On the Use of Portfolio Risk Models and Capital Requirements in Emerging Markets: The Case of Argentina

Veronica Balzarotti, Michael Falkenheim, and Andrew Powell

A portfolio-based model (CreditRisk+ of Credit Suisse First Boston) and recent Central Bank of Argentina credit bureau data are used to estimate whether current capital and provisioning regulations match actual risks. Arguing that provisions should cover expected losses and that capital requirements should cover potential losses beyond expected losses subject to some statistical level of tolerance, the article assesses how well actual capital and provisioning requirements match the estimated requirements given by the model. Actual provisioning requirements were found to be close to implied levels of expected losses. The estimate of potential losses was found to be highly sensitive to the assumptions of the model, especially the parameter relating the volatility of a loan’s rate of default to its mean value. This volatility parameter cannot be estimated accurately with the credit bureau data because of the short time span covered, so proxy data were used to estimate it, and two values around that estimate were tried. The difficulty of estimating this critical parameter implies that the results should only be regarded as suggestive. Moreover, the methodology only seeks to estimate credit risk and not interest rate risk or exchange rate risk, nor does it fully take into account the indirect effects of interest rates and exchange rates on credit risk. As recent events in Argentina have demonstrated, estimating credit risk along these lines should be thought of as just one tool in attempting to assess the appropriate level of bank provisions and capital.

Recent literature stresses the need for capital requirements and provisions to maintain a healthy financial system by limiting the risk of bank failures. In the past, the requirements reflected rules of thumb or were the outcome of complex political negotiations. More recently greater efforts have been made to quantify

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appropriate levels of regulatory capital. The methodology usually applied is to consider what stock of capital would cover potential losses in all but a small percentage of scenarios that could prevail in the time needed to take risk-mitigating actions, such as selling risky loans or replenishing capital.

The credit bureau of the Central Bank of Argentina provides a rare tool for quantifying provisions and capital requirements in this way. This credit bureau was established in 1991 to collect information on the larger debtors of the financial system and help elucidate how those debtors posed risks for the financial system and for individual banks.

The credit bureau has served other needs, including the need for more accurate information on the credit history of debtors. At an early stage the database was given to virtually all financial institutions at low cost. The power of the data to address “willingness to pay” issues prompted both an extension of the database and its wider distribution. Today the database covers virtually all loans in the financial system (more than 6 million entries). It is updated monthly and available free of charge on the Internet through the Web site of the Central Bank of Argentina at http://www.bcra.gov.ar.

In this article we describe a study that used the Central Bank of Argentina’s credit data to estimate the potential losses of a portfolio of Argentine loans. We use estimates of potential losses from a portfolio-based model, CreditRisk+ of Credit Suisse First Boston, to determine whether current capital and provisioning regulations match actual risks. We argue that provisions should cover expected losses and capital requirements should cover potential losses beyond expected losses, subject to some statistical level of tolerance. We then assess how actual capital and provisioning requirements match the estimated requirements produced by our application of the model and calibrated using a particular sample of recent data.

The results are subject to several caveats, especially considering recent events in Argentina. First, we employ a limited database, which includes barely two years of data. The period covered was one of recession, but it ended before the real crisis began. Probabilities estimated on the basis of such a database may not cover particular infrequent events. Second, we attempt to measure only credit risk; we do not analyze the direct effect of interest rate or foreign exchange risk on banks’ balance sheets. Indeed, given the limited nature of the database, it is unlikely that we fully capture the indirect effect of these risks on banks’ clients that then feed through to credit risk. Finally, we do not consider the severe effects on bank solvency of the default of the public sector in Argentina and the forced revaluation of loans and deposits at different exchange rates. These caveats underline the fact that value at risk models should be thought of as partial tools, to be used in conjunction with scenario analysis or other methods rather than as sole estimators of bank risk.

This article is organized as follows. In section I we briefly describe the role of provisioning and capital requirements and suggest that capital requirements may need to reflect portfolio considerations. In section II we describe the source of
our data, the Central Bank of Argentina’s credit bureau. In section III we present our application of CreditRisk+, explaining our methodology for choosing its input parameters. In section IV we compare the model’s estimates of expected and potential losses to actual provisioning and capital requirements. Section V summarizes our conclusions.

I. Provisions, Capital Requirements, and Credit Risk

Both provisions and capital requirements attempt to control credit risk by creating a buffer against credit losses (Basel Committee on Banking Supervision 1999a, 1999b). In practice it is sometimes difficult to differentiate them. In the Basel 1988 Accord, for example, it was agreed that a general provisioning requirement might be recorded as Tier II capital against requirements.1

We believe that provisions and capital serve two distinct purposes. In our view, provisions alone should protect banks against ordinary levels of credit loss, whereas capital requirements should protect banks against unforeseen losses. In statistical terms, provisions should reflect the expected value of credit losses, and capital requirements should protect against unexpected losses, subject to some level of statistical tolerance. This means that in theory, both provisioning and capital requirements may be specified from the same distribution (the distribution of potential credit losses), but they reflect different statistics of that distribution.

This theoretical concept of provisions and capital allows for clear comparisons between their actual levels and an estimated probability distribution. Moreover, it reflects what appears to be the emerging consensus in the regulatory community and the banking industry.

The Basel Committee on Banking Supervision (1998) stated that the “aggregate amount of specific and general [provisions] should be adequate to absorb estimated credit losses associated with the loan portfolio” (p. 23). The same committee (Basel Committee on Banking Supervision 1999a) suggests that most sophisticated financial institutions view economic capital as covering unexpected as opposed to expected losses. Part of our analysis compares the total coverage provided by both capital and provisions against the 99.9th percentile of the loss distribution, thus making no assumptions about the division of labor between capital and provisions and recognizing that capital and provisions work in tandem.

Figure 1, which plots a distribution of potential credit losses (for a single loan or a loan portfolio), illustrates our view of the appropriate level of provisions and capital requirements. In this example the appropriate level of provisions is

1. The Capital Accord defined tier I capital as “core capital,” including equity capital and published reserves from posttax retained earnings. It defined tier II capital as “supplementary capital,” including hybrid capital instruments, subordinated debt, and provisions. The Capital Accord required that at least 50 percent of capital used to meet minimum levels be tier I capital.
the expected loss, US$12,500 (for the moment we disregard the role of net interest). In contrast, capital requirements should reflect unexpected losses, usually defined as the difference between a given percentile level and the expected loss. In our example we calculate appropriate capital requirements as equal to the difference between the 99.9th percentile of credit losses and the expected value. The 99th percentile defines a line that places just 0.1 percent of the distribution to the right (in our example the value is $18,000). Appropriate capital requirements in our example are $18,000 – $12,500 = $5,500. Note that credit losses should exceed the 99.9th percentile in only 1 out of 1,000 possible economic scenarios (just over once every millennium if annual drawings are made from this distribution).

Interest complicates this picture somewhat. Provisions and capital requirements are supplemented by the interest that banks charge borrowers to compensate them for the expected cost of default and as a premium for the systematic risk of their loan portfolio (see Escudé 1999, Rochet 1992). The Rochet and Escudé models suggest that the net interest charged by banks should cover the losses expected
by the lender at the moment of origination and the nondiversifiable portion of unexpected losses. One argument is that interest compensates the financial institution for expected losses and systematic risk, partly duplicating the roles of provisions and capital. However, the Basel Committee on Banking Supervision (1998) recommended that provisions be adequate to protect against expected losses, making no mention of interest margins. Moreover, net interest is available as protection against credit losses only if it is not first paid as a dividend to bank shareholders or owners. In normal times it might be argued that shareholders will expect a normal return; provisions should hence cover normal losses without including net interest earnings. That said, it is likely that a bank will reduce or even suspend payments of dividends if its portfolio begins to deteriorate seriously and increase its provisions.

In our view, deducting future interest margin from the calculation of capital requirements would imply a much less conservative treatment of capital than that included in the current (and future) Basel Capital Accord. The accord’s definition of capital admits earnings at tier I level only if retained earnings have been appropriated into a disclosed reserve; otherwise the accumulated after-tax surplus of retained profits may be included as tier II capital, with the approval of the national supervisor. This means that these profits must be observed, not merely expected, and may be subject to the limits on tier II capital if they have not been appropriated into a reserve.

For these complications it remains controversial whether expected net interest should be counted along with capital and provisions as a buffer against credit losses. We remain agnostic on this point. We therefore make two comparisons: one that takes interest into account and another that does not. First, we compare capital requirements and provisions with expected and potential losses. Second, we add an estimate of expected net interest to provisions and capital requirements and then compare them with expected and potential losses.

In Argentina, as elsewhere, for each loan the Central Bank requires a minimum level of provisions, which depends on the economic classification of the debtor. For commercial loans financial institutions are required to rate the debtor on a scale of one to five, depending on its expected cash flow. For consumer and housing loans, financial institutions must base the classification of debtors on their current payment status. Current regulations allow commercial loans of less than $200,000 to be treated as consumer loans in terms of these requirements.

2. The Basel Committee on Banking Supervision (2001) notes that its proposed Internal Ratings Based (IRB) approach has been criticized for not taking interest margins into account. It recommends that regulators allow some technically sophisticated institutions to take interest margins into account for retail portfolios under the IRB: “For the retail portfolio, allow (by definition advanced) IRB banks to use their own internally generated estimates of [Expected Loss]-related capital charges based on a comparison of expected future credit losses and future margin income. . . . For non-retail portfolios sticking to the one year ahead [Probability of Default] times [Loss Given Default] without any [Future Margin Income] recognition would seem to be an acceptable approximation for [Expected Loss]” (p. 4).
One of the central purposes of this study is to evaluate the current system of provisioning requirements. We use the credit bureau data to assess whether the level of provisions is adequate given observed loss probabilities.

Performing loans are classified as 1 or 2, whereas loans rated 3, 4, or 5 are considered nonperforming loans. Each of the first two categories represents a broad range of risk and would cover several ratings classes in a private ratings system, such as Moody’s or Standard and Poor’s. In developing our credit risk model we use econometric techniques to distinguish between different risk levels within each category, and we give a more precise estimate of risk than that conveyed by the rating alone.

The Basel 1988 Capital Accord formally establishes the current form of capital requirements for “internationally active” banks in G-10 countries, but more than 100 countries, including Argentina, have explicitly adopted the accord in their own banking regulations or in law. In many countries the rules are applied not only to internationally active banks but also to domestic banks. Moreover, in some countries that have adopted the general Basel methodology, requirements have been stricter than the minimum 8 percent of assets at risk recommended by the accord. Countries have adopted their own limits within the general methodology depending on the perceived level of credit risk.

In Argentina the Central Bank sets capital requirements for the banking system. Since the end of 1994 it has required banks to set aside 11.5 percent of risk-weighted assets for counterparty risk. The Basel Accord defined risk weights for different assets in an attempt to capture the different levels of risk in their returns. These weights are used in Argentina, but they are complemented with a risk indicator based on the interest rate charged on each loan. This additional risk indicator is a factor by which the base capital requirement is multiplied. Under this system loans with higher interest rates have higher capital requirements because they are presumed to have a higher level of risk. Argentine capital requirements also include a factor that depends on the CAMELS (capital, assets, management, earnings, liquidity, and sensitivity) rating assigned to each financial institution by the Superintendency of Financial Institutions.

Unlike the original Basel Accord, Argentina’s regulations do not allow general provisions to be included as tier II capital. In addition to counterparty risk capital requirements, the Central Bank imposed capital requirements for market risk and interest rate risk. The current Argentine capital requirement was then specified according to the following formula:

\[
\text{(1) Overall Capital Requirement} = 11.5\% \times IR \times W \times K \times A + \text{Market Risk} + \text{Interest Rate Risk}
\]

where \(IR\) is the interest rate factor; \(W\) is the average Basel risk weight for assets, varying between 0 and 1; and \(K\) is the CAMELS factor. \(K\) ranges from 0.97, for banks with a rating of 1, to 1.15 for banks with a rating of 5. \(A\) is the outstanding value of the asset.
One shortcoming of Basel-style capital requirements is that they do not take into account how individual exposures are combined in the loan portfolio. One $100 million loan to a single company has the same capital requirement as 1,000 loans of $100,000 each to 1,000 different companies if these loans are in the same risk category. However, maintaining a diversified portfolio usually reduces the total credit risk of an institution. Moreover, requirements do not differ according to the level of correlation of asset returns in a portfolio. A portfolio of loans exclusively to companies in the textile industry would have the same capital requirement as a portfolio of loans spread across various industries, assuming they are all in the same risk category. If the standard rules do not reflect the actual risks of financial institutions’ credit portfolios, capital allocation decisions may be distorted.

A recent proposal to remedy this problem is the use of internal models to assess capital adequacy. Under this system financial institutions would apply to use their own measures of credit risk to determine the capital requirement. As Jones and Mingo (1998) suggest, regulators would define a minimum permitted probability of insolvency, and financial institutions would develop models to estimate the probability distribution of credit losses. Capital adequacy would be calculated based on that probability. Regulators would then decide which models deserve authorization based on their technical merit and historical performance.

Although senior regulators in the United States and the United Kingdom view the use of internal models as very promising, such models remain at an early stage of development. Indeed, the recent proposal to modify the Basel 1988 Accord, though including many ideas to improve credit risk assessment of individual debtors, shied away from methods of analyzing portfolio risk based on internal models. In using a credit risk model to evaluate provision and capital requirements, it is therefore important to recognize the limitations of this approach. The Basel Committee and other institutions studying credit risk models all concluded that these models are not yet sufficiently well developed to use in a capital requirement system. According to the Basel Committee on Banking Supervision (1999a, 1999b) and others (see Jackson and others 1999), important issues, such as the correct shape of the loss distribution, have not been resolved, and the short span of historical data makes it impossible to properly validate credit risk models. Furthermore, other risk factors, such as operational risk, have not been adequately studied. The basic ratio established in the Capital Accord might also provide a needed hedge against operational and other risks.

The problems associated with implementing models for credit risk regulatory capital may be magnified in emerging markets, where assumptions about structure and parameters are likely to be less stable and technical and human resources are likely to be more constrained. Faced with this reality, in the exercise that follows we consider using such models only as a check to see whether current regulations broadly match implied theoretical levels. Our concern is with the total
level of provisions and capital available to an institution or to the financial system as a whole. We do not consider how this capital is distributed across the loan portfolio. We thus address questions of overall prudential standards rather than questions of efficiency.

Another possible use of credit risk models is in supervision. Capital requirements in Argentina depend on the CAMELS rating that the Superintendency of Financial Institutions assigns to each institution. Supervisors in Argentina give institutions a rating of one to five based on the level of risk of their assets, among other things. This rating translates into a lower or higher capital requirement, because each rating causes a different multiplier to be applied to the global credit risk capital requirement (table 1). Credit risk models may help supervisors quantify the credit risk of institutions and perhaps become an explicit part of their (CAMELS) ratings decisions.

II. Data

Our source of data for studying credit risk is the Central de Deudores del Sistema Financiero (cdsf) data set, which includes information on virtually every loan in the Argentine financial system. The cdsf originated in January 1991 when the Central Bank of Argentina began collecting and disclosing information about the largest debtors in the financial system (those with debts of more than $200,000). Financial institutions provide the information, which is then validated and redistributed to all contributors.

Information on debtors originally included only the classification assigned to each debtor by each financial firm. Later the Central Bank required banks to report more detailed information, including the principal activity of the debtor, its links (if any) to the lending institution, the business group to which it belonged, debts by currency denomination, collateral, provisions, and net worth. In September 1994 the Central Bank of Argentina decided to make the information available to the public, for a modest fee, through an agency named the Risk Center (Diaz 1998, Roisenzvit 1997).

In 1995 the Central Bank decided to extend the range of debtors by creating the Credit Information Center (cic), which began operations in January 1996.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Definition</th>
<th>Current minimum provision (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Normal</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>Potential risk</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>Substandard</td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>Doubtful</td>
<td>50</td>
</tr>
<tr>
<td>5</td>
<td>Loss</td>
<td>100</td>
</tr>
</tbody>
</table>

Source: Central Bank of Argentina.
This new register includes information on debtors from the nonfinancial sector with debts greater than $50, thus covering virtually the entire range of borrowers. For each debtor the CIC collects information on principal activity, total debt, collateral, and the financial institution’s classification of the debtor. In October 1996 the Central Bank decided to disclose the information collected by the CIC for an annual fee. In July 1997 both the Risk Center and the CIC were unified in the CDsf.

Using the CDsf to study credit risk entails several practical problems. The database does not contain information on individual debts, instead grouping together all debts by an individual at a financial institution. The CDsf does not provide information about the structure of debts and only recently began to provide information on loan duration and debt interest rates.

III. Methodology

To quantify the credit risk of Argentine financial institutions, we use the CreditRisk+ model, a portfolio-based credit risk model developed by Credit Suisse Financial Products. Portfolio-based credit risk models estimate the probability distribution of total credit losses for a portfolio of loans. These models generate a probability distribution of loan losses based on certain specifications and parameters supplied by the user.

Portfolio-based credit risk models capture the two factors that create the potential for unexpected losses: the concentration of exposures in large borrowers and the correlation of changes in credit quality of separate borrowers. If exposures are concentrated in a few large borrowers their default can create larger than expected total losses. Correlation between the defaults of different borrowers creates a situation in which defaults tend to come in bunches, causing a higher than expected default rate.

We chose CreditRisk+ after considering several alternative models. Crouhy and others (2000) and Koyluoglu and Hickman (1998) make excellent comparisons of the different models. Although the presentations in the models’ technical documents give the impression that they are quite different from one another, Koyluoglu and Hickman (1998) and Gordy (2000) point out that their statistical structure is fairly similar. The differences have to do largely with calculation methods and assumptions about the correlation of loan defaults. Some models use Monte Carlo techniques, whereas others, including the CreditRisk+ model, derive analytical formulas for the probability distribution of total portfolio losses. Different models also make different assumptions to capture the correlation between the defaults of different debtors.

The CreditRisk+ technical document gives a full description of the model (Credit Suisse First Boston 1997). To illustrate our application of CreditRisk+, we highlight its main features.

The model calculates the probability distribution of total portfolio losses for a fixed time horizon—one year, for example—although it can be extended to
calculate losses over many periods or under the assumption that all loans will be held to maturity. For each loan the model requires as inputs the size of the exposure, the probability of default, the volatility of that probability over time, and the loan’s loss given default (one minus the recovery rate), assumed to be a constant. One or more stochastic factors drives the probability of default of the loans in the portfolio. These stochastic factors, which are assumed to have a gamma distribution, capture the correlation between loan defaults. The correlation of default between each pair of debtors depends on how much common risk factors drive their probabilities of default.

In applying CreditRisk+ the user needs first to define the basic design of the model, including its time horizon and the number of independent risk factors that will affect the probability of default of individual loans. The user then needs to supply parameters for each loan: the exposure, the probability of default, the volatility of that probability, and the loss given default. The formulas of the CreditRisk+ model aggregate the individual probabilities of default and volatilities to derive an analytical expression for the probability distribution of total losses.

The main benefit of CreditRisk+ for our application is its simplicity. It requires a minimal amount of data, all of which are available in the CDSF. Its analytical (as opposed to Monte Carlo) method for calculating the loss distribution of a portfolio allows us to calculate results for large portfolios relatively quickly, a key feature given that one of our goals is to incorporate its results in the supervision process. In addition, using CreditRisk+ facilitates analysis of the sensitivity of our results to key modeling assumptions. In comparing CreditRisk+ and CreditMetrics⁷⁸, Gordy (2000) notes that estimates of implied capital derived from CreditRisk+ can vary greatly with the kurtosis of the default rate’s distribution, which in turn is related to the parameters of the underlying gamma distribution.

We define the time horizon as one year. Most analysts have viewed one year as an appropriate time horizon for measuring capital adequacy because they believe that financial institutions can take risk-mitigating action or replenish their capital levels within that time period.

For the sake of simplicity we assume a single risk factor. The formulas for the probability distribution of total portfolio losses become substantially simpler when a single factor is assumed, and the model’s processing time is shorter. Assuming a single risk factor implies that the default probabilities of all loans are driven by a common factor, which one could think of as the overall macroeconomic climate. Assuming more than one risk factor potentially could have allowed us to better model the risk of institutions with portfolios concentrated in single industries by assigning a risk factor to each major industry. But assuming many risk factors would have complicated the model substantially and would have required the estimation of numerous additional parameters, many of which could not have been estimated with any accuracy. Given our main goal—to determine whether current regulations broadly match implied theoretical levels—we considered it best to avoid these complications.
Having specified a one-year time horizon and one risk factor for each loan, \( i \), we need to identify the size of the loss given default, \( \mu_i \); the mean probability of default over the one-year horizon; and the volatility of that probability, \( \sigma_i \). We assume that the exposure is the loan balance recorded in the CDSF database and that the loss given default is equal to the exposure minus 50 percent of the value of the collateral covering the credit. This assumption is consistent with the Central Bank’s provisioning requirements, which oblige each bank to allocate provisions for 100 percent of the value of an irrecoverable loan minus 50 percent of the value of the collateral guaranteeing that loan.

Using historical data from the CDSF and an econometric model, we estimate each loan’s probability of default as a function of its classification and other characteristics. We specify the model as an ordered probit. The ordered probit estimates the probability that at the end of the year a loan will have each possible classification, given its current classification and other characteristics. The estimated probability that a loan ends the year with a classification of 5 (defined as loss) gives the estimated probability of default. Using an ordered probit—which estimates the probability of obtaining any classification—as opposed to a simple probit—which would estimate only the probability of loss—we were able to take into account all the observed changes in classification, not just instances when a loan changed its classification to “loss.” Under the ordered probit the probability that the classification at the end of the year \( c_{i+1} \) is \( K \) is given by the following expression:

\[
\Pr(c_{i+1} = K | \beta; X^i) = \begin{cases} 
F[\nu + \beta'X^i] & K = 1 \\
F[\nu + \beta'X^i] - F[\nu + \beta'X^i] & K = 2, 3, 4 \\
1 - F[\nu + \beta'X^i] & K = 5
\end{cases}
\]

In this equation, \( F[.] \) is the standard cumulative normal distribution, and \( \nu_1, \ldots, \nu_5 \) are estimated parameters that define the cutoffs between each pair of adjacent classifications. The value \( X^i \) is a vector of characteristics for the individual loan, including the following variables:

- **The borrower’s classification.** Naturally borrowers with a better (lower) classification are less likely to default. For each classification, we estimate a dummy variable measuring the relative risk of default of that classification.
- **The borrower’s activity.** The database includes a three-digit code identifying the borrower’s industry or intended use of the loan. For each category defined by that code, we estimate a dummy variable to measure the relative propensity of borrowers in that industry to default.
- **The size of the exposure.** We conjecture that larger loans have on average a lower probability of default than smaller loans, because lenders may screen them more carefully.
- **The CAMELS rating of the lender.** Because the CAMELS rating should reflect the quality of the financial institution, a better rating should tend to be associated with lower probabilities of default. For each CAMELS rating we
estimate a dummy variable measuring the relative risk of default for loans made by an institution with that rating.

- The percent of the debt backed by collateral. Collateral may affect the probability of default for two offsetting reasons. On the one hand, borrowers who post collateral may work harder to avoid default to prevent losing their collateral. On the other hand, lending institutions may relax their lending requirements for borrowers with collateral.

The parameter \( \beta \) is the vector of coefficients that multiply the variables in the vector \( X \). We use maximum likelihood estimation to estimate the parameters \( \nu \) and \( \beta \) using data on the actual one-year changes in classification for all loans in the credit bureau starting in September 1999. We then use the estimate \( \hat{\beta} \) to generate estimated probabilities of default for each loan, given by the following expression.

\[
\hat{\mu}_i = \Pr(c_{i+1} = 5 | \hat{\beta}_i, X_i) = 1 - \Phi(\nu + \hat{\beta}'X_i).
\]

To estimate the econometric equation we use data from the CDISF on borrower characteristics in March 1998 and one-year changes in classification between that month and March 1999, a period in which there were about 4.5 million loans in the database.

The volatility of the probability of default reflects its sensitivity to economic and other factors that affect different loans simultaneously. High volatility indicates that the probability of default will tend to go up in difficult times, increasing the loan’s contribution to the portfolio level of unexpected risk. To simplify the estimation of the volatility parameter for each loan, we adopt a suggestion from the Technical Document and assume that the volatility to the probability of default is given by the expression \( \sigma_i = \delta \mu_i \). In other words, the ratio of the volatility of the probability of default to its mean is the same for all loans and equal to \( \delta \). Because of the short time span, we cannot depend on our data to estimate this ratio. Had we had a longer time series of data, it would have been possible to estimate a sequence of one-year default probabilities and calculate their standard deviation in order to estimate \( \delta \). Lacking such a time series, we relied on external data to generate an estimate of \( \delta \) and analyzed the sensitivity of our results to this estimate by reestimating the CreditRisk+ model with alternative values of \( \delta \) around that estimate.

The U.S. Federal Reserve collects data on the delinquency rate of bank loans in a variety of categories. Between 1985 and 2000 the loan delinquency rate averaged 3.86 percent, with a standard deviation of 1.44 percent, suggesting that \( \delta \approx 0.38 \). In our estimation, we consider two possibilities around this level, \( \delta = 0.3 \) and \( \delta = 0.5 \).

IV. Implicit Provisions and Capital Requirements

To compare the implied capital requirements from our application of CreditRisk+ with actual capital requirements and capital levels, we examine the five largest
private financial institutions in Argentina. We estimate the probability distribution of credit losses of their combined portfolio (figure 2).

The figure shows that the shape of the loss distribution is highly sensitive to the assumption about the parameter \( \delta \), which represents the ratio of the volatility of the default rate to its mean. Under the assumption \( \delta = 0.5 \), the distribution is much more skewed to the right than under the assumption \( \delta = 0.3 \), resulting in higher estimates of potential losses.

We compare both required and actual levels of capital and provisions held by financial institutions against the probability distribution of losses under each assumption about the parameter \( \delta \) (table 2). We also make another calculation that takes interest into account. To calculate the amount of interest to protect financial institutions against credit losses, we note that in recent years the interest margin of Argentine financial institutions has been about 4 percent (see Raffin 1999), whereas administrative costs and noninterest income have almost exactly offset each other. This means that for every dollar of assets, a typical institution has available to it a net income of 4 cents to cover credit losses. Given that total assets of the five institutions were equal to $2.5 billion, about $1 billion in net interest is expected on their loan portfolios. This interest creates a buffer against credit losses. We also compare the distribution of credit losses against the total of provisions, capital, and net interest income available to the five institutions (table 3).

The results of both comparisons indicate that, subject to the caveats noted earlier, Argentina’s provisions provide adequate protection against the expected value of credit losses. The capital requirement is adequate at a 99.9 percent level.

Figure 2. The Estimated Probability Distribution of Credit Losses for the Five Largest Private Banks
of tolerance under the assumption that $\delta = 0.3$ but not under the assumption that $\delta = 0.5$. Total protection against credit losses offered by provision and capital requirements is adequate under the assumption of $\delta = 0.3$ but not under the assumption that $\delta = 0.5$. Under the more conservative assumption, there is a 2 percent chance in any year that actual credit losses will exceed the required level of capital and provisions. The probability falls to 0.5 percent when the actual level of capital and provisions is considered and to 0.2 percent when the protection offered by net interest income is included.

V. Conclusions

The extensive credit bureau data of the Central Bank of Argentina can be used to evaluate the provisions and capital requirements of the Argentine financial system. Although there are significant limitations on using these data in credit risk models—a purpose for which the database was not originally intended—the data can be used to estimate implicit capital requirements for Argentine financial institutions.

Using a portfolio model, CreditRisk+, and the credit bureau data, we find actual provisioning requirements to be close to implied levels of expected losses. The estimate of unexpected losses is highly sensitive to the assumptions of the model.

Table 3. Estimated Probability That Credit Losses Exceed Indicated Values (percent)

<table>
<thead>
<tr>
<th>Level of capital, provisions, and net interest</th>
<th>CreditRisk+ ($\delta = 0.3$)</th>
<th>CreditRisk+ ($\delta = 0.5$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current required level of capital and provisions</td>
<td>Less than 0.1</td>
<td>2.0</td>
</tr>
<tr>
<td>Actual level of capital and provisions</td>
<td>Less than 0.1</td>
<td>0.5</td>
</tr>
<tr>
<td>Actual level of capital, provisions, and net interest income</td>
<td>Less than 0.1</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations.
especially to the parameter relating the volatility of a loan’s rate of default to its mean value. This implies that it is more problematic to calibrate capital requirements. However, this volatility parameter cannot be estimated accurately with the credit bureau data given its short time span. We use proxy data to estimate this parameter and tried two values around that estimate. To ensure a 99.9 percent probability of solvency, the capital levels appear to be adequate under one value of that parameter and inadequate under a more conservative assumption.

This work represents a first attempt to use a simple portfolio model of credit risk and credit bureau data to assess regulatory capital requirements. Many restrictions and caveats must accompany this type of analysis. The theoretical assumptions are strong, and the data cover only a short time span. The results reflect these limitations and should therefore be read as suggestive rather than authoritative. Given recent events in Argentina, the credit risk analyzed in this model is clearly only a partial measure of the risk on banks’ balance sheets. Moreover, we do not seek to estimate other risks, such as interest rate risk or exchange rate risk. Our results are nevertheless important because they suggest that for the many emerging countries that have developed public credit registries (see Miller 2002 for a review), the information collected may be used to develop measures of credit risk that can help assess appropriate levels of bank provisioning and capital.

References


