Offsite Bank Supervision Analysis of Bank Profitability, Risk, and Capital Adequacy: A Portfolio Simulation Approach Applied to a Set of Brazilian Banks

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Abstract

The offsite bank supervision function in most countries involves the continual monitoring of bank profitability, risk, and capital adequacy. We demonstrate the value of coupling advanced modeling techniques with data on bank asset and liability structures and credit quality. In particular we apply an integrated market and credit risk simulation methodology to a bank dataset developed by the Central Bank of Brazil to produce risk assessments for a set of six Brazilian banks. We demonstrate an ability to: (i) simulate bank loan credit transition probabilities and defaults very close to the historical ones estimated by the Central Bank of Brazil; (ii) simulate bank returns on equity and assets that are unbiased predictors of historical mean returns and standard deviations. We also show that: (i) a significant reduction in the Brazilian bank net interest margins reduces bank profitability, and increases bank failures probabilities; (ii) absent a default by the Government of Brazil most of the banks have a low failure probability. Our view is that the coupling of forward looking risk assessment methodologies with data bases, such as the one developed by the Central Bank of Brazil, have significant potential as an offsite bank supervision tool in numerous countries to identify, and manage, potential risks before they materialize.

1. Introduction

Due to the potentially large and widespread economic impacts associated with bank failures, the assessment and management of bank risk is a topic of great importance. Forward-looking risk assessment methodologies can be of significant value in that they allow for the identification and evaluation of proactive steps that may be undertaken to manage bank risk. Ideally all of the major risks faced by banks (e.g. market, credit, liquidity, etc.) would be integrated into one overall risk assessment. Nevertheless the current practice is to typically undertake market and credit risk assessments separately (e.g. Basel Accord (1988, 1996, and 2001)). Combining such separate risk measures into one overall portfolio risk measure is not easily accomplished (Jarrow and Turnbull (2000) and Barnhill and Maxwell (2002)). The absence of reliable overall portfolio risk measures creates problems in determining capital adequacy requirements, capital-at-risk measures, hedging strategies, etc. For example, Barnhill and Gleason (2002) show that Basel capital requirements appear to be too high for low risk banks operating in developed countries while they are often too low for banks operating in more volatile emerging economies.

This paper utilizes an integrated market and credit risk methodology (the portfolio simulation approach, PSA). This methodology has already proven to be able to produce very reasonable results compared to real-life cases (e.g. for South-African banks in Barnhill, Papapanagiotou, and Schumacher (2003) and for Japanese banks in Barnhill, Papapanagiotou, and Souto (2004)).

The PSA has many advantages including the ability to simultaneously deal with interest rate, foreign exchange rate and credit risk for portfolios of assets and liabilities distributed across various sectors of the economy, regions of the country, maturities and currencies. A limitation of the PSA methodology is that it requires a substantial amount of data to calibrate and populate the model.

In the current study we utilize a large dataset provided by the Central Bank of Brazil as well as data from Bank Scope to simulate the return on equity, return on assets, and capital ratio for a set of six real but unidentified Brazilian banks. In addition to asset and liability distribution, and operating information, this Brazilian bank dataset provides the distribution of bank loans by credit quality. In particular, Brazilian banks utilize a credit rating methodology starting from the highest quality grade AA and moving to A, B, D, D, E, F, G, and H categories as loans become more delinquent. G and H categories basically represent defaulted loans. In addition we collected a large data set on the financial characteristics of 543 publicly traded Brazilian companies for which we had bank loan credit ratings. This data allowed us to estimate the capital structures, systematic equity return risk, and unsystematic equity return risk of companies with various credit qualities. Finally, Brazilian banks charge high interest rate spreads (resulting in an average rate of 51 percent for business loans and 85 percent for consumer loans), on which we did not succeed to get specific information by bank. We do however propose a methodology for estimating Brazilian bank interest rate spreads for different credit qualities which reflect historical default rates for each credit category and other factors.

In addition to the high interest rate spread charged, Brazilian banks are also characterized by a significant amount of their money invested in non-interest earning assets. Our results indicate that these two features might be linked: Brazilian banks appear to be charging high interest rates as one compensatory way for the inefficiency of having such large amounts of non-interest earning assets. Moving to a scenario under which banks charge (and pay) more modest interest rate spreads clearly reduces the average simulated capital ratio.

The rest of this paper is organized as follows. In section 2 we review some of the literature on credit risk and correlated market and credit risk modeling. In section 3 we describe the conceptual framework for the Portfolio Simulation Approach for assessing integrated market and credit risk. We describe how we model Brazilian banks and the Macroeconomic environment under which Brazilian Banks operate in section 4. Section 5 presents and discusses the simulation results. A conclusion is given in section 6.

2. Modeling Credit Risk and Correlated Market and Credit Risk

The two main approaches to pricing instruments subject to credit risk are the structural approach and the reduced-form approach. The former resulted from the work of Black and Scholes (1973) and Merton (1974), who derived a theoretical formula for valuing options in a no-arbitrage framework and argued that almost all corporate liabilities can be seen as combinations of options. The latter methodology was introduced by Jarrow and Turnbull (1995), in order to circumvent difficulties inherent in Merton's contingent claims analysis, such as the lack of observable data on the firm's value.

KMV, CreditMetrics and CreditRisk+ are currently widely used in the practice of credit risk management. While the structural approach forms the basis of CreditMetrics and KMV, an actuarial approach to bond mortality underlies CreditRisk+. In KMV, a company defaults when its value goes below a certain threshold. This presents an important advantage - it implicitly incorporates market information on default probability by using the market value of equity as a proxy for firm value. Unfortunately, some of the variables used in KMV, for example the firm value, are not directly observable. Also, interest rates are deterministic, which limits the usefulness of the model when analyzing interest rate sensitive instruments (Jarrow and Turnbull, 2000).

CreditMetrics (JP Morgan) offers an alternative methodology, based on the probability of a bond migrating from one credit quality to another one, over a certain time horizon. However, this method relies on historical transition probabilities and assumes that all firms within the same rating class have the same probability of default. Alternatively, CreditRisk+ (CSFP) derives the loss distribution of a fixed-income portfolio in a framework where default risk does not relate to the capital structure of the firm. Overall, these are two very useful methodologies, but they share the main limitation of KMV - they ignore market risk and cannot deal with non-linear products like options (Crouhy et. al., 2000)

Other approaches, such as CreditPortfolioView (McKinsey), condition the probability of default on macroeconomic variables, like unemployment or interest rates, in a discrete multiperiod setting. This methodology has the important disadvantage of relying on an ad-hoc adjustment procedure for the transition matrix, which makes it doubtful whether it performs better than a simpler Bayesian model (Crouhy et. al., 2000).

There is a large body of evidence that both interest rate risk and credit risk need to be considered jointly in order to accurately price and hedge bonds and bond portfolios. Based on the conclusion of a Federal Reserve study in 1995, that none of the bank failures in the United States can be attributed to interest rate risk, Jarrow and Deventer (1998) compare Fabozzi's approach to fixed-income analysis with the risky debt model of Merton[1]. The authors assess the hedging performance of these two methodologies and find that Fabozzi's eliminates about 40% of the standard deviation in the hedged portfolio, as opposed to only 20% eliminated by Merton's risky debt model. This means that the best hedging approach eliminates less than half of the risk and a significant portion of the risk remains unhedged.

Longstaff and Schwartz (1995) corrected several drawbacks of previous fixed income valuation methods. They derived closed-form formulas for fixed-rate as well as floating-rate debt facing interest rate risk and default risk. One of the traditional limitations of the Black-Scholes-Merton framework has been that firms are assumed to default only when they exhaust all their assets, which implies much lower than actual credit spreads (e.g. Franks and Touros, 1989). Black and Cox (1976) generate credit spreads that are more consistent with the observed ones, but they still assume constant interest rates and absolute priority default allocation rules. Among others, Franks and Touros (1989, 1994) show this is not the case when firms experience financial distress.

Longstaff and Schwartz extended the literature focusing on the valuation of corporate securities with both interest rate risk and default risk by jointly allowing for default before exhaustion of assets, complex capital structures with multiple issues of debt, and deviations from strict absolute priority rules. These authors find strong evidence that interest rates are negatively correlated with the credit spreads and show this correlation has a significant effect on the

[1] Fabozzi and Fabozzi (1989) focus on interest rate levels, duration and convexity, and ignore credit risk, when undertaking bond valuation and risk analyses.

properties of credit spreads - spreads implied by this model are consistent with many of the properties of actual spreads. As such, this approach is able to explain why bonds with similar credit ratings but in different industries or sectors can have sharply different credit spreads. The properties of non-investment grade bonds were found to be highly different from those of less risky bonds.

Davis and Lischka (1999) use a two-dimensional trinomial lattice to value convertible bonds that face both interest rate and credit risk. They consider three sources of randomness - the stock price, the interest rte and the credit spread. The probability of default over the next small period is given by the hazard rate. For simplicity, and to avoid computational challenges, practitioners and researchers have traditionally analyzed models with no more than two stochastic factors. As such, Davis and Lischka consider different scenarios with limited number of stochastic variables. First, only the stock price is considered to have a stochastic behavior, while the hazard rate and the short-run interest rate are deterministic functions of time. Second, the stock and the short rate are stochastic, while the hazard rate is deterministic. Finally, all variables are modeled stochastically. This approach results in values consistent with the observed market data, and can be calibrated to match the initial term structure of interest rates, but cannot be extended to include more stochastic risk factors.

One of the earliest examples of a reduced form model is Jarrow and Turnbull (1995). In this setting, firms are allocated to credit classes and default is modeled as a point process. Bankruptcy is exogenous and not related to the firm's assets, presenting the advantage that exogenous assumptions are to be imposed only on observable variables. Jarrow, Lando and Turnbull (1997) extend this formulation in a model where the bankruptcy is characterized as a finite state Markov process in the firm's credit ratings. This model utilizes historical transition probabilities and can deal with different seniority debt via different recovery rates in case of default. The firm's bankruptcy process is assumed to be independent of the risk-free term structure.

Consistent with other authors, Jarrow and Turnbull (2000) note the considerable empirical evidence that changes in credit spreads are negatively correlated with changes in the default-free interest rates (i.e. Duffee, 1997 or Das and Tufano, 1996). They derive closed form solutions for the value of the bond with credit and market risk under different scenarios. First, when recovery rates are proportional to the value of the instrument before default (see Duffie and Singleton, 1997). Second, when bondholders claim accrued interest plus the face value of the bond (assumption that is very popular with practitioners).

Barnhill and Maxwell (2002) extend the diffusions models developed by Merton (1974) and Longstaff and Schwartz (1995) to also integrate credit and market risk. These authors propose a simulation approach that deals with the limitations of both structural models and the reduced form models in particular with respect to handling multiple correlated variables. They use a simulation approach to simultaneously model the correlated evolution of the bond's credit quality, as well as the future environment (interest rate, interest rate spread, and foreign exchange risk) where the fixed-income instruments will be valued. While they found all four mentioned risk sources to be important, credit risk is the most significant for non-investment grade bonds. This model was found to produce reasonable transition probability matrices, bond values, and portfolio risk measures. Given the large number of modeled stochastic variables, and due to the complexity of their relationships, no closed-form solution for bond prices was available.

Banks' portfolios are usually composed by large amounts of business and government loans, which can be partially modeled as a portfolio of bonds. Given the discussion above, it seems apparent that both credit and market risks affect the value of banks' portfolios. However, the integration of these risk factors represents a significant challenge. With appropriate models, one would expect to get more accurate measures of value and value-at-risk, which are very important to investors, portfolio managers, and regulators.

3. A Conceptual Framework for a Bank Risk Assessment

Given the correlated nature of credit and market risk (see Fridson et al, 1997), as we have stressed in the previous section, the importance of an integrated risk assessment methodology seems apparent. To address the above risk measurement problem Barnhill and Maxwell (2000) develop a diffusion-based methodology for assessing the value-at-risk (VaR) of a portfolio of fixed income securities with correlated interest rate, interest rate spread, exchange rate, and credit risk. Barnhill, Papapanagiotou, and Schumacher (2003) extend the model to undertake financial institution asset and liability risk assessments for South African banks and Barnhill, Papapanagiotou, and Souto (2004) use the same methodology to estimate potential losses associated with banking default in the Japanese financial system. Barnhill and Gleason (2002), and Barnhill and Handorf (2002) apply the PSA and compare simulated capital requirements to those required under the proposed new Basel Capital accord. These studies have demonstrated that with appropriate calibration the PSA model produces:

1. a simulated financial environment that matches closely the assumed parameters for the environmental variables;
2. simulated credit transition probabilities similar to reported historical transition probabilities;
3. simulated prices of bonds with credit risk close to observed market prices;
4. simulated value at risk measures for bond portfolios very similar to historical value at risk measures;
5. estimates of required bank capital that are comparable to lower than the Basel requirements for banks operating in developed markets, and comparable to higher than Basel requirements for banks operating in emerging markets.

As an overview, both the future financial environment in which the assets will be valued and the credit rating of specific loans are simulated. The financial environment can be represented by any number of correlated random variables. The correlated evolution of the market value of a business firm's equity, its debt ratio, and credit rating are then simulated in the context of the simulated financial environment. The structure of the methodology is to select a time step over which the stochastic variables are allowed to fluctuate in a correlated random process. The firm specific and property specific returns (as distinct from economic sector index and real estate index returns) and security specific default recovery rates are assumed to be uncorrelated with each other and the other stochastic variables. For each simulation run, a new financial environment (correlated interest rate term structures, FX rate, market equity returns, and regional real estate index returns) as well as firm specific and property specific debt ratios, credit rating, and default recovery rates are created. This information allows the correlated values of financial assets (including direct equity and real estate investments) to be estimated, and after a large number of simulations, a distribution of portfolio values is generated and analyzed. In the Appendix I we provide a more detailed description of the methodology, which can also be found in Barnhill and Maxwell (2002).

4. Simulating Brazilian Banks

4.1. Modeling the Macroeconomic Environment under which Brazilian Banks Operate

In the proposed simulation framework, it is of central importance to characterize the macroeconomic and financial environment under which Banks are assumed to operate. As we argued in section 3, the variables characterizing the macroeconomic scenario will be updated according to correlated stochastic processes, via Monte Carlo simulation. Thus, it is necessary to specify as reasonably as possible the initial conditions from which the simulated stochastic processes will evolve.

For the purpose of this analysis, we selected some variables that, in our opinion, will have particular influence on the Brazilian bank's portfolio simulation. They are[2]: Brazilian short-term interest rate (Brazilian Central Bank referential rate), U.S. short-term interest rate (3-Month Treasury Constant Maturity Rate), foreign exchange rate (R$/US$, bid), Brazilian c.p.i., oil

[2] Brazilian short-term interest rate (daily), FX rate (daily), Brazilian c.p.i. (monthly), and gold (daily) were obtained from the Central Bank of Brazil database. Brazilian broad market index (daily) and equity market indices (daily) were downloaded from DATASTREAM database. The seasonally adjusted unemployment indices (monthly) came from the Brazilian Institute of Geography and Statistics (IBGE). We obtained daily time series on U.S. short-term interest rate in the Federal Reserve Bank of Saint Louis web site. Daily data on Brent crude oil was downloaded from the International Petroleum Exchange (and converted to U.S. dollars/barrel)

(Brent crude), Brazilian broad market index (IBOVESPA), 12 Brazilian equity market sectorial indices (banks, basic industry, beverage, chemicals, general industry, metal, mining, oil, paper, telecommunication wireless, textile, tobacco, utility), and seasonally adjusted unemployment rates by geographical regions[3] (Brazil, Belo Horizonte, Porto Alegre, Recife, Rio de Janeiro, Salvador, São Paulo).

Volatilities and correlations for the variables above mentioned were estimated using the RiskMetrics™ exponentially weighted moving average (EWMA) methodology. The initial volatilities and correlations were estimated from the first six months of 2000. Results on EWMA volatilities and correlations, as of July 25th 2002, are presented in Tables 1 and 2.

The Brazilian Government interest rate (BR) is substantially more volatile (3.29% annualized standard deviation) than U.S. rates (0.18%), indicating that changes in interest rates have been used as one of the main tools for implementing Brazil's monetary policy. The foreign exchange rate is quite volatile (15.85%), but the period in question does not include the variations observed in the FX market in the pre-election period (August/September of 2002). Equity market indices are also very volatile (in the range of 22%-49%) and are compatible to other emerging markets.

In terms of correlations, we generally observe the expected negative relationship between Brazilian interest rate and Brazilian market indices (e.g. – 0.063 between BR rate and IBOVESPA). However, the magnitude of this correlation is not as strong as that often seen in other markets. The Brazilian interest rate is positively, although not strongly, correlated to FX rate (0.028), suggesting that, in the period in question, BR rate tends to increase (decrease) when the Real (Brazilian currency) depreciates (appreciates) relatively to the U.S. dollar.

4.2. Estimating Betas for a set of Brazilian Companies

[3] The correlation among unemployment rates and the other variables will be particularly important for the simulation of consumers' loans values.

We employ the single-factor CAPM model[4] in order to evaluate and model the risk of the business loans portfolios. For this purpose, it is necessary to estimate appropriately systemic and specific risks for Brazilian companies. Estimating betas for Brazilian companies was not an easy task, since many of them trade infrequently. As several stocks lack liquidity, price series tend to have artificial rigidities that might lower the estimated betas, misleading empirical evidence.

Using 12 equity sector indices for Brazil (banks, basic industry, beverage, chemicals, general industry, metal, mining, oil, paper, telecommunication wireless, textile, tobacco, utility), betas for 543 companies were estimated accordingly to their respective industry sector[5]. Data on prices for sector indices and individual stocks were collected from DataStream. We assume that the credit risk profile of those firms will be representative for all borrowers composing banks' portfolios.

Initial estimations using daily data resulted in many betas close to zero. To circumvent this problem, several attempts were made to estimate the betas: (i) using monthly observations, (ii) Scholes-Williams (1977) approach, and (iii) using unleveraged betas as defined in the following expression:

$$\beta_U = \frac{\beta_L}{1+\left(1-\tau_c\right)\frac{D}{S}}, \quad (1)$$

where β_U is the unleveraged beta, β_L is the leveraged beta, τ_C is the tax rate, D represents the current market value of outstanding debt and S is the market value of equity.

Monthly observations produced the most consistent estimations for betas, considering the financial characteristics of Brazilian companies (we obtained values in the range of 0.032 to

[4] We opted for the CAPM single-factor model to evaluate the systematic and unsystematic portions of risk, because of its simplicity to implement and its appealing intuition of the risk/return relationship. However, multi-factor models could be used as well.
[5] Estimating betas using sector indices instead of a broad market index allows us to capture the diversification benefit, as banks lend to companies in different sectors of the economy.

1.497). Final results for betas, firm-specific risk and respective credit rating, as assigned by two large Brazilian banks[7], are given in Table 3.

Also given in Table 3 is information on the company debt-to-value ratios by credit rating. This information was initially developed by calculating debt-to-value ratios on all publicly traded companies in Brazil and then analyzing the distribution of such debt-to-value ratios by credit rating[8]. As a further refinement to calibrating the model, a series of simulation runs were undertaken to identify target, upper and lower bounds for the debt-to-value ratios, which both fell within the observed range of debt-to-value ratios for each credit rating and produced credit transition probabilities similar to those observed over the 2000 to 2001 and 2001 to 2002 periods. The target was taken to be the firms' current and planned future debt-to-value ratio. The upper and lower bounds reported in Table 3 represent the values of debt ratios at which a company would move to a higher/lower credit rating. So, for example, in the case of companies in the B credit level, if the simulated debt ratios increase to more than 0.90 then they would fall to credit rating C. These results are consistent to the theory: credit risk rating deteriorates as systematic and unsystematic components of risk increase, and as debt-to-value ratio increases.

4.3. Loans Credit Rating Distribution

Business and consumer loans represent a significant percentage of Brazilian banks' assets[9]. Thus, defining the credit rating distribution of the loans is very important when modeling the banks' portfolio.

As a matter of simplicity, we consider that consumers' loans can be modeled in the same way as business loans[10]. We show in the next section that this assumption is quite reasonable and

[7] More details on the simulated banks and on the transition probability matrix employed in this paper can be found in Barnhill, Souto, and Tabak (2003).
[8] The two banks provided information on companies rating directly to the Central Bank of Brazil. For confidentiality reasons, it cannot be disclosed.
[9] In some cases it sums up to more than 56 percent of the total assets.

that we were able to produce a simulated credit transition matrix that is very close to the historical credit transition matrix estimated by the Credit Risk Bureau in the Central Bank of Brazil.

It is important to mention that the Central Bank of Brazil utilizes a different credit risk rating scale than Moodys or Standard and Poors[11]. Brazilian credit rating is divided into the following categories (from higher to lower credit quality): AA, A, B, C, D, E, F, G, and H. Categories AA and A represent investment grade, while categories G and H are mostly defaulting loans.

Tables 4 and 5 present the aggregate distribution of business and consumers loans, across different industry sectors and geographical regions respectively, for 6 real, but unidentified, Brazilian banks[12]. Some comments are in order regarding the loans distribution. First, these banks apparently are very successful in selecting the companies to whom they will lend money. An average of 60.9 percent of the business loans are AA or A grade level, while 78.87 are grade B or better. Second, these banks' portfolios are relatively concentrated with regard to the industrial sectors to which they lend money: an average of 83.36 percent of the loans are concentrated in the basic industry, cyclical services, food (retail or production), and utilities sectors. Concentration of loans to certain industry sectors often comes to the expense of deteriorating banks' portfolios risk profiles. Third, the fraction of consumers' loans in the AA category is very small (0.5 percent or lower). However, these banks still have a huge fraction of their consumers' loans classified as grade B or better (77.05 percent). Finally, consumers' loans distribution per geographical region is consistent with the population and wealth distribution in Brazil: the southeast has the largest and wealthiest population, followed by the south, the north, the central, and finally the north regions.

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[10] In the simulation context, the value of each corporate loan is calculated by discounting the future cash flows with the simulated interest rates that correspond to the simulated credit grade of the corporate client. In the event of default the pay-off of the loan is given by its recovery value net of transaction costs.

[11] Each bank may have its own specific procedures to assign ratings to the loans, as long as it follows the general guidelines prescribed by the Central Bank of Brazil. Mapping Brazilian credit rating into Moody's and Standard and Poors standards is not trivial. Barnhill, Souto, and Tabak (2003) suggest a mapping based on the probability that each of the credit risk rating will fall into the lowest credit category, before defaulting, as well as on the probabilities that a particular credit rating will stay at a similar credit risk category.

[12] More detailed Tables on the banks' loans distribution can be provided upon request.

4.4. Credit Transition Matrix

Once the betas were estimated and distributed according to credit rating categories, we can proceed to estimating the transition probability matrix. For each simulation run, we estimate returns on market index (assumed to follow a geometric Brownian motion) and on companies, via CAPM. Then these returns are used to estimate a distribution of possible future equity market values and debt ratios. The simulated debt ratios are then mapped into credit ratings, according to the model calibrations presented in Table 3[13]. Finally, a distributional analysis is used to generate the transition probabilities for each credit rating. We present the results of this analysis in Table 6, together with the historical transition probability matrix (as estimated by the Brazilian Credit Risk Bureau and presented in Table 7). As we can see, those two transition probability matrices are quite similar. For example, in Table 8 the average absolute difference between the two transition matrices is 0.0002, while the maximum absolute difference never goes beyond 0.1060, and the simulated default rates for each credit risk category is similar to reported historical levels. This is a very important result in our analysis because it provides support for our belief that the simulations will produce reasonable bank capital ratios estimates.

4.5. Banks Balance Sheet

We report in Table 9 a simplified version of the balance sheet for Brazilian banks, as provided by the Research Department of the Central Bank of Brazil. These banks share one striking common feature: a significant fraction of their assets are non-interest earning, which likely erodes the banks' efficiency[14]. Other than this, the banks are very heterogeneous with regard to their assets distribution. We present the mean and the range for the balance sheet. It is important to notice that one of the banks is specialized in lending money to consumers, with

[13] This methodology assumes a deterministic relationship between a firm's debt ratio and its credit rating, which, in a contingent claims framework, is equivalent to assuming a constant volatility for the value of the firm.

[14] We suspect that the fact that Brazilian banks have such a huge amount of money invested on non-interest earning assets may be one of the reasons they charge high interest rate spread (we discuss the issue of interest rate spreads in section 4.7).

more than 50% of its assets in consumers' loans, and which have the best portfolio credit quality with respect to consumers' loans: almost 90 percent of then are grade A loans. Other two banks do also have a considerable amount of their assets in consumers and business loans. Another two banks are specialized in risk-free government loans. Finally, Brazilian commercial banks have very little (almost insignificant) exposure to real estate loans. This type of loan is mainly concentrated (more than 90%) on the hands of one Brazilian government bank (Caixa Econômica Federal).

4.6. Asset and Liability Maturity Structure

We did not succeed in obtaining detailed information on asset and liability maturity structure for all banks. We did, however, obtain some information on asset and liability maturities for bank 4, which we used as a standard for all banks simulated in this study. For this bank, all liabilities and most of the assets are short-term (one-year maturity or less).

4.7. Interest Rate Spreads

Brazilian banks are known for charging high interest spreads. As of December 2002 the referential interest (Selic) was 24 percent[15]. At the same time the average rate on business loans and consumer loans was approximately 51 percent and 85 percent respectively. Even considering the default rates on business and consumer loans these spreads are indeed very big.

Ideally we would have good estimates of the interest rate spreads that each bank charged on each type and credit quality loan. Unfortunately we were unable to obtain this precise interest rate spread data. For this reason, we estimate market wide interest rate spreads for different credit qualities utilizing the following methodology. First we estimate the average default losses for each credit rating category as the product of the average historical default rate times an assumed loss rate in the case of default. For example, for AA business loans the default rate over

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[15] The inflation rate in the same period was around 10 percent thus the real interest rate on short-term government debt was approximately 14 percent.

one-year is 0.68 percent with an assumed loss rate of 85 percent (banks succeed on recovering 15 percent of the loan value), which gives an average default loss of 0.58 percent (0.68 percent times 0.85). To this average default loss we add an additional spread that is scaled accordingly to stylized U.S. banks average risk spread profiles[16]. For the AA category, the additional risk spread scaled by the U.S. spread would be 0.0013x. For the A category, the additional risk spread would be .005x, etc. With knowledge of the percentage of loans in each rating category one can solve for the value of x that produces an average rate on business loans of 51 percent and an average rate on consumer loans of 85 percent. This additional risk spread is 5.01 percent in the case of AA business loans. The total interest rate spread will be the sum of the two components: 0.58 + 5.01 = 5.59 percent for AA loans. This procedure produced the assumed market wide distribution of bank loan interest rates given in Table 10. It is important to mention that, even though this procedure is somewhat arbitrary, it produced interest rate spreads for different credit categories that are very close to the average real values charged by the Brazilian banks, according to the Off-Site Supervision Department.

Finally for each bank we had from Bank Scope the bank's average net interest margin. Thus for each bank we made one final adjustment to the above market wide interest rate spreads to produce average net interest margins consistent with that reported in bank scope.

5. Simulation Results

In order to investigate the future profitability, risk, and capital adequacy of the six banks simulated in this study, we constructed two main scenarios under which these banks are assumed to be operating: (i) a high interest rate scenario where banks are charging higher interest rate spreads as estimated in the previous section; and (ii) a low interest rate scenario (without government default), where banks are assumed to charge (and pay) 60 percent of the interest rates in high interest rate scenario. Capital ratios are simulated over a one-year timeframe. The results for these simulations are presented in Table 10.

[16] For example, we assume that U.S. banks would charge, on average, 0.13% comparable interest rate spreads for the AA category, 0.50% for the A grade level and so forth (Table 9).

5.1. Bank Profitability under the High Interest Rate Scenario

The PSA allows for simulating distributions of future bank returns on equity and on asset (ROE and ROA, respectively) given assumptions regarding the volatility of the financial and economic environment, credit quality of the bank's loan portfolio, etc. A reasonable question is how reliable and thus useful are these profitability estimates. To address this question we wish to explore how well the simulated means and standard deviations of the bank returns explain the historical means and standard deviations of returns for the six banks in question. The historical returns for the banks were calculated over the period 1998 to 2002. For the simulation analysis we chose the high interest rate environment not including government default.

Table 11 presents the goodness of fit of regressions for ROE and ROA. The regressions are as follows:

$$mean\_historical\_ROE = \alpha + \beta mean\_simulated\_ROE + \varepsilon \qquad (2)$$

$$mean\_historical\_ROA = \alpha + \beta mean\_simulated\_ROA + \varepsilon \qquad (3)$$

$$std\_historical\_ROE = \alpha + \beta std\_simulated\_ROE + \varepsilon \qquad (4)$$

$$std\_historical\_ROA = \alpha + \beta std\_simulated\_ROA + \varepsilon \qquad (5)$$

where *std* stands for standard deviation.

Table 11 presents adjusted R^2 for these regressions, which provides a measure of goodness of fit for these regressions. Adjusted R^2 are high for both ROE and ROA regressions, for regressing means and standard deviations. The simulated ROE and ROA are unbiased if the joint hypothesis $\alpha = 0, \beta = 1$ is true. The Wald Statistic in the last column suggests that only for mean ROA regressions this hypothesis does not hold. However, when we pool observations, increasing the number of degrees of freedom in our regressions we cannot reject this hypothesis.

If we employ all observations by pooling the data (24 observations) the beta coefficient is 0.97, with an adjusted R^2 of 81.13%, and we cannot reject the null hypothesis that simulated mean and standard deviations on ROE and ROA are unbiased. These results altogether suggest that simulated mean and standard deviations on ROE and ROA are very close to historical observed values, illustrating that the PSA does a good job in replicating real observed data. When considering this result, it should be recalled that the six banks have a wide range of asset and liability structures, credit quality distributions, and historical profitability.

5.2. Bank Risk and Capital Adequacy under the High Interest Rate Scenario

Table 12 provides a distributional analysis of the simulated bank capital ratios at a one-year time step under the two alternative scenarios. Under a high interest rate scenario the mean simulated capital ratios are consistently above their initial values. This shouldn't be surprising given the level of interest rate spreads in Brazil and the credit quality of these banks' portfolios. We also note that the standard deviation of the simulated capital ratios for the banks vary widely from about .008 for bank 2 and bank 3 to 0.023 for bank 6. These variations are of course reflective of the banks' asset and liability structures and credit qualities. Overall we find that under the current high interest rate environment, and not considering sovereign risk, the six Brazilian banks we have studied have a relatively low risk of default. In particular none of the banks have simulated capital ratios below 2% at the 99% confidence interval. Only bank 2 and bank 5 have simulated capital ratios below 3% at the 99% confidence interval. This analysis would suggest that the banks are adequately capitalized under for the assumed scenario conditions.

An important feature of this forward-looking risk assessment methodology is that it provides quantitative risk assessments for each bank on a consistent basis (i.e. same assumptions regarding the financial and economic environment, consistent treatment of correlate market and credit risk, consistent treatment of portfolio diversification effects, consistent treatment of credit risk etc.). Thus the relative risk and capital adequacy of banks can be assessed directly from the quantitative results of the simulations. It is also important to note that the analysis was undertaken from data collected systematically by the Brazilian Central Bank Risk Bureau and from public sources. Thus there is no reason that such an analytical process could not be automated and applied to every bank in Brazil and undertaken on whatever frequency found to be useful. Again this type risk analysis is sensitive to changes in financial environment volatility, changes in banks asset and liability structure (e.g. FX exposure, interest rate risk exposure), changes loan portfolio diversification or concentration, and changes in loan portfolio credit quality.

5.3. Bank Risk and Capital Adequacy under the Lower Interest Rate Scenario

We now consider what happens to simulated bank capital ratios if the Brazilian financial environment changes in such a way that banks charge (and pay) more modest interest rates (equal to 60% of the higher interest case). The impact on Banks performance is visible: average simulated capital ratios typically dropped by .015 to .02 compared to the higher interest case. Standard deviations of capital ratios remain practically unaltered compared to the high interest case, mostly because we do not change the credit quality assumption of these banks' loan portfolio. Importantly however the risk of several banks having unacceptable low or even negative capital ratios increases. In particular at the 99% confidence level bank 2 now has a negative capital ratio (-0.013) and bank 5 has a capital ratio of 0.008. Clearly the direct impact of a contraction in the high interest rate spreads currently earned by Brazilian banks is to reduce their profitability and ability to absorb credit losses through current earnings. This suggests that absent some systematic improvement in loan portfolio credit quality a reduction in interest spreads would result in some banks being inadequately capitalized. Again the forward looking PSA methodology is well suited to identifying such risk and allowing bank management and regulators to take appropriate corrective action before problems develop.

6. Conclusions

We present in this paper a simulation framework – the Portfolio Simulation Approach – that allows for the modeling of integrated market and credit risk in bank asset and liability portfolios. We argue that this methodology has several advantages over other theoretical models (e.g. the possibility of modeling comprehensive banks' portfolio) and over *ad hoc* methodologies, such as the Basel Accord (1988, 1996, 2001) (e.g. the role of integrated and market risk). We do also argue that this simulation methodology has strong credit risk analytical capabilities. For example, the credit transition probability matrix we simulated is very close to the one estimated by the Brazilian Credit Risk Bureau. Also the simulated bank returns are shown to be unbiased predictors of historical returns (both means and standard deviations).

Our simulations indicate that in Brazil current high interest rate spreads more than offset typical portfolio credit losses. Therefore, Brazilian banks generally are profitable and have a low default risk, even though they have a significant amount of money invested in non-interest earning assets. When we move to a scenario where banks are assumed to charge (and pay) smaller interest rates, the simulated capital ratios dropped noticeably and for some banks the risk of failure increases. Under such an environment some the banks may not be adequately capitalized.

We believe that forward looking methodologies such as the PSA coupled with systematically collect detailed data bases offer the possibility for offsite banks supervision to undertake useful consistent quantitative assessments of bank profitability, risk and capital adequacy for all banks. We believe these opportunities would be available to any country, which chooses to systematically collect the data required to undertake such analyses.

Clearly there are several useful extension and refinements for this study. For example, Barnhill and Kopits (2003) model the Government of Ecuador's entire balance sheets in order to assess the Ecuador fiscal vulnerability. Such an approach could be incorporated into the above PSA. Given the importance of interest rate spreads on Brazilian banks performance, obtaining more precise data on spreads charged by specific banks would also improve our analysis. The PSA model could also be enhanced to include stochastic updates of volatilities and correlations (e.g. via RiskMetrics), which would perhaps provide a more precise accounting for some potential shocks that could affect banks performance. Finally it is clearly possible to model multiple banks in the same financial and economic environment to undertake systemic banking system risk assessments.

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Table 1
EWMA Volatilities

Volatilities for a set of Brazilian financial and macroeconomic variables were estimated via exponentially weighted moving average (RiskMetrics^{TM}) methodology, as of 07/25/2002. The values are annualized and presented in percentages. BR rate is the Brazilian short-term interest rate (Brazilian Central Bank referential interest rate), US rate is the 3-Month U.S. Treasury Constant Maturity Rate, FX rate is the foreign exchange rate (Brazilian currency, R$, over US$), BR c.p.i. is the Brazilian consumer price index, oil represents the Brent crude oil as quoted in the International Petroleum Exchange, Ibovespa is the Brazilian broad market index, which is followed by Brazilian equity market indices by sectors (as defined in DataStream): Banks, BasicInd (Basic Industry), Beverage, Chemicals, GenInd (General Industry), Metal, Mining, Oil_Sec (Oil Equity Sector), Paper, Telewire (Telecommunications Wireless), Textile, Tobacco, and Utility. URBH, URPA, URRE, URRJ, URSA, URSP, are the seasonally adjusted unemployment rates for the cities of Belo Horizonte, Porto Alegre, Recife, Rio de Janeiro, and São Paulo respectively and URBR is the seasonally adjusted unemployment rate for Brazil.

BR rate	3.29%	Beverage	31.10%	Tobacco	48.57%
US rate	0.18%	Chemicals	30.69%	Utility	33.90%
FX rate	15.85%	GenInd	22.09%	URBH	20.02%
BR c.p.i.	2.47%	Metal	30.48%	URPA	23.10%
oil	26.51%	Mining	23.51%	URRE	22.49%
Gold	24.51%	Oil_Sec	49.20%	URRJ	22.00%
Ibovespa	39.11%	Paper	30.61%	URSA	16.69%
Banks	37.42%	TeleWire	34.12%	URSP	16.78%
BasicInd	26.03%	Textile	40.42%	URBR	11.19%

Table 2
EWMA Correlations

Correlations for a set of Brazilian financial and macroeconomic variables were estimated via exponentially weighted moving average (RiskMetrics^{TM}) methodology, as of 07/25/2002. BRrate is the Brazilian short-term interest rate (Brazilian Central Bank referential interest rate), USrate is the 3-Month U.S. Treasury Constant Maturity Rate, FXrate is the foreign exchange rate (Brazilian currency, R$, over US$), BRcpi is the Brazilian consumer price index, oil represents the Brent crude oil as quoted in the International Petroleum Exchange, Ibov is the Brazilian broad market index, which is followed by Brazilian equity market indices by sectors (as defined in DataStream): Banks, BasInd (Basic Industry), Bev (Beverage), Chem (Chemicals), GenInd (General Industry), Metal, Mining, OilSec (Oil Equity Sector), Paper, Tlwire (Telecommunications Wireless), Text (Textile), Tobac (Tobacco), and Utility. URBH, URPA, URRE, URRJ, URSA, URSP, are the seasonally adjusted unemployment rates for the cities of Belo Horizonte, Porto Alegre, Recife, Rio de Janeiro, and São Paulo respectively and URBR is the seasonally adjusted unemployment rate for Brazil.

	Brrate	USrate	FXrate	Brcpi	oil	Gold	Ibov	Banks	BasInd	Bev	Chem	GenInd	Metal	Mining
Brrate	1	-0.064	0.028	-0.036	0.017	0.064	-0.063	-0.095	-0.091	-0.132	0.051	-0.080	-0.122	0.075
USrate		1	-0.042	0.046	0.002	-0.165	0.079	-0.037	0.086	0.010	0.053	0.166	0.157	-0.089
FXrate			1	-0.035	0.050	0.541	-0.336	-0.508	-0.041	-0.201	-0.229	-0.258	-0.106	-0.027
Brcpi				1	-0.108	-0.058	-0.172	0.039	0.006	-0.030	-0.366	-0.093	0.102	-0.021
oil					1	-0.023	0.360	0.274	0.240	0.165	0.363	0.225	0.200	0.049
Gold						1	-0.640	-0.462	-0.278	-0.395	-0.255	-0.284	-0.347	0.009
Ibov							1	0.745	0.673	0.602	0.449	0.564	0.684	0.171
Banks								1	0.418	0.634	0.386	0.463	0.420	0.170
BasInd									1	0.581	0.313	0.665	0.934	0.259
Bev										1	0.166	0.315	0.490	0.041
Chem											1	0.420	0.256	0.478
GenInd												1	0.670	0.332
Metal													1	0.196
Mining														1
OilSec														
Paper														
TlWire														
Text														
Tobac														
Utility														
URBH														
URPA														
URRE														
URRJ														
URSA														
URSP														
URBR														

Table 2 (cont.)
EWMA Correlations

Correlations for a set of Brazilian financial and macroeconomic variables were estimated via exponentially weighted moving average (RiskMetrics^{TM}) methodology, as of 07/25/2002. BRrate is the Brazilian short-term interest rate (Brazilian Central Bank referential interest rate), USrate is the 3-Month U.S. Treasury Constant Maturity Rate, FXrate is the foreign exchange rate (Brazilian currency, R$, over US$), BRcpi is the Brazilian consumer price index, oil represents the Brent crude oil as quoted in the International Petroleum Exchange, Ibov is the Brazilian broad market index, which is followed by Brazilian equity market indices by sectors (as defined in DataStream): Banks, BasInd (Basic Industry), Bev (Beverage), Chem (Chemicals), GenInd (General Industry), Metal, Mining, OilSec (Oil Equity Sector), Paper, Tlwire (Telecommunications Wireless), Text (Textile), Tobac (Tobacco), and Utility. URBH, URPA, URRE, URRJ, URSA, URSP, are the seasonally adjusted unemployment rates for the cities of Belo Horizonte, Porto Alegre, Recife, Rio de Janeiro, and São Paulo respectively and URBR is the seasonally adjusted unemployment rate for Brazil.

	OilSec	Paper	TlWire	Text	Tobac	Utility	URBH	URPA	URRE	URRJ	URSA	URSP	URBR
Brrate	0.009	-0.002	-0.181	-0.008	-0.058	-0.086	0.279	-0.087	-0.024	0.215	-0.197	0.106	0.007
USrate	-0.038	-0.070	-0.039	0.124	-0.368	0.027	0.123	0.079	-0.133	0.303	-0.002	0.101	0.230
FXrate	-0.129	0.099	-0.237	-0.145	-0.333	-0.319	0.457	-0.364	-0.098	0.153	-0.169	0.111	-0.075
Brcpi	-0.093	-0.044	-0.141	-0.128	-0.064	0.048	-0.013	0.105	-0.223	0.110	-0.085	-0.072	-0.060
oil	0.486	0.224	0.249	-0.060	0.172	0.308	0.283	-0.141	-0.040	-0.036	-0.221	-0.086	-0.120
Gold	-0.302	-0.058	-0.599	-0.425	-0.176	-0.644	0.487	-0.401	-0.097	0.077	-0.135	0.132	-0.067
Ibov	0.763	0.435	0.857	0.377	0.323	0.930	0.065	-0.100	-0.123	0.199	-0.169	0.069	-0.054
Banks	0.550	0.267	0.527	0.282	0.507	0.647	-0.195	0.132	0.082	0.087	0.030	-0.135	-0.083
BasInd	0.624	0.812	0.544	0.442	0.233	0.610	0.295	-0.414	-0.178	0.256	-0.210	0.321	0.102
Bev	0.610	0.560	0.449	0.132	0.359	0.503	0.067	-0.118	-0.193	0.020	-0.085	-0.145	-0.273
Chem	0.438	0.227	0.266	-0.089	0.397	0.353	0.050	-0.299	0.240	0.070	-0.020	0.056	-0.040
GenInd	0.492	0.435	0.397	0.436	0.343	0.585	-0.116	0.198	-0.127	0.121	-0.018	-0.153	-0.157
Metal	0.523	0.555	0.580	0.455	0.154	0.647	-0.129	0.042	-0.256	0.134	-0.044	0.193	0.186
Mining	0.279	0.249	0.035	0.098	0.190	0.128	0.427	-0.557	0.015	0.200	-0.251	0.294	-0.001
OilSec	1	0.588	0.502	0.138	0.217	0.687	-0.020	0.068	0.008	-0.017	-0.104	0.217	0.178
Paper		1	0.317	0.302	0.275	0.355	0.514	-0.581	-0.102	0.261	-0.213	0.263	-0.016
TlWire			1	0.356	0.317	0.833	-0.291	0.226	-0.027	0.037	-0.168	-0.045	-0.126
Text				1	0.000	0.353	0.180	-0.086	-0.089	0.091	-0.346	0.015	-0.058
Tobac					1	0.315	0.246	-0.201	-0.264	0.090	-0.064	0.122	-0.063
Utility						1	-0.197	0.118	-0.251	-0.045	-0.035	-0.093	-0.119
URBH							1	-0.261	0.052	0.255	-0.399	0.246	0.251
URPA								1	-0.032	0.090	0.122	-0.234	0.092
URRE									1	-0.098	-0.297	0.005	0.086
URRJ										1	0.084	0.583	0.717
URSA											1	0.000	0.164
URSP												1	0.866
URBR													1

Table 3
Distribution of Debt Ratios, Betas and Firm-Specific Risk for Brazilian Companies by Credit Risk Rating

Based on the simulated transition probability matrix, we distributed Brazilian companies' debt-to-value ratios (downloaded from DataStream) by credit risk rating. AA corresponds to the best credit risk rating while G and H represents companies in the worse credit quality category. The upper and lower bounds represent the values of debt ratios at which a company would move to a higher/lower credit rating. So, for example, in the case of companies in the B credit level, if their debt ratios increase to more than 0.90 then they would fall to credit rating C. The target was taken to be the firms' current and planned future debt-to-value ratio. Correspondent mean values for beta and firm-specific risk are provided for each risk category as well.

	AA	*A*	*B*	*C*	*D*	*E*	*F*	*G + H*
Debt Ratios								
Lower bound	-	0.51	0.67	0.78	0.79	0.80	0.85	0.96
Target	0.38	0.61	0.82	0.84	0.88	0.89	0.89	0.96
Upper bound	0.53	0.78	0.90	0.92	0.93	0.93	0.95	0.96
Beta	0.67	0.85	1.00	1.10	1.20	1.30	1.36	-
Firm-specific risk	0.38	0.55	0.69	0.71	0.77	0.78	0.72	-

Table 4
Business Loans Distribution

This table presents information on the distribution of business loans for the set of six Brazilian banks by credit risk categories and across different industry sectors. Brazilian bank loan credit ratings are divided into the following categories (from higher to lower credit quality): AA, A, B, C, D, E, F, G, and H. Categories AA and A represent investment grade, while categories G and H are mostly defaulting loans.

Distribution of business´ loans by industrial sector

	Média	Mínimo	Máximo
Ibovespa	0.0552	0.0070	0.0890
Aero	0.0017	0.0000	0.0075
Basic Industries	0.3415	0.2936	0.4264
Chemical	0.0416	0.0004	0.0600
Cyclical Services	0.2734	0.2322	0.3347
Food – production	0.0809	0.0043	0.1073
Food – Retail	0.0520	0.0149	0.1622
Forest	0.0160	0.0000	0.0282
Paper	0.0047	0.0000	0.0086
Mining	0.0067	0.0014	0.0125
Oil and Gas	0.0254	0.0000	0.1232
Financial	0.0120	0.0013	0.0298
Services	0.0888	0.0418	0.1770

Table 5
Consumers' Loans Distribution

This table presents information on the distribution of consumer loans for the set of six Brazilian banks by credit risk categories and across different industry sectors. Brazilian bank loan credit ratings are divided into the following categories (from higher to lower credit quality): AA, A, B, C, D, E, F, G, and H. Categories AA and A represent investment grade, while categories G and H are mostly defaulting loans.

Distribution of business´ loans by credit quality

	AA	A	B	C	D	E	F	G + H
Mean	0.2691	0.3403	0.1793	0.1286	0.0362	0.0149	0.0088	0.0227
Minimum	0.0002	0.2351	0.0797	0.0499	0.0190	0.0007	0.0036	0.0019
Maximum	0.4158	0.5108	0.2550	0.2293	0.0616	0.0350	0.0150	0.0365

Table 6

Estimated transition matrix, for Brazilian companies using the PSA approach.

	AA	A	B	C	D	E	F	G+H
AA	90,35%	9,65%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
A	11,40%	79,63%	8,93%	0,05%	0,00%	0,00%	0,00%	0,00%
B	0,40%	4,95%	75,33%	10,00%	3,10%	1,55%	3,45%	1,23%
C	0,15%	2,70%	12,60%	68,63%	4,88%	2,23%	5,48%	3,35%
D	0,03%	0,70%	4,45%	1,48%	61,48%	4,88%	8,85%	18,15%
E	0,00%	0,58%	3,78%	1,25%	0,85%	56,18%	10,48%	26,90%
F	0,00%	0,23%	2,33%	1,23%	0,75%	7,30%	60,38%	27,80%

Table 7
Estimated Transition Probabilities Matrices: The Case of Brazilian Companies

In Panel A we present a simulated credit transition probability matrix for Brazilian banks' loans. Panel B gives credit transition probabilities by the Brazilian Credit Risk Bureau, for two large banks. In Panel C we present the difference between the two transition matrices.

Brazilian credit risk bureau´s transition matrix (Adjusted for repayments, for two large Brazilian banks , and weighted averaged between the periods of June 2000 to June 2001, and June 2001 to June 2002).

	AA	A	B	C	D	E	F	G+H
AA	90,08%	6,43%	2,05%	0,53%	0,18%	0,03%	0,03%	0,68%
A	11,90%	69,03%	10,15%	4,73%	2,13%	0,30%	0,43%	1,40%
B	3,28%	11,03%	71,88%	9,23%	2,00%	0,48%	0,55%	1,63%
C	3,28%	4,18%	15,25%	67,35%	4,65%	0,90%	1,33%	3,08%
D	1,08%	1,85%	4,00%	5,13%	60,20%	3,90%	5,43%	18,43%
E	0,13%	7,75%	0,53%	0,83%	4,05%	55,80%	4,03%	26,83%
F	0,78%	0,60%	1,15%	2,25%	3,10%	7,60%	56,80%	27,63%

Table 8
Descriptive Statistics – Simulated versus Historical Transition Probability Matrices: The Case of Brazilian Banks

In this table we present descriptive Statistics on the absolute differences between simulated and historical transition matrices, as reported in Table 6.

Difference between simulated and historical transition matrices.

	AA	A	B	C	D	E	F	G+H
AA	0,27%	3,23%	-2,05%	-0,53%	-0,18%	-0,03%	-0,03%	-0,68%
A	-0,50%	10,60%	-1,23%	-4,68%	-2,13%	-0,30%	-0,43%	-1,40%
B	-2,88%	-6,08%	3,45%	0,78%	1,10%	1,08%	2,90%	-0,40%
C	-3,13%	-1,48%	-2,65%	1,28%	0,23%	1,33%	4,15%	0,28%
D	-1,05%	-1,15%	0,45%	-3,65%	1,28%	0,98%	3,43%	-0,28%
E	-0,13%	-7,18%	3,25%	0,43%	-3,20%	0,37%	6,45%	0,08%
F	-0,78%	-0,38%	1,18%	-1,03%	-2,35%	-0,30%	3,58%	0,18%

Table 9
Brazilian Banks Balance Sheets

This table presents information on a very stylized version of the balance sheets for the 6 real but unidentified Brazilian banks on a percentage basis. Percentages are estimated based on reported book values, as of December 31, 2000. Domestic funding account includes mainly inter-bank, demand, savings, fixed deposits, NCD's, repos, and others. Capital ratio book value is estimated as capital and reserves account divided by total assets. Operating expense ratio is estimated as income fee plus other income minus operating expenses, all divided by total assets.

	Mean	Min.	Max.
Liabilities			
Domestic funding	0.5694	0.5168	0.6194
Foreign funding	0.1047	0.0708	0.1768
Non-Interest Liabilty	0.0659	0.0264	0.0809
Capital and Reserves	0.1185	0.0440	0.2362
Debt	0.1414	0.0383	0.2219
Total Liabilities	100,00%	100,00%	100,00%
Assets			
Money	0.0336	0.0003	0.0705
Risk-Free Loans	0.2556	0.0226	0.5229
Business Loans	0.1859	0.0002	0.3494
Consumer Loans	0.1959	0.0001	0.5630
Foreign Loans	0.0745	0.0000	0.1721
Equity Investments	0.0096	0.0000	0.0183
Real Estate Investments	0.0118	0.0102	0.0146
Other Assets (Non-Interest)	0.2330	0.1353	0.3251
Total Assets	100,00%	100,00%	100,00%
Capital Ratio	0.1185	0.0440	0.2362
Operating Expense Ratio	-0,013	-0,020	-0,007
Tax Rate	0.3400	0.3400	0.3400

Table 10
Estimated Interest Rate Spreads by Credit Risk Category

Assumed interest rate spreads are broken down into two components. The first one relates to default loss rate and is estimated simply by multiplying the default rate by the loss rate. The second component is estimated based on a stylized average profile for U.S. banks. For example, for the corresponding AA credit category the comparable U.S. average spread would be 0.13%. The associated spread for the same category for Brazilian banks would then be 0.0013·x. Same calculation is made for all categories. The total spread per category is a sum of the two components (in the case of AA it is 0.58% + 0.0013·x). the base interest rate plus spreads for all categories should average up to 51% in the case of business loans. Spreads for a lower interest rate scenario under which charged (and paid) spreads would be 60% of the spreads charged (and paid) in the high interest rate scenario.

Interest rate spreads for business´ loans
(High interest rate scenario)

Credit Risk Categories	Default Rate	Loss Rate	*Loss Rate Spread*	US Risk Spread *Profile*	*Assumed Risk* Spread (US Scale)	*Assumed Risk* Spread (Total)
AA	0,68%	0,85	0,58%	0,13%	5,01%	5,59%
A	1,40%	0,85	1,19%	0,50%	20,04%	21,23%
B	1,63%	0,85	1,39%	0,75%	30,06%	31,45%
C	3,08%	0,85	2,62%	1,00%	40,08%	42,70%
D	18,43%	0,85	15,67%	1,50%	60,12%	75,79%
E	26,83%	0,85	22,81%	2,00%	80,16%	102,97%
F	27,63%	0,85	23,49%	2,50%	100,20%	123,69%
G + H	100,00%	0,85	85,00%	3,00%	120,24%	205,24%

Interest rate spreads for consumer´s loans

(High interest rate scenario)

Credit Risk Categories	Default Rate	Loss Rate	*Loss Rate Spread* *Profile*	US Risk Spread Spread	*Assumed Risk* Spread (US Scale)	Spread	*Assumed Risk* Spread (Total)
AA	0,68%	0,85	0,58%	0,13%	7,69%		8,27%
A	1,40%	0,85	1,19%	0,50%	30,76%		31,95%
B	1,63%	0,85	1,39%	0,75%	46,15%		47,53%
C	3,08%	0,85	2,62%	1,00%	61,53%		64,15%
D	18,43%	0,85	15,67%	1,50%	92,29%		107,96%
E	26,83%	0,85	22,81%	2,00%	123,06%		145,86%
F	27,63%	0,85	23,49%	2,50%	153,82%		177,31%
G + H	100,00%	0,85	85,00%	3,00%	184,58%		269,58%

Table 11. Goodness of Fit of Simulated versus Historical after-tax return on equity (ROE) and return on assets (ROA) and Unbiasedness Tests. **Erro!**

	Coefficient	Adjusted R2	Wald statistic
Panel A: ROE Regressions			
		41,66%	0,09
Mean	0,87***		
Standard error	(0,41)		
t-statistic	[2,14]		
Standard deviation	1,19**	69,38%	0,70
Standard error	0,34		
t-statistic	[3,51]		
Panel B: ROA Regressions			
Mean	1,49*	97,07%	18,10*
Standard Error	(0,12)		
t-statistic	[12,90]		
Standard deviation	1,19***	49,47%	0,23
Standard error	(0,49)		
t-statistic	[2,43]		
Panel : Pool			
ROE	1,004*	63,17%	0,1294
Standard error	(0,23)		
t-statistic	[4,46]		
ROE	1,31*	85,17%	3,71
Standard error	(0,23)		
t-statistic	[8,01]		
All	0,97*	81,13%	0,22
Standard error	(0,10)		
t-statistic	[9,99]		

*,** e *** correspond to the levels of significance of 1,5 and 10%, respectively.

Table 12

In this table we show the distribution of simulated capital ratios for a set of six unidentified Brazilian commercial banks over a one-year time step. Banks were simulated under two different scenarios: (i) an average net interest margin and operating expense scenario similar to that for the period 1998-2002; and (ii) a lower net interest margin scenario, where banks are assumed to earn net interest rate spreads equal to 60% of the average over the preceding five years.

Bank	1	1	2	2	3	3
Interest Rate	High	Low	High	Low	High	Low
Mean	0,256	0,237	0,056	0,028	0,139	0,124
Standard Dev.	0,011	0,013	0,008	0,012	0,008	0,009
Maximum	0,288	0,271	0,071	0,047	0,160	0,145
Minimum	0,189	0,156	-0,005	-0,049	0,097	0,072
VaR						
99%	0,227	0,196	0,028	-0,013	0,118	0,096
98%	0,231	0,203	0,033	-0,007	0,119	0,098
97%	0,233	0,206	0,037	-0,002	0,122	0,103
96%	0,235	0,209	0,039	0,001	0,123	0,104
95%	0,236	0,211	0,040	0,004	0,124	0,106
94%	0,237	0,213	0,041	0,006	0,125	0,107
93%	0,239	0,216	0,043	0,008	0,126	0,109
92%	0,240	0,217	0,044	0,010	0,127	0,111
91%	0,241	0,219	0,044	0,011	0,128	0,112
90%	0,242	0,220	0,045	0,012	0,128	0,113
75%	0,249	0,231	0,052	0,024	0,134	0,119
50%	0,256	0,238	0,057	0,032	0,140	0,125
25%	0,263	0,245	0,061	0,036	0,145	0,130
1%	0,278	0,260	0,067	0,043	0,153	0,138

Bank	4	4	5	5	6	6
Interest Rate	High	Low	High	Low	High	Low
Mean	0,104	0,085	0,075	0,060	0,120	0,105
Standard Dev.	0,010	0,012	0,014	0,017	0,023	0,026
Maximum	0,124	0,108	0,111	0,100	0,177	0,165
Minimum	0,042	0,012	0,010	-0,012	-0,007	-0,034
VaR						
99%	0,071	0,044	0,029	0,008	0,055	0,031
98%	0,077	0,050	0,039	0,019	0,063	0,039
97%	0,083	0,055	0,043	0,023	0,069	0,046
96%	0,085	0,058	0,045	0,026	0,074	0,051
95%	0,087	0,060	0,048	0,028	0,077	0,055
94%	0,088	0,062	0,050	0,031	0,081	0,059
93%	0,089	0,064	0,052	0,033	0,084	0,062
92%	0,090	0,065	0,054	0,035	0,086	0,064
91%	0,091	0,067	0,056	0,036	0,088	0,066
90%	0,091	0,068	0,056	0,037	0,090	0,068
75%	0,099	0,080	0,068	0,049	0,106	0,091
50%	0,105	0,088	0,077	0,063	0,122	0,109
25%	0,110	0,094	0,085	0,073	0,136	0,123
1%	0,119	0,103	0,099	0,088	0,162	0,150

Appendix I
The Portfolio Simulation Approach

I.1. Simulating Interest Rates

The Hull and White extended Vasicek model (Hull and White (1990a, 1993, 1994)) is used to model stochastic risk-free (e.g. Japanese Treasury) interest rates. In this model interest rates are assumed to follow a mean-reversion process with a time dependent reversion level. The simulation model is robust to the use of other interest rate models.

The model for *r* is:

$$\Delta r = a\left(\frac{\theta(t)}{a} - r\right)\Delta t + \sigma \Delta z\,, \tag{A.1}$$

where:

Δr	=	the risk-neutral process by which *r* changes,
a	=	the rate at which *r* reverts to its long term mean,
r	=	the instantaneous continuously compounded short-term interest rate,
$\theta(t)$	=	"Theta" is an unknown function of time that is chosen so that the model is consistent with the initial term structure and is calculated from the initial term structure,
Δt	=	a small increment to time,
σ	=	"sigma" the instantaneous standard deviation of *r*, which is assumed to be constant, and
Δz	=	a Wiener process driving term structure movements with Δr being related to Δt by the function $\Delta z = \varepsilon\sqrt{\Delta t}$.

The above mean reversion and volatility rates can be estimated from a time series of short-term interest rates or implied from cap and floor prices. Given the very low risk-free Japanese rates, in this study the short rate r is constrained to have positive values. Further given the lack of a time series of credit spreads such spreads are assumed to be constant.

I.2. Simulating Asset Returns and Prices

We employ the same model to simulate the value of the equity market indices and the FX rate, assuming that they follow a geometric Brownian motion, with constant expected growth rate and volatility (Hull (2000), p. 225). The expected growth rate is estimated as the expected return on the asset minus its dividend yield[1]. For a discrete time step, Δt, it can be shown that

$$S + \Delta S = S \exp\left[\left(m - \frac{\sigma^2}{2}\right)\Delta t + \sigma\varepsilon\sqrt{\Delta t}\right], \tag{A.2}$$

where:

S	=	*equity market index (or FX rate),*
m	=	expected growth rate ($m = \mu - q$),
μ	=	expected return on equity market indices (or on FX rate),
q	=	dividend yield,
σ	=	volatility,
ε	=	a random sample from a standardized normal distribution, and
Δt	=	a small increment to time.

The return on the market index (or FX rate) is estimated as

$$K_m = ln((S + \Delta S)/S) + q\ , \tag{A.3}$$

where:

K_m	=	return on the market index (or FX rate),
S	=	*equity market index (or FX rate), and*
q	=	dividend yield.

[1] We are using the very simple model of non-dividend-paying stock, as described in Hull (2000) to deal with stochastic prices and FX rates. However, it is possible to assume, for example, that the stock price is the sum of a riskless component corresponding to the known dividends and a risky component (the price of the stock *per se*). We would need data on dividends for firms in order to be able to accomplish this. Change in the dividend yields during the time periods analyzed would surely affect the outcomes of this analysis. However, as a simplifying assumption, we take the dividend yield as a constant factor.

The return on equity for individual firms and individual real estate properties is simulated using a one-factor model[2].

$$K_i = R_F + Beta_i\,(Km\text{-}R_F) + \sigma_i \Delta z\,, \tag{A.4}$$

where:

K_i	=	the return for the asset$_i$
R_F	=	the risk-free interest rate,
$Beta_i$	=	the systematic risk of asset$_i$,
K_m	=	the simulated return on the equity or real estate index from equation 3,
σ_i	=	the asset specific return volatility, and
Δz	=	a Wiener process with Δz being related to Δt by the function $\Delta z = \varepsilon\sqrt{\Delta t}$.

As discussed in the next section the parameters needed to implement the above model for the positive and negative financial environment cases were estimated from historical data.

I.3. Simulating an n-variate Normal Distribution

Many authors have reported positive correlations between default rates and financial environment variables such as interest rates (see Fridson et. al. (1997)), and negative correlations with variable such as GNP growth rates. This is consistent with negative correlations between interest rate changes and equity returns.

In the proposed portfolio risk assessment model, the equity indices and FX rate returns are simulated as stochastic variables correlated with the simulated future risk-free interest rate and

[2] There are several articles stating that the CAPM single factor model does not capture the relation risk-return appropriately (Fama and Macbeth (1973), Black, Jensen, and Scholes (1972), Black (1972), Black and Scholes (1974), Roll (1977, 1979, 1988), to cite quite a few). Fama and Jensen (1992) propose a three-factor model where size and book-to-market ratio captured most of the risk/return relationship. One of the drawbacks of the CAPM is related to the fact that it is a single period model, which needs time series on expected returns (or realized returns as unbiased estimators for expected returns) over some period of time in order to estimate the systematic risk (beta). As a consequence, beta might be quite sensitive depending upon the time period chosen. Several researchers have attempted to include time-varying betas in the model (Gibbons and Ferson (1985), Bollerslev, Engle, and Wooldridge (1988), Harvey (1989), and Ferson and Foerster (1994)), which ended up having some effect on the asset pricing model's predictive ability (Megginson (1997)). We made the simplifying assumption of using the CAPM single factor model, because of its simplicity of being implemented, although it is entirely possible to include a more sophisticated asset pricing model in our simulation methodology, given appropriate data.

interest rate spreads. Hull (1997) describes a procedure for working with an *n*-variate normal distribution. This procedure requires the specification of correlations between each of the *n* stochastic variables. Subsequently n independent random samples ε are drawn from standardized normal distributions. With this information the set of correlated random error terms for the *n* stochastic variables can be calculated. For example, for a bivariate normal distribution,

$$\varepsilon_1 = x_1, \tag{A.5}$$

$$\varepsilon_2 = \rho x_1 + x_2\sqrt{1-\rho^2}\ , \tag{A.6}$$

where:

x_1, x_2	=	independent random samples from standardized normal distributions,
ρ	=	the correlation between the two stochastic variables, and
ε_1, ε_2	=	the required samples from a standardized bivariate normal distribution.

It can be shown that the simulated volatilities and correlations for all of the stochastic variables match closely the assumed values that are typically estimated from historical time series data.

I.4. Mapping Debt Ratios into Credit Ratings

The above discussed simulated equity and real estate returns are then used to estimate a distribution of possible future equity and real estate market values and debt ratios. The simulated debt ratios are then mapped into credit ratings. This methodology assumes a deterministic relation between a firm's or property's debt ratio and its credit rating[3]. In a contingent claims framework this is equivalent to assuming a constant volatility for the value of the firm.

After simulating the loan's future credit rating its value is calculated using the simulated term structure of interest rates appropriate for that risk class. If the simulated loan defaults, the

[3] Blume, Lim, and MacKinlay (1998) suggest that leverage ratios and credit ratings are not constant over time. However, their results are over a longer time frame than simulated in this framework.

recovery rate on the loan is estimated as a beta distribution[4] with a specified mean value and standard deviation.

[4] Utilizing a beta distribution allows the recovery rate to fall within 0% and 100% while maintaining the same mean and standard deviation.