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SOME MEASURES OF FINANCIAL FRAGILITY IN THE CHILEAN BANKING SYSTEM: AN EARLY WARNING INDICATORS APPLICATION

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Resumen

Existe una amplia literatura cuyo principal interés es construir modelos capaces de anticipar o brindar algunas señales tempranas de alarma sobre instituciones financieras problemáticas. Este artículo revisa esta literatura en un intento de detectar fragilidades latentes en el sistema financiero chileno. La mayor parte de las aplicaciones en esta área estiman algún modelo de probabilidad con variables dependientes discretas que separan, ex post, instituciones quebradas o rescatadas, de aquellas saludables, un ejercicio que durante los noventa no es posible para el caso chileno. Adoptamos un enfoque más simple al estimar un modelo lineal en forma reducida de determinación de préstamos vencidos y diferenciales de tasas interbancarias como medidas de fragilidad financiera, que pueden ser interpretadas como indicadores de probabilidad de riesgo de crédito y de liquidez. Ratios financieros bancarios y variables macroeconómicas forman nuestro conjunto de variables explicativas. Los modelos estimados en este artículo intentan capturar la fragilidad financiera en un contexto sin crisis, que caracteriza al sistema financiero chileno durante la presente década. Aunque algunas instituciones han salido del mercado, la quiebra o la insolvencia no han sido el motivo principal.

Abstract

There is an ample literature whose main subject is to build models able to anticipate or provide some early warning signals of problematic financial institutions. This article overview these literature in an attempt to detect latent fragility in the Chilean financial system. Most applications in this area estimate some probability model with discrete dependent variables that separate, ex-post, failed or bailed-out institutions from the healthy ones, an exercise that during the nineties is not feasible in the Chilean case. We adopt a simpler approach by estimating a linear reduced form model of determination of past due loans and inter-bank spread as measures of financial fragility, which can be interpreted as probability indicators of credit and liquidity risk. Bank financial ratios and macro variables form our set of explanatory variables. The models estimated in this article intend to capture financial fragility in the context of non-crisis environment, which characterizes the Chilean financial system during the present decade. Although some institutions had left the market, failure or insolvency was not the main cause.

This paper is a chapter of the forthcoming book Banking, Financial Integration, and International Crises, edited by Leonardo Hernández and Klaus Schmidt-Hebbel, Santiago, Chile.
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Some Measures of Financial Fragility in the Chilean Banking System: An Early Warning Indicators Application

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The regulatory framework of the Chilean financial system includes a number of regulations that seek to maintain the financial stability of banks. On one hand, the Central Bank of Chile in its role as regulator and, on the other hand, the Superintendency of Banks in its role as supervisor have set a variety of prudential regulations such as margin lending requirements, property-related concentration margins, limits on market risk exposure, and capital adequacy requirements. (The capital adequacy requirements are based on Basle principles and were established after the enactment of a new banking law sought to replace leverage ratios.) This set of regulations is reinforced through periodic on-site supervision of financial institutions, a task for which the Superintendency of Banks is responsible.

The goal of banking regulation is to narrow or constrain the risk that banks encounter in their business. However, it is difficult or extremely costly to eliminate these sources of risk, unless the regulatory authorities are willing to severely limit banking activity. Therefore it is always a possibility that a large bank or group of banks will become

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fragile, to such an extent that they or the regulatory authorities are forced to undertake a process of intervention or liquidation, which can affect the public trust. In order to avoid reaching this stage in the deterioration of the financial condition of institutions, methods of on-site supervision have been improved in recent years. Although on-site supervision is by far the most reliable mechanism for drawing a definitive picture of a bank, it is nonetheless an expensive and sometimes gradual process. In fact, depending on the size and complexities of the activities of the institution, it can take months before supervisors have an accurate idea of the financial condition of a bank.

During the 1980s as well as in recent years, several countries at different stages of economic development have suffered from episodes of banking crises of considerable magnitude. Many of these crises arose from macroeconomic imbalances that led to the collapse of the financial system. Generally, the causes of systemic banking crises are rooted in processes of rapid financial liberalization, which creates lending booms and asset price bubbles fueled by excessive capital inflows, large fiscal and current account deficits, excessive currency appreciation in terms of the real exchange rate, or sudden and large increases in real interest rates. It is well established in the literature that, although the two types of crisis are different in nature, banking crises are usually accompanied by balance of payments crises. On several occasions, however, the eruption of banking crises has been due to microeconomic factors, which commonly put the blame on poor management by banks of the risks they face (moral hazard).

Welfare costs associated with banking crises are often of considerable magnitude in relation to GDP.[1] This fact has caused great concern and motivated authorities in many countries to establish a permanent process for assessing the stability and soundness of financial systems against possible threats, and to design early warning systems capable of alerting the authorities of potential bank failures. Also, the literature on early warning indicators of fragile banks has attracted interest in countries like the United States, because of the large number of banks in the market. This abundance of banks makes it impossible to practice

1. Caprio and Klingebiel (1996) report over a hundred systemic banking crises and smaller banking crises in many countries since 1970, as part of a large group which they define as bank insolvency episodes. The costs of these episodes range from as little as 1 percent of GDP in the case of Thailand in 1983-87 to a 55 percent loss of GDP in the case of Argentina in 1980-82. Eyzaguirre and Larrañaga (1991) estimate the loss for the Chilean banking crisis at 23 percent of GDP, spread across various aid programs.

periodic on-site supervision of all institutions at least once a year, and therefore it becomes crucial to rely on early warning models. In addition, poor management practices and the risk of contagion to nearby institutions have forced regulators to design some mechanism of detecting weaknesses among banks. An early warning model based on financial ratios provides such a mechanism at a relatively low cost.

The purpose of this paper is to explore different measures of financial fragility within the Chilean financial system and the extent to which reduced-form models of these measures fit the sample data. The evolution of the Chilean financial system during the 1990s was far from being as turbulent and crisis-prone as that in other developing economies. On the contrary, Chile is among the group of countries that have had a stable financial system dating back to the mid-1980s and has managed to avoid banking crises as defined, for example, in Kaminsky and Reinhart (1996). This fact forces us to be cautious both in defining the variables considered as measures of financial fragility and in our general approach to estimation. Despite the stability of Chile's financial system, it should be possible to identify a group of less favored banks, and the inferences drawn from such an exercise should provide valuable information. In this sense, we adopt mainly a microeconomic approach. That is, we work on a bank-by-bank basis, defining fragility as depending on two variables: the interest rate spread on interbank lending and the ratio of nonperforming loans to total loans.

The rest of the paper is organized as follows. Section 1 briefly reviews the literature about early warning systems and its application under various types of banking crises. Section 2 introduces the reduced-form models adopted for the estimation of our measures of financial fragility and discusses the relevant empirical findings for the financial system and banking groups. Section 3 presents final comments and conclusions.

1. Early Warning Systems: Review and Motivation

During the 1980s and more recently, many countries in various circumstances have suffered banking crises of various kinds. Many of these episodes started from a situation of macroeconomic disequilibrium in some fundamental factors that ended with the collapse of the financial system. These crises forced central banks to intervene, adopting a variety of measures to rescue the bankrupt institutions. Demirgüç-Kunt and Detragiache (1997) conclude that the macroeconomic environment plays a fundamental role in the generation of banking crises.[2] For instance, a low rate of GDP growth is associated with an increase in credit risk due to an increase in the probability of default on loans. These authors point out that increasing credit risk could well be reduced through international diversification of the portfolio of loans. If credit risk is effectively diversified by extending loans to other countries whose growth rates show a negative correlation with that of the home country, it could benefit banks from small, open economies that have a significant concentration of loans related to domestic income sources.

Demirgüç-Kunt and Detragiache conclude that interest rates are also an important factor in explaining banking crises. Increases in interest rates raise the probability of a financial crisis when they are driven by policies aimed at inflation stabilization and financial liberalization. Examples include the case of Brazil and its program to end hyperinflation, and the case of Chile in the late 1970s. On the other hand, high nominal interest rates are seen as a factor in explaining banking crises when they reflect high and volatile inflation rates, which make it difficult for banks to perform the maturity transformation of assets and liabilities. In environments like these, banks face increasing financial and credit risk and a reduction in revenue due to the inflation tax.

In a related article, González-Hermosillo, Pazarbasioglu, and Billings (1996) take into consideration the interaction of microeconomic variables, namely, financial ratios taken from the financial statements of banks, with a set of macroeconomic factors to estimate an early warning model of the Mexican financial crisis of 1994. These authors found that a reduction of economic activity, an increase in real interest rates, and a depreciation in terms of the real exchange rate are important factors anticipating an increasing vulnerability of the financial system. Macroeconomic factors play an important role in determining the timing of failure. In particular, the authors found that the negative macroeconomic shocks suffered by the Mexican economy increased the vulnerability of the country's financial system. On the other hand, variables relating to specific banks and the banking sector helped

2. Demirgüç-Kunt and Detragiache (1997) define a systemic banking crisis as the occurrence of at least as one of the following: the ratio of nonperforming loans to total assets in the banking system exceeds 10 percent; the cost of a rescue operation is at least 2 percent of GDP; an extensive nationalization of banks occurs; or there are extensive bank runs, deposit freezes, or prolonged bank holidays at the time of the crisis.

explain the likelihood of bank failure more than the timing of the crisis. Among the bank-specific variables considered by the authors are the risk-adjusted capital ratio, the ratio of nonperforming loans to total loans, loan concentration in certain sectors (such as the agricultural and household sectors) as a proportion of total loans, relative bank size, and operating expenses. Among the banking sector variables considered are the ratio of banking sector loans to GDP, the ratio of nonperforming loans to total loans, and the banking sector's contributions to the deposit guarantee fund in relation to total nonperforming loans. These variables capture the vulnerability of the banking sector.

A large literature considers only bank-specific variables in estimating early warning models. Its development coincides with the large number of bankruptcies that occurred at the beginning of the 1980s in developed countries; examples include Martin (1977), Whalen and Thompson (1989), Jones and Kuester-King (1995), Atle Berg and Hexeberg (1994), and Cole (1995). A very good survey can be found in Demirgüç-Kunt (1989). In general, the variables considered as predictors of insolvency in this literature are variations of those mentioned in the previous paragraph, as well as proxy variables of profitability and liquidity. The standard approach is to construct a set of explanatory variables that closely resembles the on-site supervision process that gives rise to the CAMEL evaluation of banks in the United States.[3] Recent articles have emphasized the need to add variables that may be more sensitive to the assessment by the market (that is, by other financial intermediaries) of a bank's soundness and stability. Among the variables suggested are the interest rate paid on deposits, measures of the cost of funds, the spread between lending and deposit rates, and loan growth rates. These variables presumably can more rapidly reflect the deterioration of problem institutions and, in the case of variables related to the interest rate paid on deposits, are less affected by discretionary accounting standards.[4]

In the early warning literature, a common estimation technique has been used at each of the different stages of its development. Earlier articles employed multivariate discriminant analysis (MDA), which, rather than identifying a single dependent variable a priori, instead

3. CAMEL is an acronym for capital, asset, management, equity, and liquidity, which are the factors evaluated in on-site supervision of financial institutions in the United States. The system was established in 1979 by the U.S. regulatory agencies to help identify those institutions that require closer supervision.

4. For a more detailed discussion see Rojas-Suárez (1998) and Honohan (1997).

tried to distinguish between troubled and healthy banks by looking at the joint distribution of a number of financial ratios. MDA requires that the financial ratios considered to distinguish among a group of banks be distributed normally—an assumption that in many instances could limit the analysis.

More recent articles have completely discarded the MDA approach and instead estimate models of the probability of failure or nonfailure of banks, using models with discrete dependent variables. These models are distinguished according to the cumulative distribution function that describes the behavior of the dependent variable: *probit* models are used for a cumulative normal density function, and *logit* models for a cumulative logistic density function; these two are the most popular specifications. These models seek to establish a causal relationship between a discrete event (specified such that 1 = failure and 0 = no failure) and a set of explanatory macroeconomic and financial variables considered for an arbitrary number of periods before a given event took place. Since it is thought that failing banks deteriorate slowly rather than suddenly, this regression approach is a natural one to embrace. From the results of the probit or logit estimation one obtains an expected probability of failure, so that institutions can be distinguished according to their inherent degree of risk.

The usual goodness-of-fit statistics such as the adjusted R^2 can no longer be directly calculated in the context of logit or probit estimation, since the dependent variable is discrete.[5] However, in order to assess the accuracy of the model in predicting failures, it is customary to compute the percentage of sample predictions that prove correct ex post. Two types of error are usually computed. A type I error is said to take place when the model fails to predict problems in a bank that later actually encounters problems. Conversely, a type II error occurs when the model predicts that a bank will show signs or symptoms of problems, but instead it does not. An early warning model is considered good if the probability of committing type I error is low. However, given the inherent trade-off between the two types of error, a search for a lower type I error implies a higher type II error. That is, the more banks the model identifies as problematic, the more will be identified as problematic when in fact they are not. However, the cost

5. An analog measure to the conventional R^2 in these models is the likelihood ratio index (LRI), which is constructed by comparing the log-likelihood of the model and the same statistic that results from estimating the model with a constant term only: LRI = 1 – ln L/ln L_0, where L_0 is the log-likelihood computed only with a constant term.

of a larger number of type II errors is relatively low, because it only implies additional revisions or a stricter supervision of those institutions identified as problematic. In contrast, failure to correctly anticipate the insolvency of institutions that are in fact weak might result in the expenditure of a large amount of resources. For instance, it might require an explicit deposit insurance scheme or liquidity support to maintain the normal functioning of the payments system, to avoid the propagation of a crisis to the whole financial system.

The identification of the dependent variable (failed institutions) becomes trivial when we confront severe crises, characterized, for example, by massive interventions of the government or the monetary authorities. Fortunately, Chile did not suffer massive disruptions of its financial system during the 1990s. However, this fact makes it more difficult to isolate events in Chile that could clearly jeopardize the solvency of financial institutions. Following the definition of a crisis by Kaminsky and Reinhart (1996) as "i) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions, or ii) the closure, merging, or takeover, or large-scale government assistance of an important financial institution (or group of institutions)," Chile has not even come close. During the 1990s, Chile developed a process of market consolidation, starting with the solution of problems inherited from the 1983 crisis that led to a conservative regulatory scheme. This process of market consolidation was characterized by banking company mergers that led to the disappearance of nine institutions, a process that increased market concentration as reflected in such measures as the Herfindahl index. At the same time, substantial investment in new technologies and steady economic growth contributed to a system with a greater capital base and a low percentage of nonperforming loans. However, none of the nine cases of bank disappearance could be clearly identified as a solution to a latent insolvency problem or failure of these institutions. In fact, none of these exits from the market caused a disruption in the functioning of the financial system. Therefore, for Chile in the 1990s it is very difficult to adopt a dichotomous approach—crisis versus noncrisis, or failure versus nonfailure—because such events have not occurred.

Alternative definitions of banking crises are postulated by Rojas-Suárez (1998). These are summarized as follows: intervention by the authorities; periods when the ratio of nonperforming loans to total loans is greater than the average for the system as a whole, during a tranquil period plus two standard deviations; periods when a bank loses at least 5 percent of its deposits; and periods when a properly computed crisis index that combines the two previous criteria exceeds the system average during a tranquil period plus two standard deviations. This paper uses the ratio of nonperforming loans, since it is consistent with the concept of fragility found in other articles. This definition assumes that credit risk is the main source of instability of financial institutions; hence, troubled institutions are those with a greater proportion of nonperforming loans in their portfolios. This approach is congruent with the characterization of a banking crisis as a period with a greater proportion of nonperforming loans.

Given the increasing importance of new banking activities beyond traditional commercial lending, we believe that other sources of risk, such as liquidity risk, are gaining relevance. Therefore we adopt an alternative measure of financial fragility (not an overall index) that better captures liquidity risk through the interest rate spread on interbank lending. This indicator is constructed as the difference between the real interest rate charged among banks for short-term daily liquidity loans and the liquidity interest rate for overnight deposits in domestic currency at the central bank (the lowest interest rate paid by this institution). We believe that the interbank spread, thus defined, provides an indirect market assessment of the financial condition of banks, since interbank credit operations are not directly covered by some deposit guarantee scheme, forcing lender institutions to assess the borrower's financial situation on an ongoing basis.

2. Early Warning System: Estimation during a Noncrisis Period

2.1 Measuring and Estimating Fragility

This section presents the results from the estimation of a simple, reduced-form equation for the determination of two variables: nonperforming loans as a percentage of total loans, and interbank spreads. Since the number of institutions that comprise the Chilean financial system is relatively small, and given the large number of financial ratios that could explain the behavior of the dependent variables, we estimate the models using a longitudinal data regression to increase the degrees of freedom of the model and the efficiency of the parameter estimates. As explained above, we adopt a nondichotomous approach for the dependent variables.

The sample size varies according to the dependent variable. In the case of the ratio of nonperforming loans to total loans, the sample ranges from January 1990 to October 1998 on a monthly basis, an ample period over which to model this variable. Unfortunately, in the case of interbank spreads, the liquidity overnight banking deposit rate is a recently created instrument, and data are available only since May 1995. Although this interest rate is determined daily, we collected data monthly for purposes of estimation. One additional drawback of the interbank spread data is that individual banks do not transact on the interbank lending market in every period; therefore in several periods data for some banks are nonexistent. For simplicity, we ignore the problem of missing observations for interbank spread data, since it is not clear that filling in the blanks with some average or regression-based interpolation would improve the efficiency of the estimates. The missing-variable problem could, however, become severe during critical periods if it is assumed that nonexistent information regarding interbank lending operations for some banks signals an unwillingness to lend to those banks considered more risky.[6]

The list of regressors can be separated into bank-specific, or microeconomic, variables and a set of macroeconomic variables that may have an impact on the solvency of banking institutions. The first group of variables is believed to have an impact on overall fragility, for instance on the quality of loans, through an indirect mechanism that basically is related to the quality of bank management. The macroeconomic variables eventually have a direct impact on the quality of loans since they are more related to the nature and development of the business activities of the bank's borrowers. That is, it could be argued that some loans get into trouble because certain sectors of the real economy deteriorate, but certainly this explanation is not sufficient to explain why some firms fail whereas others do not, except in the case of a widespread shock to the economy. This group of variables includes a measure of economic activity such as the twelve-month variation on a seasonally adjusted monthly index of economic activity (this index is called ECA in the model). A market interest rate that captures intertemporal substitution and wealth effects is also included, namely, the real lending rate for 90 to 365 days (called IRR in the model). There is also a measure of the international competitiveness of the economy: the real exchange rate as reported by the Central Bank of Chile (RER). Table 1 lists the bank-specific variables.

6. There is an identification problem with banks that do not operate in the interbank market at all. They might have chosen voluntarily to abstain, or they may have been excluded from the market because of their riskiness.

Table 1. Bank-Specific Variables Used in the Regressions

Criterion	*Variable name*	*Description*
Capital	CAP	Capital plus reserves, divided by total assets
Efficiency	MEX	Managerial expenditure divided by total assets
	AOL	Productive assets divided by costly liabilities
Liquidity	LIQ	Portfolio liquid assets plus central bank paper, divided by total deposits
Earnings	MOP	Operating margin divided by total assets
Growth	LOG	Twelve-month logarithmic difference in total loans
Market based	INL	Interbank lending divided by total deposits

The estimation of measures of bank fragility is carried out by grouping the banks over time to form a panel data set (a longitudinal database), because of the statistically small number of banks in the Chilean financial system. Panel data estimation provides more degrees of freedom and greater efficiency in the parameter estimates, given the large number of explanatory variables and observations. Hence, in addition to the natural but possibly less clear-cut cross-banking differences due to the limited number of banks in the market, we incorporate variation over time between them. The estimation is simple in the sense that we assume that the slope coefficients as well as the intercepts are constant for all banks. This model represents the most restricted version of a longitudinal data estimation, and so its results in terms of goodness-of-fit measures can only be improved by adopting a more general model specification. In the case of nonperforming loans we proceed even further and estimate the model on the assumption that there are three different groups of banks in the market: larger domestic banks (which include the larger foreign banks Banco Santander and Citibank), foreign banks, and the small domestic banks called *sociedades financieras* (financial companies). This separation into different groups allows us to check for differences in parameter values across groups and to take into account the widespread belief that some strategic groups are always present in a financial system, each of which has a different business orientation and therefore should be treated separately. The division into these three groups is taken from the traditional categories published by the

Superintendency of Banks, modified to include those larger foreign banks with active involvement in the domestic market in the group of domestic banking institutions that have a similar product profile.

The estimated equation can be summarized as

$$y_{it} = \alpha_i + \rho y_{it-1} + \beta' x_{it} + \varepsilon_{it} \quad ; \qquad i = 1,\ldots,N \; ; \quad t = 1,\ldots,T \, . \tag{1}$$

where x_{it} is a vector of explanatory variables, y_{it} is the dependent variable (the ratio of nonperforming loans to total loans, or, alternatively, the interbank spread), N is the number of banks, and T is the number of months covered by the estimation. The estimation imposes the restriction of parameter constancy for all banks; therefore the ordinary least-squares method provides consistent and efficient estimates of α and β. The model with lagged dependent variables is applied only for the case of nonperforming loans, given that this series, unlike the interbank spread, shows a clear persistence that can be well approximated by including the lagged dependent variable among the regressors.[7] The results can be interpreted as an average systemic response of measures of both credit and liquidity risk to expected changes in the explanatory variables. The model is estimated with various lags, starting from twelve lags of each explanatory variable, and includes a correction for autocorrelation for the nonperforming loans variable, which means including an arbitrary number of lagged dependent variables to reduce the autocorrelation of the residual process. In the case of nonperforming loans, this variable is measured as a twelve-month percentage difference to eliminate possible deterministic trending and seasonal behavior. Also, variables that are measured as flows, for instance operational margins and managerial expenditures, are measured as monthly differences of the accumulated flow of a given year divided by total assets from the previous period. For example, operating income for June 1998 was generated using assets available at the end of May of the same year. Table 2 summarizes the results using both measures of fragility as the dependent variable.

7. There are some problems with the estimation of the model using panel data in terms of the parameter's inconsistency in the presence of lagged dependent variables. However, in this case the number of time observations exceeds the number of banks, which resembles the case when T goes to infinity. Therefore the inconsistency problem is less important during the estimation. The samples that we use can be better classified within the category of longitudinal data instead of panel data.

2.2 Analyzing the Evidence

The results for the pooled banking system (table 2a) suggest that a number of bank-specific variables are important in explaining the future behavior of nonperforming loans. For instance, an increase in the level of capital tends to decrease banking fragility in terms of credit risk. This can be interpreted as indicating that when a greater proportion of owners' capital is at stake, the bank will implement a more risk-averse (that is, conservative) lending process. This finding supports the current trend in regulation, which requires more capital for banking operations to improve the solvency of these intermediaries. Higher liquidity tends, in the short run, to reduce the percentage of nonperforming loans; this, too, makes sense if we consider that more liquid institutions tend to be more risk averse. Higher interest rates that result from a tightening of monetary policy increase banking fragility no later than a year after the rise in interest rates. The results in table 2a indicate that the effect of interest rates is persistent, given the significance of the parameter at various lags. This result suggests that during periods of high interest rates we should expect an increase in nonperforming loans on a bank-by-bank basis. A different interpretation is to assume a close relationship between interest rates in the market and the cost of funds to banks to support active operations. In that case higher interest rates would reveal those institutions with reckless procedures in their credit policy, which should therefore have, on average, a higher proportion of nonperforming loans. Table 2a also shows loan growth to be an important factor in explaining a subsequent deterioration in loan quality. Banks that enjoy a rapid expansion of credit, possibly because a less stringent credit policy allows them to reach more risky customers, will have a greater proportion of loans past due. The results also indicate that the impact of a loose credit policy surface only after some time; hence a rapid increase in market share and profits, although it may look positive in the short run, may reveal itself later on to be a source of banking fragility.

An interpretation of the regression results suggests the possibility that nonperforming loans can be taken as the percentage of loans that are actually not paid. Implicitly, this interpretation allows us to take the ratio of nonperforming loans itself as an ex post average probability measure of default on loans for the bank as a whole. Therefore, following the model, an increase in, for example, managerial expenses can be understood as increasing the average probability that

Table 2a. Longitudinal Data Estimation of the Behavior of Nonperforming Loans, Sample Including All Banks[a]

Independent variable	Number of lags											
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Constant	−0.0003	−0.0017	−0.0031	−0.0025	−0.0030	−0.0014	−0.0006	−0.0008	−0.0007	−0.0009	−0.0008	−0.0010
	(−0.42)	(−1.99)	(−3.64)	(−2.86)	(−3.41)	(−1.67)	(−0.67)	(−0.87)	(−0.74)	(−0.98)	(−0.89)	(−1.08)
NPL (-1)	0.7599	0.7622	0.7557	0.7594	0.7616	0.7624	0.7612	0.7575	0.7566	0.7583	0.7576	0.7523
	(41.30)	(41.68)	(41.17)	(41.13)	(41.09)	(41.05)	(40.66)	(40.32)	(39.90)	(39.81)	(39.87)	(39.35)
NPL (-2)	0.1835	0.1781	0.1939	0.1862	0.1819	0.1829	0.1850	0.1879	0.1887	0.1879	0.1871	0.1914
	(8.05)	(7.82)	(8.49)	(8.13)	(7.89)	(7.92)	(7.96)	(8.05)	(8.04)	(7.96)	(7.95)	(8.12)
NPL (-3)	−0.0758	−0.0646	−0.0723	−0.0694	−0.0672	−0.0698	−0.070	−0.0692	−0.0687	−0.0700	−0.0662	−0.0654
	(−4.11)	(−3.51)	(−3.93)	(−3.72)	(−3.59)	(−3.74)	(−3.73)	(−3.67)	(−3.61)	(−3.66)	(3.47)	(−3.43)
AOL	−0.0005	0.0015	0.0011	0.0006	0.0010	0.0005	0.0007	0.0010	0.0005	0.0002	0.0006	0.0005
	(−1.76)	(5.35)	(3.79)	(1.95)	(3.43)	(1.68)	(2.31)	(3.33)	(1.61)	(0.50)	(2.01)	(1.56)
MEX	0.0161	0.0092	−0.0223	−0.1362	0.0295	−0.1564	−0.0307	−0.0852	−0.0220	−0.0201	−0.1568	−0.1906
	(0.23)	(0.14)	(−0.34)	(−2.05)	(0.44)	(−2.33)	(−0.45)	(−1.26)	(−0.32)	(−0.29)	(−2.27)	(−2.75)
CAP	0.0026	−0.0033	−0.0019	−0.0008	−0.0017	−0.0010	−0.0016	−0.0027	−0.0019	−0.0110	−0.0033	−0.0032
	(2.40)	(−2.67)	(−1.59)	(−0.60)	(−1.37)	(−0.81)	(−1.28)	(−2.05)	(−1.42)	(−0.81)	(−2.47)	(−2.40)
INL	0.0028	0.0013	0.0014	0.0025	0.0013	0.0021	0.0019	0.0014	0.0018	0.0017	0.0017	0.0021
	(2.12)	(0.98)	(1.09)	(1.89)	(0.95)	(1.52)	(1.41)	(1.04)	(1.28)	(1.20)	(1.19)	(1.39)
LIQ	−0.0017	−0.0012	−0.0009	−0.0011	−0.0003	−0.0004	−0.0002	0.0004	0.0012	0.0013	0.0016	0.0023
	(−2.07)	(−1.39)	(−1.07)	(−1.31)	(−0.39)	(−0.45)	(−0.31)	(0.48)	(1.30)	(1.38)	(1.75)	(2.48)
LOG	−0.0002	−0.0004	0.0002	0.0004	0.0004	0.0002	0.0007	0.0008	0.0009	0.0095	0.0011	0.0014
	(−0.58)	(−1.13)	(0.58)	(0.99)	(1.08)	(0.61)	(1.88)	(2.08)	(2.25)	(2.42)	(2.71)	(3.55)
MOP	−0.0202	−0.0182	−0.0059	0.0657	−0.0298	0.0827	−0.0005	0.0272	0.0181	0.0171	0.0826	0.1204
	(−0.60)	(−0.53)	(−0.17)	(1.89)	(−0.85)	(2.36)	(−0.01)	(0.76)	(0.50)	(0.47)	(2.29)	(3.33)
IRR	0.0129	0.0127	0.0225	0.0197	0.0212	0.0091	0.0024	−0.0011	−0.0017	0.0028	−0.0030	−0.0034
	(2.13)	(1.78)	(3.13)	(2.66)	(2.84)	(1.21)	(0.32)	(−0.14)	(−0.22)	(0.37)	(−0.39)	(−0.45)
RER	0.0107	0.0127	−0.0132	−0.0217	−0.0215	−0.0105	0.0005	0.0029	0.0081	−0.0097	0.0054	−0.0049
	(0.93)	(1.08)	(−1.11)	(−1.80)	(−1.79)	(−0.87)	(0.03)	(0.24)	(0.66)	(−0.79)	(0.44)	(−0.39)
ECA	−0.0055	−0.0029	−0.0030	−0.0029	−0.0023	−0.0010	−0.0028	−0.0015	−0.0006	−0.0019	0.0015	0.0006
	−1.72)	(−0.92)	(−0.93)	(−0.90)	(−0.69)	(−0.31)	(−0.86)	(−0.47)	(−0.19)	(−0.57)	(0.44)	(0.19)
Summary statistic												
Adjusted R^2	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.74	0.74	0.75	0.75
DW	2.00	2.01	2.01	2.01	2.00	2.01	2.02	2.01	2.01	1.99	2.01	1.98

Source: Authors' calculations.

a. NPL, nonperforming loans; IRR, real lending rate on loans of 90-365 days; RER, real exchange rate; ECA, index of economic activity; other variables are defined as in table 1. The number below each regression coefficient is its *t* statistic.

some loans will not be recovered. Therefore these models, although simpler, yield some early warning signs about the future behavior of individual banks.

A similar conceptual framework can be devised for the interbank spread. If we call d the liquidity overnight banking deposit rate and s the spread, which is determined entirely among the banks themselves, then a proportion of the institutions will pay $d + s$ at the expiration of the contract, and the rest will not have paid at the expiration date. To illustrate this point, we present a restricted model that assumes, for simplicity, risk-neutral behavior on the part of lenders. For instance, on average the payment received by a bank that is in a lender position will be $p(d + s)$, which will be equal to d.[8] Hence p will represent the probability of repayment and $1 - p$ the probability of default on interbank lending operations:[9]

$$p = \frac{d}{s + d}\ , \qquad 1 - p = \frac{s}{s + d} = \frac{1}{1 + d/s}\ . \tag{2}$$

We see that, as the spread charged to a bank for interbank operations goes to infinity, the probability of default tends toward one, excluding that institution from this market.

We can use this interpretation to analyze the output estimation of the model for interbank lending. For instance, table 2b shows that an increase in the market rate of interest produces an increase in the spread charged for interbank lending in the short run (with lags of one and two periods). The t statistics for the estimated parameters show that the variables have a significant impact on the interbank spread, as we observe during the episodes of liquidity shortages in 1998. The sign on the regression coefficient suggests that an increase in the level of interest rates increases the interbank spread. One should expect a strong association between market interest rate and the cost of funding liabilities among banks: institutions with a higher cost of funding should be charged a higher spread. This makes sense if one considers this latter

8. Risk neutrality implies that the bank is indifferent between lending to a private bank or to the central bank and will accept rate d in either case. Risk-averse behavior on the part of the lender will imply an additional risk premium; therefore the expected value of the lending operation will not be the same as d.

9. The interpretation of the interbank spread in terms of liquidity risk assumes that it measures the probability that banks will not pay on time, because of liquidity constraints. Liquidity risk is related to but slightly different from credit risk, and so the two should be treated separately. Under Chilean legislation the Central Bank of Chile fully insured liabilities on demand, to prevent systemic instability.

Table 2b. Longitudinal Data Estimation of Interbank Spread Behavior, Sample Including All Banks[a]

Independent variable	Number of lags											
	1	2	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Constant	−0.0792	−0.0752	0.0084	0.0371	−0.0417	0.0318	0.0369	0.0300	0.0354	−0.0110	0.0262	0.0205
	(−3.59)	(−3.94)	(0.40)	(1.55)	(−1.63)	(1.37)	(1.64)	(1.34)	(1.61)	(−0.49)	(1.21)	(0.95)
NPL	−0.1613	−0.2318	−0.1814	−0.1167	−0.0521	−0.0491	−0.0836	−0.0607	−0.0366	−0.1445	−0.2354	−0.2476
	(−1.18)	(−1.68)	(−1.30)	(−0.83)	(−0.38)	(−0.36)	(−0.62)	(−0.46)	(−0.29)	(−1.19)	(−1.87)	(−1.88)
AOL	−0.0003	−0.0007	−0.0017	−0.0010	−0.0003	−0.0014	0.0013	0.0017	−0.0007	−0.0019	−0.0008	−0.0003
	(−0.11)	(−0.29)	(−0.70)	(−0.40)	(−0.14)	(−0.47)	(0.41)	(0.60)	(−0.24)	(−0.71)	(−0.26)	(−0.10)
MEX	−0.4300	−2.1224	−2.2985	−2.1591	−0.4704	1.3814	0.0575	1.6696	0.6996	0.7875	−0.0678	−1.91
	(−0.41)	(−2.14)	(−2.09)	(−1.81)	(−0.46)	(1.35)	(0.05)	(1.69)	(0.75)	(0.85)	(−0.07)	(−2.00)
CAP	−0.0027	−0.0077	−0.0018	−0.0036	0.0002	0.0185	0.0068	0.0090	0.0074	0.0111	0.0068	0.0044
	(−0.20)	(−0.56)	(−0.13)	(−0.25)	(0.01)	(1.17)	(0.43)	(0.60)	(0.49)	(0.77)	(0.46)	(0.30)
INL	−0.0121	−0.0125	−0.0070	−0.0014	−0.0060	−0.0066	−0.0069	−0.0117	−0.0103	−0.0184	−0.0127	−0.0132
	(−1.31)	(−1.38)	(−0.75)	(−0.14)	(−0.58)	(−0.60)	(−0.61)	(−1.02)	(−0.92)	(−1.67)	(−1.10)	(−1.10)
LIQ	0.0003	0.0012	−0.0054	−0.0093	−0.0093	−0.0161	−0.0150	−0.0101	−0.0051	−0.0019	−0.0083	−0.0128
	(0.04)	(0.15)	(−0.70)	(−1.15)	(−1.11)	(−1.78)	(−1.65)	(−1.12)	(−0.59)	(−0.24)	(−0.99)	(−1.55)
LOG	−0.0028	−0.0051	−0.0045	−0.0005	−0.0004	0.0058	0.0068	0.0083	0.0053	−0.0002	−0.0011	−0.0012
	(−0.52)	(−0.97)	(−0.82)	(−0.09)	(−0.08)	(1.01)	(1.16)	(1.40)	(0.95)	(−0.03)	(−0.18)	(−0.21)
MOP	0.1069	1.0646	1.0057	0.8994	0.0805	−1.0720	−0.4660	−1.2101	−0.6093	−0.5307	−0.2182	0.5576
	(0.19)	(1.94)	(1.71)	(1.44)	(0.16)	(−2.04)	(−0.82)	(−2.44)	(−1.26)	(−1.18)	(−0.46)	(1.19)
IRR	0.9757	0.8006	−0.0147	−0.2431	0.5689	−0.0949	−0.1900	−0.0859	−0.0728	0.4061	0.0318	0.0741
	(4.60)	(4.30)	(−0.07)	(−0.98)	(2.16)	(−0.39)	(−0.81)	(−0.36)	(−0.31)	(1.75)	(0.14)	(0.33)
RER	−0.4324	−0.7307	−0.7063	−0.6597	−1.3337	−0.2003	0.2537	−0.0879	−0.8930	−1.4294	−0.8190	−0.4828
	(−2.21)	(−4.36)	(−4.27)	(−3.68)	(−5.64)	(−1.12)	(1.52)	(−0.52)	(−5.29)	(−8.26)	(−4.72)	(−3.04)
ECA	0.0662	0.1985	0.0897	−0.0279	−0.0489	−0.0708	0.0437	−0.0975	−0.3104	−0.3303	−0.2577	−0.1350
	(1.03)	(3.21)	(1.43)	(−0.46)	(−0.83)	(−1.18)	(0.73)	(−1.64)	(−5.87)	(−6.16)	(−4.63)	(−2.58)
Summary statistic												
Adjusted R^2	0.03	0.07	0.07	0.06	0.06	0.01	0.003	0.01	0.08	0.14	0.06	0.04
DW	1.50	1.53	1.56	1.56	1.48	1.45	1.44	1.46	1.56	1.63	1.61	1.47
P value (F statistic)	0.007	0.000	0.000	0.000	0.000	0.262	0.302	0.116	0.000	0.000	0.000	0.002

Source: Authors' calculations.

a. NPL, nonperforming loans; IRR, real lending rate on loans of 90-365 days; RER, real exchange rate; ECA, index of economic activity; other variables are defined as in table 1. The number below each regression coefficient is its t statistic.

variable as a signal of liquidity problems in those institutions; hence banks that have liquidity problems are seen by other banks as more risky and hence are charged a higher spread.

An overall assessment of the results for the interbank spread suggests that macroeconomic or market variables play a much more important role in the determination of this variable than do financial ratios from institutions. Apart from some isolated effects from managerial expenditure, nonperforming loans, and the operating margin, the rest of the variables are irrelevant. In fact, when the macroeconomic variables are not significant, neither is the regression as a whole (see the results for specifications with six, seven, and eight lags). Moreover, the sign of the coefficient on the financial ratios variables is hard to interpret. For example, an increase in managerial expenditure decreases the spread charged by other banks, as if institutions that are less efficient had a lower probability of default.

The interpretation of the parameter estimates for the macroeconomic factors is less troublesome. It is clear that an improvement in economic activity decreases the overall spread charged among banks. Nonetheless, the response of the interbank spread to changes in economic activity becomes important only after several periods. This finding is clearly the opposite of the interpretation of the market interest rate, indicating that, in the very short run, the interbank spread is clearly determined by market rates.

The fact that most of the bank-specific variables are not significant in explaining the behavior of the spread over time and across banks suggests that the interbank spreads charged to different banks may be similar, reacting mainly to market rates. If so, it is not a good indicator of inherent bank risk. This observation is also consistent with the role of the central bank in safeguarding systemic risk in the Chilean financial system. These comments should be interpreted with care, however, because of the missing-observation problem already mentioned. Missing data on spreads could be the result of inability to access the interbank market for inconvenience either to the borrower or to the lender.

2.3 Results from Separating Banks into Groups

Table 3 summarizes the results of regressions in which banks are separated into groups, in recognition that some banks have different business strategies and responses to aggregate shocks and therefore should be treated differently. To account for such differences, we used system estimation regression with cross-equation restrictions separating banks into those groups described in section 2.1, as a restricted model. That is, we assume that the group consisting of the larger domestic banks and the two large foreign banks behaves differently from the smaller foreign banks and from the financial companies. (These institutions operate for the most part in the consumer loan market.) The system estimation technique provides a more general specification than running three separate regressions, since it allows us to formally test for differences among banking groups using all the information provided by the variance-covariance matrix of the residuals from each regression.[10]

The estimated parameter values in table 3 suggest that the banking industry can effectively be described as three separate groups during the sample period. The dependent variables for the financial companies display practically no relationship with the group of explanatory variables (the financial ratios or the macroeconomic variables), except for the ratio of assets to liabilities. This result shows that the business of the financial companies is not the same as that of the other institutions, which are characterized by a wide variety of products. Table 3 clearly shows that capital ratios are important factors in banking fragility among banks as opposed to financial companies. Unlike in table 2a, where the capital ratio has an unbalanced effect (it is significant at very short lags and at very long lags, but generally not in between), the capital ratios for both domestic and foreign banks are important irrespective of the lag the model considers. In a sense, the estimation of a single large regression incorporating the financial companies was obscuring the strong and stable relationship between capital ratios and credit risk in the other institutions. The behavior of nonperforming loans in the domestic and foreign banks also is strongly dependent on the market interest rate used in the estimation. In contrast, the financial companies show no reaction to the evolution of the short-term interest rate used in the estimation. One explanation for this lack of response is that the main product of financial companies is

10. Conventional goodness-of-fit statistics are no longer useful in the context of systems of regression equations. Therefore an alternative measure involves computing the following statistic:

$$R^2 = 1 - \left[M / tr\left(\Sigma^{-1} S_{yy}\right)\right],$$

where M is the number of banks in the system, Σ is an estimate of the variance-covariance matrix of the residual, and S_{yy} is the sum of squared differences with respect to the mean of the dependent variable (nonperforming loans) of each bank.

Table 3. System Equation Regressions of the Behavior of Nonperforming Loans, Sample Divided into Banking Groups[a]

Independent variable	*Number of lags* 1	2	3	4	5	6	7	8	9	10	11	12
Constant	−0.0004	−0.0005	−0.0013	−0.0015	−0.0016	−0.0010	−0.0004	−0.0006	−0.0002	−0.0005	−0.0005	−0.0004
	(−1.42)	(−1.58)	(−4.17)	(−4.82)	(−5.41)	(−3.91)	(−1.80)	(−2.54)	(−0.70)	(−2.34)	(−2.59)	(−1.54)
NPL (-1)	0.8928	0.8970	0.8992	0.8978	0.8951	0.8950	0.8965	0.8901	0.8916	0.8948	0.8955	0.8945
	(106.6)	(106.8)	106.3	(105.4)	(105.0)	(105.4)	(105.0)	(106.0)	(103.4)	(104.1)	(104.2)	(101.9)
Sample = domestic banks												
AOL	−0.0001	0.0001	0.0002	0.0001	0.0003	0.0001	0.0000	0.0002	0.0002	0.0005	0.0005	0.0003
	(−0.61)	(0.41)	(1.05)	(0.79)	(1.48)	(0.44)	(0.20)	(1.44)	(1.33)	(3.10)	(2.66)	(1.59)
MEX	−0.0268	0.0009	−0.0216	−0.0064	−0.0469	−0.0396	−0.0307	−0.0123	−0.0538	−0.0501	−0.0685	−0.0685
	(−0.74)	(0.03)	(−0.60)	(−0.18)	(−1.31)	(−1.10)	(−0.85)	(−0.36)	(−1.47)	(−1.46)	(−2.00)	(−2.00)
CAP	−0.0046	−0.0049	−0.0047	−0.0049	−0.0046	−0.0043	−0.0056	−0.0045	−0.0054	−0.0033	−0.0046	−0.0046
	(−3.79)	(−3.79)	(−3.75)	(−3.75)	(−3.56)	(−3.47)	(−4.60)	(−3.85)	(−4.44)	(−2.78)	(−3.70)	(−3.70)
INL	−0.0004	−0.0001	0.0002	0.0003	0.0004	0.0006	0.0004	0.0003	0.0017	0.0017	0.0018	0.0018
	(−0.43)	(−0.10)	(0.19)	(0.34)	(0.42)	(0.67)	(0.43)	(0.40)	(1.85)	(1.96)	(2.10)	(2.10)
LIQ	0.0008	0.0010	0.0011	0.0011	0.0012	0.0009	0.0009	0.0013	0.0004	0.0006	0.0007	0.0007
	(1.92)	(2.24)	(2.56)	(2.48)	(2.99)	(2.04)	(2.05)	(3.08)	(0.95)	(1.48)	(1.73)	(1.73)
LOG	−0.0002	−0.0002	0.0000	0.0001	0.0001	0.0003	0.0002	0.0003	−0.0002	−0.0001	0.0002	0.0002
	(−0.93)	(−0.79)	(−0.08)	(0.30)	(0.53)	(1.22)	(0.97)	(1.63)	(−0.75)	(−0.59)	(0.91)	(0.91)
MOP	0.0105	−0.0119	−0.0014	−0.0134	0.0136	−0.0088	−0.0092	−0.0124	−0.0261	−0.0283	−0.0050	−0.0050
	(0.53)	(−0.60)	(−0.07)	(−0.69)	(0.71)	(−0.46)	(−0.50)	(−0.71)	(−1.40)	(−1.61)	(−0.27)	(−0.27)
IRR	0.0092	0.0078	0.0129	0.0144	0.0127	0.0097	0.0052	0.0026	0.0027	0.0004	0.0004	0.0004
	(4.78)	(3.44)	(5.33)	(6.78)	(5.84)	(5.30)	(3.00)	(1.58)	(1.53)	(0.25)	(0.21)	(0.21)
RER	0.0046	0.0115	−0.0015	−0.0068	−0.0097	−0.0115	−0.0069	−0.0057	0.0012	0.0051	0.0058	0.0058
	(1.24)	(3.05)	(−0.39)	(−2.02)	(−2.87)	(−4.02)	(−2.55)	(−2.22)	(0.45)	(1.93)	(1.99)	(1.99)
ECA	−0.0016	0.0000	0.0000	0.0001	0.0006	0.0003	0.0005	−0.0002	0.0021	0.0027	0.0028	0.0028
	(−1.37)	(−0.02)	(0.00)	(0.10)	(0.59)	(0.37)	(0.52)	(−0.23)	(2.29)	(3.02)	(2.89)	(2.89)
Sample = foreign banks												
——	−0.0003	0.0008	0.0007	0.0008	0.0011	0.0004	0.0005	0.0006	0.0001	0.0003	0.0004	0.0004
	(−1.06)	(3.04)	(2.90)	(2.32)	(3.90)	(1.21)	(1.86)	(2.42)	(0.23)	(1.11)	(1.84)	(1.84)
MEX	0.0298	0.0198	−0.0259	−0.0268	−0.0329	−0.0226	−0.0144	−0.0014	0.0087	−0.0015	−0.0129	−0.0129
	(2.00)	(1.32)	(−1.78)	(−1.86)	(−2.36)	(−1.60)	(−1.04)	(−0.12)	(0.79)	(−0.13)	(−1.11)	(−1.11)
CAP	0.0015	−0.0030	−0.0023	−0.0025	−0.0026	−0.0009	−0.0011	−0.0016	−0.0010	−0.0006	−0.0019	−0.0019
	(1.61)	(−3.17)	(−2.77)	(−2.12)	(−2.87)	(−0.90)	(−1.29)	(−2.01)	(−1.21)	(−0.85)	(−3.03)	(−3.03)
INL	0.0009	−0.0007	−0.0001	0.0009	0.0009	0.0013	0.0013	0.0005	0.0005	0.0005	0.0003	0.0003
	(0.86)	(−0.70)	(−0.06)	(0.78)	(0.83)	(1.22)	(1.27)	(0.51)	(0.52)	(0.46)	(0.27)	(0.27)

Table 3. (continued)

Independent variable	Number of lags 1	2	3	4	5	6	7	8	9	10	11	12
LIQ	–0.0012	–0.0012	–0.0011	–0.0009	–0.0001	–0.0001	0.0000	0.0003	0.0005	0.0008	0.0012	0.0012
	(–2.91)	(–3.22)	(–3.07)	(–1.87)	(–0.33)	(–0.21)	(0.07)	(0.70)	(1.14)	(2.22)	(3.25)	(3.25)
LOG	–0.0004	–0.0006	0.0001	0.0002	0.0001	–0.0003	0.0004	0.0005	0.0006	0.0006	0.0007	0.0007
	(–1.32)	(–2.13)	(0.28)	(0.57)	(0.37)	(–1.04)	(1.61)	(1.90)	(2.37)	(2.73)	(3.43)	(3.43)
MOP	–0.0108	–0.0062	–0.0089	0.0365	–0.0106	0.0456	–0.0212	–0.0338	0.0101	–0.0071	0.0087	0.0087
	(–0.73)	(–0.43)	(–0.73)	(1.66)	(–0.78)	(2.47)	(–1.74)	(–2.89)	(0.88)	(–0.82)	(1.11)	(1.11)
IRR	0.0125	0.0082	0.0142	0.0121	0.0090	0.0067	0.0019	0.0025	0.0006	0.0016	–0.0003	–0.0003
	(3.97)	(2.30)	(4.15)	(2.92)	(2.64)	(1.89)	(0.67)	(0.91)	(0.22)	(0.73)	(–0.15)	(–0.15)
RER	0.0048	0.0116	–0.0101	–0.0167	–0.0079	–0.0026	0.0051	0.0063	0.0056	–0.0074	0.0004	0.0004
	(0.72)	(1.76)	(–1.68)	(–1.85)	(–1.34)	(–0.37)	(0.99)	(1.26)	(1.14)	(–1.96)	(0.13)	(0.13)
ECA	–0.0040	–0.0012	–0.0027	–0.0027	–0.0003	0.0005	–0.0022	–0.0016	–0.0018	–0.0041	–0.0012	–0.0012
	(–1.94)	(–0.57)	(–1.50)	(–0.97)	(–0.16)	(0.22)	(–1.40)	(–1.04)	(–1.18)	(–3.48)	(–1.15)	(–1.15)
Sample = financial companies												
——	0.0007	0.0004	0.0022	0.0021	0.0021	0.0032	0.0021	0.0034	0.0015	0.0010	0.0012	0.0012
	(0.95)	(0.54)	(2.75)	(2.72)	(2.63)	(4.25)	(2.79)	(4.60)	(2.04)	(1.35)	(1.66)	(1.66)
MEX	0.0167	0.0179	–0.0026	0.0589	0.0461	0.0235	0.0286	–0.0430	0.0722	–0.0427	0.0142	0.0142
	(0.78)	(0.80)	(–0.11)	(2.50)	(1.95)	(1.01)	(1.30)	(–1.90)	(3.19)	(–1.88)	(0.61)	(0.61)
CAP	0.0055	0.0039	0.0002	–0.0024	–0.0020	–0.0012	–0.0028	0.0026	0.0045	–0.0037	–0.0044	–0.0044
	(1.73)	(1.18)	(0.05)	(–0.67)	(–0.58)	(–0.36)	(–0.85)	(0.77)	(1.36)	(–1.11)	(–1.26)	(–1.26)
INL	–0.0008	–0.0018	–0.0010	–0.0019	0.0004	0.0005	0.0010	0.0019	0.0018	0.0016	0.0016	0.0016
	(–0.28)	(–0.61)	(–0.34)	(–0.63)	(0.15)	(0.15)	(0.33)	(0.64)	(0.58)	(0.63)	(0.63)	(0.63)
LIQ	0.0012	0.0029	0.0035	0.0064	0.0016	0.0008	0.0030	–0.0032	–0.0010	0.0013	0.0041	0.0041
	(0.21)	(0.54)	(0.62)	(1.13)	(0.28)	(0.15)	(0.53)	(–0.56)	(–0.18)	(0.29)	(0.88)	(0.88)
LOG	–0.0001	0.0000	0.0001	0.0000	0.0000	–0.0001	0.0000	–0.0001	–0.0003	0.0001	–0.0001	–0.0001
	(–0.60)	(–0.17)	(0.49)	(0.25)	(–0.27)	(–0.75)	(–0.15)	(–0.61)	(–2.01)	(0.53)	(–0.39)	(–0.39)
MOP	–0.0062	–0.0050	–0.0113	–0.0341	–0.0297	–0.0409	–0.0069	–0.0219	–0.0389	0.0236	0.0113	0.0113
	(–0.38)	(–0.29)	(–0.63)	(–1.90)	(–1.63)	(–2.30)	(–0.41)	(–1.28)	(–2.19)	(1.37)	(0.64)	(0.64)
IRR	–0.0092	–0.0053	–0.0107	–0.0086	–0.0052	–0.0175	–0.0187	–0.0227	–0.0161	–0.0036	–0.0078	–0.0078
	(–2.31)	(–1.02)	(–1.94)	(–1.53)	(–0.90)	(–3.21)	(–3.52)	(–4.41)	(–2.95)	(–0.70)	(–1.46)	(–1.46)
RER	0.0144	0.0026	0.0092	–0.0004	–0.0139	–0.0069	–0.0042	0.0041	0.0001	–0.0064	0.0009	0.0009
	(2.18)	(0.37)	(1.24)	(–0.05)	(–1.83)	(–0.99)	(–0.61)	(0.59)	(0.02)	(–0.96)	(0.12)	(0.12)
ECA	0.0039	0.0023	0.0016	0.0003	–0.0017	–0.0039	–0.0032	–0.0031	–0.0046	–0.0016	–0.0032	–0.0032
	(1.97)	(1.07)	(0.75)	(0.13)	(–0.79)	(–1.92)	(–1.58)	(–1.55)	(–2.23)	(–0.82)	(–1.62)	(–1.62)
Summary statistic												
R^2	0.862	0.860	0.863	0.884	0.877	0.863	0.897	0.931	0.932	0.941	0.962	0.957

Source: Authors' calculations.

a. NPL, nonperforming loans; IRR, real lending rate on loans of 90-365 days; RER, real exchange rate; ECA, index of economic activity; other variables are defined as in table 1. The number below each regression coefficient is its *t* statistic.

consumer credits, which are usually lent for twenty-four or thirty-six months at fixed nominal interest rates. Therefore, nonperforming loans in the case of the financial companies could be related more to the evolution of long-term interest rates or to other macroeconomic factors pertaining to the consumer's ability to repay (such as changes in net income), which in turn may be directly influenced by unemployment rates. We explore this possibility below.

Economic activity in table 3, unlike in the pooled regression in table 2a, is important in explaining the behavior of credit risk for domestic banks. For these banks, increases in economic activity increase bank fragility after many periods. However, the reaction of foreign banks to increases in economic activity shows the opposite sign, although it is less clear or persistent. The liquidity ratio shows the same pattern as the economic activity index; that is, its parameter values are positive for domestic banks, suggesting that greater liquidity leads to a greater proportion of nonperforming loans. Foreign banks instead have negative parameter values, showing perhaps a result more consistent with risk aversion, in the sense that an increase in liquidity decreases the proportion of nonperforming loans.

Finally, loan growth is a significative explanatory variable only for the group of foreign banks. For lags of nine to twelve periods there is a positive response of nonperforming loans to an increase in loan growth among these banks. This result is informative in that it contradicts the pooled estimates in table 2a, which suggest that all banks are responsive to loan growth.

Table 3 also reveals that the financial ratios and macroeconomic variables are essentially unable to explain the evolution of nonperforming loans for financial companies. An alternative model was estimated for this group of institutions using a proxy for household income as a determinant of the repayment ability of consumers. This proxy is computed on a monthly basis as the real wage index times the percentage of working-age people employed in the economy. The goodness of fit of the model did not increase, however, and the household income variable was not significant at various lags. In order to check the results of the longitudinal estimation, we tested the sensitivity of aggregate household income on a company-by-company basis, but still found that it was not significant. We also incorporated the unemployment rate directly in the estimation, but the parameter estimates were not significant at any lags. Therefore we can argue that, in the case of financial companies, the evolution of nonperforming loans is determined exogenously by its own dynamic.

3. Concluding Comments

This paper has attempted a simple estimation of the determination of some measures of banking fragility, to identify which bank-specific and macroeconomic variables could explain their behavior. Despite the model's simplicity, we were able to extract some interesting insights regarding the ratio of nonperforming loans to total loans and how managerial efficiency, liquidity position, and the cost of funding affect its performance.

We concentrated on only two types of risk in this paper: credit risk, which is considered the more relevant, and a proxy of liquidity risk. Certainly banks face other risks in their business, namely, interest rate risk, currency risk, maturity risk, technology risk, and sovereign risk. Nonetheless, in Chile currency risk is severely constrained by central bank regulations, and banks can lend directly in foreign currency only to exporters. Risk arising from interest rate volatility is hedged to some extent for mortgage credit operations. On the other hand, banks normally may have some net open positions with the central bank related to their participation in the payments system. It remains for future study to consider these additional risks, how to measure them and how to identify which variables could explain their evolution and their impact on bank fragility, within the context of reduced-form model specifications.

The results for the interbank spread are also encouraging, but they should be interpreted with care because of the missing-observations problem. An alternative, continuous measure of liquidity risk could be used instead to validate these results. Finally, other sources of banking fragility should be explored, even though credit risk has been traditionally considered the most relevant for the long-term assessment of banks' financial stability.

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