorption ratio

The *standardized shift of the absorption ratio* measures significant changes in the AR that are big enough to worry about systemic risk. Following Kritzman et al. (2011), we define SAR as the difference between the 12-month moving average AR and its 5-year moving average and normalizing it by its standard deviation:¹⁸

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

¹⁶PCA can be applied to covariance or correlation matrices, but we choose to apply it to the covariance matrix in order to take into account possible scale effects.

¹⁷Note that for the purpose of this article the asset return of bank j (A_j) corresponds to either the returns on assets (ROA) or the interest rate margin (IRM).

¹⁸We choose 12 months and 5 years as the respective timespans as a way to gather enough information in order to make SAR meaningful enough, and not to oversmooth the result.

where:

$$\begin{aligned} AR_{12-Month} &= 12\text{-month moving average of AR} \\ AR_{5-Year} &= 5\text{-year moving average of AR} \\ \sigma_{AR_{5-Year}} &= \text{standard deviation of the 5-year AR} \end{aligned}$$

The resulting ΔAR is a measure of how the last year average AR deviates from the last 5-year average. When the $\Delta AR \geq 1$, the jump in the AR is big enough to consider that sources of risk have tightened to dangerous levels. On the other hand, when the $\Delta AR \leq -1$, the sources of risk are particularly lously linked.

As Kritzman et al. (2011) emphasize, the SAR not only measures the variability of the AR, but also can be used as a good leading indicator of financial distress. In fact, when analyzing American stock returns around the 1998 and 2008 period, Kritzman et al. (2011) find that the SAR adequately anticipates financial turbulence. Moreover, SAR goes down very quickly after the crisis, evidencing a strong decoupling across financial assets.

4.4 The centrality score

The *centrality score* measures the degree to which a particular asset returns drive aggregate market variance, and is used mainly to measure the contribution of an specific asset class (in our case, a bank) to systemic risk. After identifying those periods of implied high systemic risk (i.e when $\Delta AR \geq 1$), the CS can be used to rank banks according to their contribution to systemic risk (aggregate variability).

In particular, we follow Kinlaw et al. (2011) and Bonacich (1972), and reinterpret their contribution to systemic risk as a measure of banks' systemic importance. More specifically, our CS measure takes into account three features: (i) it captures how broadly and deeply a bank is connected to other banks in the system;¹⁹ (ii) it captures the bank's vulnerability to failure;²⁰ and (iii) it captures the risk of failure of the other banks to which it is connected. For our purpose, none of these features by itself is a particularly effective measure of systemic importance, but collectively, they represent a reasonable indicator of contribution to systemic risk.²¹

Formally, the *centrality score* or systemic importance of a bank i at time t is given by the following expression:

$$CS_{it} = \frac{\sum_{j=1}^{n_t} AR_t^j \cdot \frac{|EV_{it}^j|}{\sum_{k=1}^{N_t} |EV_{kt}^j|}}{\sum_{j=1}^{n_t} AR_t^j}$$

¹⁹I.e how many assets (banks) are correlated, and how strong is this correlations.

²⁰The vulnerability to failure refers to banks' default, which in our case is proxied by the level of the banks' performance volatility.

²¹For example, if a bank is well connected but unlikely to default, or vulnerable to default but not well connected, or even vulnerable to default and well connected, but only to banks that are themselves safe, then there is little reason to fear the default of such bank, or that such default may affect the system as a whole.

where

$$\begin{aligned}
 AR_t^j &= \text{absorption ratio of the } j^{\text{th}} \text{ eigenvector} \\
 EV_{it}^j &= \text{exposure of the } i^{\text{th}} \text{ bank within the } j^{\text{th}} \text{ eigenvector} \\
 n_t &= \text{number of eigenvectors in the numerator of the absorption ratio} \\
 N_t &= \text{total number of banks in the banking system}
 \end{aligned}$$

To make this measure more functional to our needs, we rank banks according to its average behavior during periods when the SAR shows a concern (i.e $\Delta AR \geq 1$). For example, if the $\Delta AR \geq 1$ for the period Dec. 2007-Mar. 2008, we average the CS of each bank over that period, and then we rank the banks according to these averages. This procedure gives us a better understanding of the systemic importance of each bank during the distress period.

5 Results

In what follows, we apply PCA and the related tools described above (AR, SAR, and CS) to the monthly Chilean banks' performance indicators (ROA and IRM) for the 1989 – 2012 period. In doing so, we take into account several issues. First, we deal with banks' mergers and acquisitions, as we consider two different datasets (mergers- and full-dataset).²² Second, we apply PCA to covariance matrices instead of correlations in order to account by the differences in magnitude that characterize ROA and IRM across banks. Third, we "demean" each indicator before performing the eigen decomposition, so each indicator is affected by its variance but not its level. Fourth, we weight each indicator by the respective market share of the corresponding bank.²³ This adjustment allows us to make the performance indicators more comparable in terms of the banks' size and impact on the whole banking system. Finally, we use a small number of PCs in order to make our presentation parsimonious.²⁴

5.1 Determining periods of financial distress

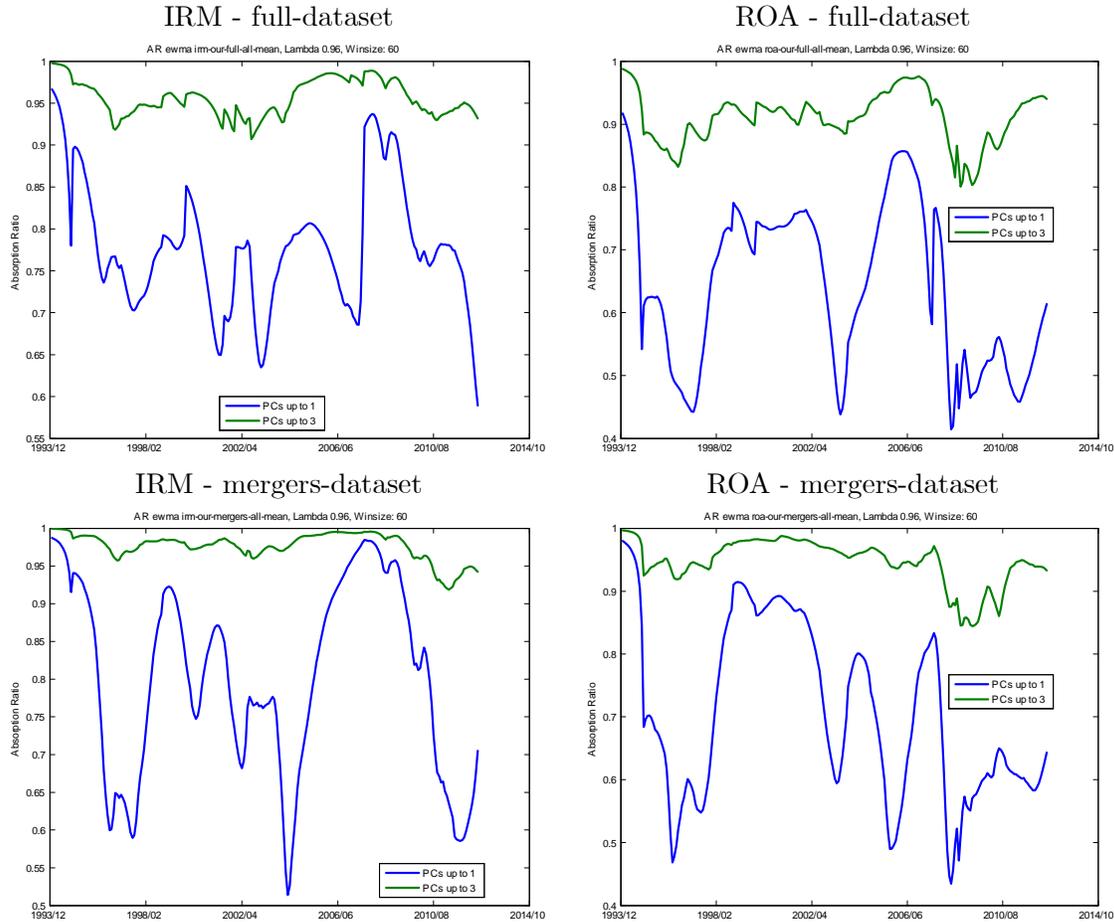
First of all, we compute the AR for the two performance indicators (ROA and IRM), using the two datasets (*full-* and *mergers-dataset*), and considering up-to 10 PCs. Figure 5 displays these results taking into account one and up-to 3 PCs. As can be seen, using different datasets does not change significantly the pattern of the AR for the period being considered. In fact, in all cases, most of the aggregate variance (about 80%) is captured when considering up to the third PC. This indicates that the banking system is mostly affected by a small number of important sources of variability. However, even when the sources of risk appear to be very tighten, the degree of tightness changes over time.

²²See section 3.1 for more details about the two dataset we use in this paper (mergers and full), and Appendix A for the list of banks included.

²³To measure market share we use total assets.

²⁴A complete set of results (including different alternatives of data adjustment, weights, and the inclusion of up to 10 PCs in the AR) is available upon request.

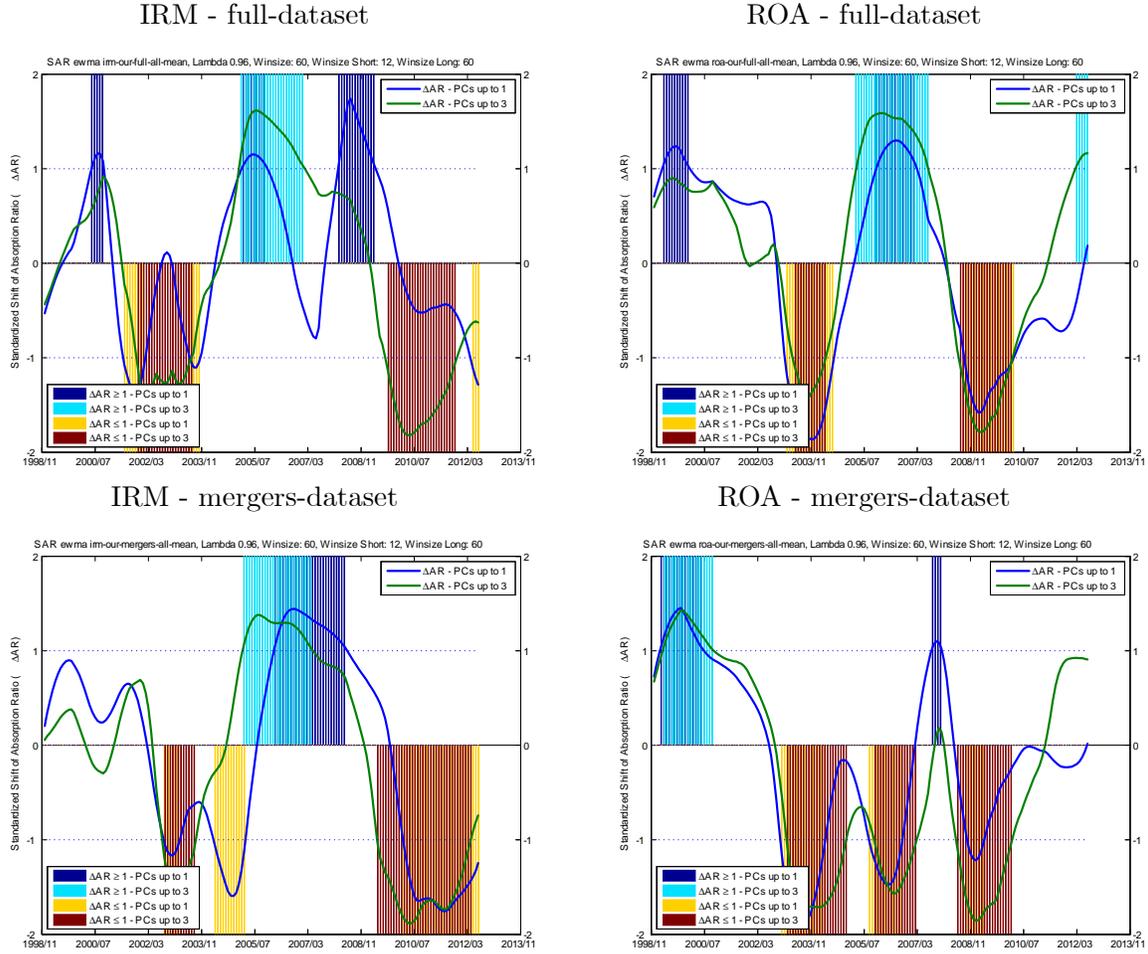
Figure 5. Absorption ratio



Source: authors' own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

Secondly, we turn to the computation of the SAR to analyze when changes in the AR are important enough to worry about systemic risk. Figure 6 shows the SAR for the first and up to the third PC (blue and green lines, respectively). In addition, these charts show the periods when $\Delta AR \geq 1$ and $\Delta AR \leq -1$ (shaded areas in the charts). Notice that the results coming from the full database are more sensitive to changes in market tightening as compared to the outcomes of the mergers database. This result appears to be reasonable given that in the mergers dataset, we are forcing common behavior for the set of absorbed and merged banks (those constituting the fictitious banks). Thus, much of the variability contributed by disappearing banks is netted against the behavior of surviving banks that are taking over the business.

Figure 6. Standardized shift of the AR and distress periods



Source: authors' own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

Although these results differ somehow depending on the database we use, specially when looking back in time, both databases consistently identify the period prior to the 2008 global financial crisis. This period is characterized by significant tighten banks' performance, and therefore, by higher systemic risk. These findings match the conclusions by Kritzman et al. (2011) in the sense that the AR and the SAR may be good leading indicators of market tightening and increased systemic risk. However, it is important to recall that increased market tightening is not necessarily a signal of market distress and crisis, but an alert signal that indicates that market conditions may favor quick and broad contagion if a crisis arises. This is important since the Chilean banking system did not face a crisis as a consequence of the global financial crisis.

5.2 Contributions to systemic risk

The final step in our analysis is to identify those banks that are systemically more important. In order to do so, we estimate the contribution of each bank to systemic risk when the AR shows higher market tightening (i.e. when $\Delta AR \geq 1$). In the panels of Table 2, we show the contribution to risk of different banks for two financial distress periods. The first period covers Jan. 2005 - Dec. 2006 and was determined using the IRM. The second period covers Mar. 2005 - Jun. 2006 and was determined using the ROA. In both cases, we considered the period when the $\Delta AR \geq 1$ using the AR with up to 3 PCs for the full dataset. These contributions to systemic risk, as measured by the centrality score, are compared to the respective size of banks, as measured by the shares of the banks in the system total assets.

Table 2. Ranking of banks' contributions to systemic risk

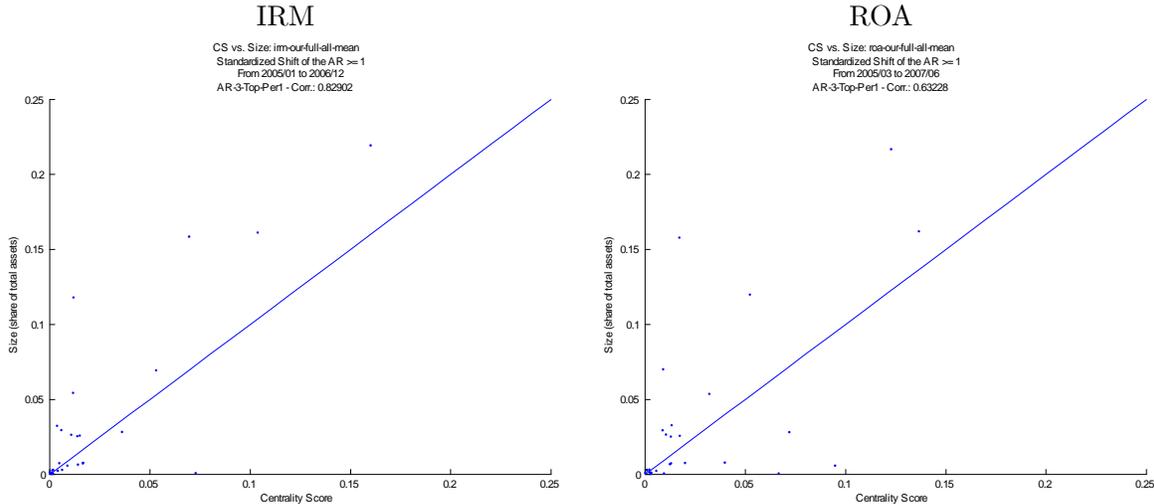
IRM - Full database - AR up to 3 PCs Standardized Shift of the AR ≥ 1 From 2005/01 to 2006/12						ROA - Full database - AR up to 3 PCs Standardized Shift of the AR ≥ 1 From 2005/03 to 2007/06					
Rank	CS	Share	Rank	CS	Share	Rank	CS	Share	Rank	CS	Share
1	16.00	21.93	15	0.88	0.59	1	13.66	16.21	15	1.23	0.69
2	10.36	16.11	16	0.61	0.30	2	12.27	21.68	16	1.04	2.66
3	7.27	0.09	17	0.57	2.96	3	9.47	0.59	17	0.93	0.06
4	6.94	15.85	18	0.47	0.75	4	7.18	2.82	18	0.90	7.02
5	5.31	6.94	19	0.40	0.23	5	6.65	0.05	19	0.87	2.94
6	3.60	2.83	20	0.36	3.23	6	5.23	11.98	20	0.55	0.24
7	1.67	0.78	21	0.17	0.30	7	3.97	0.79	21	0.31	0.11
8	1.64	0.73	22	0.16	0.06	8	3.20	5.37	22	0.27	0.03
9	1.49	2.58	23	0.12	0.11	9	1.99	0.77	23	0.22	0.14
10	1.40	0.66	24	0.12	0.26	10	1.72	2.57	24	0.21	0.32
11	1.38	2.55	25	0.07	0.03	11	1.70	15.79	25	0.11	0.27
12	1.18	11.79	26	0.03	0.10	12	1.32	3.28	26	0.09	0.30
13	1.16	5.45	27	0.00	0.15	13	1.29	0.74	27	0.01	0.10
14	1.07	2.65				14	1.28	2.52			

Source: own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

Four important conclusions arise from these tables. First, a small number of banks (the largest ones) are always at the top of the ranking. This result shows that the strong heterogeneity in size that characterizes the Chilean banking system overcomes the effect of risk diversification that is usually present in biggest banks. Second, while in both tables the set of banks that lead the contributions to systemic risk are the biggest ones, we found that smaller banks' contributions to aggregate risk could also be high. These high contributions to aggregate risk are generally associated with aggressive expansion of loan portfolios, or the concentration on certain market niches that may be more affected by external factors. Third, notice that rankings differ according to what information we take into account. This conclusion proceeds even when the ranking do not cover exactly the same period because asset size varies slowly over time, so it can be taken as a reference to compare the ordering. This implies that using a single indicator may be misleading in the assessing of risk contributions. Finally, when comparing these rankings with those from previous distress periods we observe that they also change over time, and institutions once systemically important can be relegated to lower positions in more contemporary rankings. This indicates that the contributions to systemic risk may be dynamic and that the tools we are using in this paper are sensitive enough to capture these changes.

Overall, the main lesson from this section is that higher market share is not necessarily a synonym of higher contribution to systemic risk. To make this point clearer, observe Figure 7 in which we compare the information provided by the centrality score and the average size of the banks during the period when $\Delta AR \geq 1$. When contributions to risk are highly associated to market share, they lay along the 45° line. However, as discussed, dispersion around the 45° line reflects that contributions to systemic risk, as measured by the CS, are not always associated to size. In fact, if we check the left panel of Figure 7, the correlation between the CS estimated using the IRM is 0.83, but using the ROA, this correlation is 0.63 which can be considered a weak association between contribution to risk and banks' size.

Figure 7. Centrality score vs. banks' size



Source: authors' own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

6 Concluding remarks

In this paper we study to what extent the degree of common risk exposures in the Chilean banking system has changed over the past decades, during which periods this exposure increased the most, and when this degree of commonality became a systemic concern. We do so by applying PCA and a set of related tools to two accounting indicators of banks' performance (ROA and IRM).

In particular, we identify periods of high common exposure to risk that can be associated to systemic risk using the absorption ratio and the standardized shift of the absorption ratio. We find that the degree of common exposure changes over time and may be associated to systemic risk. In particular, we identify the period prior to the 2008 global financial crisis as a period when banks' performance in Chile became highly tighten.

In addition, we identify systemically important financial institutions in Chile based on their contribution to the degree of common risk exposures, using a measure derived from

vector centrality. We find that banks that contributed the most were not necessarily the biggest ones in size, as measured by their shares in the banking system assets.

The methodology applied in this paper has several advantages. First, it does not rely on the existence of a systemic event as a way to measure systemic risk, which we claim is suitable for countries that have not experienced recently banking crises. Second, the focus on accounting data may be particularly appealing to less advanced countries where market information is limited or even nonexistent. Third, since PCA and related metrics applied in this paper can be updated monthly, they can be used as tools for systemic risk surveillance by policymakers and supervisory authorities.

Finally, we identify at least two avenues for future research: (1) dealing with the sources of common exposures (direct exposures to macro-financial variables and indirect exposures through dominant banks and interconnections among banks), and (2) evaluating the role of a multidimensional setting (e.g. N-Way PCA), which can help us to get a better picture of the systemic risk configuration as it allows to incorporate more information of banks' behavior.

References

- Acharya, V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, 5(3):224–255.
- Acharya, V., Pedersen, L., Philippon, T., and Richardson, M. (2009). Regulating systemic risk. In Acharya, V. and Richardson, M., editors, *Restoring Financial Stability: How to Repair a Failed System*, New York. Wiley.
- Acharya, V., Pedersen, L., Philippon, T., and Richardson, M. (2012). Measuring systemic risk. *CEPR Discussion Papers No. 8824*.
- Adrian, T. and Brunnermeier, M. (2011). CoVaR. *NBER Working Paper No. 17454*. National Bureau of Economic Research.
- Ahumada, A. and Marshall, J. (2001). The banking industry in Chile: Competition, consolidation and systemic stability. *BIS background paper No. 4*. Bank for International Settlements.
- Anginer, D. and Demirguc-Kunt, A. (2011). Has the global banking system become more fragile over time? *Policy Research Working Paper No. 5849*. The World Bank.
- Billio, M., Getmansky, M., Lo, M., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559.
- Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology*, 2(1):113–120.
- Brownlees, C. and Engle, R. (2011). Volatility, correlation and tails for systemic risk measurements. *NYU Stern School of Business Vlab*, June.

- Caballero, R. (2010). The "other" imbalance and the financial crisis. *NBER Working Paper No. 15636*. National Bureau of Economic Research.
- Central Bank of Chile (2007). Agrupación de los bancos a partir del análisis de conglomerados. *Financial Stability Review*, Recuadro IV.2.
- Chan-Lau, J. (2010). Regulatory capital charges for too-connected-to-fail institutions: A practical proposal. *Financial Markets, Institutions & Instruments*, 19(5):355–379.
- Danielsson, J. (2011). *Financial Risk Forecasting: The Theory and Practice of Forecasting Market Risk with Implementation in R and Matlab*. John Wiley & Sons Ltd, United Kingdom.
- Drehmann, M. and Tarashev, N. (2011). Measuring the systemic importance of interconnected banks. *BIS Working Paper No. 342*. Bank for International Settlements.
- European Central Bank (2010). Analytical models and tools for the identification and assessment of systemic risks. *Financial Stability Review*, June.
- Financial Stability Board (2010). *Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations*. Report to the G-20 Finance Ministers and Central Bank Governors.
- Finch, T. (2009). Incremental calculation of weighted mean and variance. *Lecture Notes, University of Cambridge Computer Service*, February.
- Gauthier, C., Lehar, A., and Souissi, M. (2010). Macroprudential regulation and systemic capital requirements. *Working Paper No. 2010-4*. Bank of Canada.
- Hawkins, D. M. and Maboudou-Tchao, E. M. (2008). Multivariate exponentially weighted moving covariance matrix. *Technometrics*, 50(2):155–166.
- Hotelling, H. (1936). Simplified calculation of principal components. *Psychometrika*, 1(1):27–35.
- Jolliffe, I. T. (2002). *Principal component analysis*. Springer Verlag, New York, 2nd. edition.
- JP Morgan (1996). Riskmetrics® technical document. *Morgan Guaranty Trust Company, Reuters Ltd, 4th edition, New York*.
- Kinlaw, W., Kritzman, M., and Turkington, D. (2011). Toward determining systemic importance. *The Journal of Portfolio Management*, 38(4):100–111.
- Kritzman, M., Li, Y., Page, S., and Rigobon, R. (2011). Principal components as a measure of systemic risk. *The Journal of Portfolio Management*, 37(4):112–126.
- Lee, W. (2012). Risk on/risk off. *Journal of Portfolio Management*, 38(3):28–39.
- Mishkin, F. S. (2007). Financial instability and the federal reserve as a liquidity provider. *Speech at the Museum of American Finance Commemoration of the Panic of 1907, New York*.

- Pearson, K. (1901). Principal components analysis. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 6(2):559–572.
- Pukthuanthong, K. and Roll, R. (2009). Global market integration: An alternative measure and its application. *Journal of Financial Economics*, 94(2):214–232.
- Rosengren, E. (2010). Asset bubbles and systemic risk. *Federal Reserve Bank of Boston Speech*, Mar 3.
- Segoviano, M. and Goodhart, C. (2009). Banking stability measures. *IMF Working Paper WP/09/4*. International Monetary Fund.
- Staum, J. and Liu, M. (2012). Systemic risk components in a network model of contagion. Available at SSRN 1726107.
- Tarashev, N. A., Borio, C. E., and Tsatsaronis, K. (2010). Attributing systemic risk to individual institutions. *BIS Working Paper No. 308*. Bank for International Settlements.

A Datasets

The *full-dataset* comprises the original list of banks that at any point in time have existed in the Chilean banking system during the period of 1989 and 2012. On the other hand, the *mergers-dataset* considers the fact that some banks and financial institutions cease to exist either because they were absorbed, merged or their licence expired. The list of these banks includes all banks actively operating by June 2012.

A.1 Banks included in the *full-dataset*

	Commercial banks		Treasury banks	
Megabanks	Medium-size banks			
	others	Consumption		
Chile	Internacional	Falabella	Dresdner	American
OHiggins	Scotiabank	Ripley	DoBrasil	BNA
Osorno	Corpbanca	Paris	Banesto	Chicago
Estado	Bice	Atlas	HSBC	Tokyo
BCI	Citibank	Fusa	America	RBS
Edwards	Itau	Condell	Real	Centrohispano
Santiago	Security	Conosur	SaoPaulo	HongKong
Santander	Rabobank		Exterior	Deutsche
	BBVA		Sudameris	Consortio
	Desarrollo		JPMorgan	Penta
			DnBNor	

A.2 Banks included in the *mergers-dataset*

	Commercial banks		Treasury banks	
	Megabanks	Medium-size banks		
		others	Consumption	
Chile	Internacional	Falabella		Dresdner Chicago
Estado	Scotiabank	Ripley		DoBrasil Tokyo
BCI	Corpbanca	Paris		HSBC Consorcio
Santander	Bice			America Penta
	Itau			SaoPaulo DnBNor
	Security			JPMorgan
	Rabobank			American
	BBVA			BNA

B Cross-correlation of banks' performance

Table B.1. Cross-correlations of banks' performance
(averages Jan. 1989 - Jun. 2012)

		ROA														IRM															
		Mega banks				Medium banks										Mega banks				Medium banks											
		b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12	b13	b14	b15	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12	b13	b14	b15
Mega banks	b1	1.00																													
	b2	0.52	1.00																												
	b3	0.85	0.42	1.00																											
	b4	0.39	-0.01	0.38	1.00																										
Medium-size banks	b5	-0.24	-0.47	-0.02	-0.20	1.00																									
	b6	0.53	0.24	0.61	0.60	-0.10	1.00																								
	b7	0.81	0.54	0.75	0.64	-0.37	0.59	1.00																							
	b8	0.49	0.21	0.54	0.79	-0.27	0.62	0.75	1.00																						
	b9	0.19	-0.15	0.30	0.47	-0.04	0.39	0.26	0.66	1.00																					
	b10	0.43	0.27	0.56	0.39	-0.19	0.54	0.61	0.65	0.31	1.00																				
	b11	-0.51	-0.40	-0.53	0.06	0.20	0.01	-0.34	-0.13	-0.16	-0.19	1.00																			
	b12	0.70	0.29	0.38	0.22	-0.33	0.63	0.03	0.08	0.12	0.28	0.12	1.00																		
	b13	0.41	0.06	-0.15	0.02	-0.34	0.11	-0.46	0.03	-0.02	-0.07	-0.15	0.52	1.00																	
	b14	0.49	0.35	0.36	0.22	0.23	0.34	0.47	0.50	-0.21	0.71	0.62	0.48	0.49	1.00																
	b15	0.48	0.37	0.43	0.04	0.06	0.20	0.26	0.02	-0.11	-0.09	-0.31	-0.24	-0.39	-0.39	1.00															

Note: Based on the *mergers-dataset* (see the text for details).

Source: own elaboration based on data from the Superintendency of Banks and Financial Institutions (SBIF).

C Exponentially weighted moving covariance matrix

Lets assume that our dataset of banks' performance used in the empirical approach (ROA or IRM) is arranged in a multivariate panel $X_{b,t}$ with $b = 1, \dots, B$, and $t = 1, \dots, T$, representing the behavior of B banks during T time periods. Without loss of generality, assume that each vector in the panel behaves approximately as a multivariate normal distribution, with mean vector μ and covariance matrix Σ . Then we can multi-standardize the data vectors finding a matrix A with the property $A\Sigma_0A' = I_B$ and obtain $U_t = A(X_t - \mu_0)$, where I_B is an identity matrix of order B , and U_t is defined for all B banks at each t . Let λ be

a "tuning" constant that reflects the importance of observations over time, giving more importance to more recent information. Assuming $0 \leq \lambda \leq 1$, we define the sequence of multivariate exponentially weighted moving covariance matrices (EWMCM) by recursion for $t = 1, \dots, T$, such as:

$$\begin{aligned} S_0 &= I_B \\ S_t &= (1 - \lambda)S_{t-1} + \lambda U_t U_t' \end{aligned}$$

Given the recursion argument, the EWMCM at moment T , S_T , can be written as:

$$S_T = (1 - \lambda)^T I_B + \lambda \sum_{t=0}^{T-1} (1 - \lambda)^t U_{T-t} U_{T-t}'$$

When $\lambda \rightarrow 0$, the sequence S_1, \dots, S_T tends to be a smoother version of the initial sequence $U_1 U_1', \dots, U_T U_T'$. In the extreme, when $\lambda = 0$, then $S_T = S_{T-1} = \dots = S_0 = I_B$. On the other hand, when $\lambda \rightarrow 1$, the sequence S_1, \dots, S_T tends to be similar to the initial sequence $U_1 U_1', \dots, U_T U_T'$. In the extreme, when $\lambda = 1$, then $S_t = U_t U_t'$ for $t \geq 1$ (the usual 'unweighted' covariance matrix).

<p>Documentos de Trabajo Banco Central de Chile</p> <p>NÚMEROS ANTERIORES</p> <p>La serie de Documentos de Trabajo en versión PDF puede obtenerse gratis en la dirección electrónica:</p> <p>www.bcentral.cl/esp/estpub/estudios/dtbc.</p> <p>Existe la posibilidad de solicitar una copia impresa con un costo de Ch\$500 si es dentro de Chile y US\$12 si es fuera de Chile. Las solicitudes se pueden hacer por fax: +56 2 26702231 o a través del correo electrónico: bcch@bcentral.cl.</p>	<p>Working Papers Central Bank of Chile</p> <p>PAST ISSUES</p> <p>Working Papers in PDF format can be downloaded free of charge from:</p> <p>www.bcentral.cl/eng/stdpub/studies/workingpaper.</p> <p>Printed versions can be ordered individually for US\$12 per copy (for order inside Chile the charge is Ch\$500.) Orders can be placed by fax: +56 2 26702231 or by email: bcch@bcentral.cl.</p>
--	---

DTBC – 706

Coordination of Expectations and the Informational Role of Policy

Yang Lu y Ernesto Pastén

DTBC – 705

Wicksell versus Taylor: A Quest for Determinacy and the (Ir)relevance of the Taylor Principle

Sofía Bauducco y Rodrigo Caputo

DTBC – 704

The Changing Roles of Education and Ability in Wage Determination

Gonzalo Castex y Evgenia Dechter

DTBC – 703

Proceso de Endeudamiento y Sobre Endeudamiento de los Hogares en Chile

Jaime Ruiz-Tagle, Leidy García y Álvaro Miranda

DTBC – 702

The Wealth Distribution in Developing Economies: Comparing the United States to Chile

Sofía Bauducco y Gonzalo Castex

DTBC – 701

Impacto de Sorpresas Macroeconómicas y Anuncios en Factores de la Estructura de Tasas de Chile

Luis Ceballos

DTBC – 700

A Note on Yield Spread and Output Growth

Rodrigo Alfaro y Damián Romero

DTBC – 699

Comportamiento de no Pago en Créditos de Consumo: Indicadores y Determinantes

Andrés Alegría, Rodrigo Alfaro y Carlos Saavedra

DTBC – 698

A Simple Out-of-Sample Test for the Martingale Difference Hypothesis

Pablo Pincheira

DTBC – 697

Vulnerability, Crises and Debt Maturity: Do IMF Interventions Shorten the Length of Borrowing?

Diego Saravia

DTBC – 696

Are All Capital Inflows Associated with *Booms* in House Prices? An Empirical Evaluation

Alejandro Jara y Eduardo Olaberría

DTBC – 695

Household Debt During the Financial Crisis: Micro-Evidence from Chile

Roberto Álvarez y Luis Opazo

DTBC – 694

Efficient CPI-Based Taylor Rules in Small Open Economies

Rodrigo Caputo y Luis Oscar Herrera

DTBC – 693

Interventions and Inflation Expectations in an Inflation Targeting Economy

Pablo Pincheira

DTBC – 692

The Response Speed of the International Monetary Fund

Ashoka Mody y Diego Saravia



BANCO CENTRAL
DE CHILE

DOCUMENTOS DE TRABAJO • Diciembre • 2013