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Abstract: This paper implements an integrated market and credit risk simulation model for assessing the risk of multiple bank failures. We are not aware of other portfolio analytical models that can deal effectively with the integrated market and credit risk issues required to complete a systemic bank risk analysis of this type. After calibrating the model using an extensive Brazilian database we demonstrate a capacity to model closely Brazilian bank loan credit transition probabilities and defaults. This strong credit risk analytical capability supports the belief that reasonable Brazilian bank failure rate simulations are possible. Simulations of up to three banks' portfolios simultaneously indicate that high initial bank capital ratios, and very wide interest rate spreads on loans result in low bank failure probabilities and low systemic bank risk. These results are conditioned on the assumption that the Brazilian Government does not default on its debts. If more smaller, and more typical, interest rate spreads are assumed then both inter-bank credit risk and loan portfolio credit risk are shown to substantially increase simulated bank default rates and multiple bank default rates. This model can be extended in at least four directions: (i) model more than three banks simultaneously (ii) model stochastic updates for volatilities and correlations, (iii) develop a methodology for explicitly modeling the credit risk of consumers loans, (iv) model the risk of a correlated government default and its impact on banks.

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1. Introduction

It is expected that from time to time, bank specific problems will cause certain institutions to fail (or be merged into stronger institutions). Mechanisms are typically in place to handle such occurrences. However, much more troublesome is a potential cascade of failures in the banking sector, which raises the possibility of driving the whole economy of a country into a deep recession or depression. Further, the direct cost of dealing with multiple bank failures can be exceedingly large. In the case of an emerging economy, for example, the government may have difficulty in accessing adequate funds to resolve this type of crisis. Because of these large potential costs, financial regulators are eager to be able to identify potential sources of systemic risk and design appropriate prudential rules capable of avoiding, or at least minimizing, the effects of a ‘domino’ sequence of failures in the banking system.

Due to the potentially large and widespread economic impacts associated with bank failures, the assessment and management of systemic risk is a topic of great importance. Forward-looking risk assessment methodologies can be of central importance in alleviating this problem and, more importantly, they allow for the identification and evaluation of proactive steps that may be undertaken to manage such risks. Risk assessment methodologies seek to assess the maximum potential change in the value of a portfolio with a given probability over a pre-set horizon resulting from changes in market factors, credit risk, and liquidity risk. The current practice is to undertake market and credit risk assessments separately (e.g. Basel Accord (1988, 1996, 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 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.

Modeling systemic risk is a quite challenging task. Most of the theoretical models developed so far are based on partial or general equilibrium-based frameworks, or use the tools of game theory. Usually, a liquidity shock is necessary to trigger a systemic failure of the Banking sector (see Chen (1999), Frank and Gale (2000), and Acharya (2002)). Applying these models is very difficult and many simplifying assumptions are typically required to make them tractable. In the current paper we present a simulation model (the Portfolio Simulation Approach – PSA) that allows for the modeling of integrated market and credit risk in bank asset and liability portfolios, applied to the case of Brazilian commercial banks. As we will discuss in more details in the next section, it is possible, using the PSA methodology, to model comprehensively banks’ portfolios (business and commercial loans, mortgage loans, equity investments, real estate investments, etc.) distributed across business sectors and geographical regions. Our methodology shares some features with Acharya’s (2002) model, in which he considers the correlation between banks’ assets.

We are particularly interested in assessing banking system systemic risk¹ as inter-bank credit exposures and bank loan credit quality change. In section 6 we show that, although the banks’ simulated failure rates increase as inter-bank credit exposure increases (consistent with the results of Frank and Gale (2000)) and as credit quality of banks’ portfolios deteriorates, the impact is not as significant as one would expect considering that these hypothetical banks operate in a volatile emerging economy. We find that this is mainly due to the wide interest rate spreads applied on Brazilian bank loan (e.g. approximately a 20% difference between ‘risk-free’ interest rate and the average interest rate for business loans), which substantially exceeds the default rates on such loans. If more typical (i.e. smaller) interest rate spreads² are assumed then increasing inter-bank credit exposure as well as credit risk exposure is shown to substantially increase simulated bank default rates and systemic bank risk.

¹ We define banking sector systemic risk to be the probability of multiple bank failures occurring in a particular time period.

² In section 6, we model hypothetical banks applying half of the typical interest spread, as reported by the Central Bank of Brazil.

The risk of government default is not addressed in this paper. However Barnhill and Kopits (2003) model a government's balance sheet, using a very similar approach to the one discussed in this paper. Thus, in principle, an integrated banking system and government risk analysis is possible. However such an analysis is well beyond the scope of the present paper.

A significant limitation of most risk assessment methodologies is that they utilize historical data to estimate the volatilities and correlations of important financial and economic variables. Such historically estimated risk parameters may not fully capture the impact of future potential shocks. However, we do claim a significant improvement of our methodology, based on much more theoretical framework, over *ad hoc* methods such as the Basel Accord (1988, 1996, 2001)³.

Potential extension of this study would include the modeling of stochastic volatilities and correlations using the Dynamic Conditional Correlation approach proposed by Engle (2002), and the modeling of consumer loan default rates separately from business loans. In particular, the more realistic modeling of stochastic volatilities and correlations should improve our ability to account for periodic financial shocks that might have important impacts on emerging economies.

The rest of this paper is organized as follows. In section 2 we discuss some of the main research developed on modeling systemic risk and how it is related to the PSA. A review of the literature on credit risk and correlated market and credit risk modeling is given in section 3. In section 4 we describe the conceptual framework for the PSA method of assessing systemic bank risk. The Macroeconomic/Financial environment under which Brazilian Banks operate is described in section 5. Section 6 presents and discusses the simulation results. We suggest some interesting extensions to the analysis made in this paper in section 7. A conclusion is given in section 8.

2. Modeling Systemic Risk

A substantial amount of research has been developed on modeling the framework in which banks operate and the potential for financial contagion. It would be virtually impossible to survey all the relevant work that has been done so far in this area in one single section, given space limitations. De Bandt and Hartman (2000) provide a comprehensive survey of this literature up to 2000. We will rather focus on stressing the contributions of the Portfolio Simulation Approach (PSA henceforth), briefly⁴ described in section 4 and presented in more details in the Appendix A, compared to other studies.

In a framework where the First-Come, First-Served rule prevails, Chen (1999) argues that depositors may react earlier to noise information, such as failure of other banks, and withdraw their funds, provoking a systemic run in the banking system. The PSA does not account explicitly for liquidity shocks in the sense of massive depositors' withdrawals. In fact our methodology assumes that the Central Bank will provide any necessary liquidity to otherwise sound banks (i.e. banks with positive net worth). However, the PSA does model the possibility of sudden changes in the (stochastic) macroeconomic/financial variables (perhaps related to liquidity shocks), which can cause sharp declines in a bank's net worth⁵ due to asset and liability maturity and currency mismatches as well as loan defaults.

Rochet and Tirole (1996) argue that the recent increase in the amount of inter-bank transactions, which may not be properly collateralized or insured, increased the likelihood of systemic crash in the banking industry. They developed a three-period equilibrium model, with risk-neutral banks and depositors. There are two banks: one is the lender, and the other is the borrower (lending in only one direction). The lender has the incentive to monitor the borrower. Monitoring is examined in two different

³ The Basel Accord (1988, 1996, 2001) suggests the estimation of market and credit risk separately, to add them together later on, which is a very strong assumption. Market and credit factors do interact among themselves and they are not simply additive (see Jarrow and Turnbull (2000) and Barnhill and Gleason (2002)).

⁴ For more detailed discussion on the methodology, see Barnhill and Maxwell (2002).

⁵ See Barnhill, Papapanagioutou, and Souto, 2002, for the example of the Japanese Bank System, which ended up simultaneously with a greatly reduced value and a large amount of rotten loans with almost no collateral at all.

timings: in date 1, it has the objective to stimulate borrowers to engage in commercial projects (investments) that are not subjected to significant liquidity shocks; in date 2, lenders' monitoring are intended to stimulate borrowers' commercial projects that are significantly profitable. Under this framework, Rochet and Tirole show that decentralized systems may increase the likelihood of financial contagion, by showing that, in an extreme case, small liquidity shocks may cause the failure of the two banks. We assume different degrees of inter-bank lending among several banks and we show how the increase in inter-bank credit exposure do indeed increase the probability of systemic default, consistent to Rochet and Tirole results.

Allen and Gale (2000) propose to divide the economy, under which banks operate, into regions or sectors. In order to minimize liquidity shocks, which are assumed to have correlated regional preferences, Allen and Gale argue that banks operating in distinct regions (or sectors) can prudentially engage in inter-bank (interregional) claims. Depending on the structure of the inter-bank market (e.g. incomplete markets), it is possible that a liquidity shock in one region (or sector) can infect other regions (or sectors). In our methodology, we allow banks to lend to firms operating in several different sectors of economy. It is also possible to model a bank portfolio partially constituted by mortgage loans and/or loans to individuals spread over different geographical regions⁶.

Acharya (2001) provides a very interesting game-theoretical model to deal with systemic risk. According to his model, the systematic risk arises when banks tend to lend to similar industries, with high correlation of returns on assets. In the PSA, we define systemic risk as the joint probability that two banks' capital ratio will fall below a certain threshold⁷. Acharya considers the possibility of two banks lending to different sectors (or geographical regions) in a multi-period framework. The correlation of returns is higher when the two banks choose to lend to same sector (or region). The PSA also models the banks' portfolios considering the correlation between returns on macroeconomic and financial variables that directly affect the value of a bank's assets and liabilities and are systematically related to the credit quality of the bank's loans (e.g. FX rate, equity indices, broad market equity indices, real estate price indices, etc). We agree with Acharya that correlations of return on assets represent a very important factor to be considered in modeling banks. However, the PSA also deals with variations on the macroeconomic/financial variables, that characterize the framework under which banks operate, as correlated stochastic processes and takes into account the mean and volatility of return on assets as well.

Another advantage of the PSA is that it allows for simulating more realistic bank portfolios, with business loans, mortgage loans, consumer loans spread over several different sectors and/or geographical regions. It is also entirely possible to simulate banks' portfolio that are well diversified or that have assets concentrated in a particular sector or region, as well as banks that are specialized in a specific activity⁸. We can also simulate loans with different grading categories and different recovery rates. In our methodology, banks can also have a part of their assets and liabilities denominated in different currencies. Finally, foreign exchange rate risk at the bank borrower level could be modeled as well.⁹

Due to specific portfolio composition, Acharya also stress the importance of banks reporting not only value-at-risk numbers, but also their portfolio compositions. This point is also stressed in Barnhill and Gleason (2002), where it is suggested a number of modifications on capital adequacy, regulation and monitoring activities in the New Basel Accord (1988, 1996, 2001).

⁶ Such exercise was made in Barnhill, Papapanagiotou, and Schumacher (2003), in the case of South African banks, and in Barnhill, Papapanagiotou, and Souto (2003) in the case of Japanese Banks. In the case of Brazilian banks, however, we do not deal with modeling real estate loans since these loans are concentrated in the hands of one government bank: Caixa Econômica Federal.

⁷ This threshold can be defined by Banks' Regulators or even by the banks themselves, in the case the banks decide for operating with a 'safer' capital margin than the one suggested by regulators. Barnhill and Gleason (2002) provide some interesting values for required capital ratios for hypothetical banks operating in different financial/macro-economic environments, compared to the Basel standards.

⁸ As it is the case of '*Caixa Econômica Federal*' in Brazil, a government bank very specialized in mortgage loans, concentrating more than 90% of the total mortgage loans in Brazil.

⁹ Due to data limitations the modeling of bank borrower FX risk is not undertaken in the present paper.

The vast majority of systemic risk studies, however, rely on equilibrium-based or game-theoretical models in which banks may face liquidity shocks. Relative to the PSA these models have serious limitations. First, they cannot deal with realistic bank portfolios containing both business and mortgage loans spread over multiple sectors of economy and geographical regions that are being impacted by multiple correlated risk factors. Second, another important feature of the PSA, not found in other methodologies is its ability to integrate market and credit risk into one overall risk assessment. Such realistic, but complex models, often do not have closed-form solutions and numerical simulation can be a very powerful tool. We will discuss the issue of modeling integrated market and credit risk in more details in section 3.

3. Modeling Credit Risk and Correlated Market and Credit Risk (too much on Bonds)

The main two 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 multi-period 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 Merton¹⁰. 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.

¹⁰ Fabozzi and Fabozzi (1989) focus on interest rate levels, duration and convexity, and ignore credit risk, when undertaking bond valuation and risk analyses.

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 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 rate 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.

4. A Conceptual Framework for a Systemic 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 (2003) 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 terms of assessing the systemic risk, our approach is, within each simulation run, calculate the value of the capital ratio for multiple banks. Then we estimate the probability of several banks defaulting at the same time as the simple quotient of the number of times all simulated banks' capital ratio fell

simultaneously below a specific target capital ratio¹¹, over the total number of simulations runs. Using a similar approach we can also estimate the probability that at least one bank will fall below the target capital ratio.

For estimating stochastic updates of volatilities and correlations we considered two different approaches: (i) the exponentially weighted moving average process (EWMA), and (ii) the dynamic conditional correlation model (DCC) developed by Engle (2002), which we present in more details in appendix B. The choice for the EWMA methodology relates mainly to its simplicity and to the fact that it is widely known by academics and practitioners. The DCC methodology is not only reasonably simple to be implemented, but it has proven to produce consistent results, as pointed out by Engle and Sheppard (2001). For this study, however, we implemented only the EWMA methodology as an alternative to the simple static estimation procedure, even though we have already developed the tools for setting up the DCC estimation, as described in Appendix B.

5. Modeling the Macroeconomic/Financial 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 4, the variables characterizing the macroeconomic/financial scenario will be updated according to correlated stochastic processes. Hence, it is necessary to specify as reasonably as possible the initial step.

For the purpose of this analysis, we selected some variables that, in our opinion, will have particular influence in the bank's portfolio simulation. They are¹²: 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), gold, Brazilian c.p.i., oil (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 regions¹³ (Brazil, Belo Horizonte, Porto Alegre, Recife, Rio de Janeiro, Salvador, São Paulo).

Volatilities and correlations for the variables above mentioned were estimated using the RiskMetricsTM exponentially weighted moving average (EWMA) methodology. Although RiskMetricsTM recommends to use the product between variables returns as the initial guess for volatilities and covariances, because this methodology showed to be quite sensitive to the initial guess chosen, we decided to use some historical period to estimate this initial guess. The year of 1999, when Brazil adopted a floating-rate regime for the foreign exchange (R\$/US\$) after more than 4 years of a fixed-rate regime, was characterized by huge volatilities¹⁴ in the interest rate (11.2%), foreign exchange rate (26.18%), and other market indices (in the range of 22% -62%). Since this was not the pattern we found in the subsequent years of 2000-2002, we selected the first six months of 2000 and estimated the initial values

¹¹ See footnote 8.

¹² 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)

¹³ The correlation among unemployment rates and the other variables will be particularly important for the simulation of consumers' loans values.

¹⁴ Annualized values estimated for the year of 1999. Although the interest rate and foreign exchange rate do not appear to be extremely high, it is important to mention that there was an accentuated peak in both time series in the beginning of 1999, corresponding to the change in the floating regime. After this period, in the end of 1999, the Brazilian interest rate stabilized in the 19% (per year) level, while the FX rate oscillated in the range of 1.8-1.9 R\$/US\$ (against the 1.2 R\$/US\$ rate in the fixed-rate regime). The equity market, however, stayed very volatile during the whole 1999 year.

for volatilities and correlations to feed the EWMA autoregressive equations. 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.

5.1. *Banks Balance Sheet*

For confidentiality reasons, we cannot disclose specific information on banks' balance sheet accounts and financial ratios, utilized in this simulation exercise. We do, however, provide some general characteristic features of these banks. First, these two banks possess a very significant amount of business and commercial loans. What makes this feature so important is the impressive interest rate spread earned by Brazilian Banks: as provided by the Central Bank of Brazil, the average yield for business loans is in the range of 51% per year, while the average yield for consumers' loans is above 85% per year, for a real referential interest rate of about 20%! When we add to this picture the expected default rates, as estimated by the Brazilian Credit Risk Bureau (see the historical transition probability matrix, table 3), we can see that these two banks are making a significant profit out of the interest income. As we shall see later in section 6, this is, in our opinion, the main reason why, absent a government default, the hypothetical Brazilian banks have a small probability of defaulting.

A second interesting feature is the impressive amount of government loans the two banks hold. In the particular case of this exercise, we make the assumption that Brazilian government loans are 'risk-free'¹⁵, i.e. their probability of default is zero. With such a large amount in government loans considered to be 'default-free', we expect smaller probabilities of default for the hypothetical banks we are simulating.

Third, Brazilian commercial banks have very little (almost insignificant) exposure to real estate loans, since this type of loan is mainly concentrated (more than 90%) in the hands of one Brazilian Government Bank (Caixa Econômica Federal). Fourth, Brazilian banks are reasonably well capitalized. They operate well above the 10% level.

Finally, the two banks are mostly funded domestically and may very well have significant inter-bank exposure (unfortunately we did not have access to more detailed information on inter-bank lending). As we will show in section 6, increasing inter-bank exposure does increase the probability that various banks can default at the same time (systemic failure), consistent to the results of Allen and Gale (2000). The magnitude of the probability, however, is very small because of the factors we have already discussed above.

¹⁵ The main purpose of this paper is to show the impact of systemic risk and how the probability of multiple bank failure might increase as inter-bank credit exposure increases and as credit quality of loans deteriorates. We understand that government default might play a significant role in modeling Brazilian banks. We will discuss the potentiality of extending this analysis to include government default in section 7.

5.2. *Loans Credit Rating Distribution*

Since, as we saw in the previous section, business and consumer loans represent a significant percentage of Brazilian banks' assets, 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 loans¹⁶. We show in the next section that this assumption is quite reasonable and 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 uses a different credit risk rating scale than Moodys or Standard and Poors. We suggest a mapping relation for the credit ratings employed by Moody and by the Brazilian Bureau¹⁷. For this purpose, we contrast the historical credit risk transition probabilities obtained by these institutions (table 3) and compare the probability that each of the credit risk rating will fall into the lowest credit category, before defaulting (Caa-C for Moody and F for Brazilian Credit Risk Bureau), as well as the probabilities that a particular credit rating will stay at a similar credit risk category. So, for example, the Brazilian F grading has a 55.15% probability of staying in the same risk category, which we believe to match closer the Moody Caa-C grading (78.78%). According to this approach, we were able to produce the following mapping between the two institutions: AA and A = Baa, B and C = Ba, D and E = B, F = Caa-C, and G and H = Default.

For the sake of this exercise, we define two credit risk credit distributions for business and consumer loans, as reported in tables 4 and 5: (i) the lower credit risk profile is characterized by about 67.5% of the total loans in the lowest credit risk categories (40.3% in AA and 27.4% in A), while (ii) the higher credit risk profile has 46.5% of the total loans in the AA (19.6%) and A (27.1%) risk categories.

5.3. *Simulated Credit Transition Matrix*

A final piece in setting up the simulation framework is the modeling of banks' borrowers credit rating. The first step in accomplishing this task is the estimation of betas and firm-specific risk¹⁸ for the publicly traded companies. 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 sector¹⁹. Data on prices for sector indices and individual stocks were collected from DataStream. We will assume that the credit risk profile of those firms will be representative for all borrowers composing banks' portfolios.

Estimating betas for Brazilian companies was not an easy task, since many Brazilian companies trade infrequently. As several stocks lack liquidity, price series tend to have artificial rigidities that might lower the estimated betas, misleading empirical evidence²⁰. Final results for betas, firm-specific risk and

¹⁶ 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.

¹⁷ In Brazil, commercial banks are allowed to have its own specific procedures to assign ratings to the loans, as long as they follow the general guidelines prescribed by the Central Bank of Brazil.

¹⁸ 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.

¹⁹ The idea of estimating betas using sector indices instead of a broad market index represents an effort to measure the diversification benefit, as banks lend to companies in different sectors of the economy.

²⁰ 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) building series that didn't have any repetitions in the price values, and (iii) using unleveraged betas as defined in the following expression, a la Modigliani and Miller:

$$b_U = \frac{b_L}{1 + (1 - t_c) \frac{B}{S}}, \quad (1)$$

respective credit rating, as assigned by the two hypothetical banks modeled in this paper, are given in table 6.

Also given in table 6 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. 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 6 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.

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 6²¹. Finally, a distributional analysis is used to generate the transition probabilities for each credit rating. We present the results of this analysis in table 7, together with the historical transition probability matrix (as estimated by the Brazilian Credit Risk Bureau and already presented in table 3). As we can see, those two transition probability matrices are quite similar. For example, in table 8 we can see that 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 failure rate estimates.

6. Simulation Results

In this section we will present and discuss the results obtained from our simulations. Each simulation has 2000 runs. We defined combinations of different hypothetical banks, constructed by using the data described in the previous section, in such a way that allowed us to assess the impacts of credit risk exposure, inter-bank exposure, and the amount of risk-free loans a bank holds.

For the case of credit risk exposure, we consider two banks with same asset/liability structure, operating under the same financial/macroeconomic scenario, but with different credit risk exposure (high and low, as defined in tables 4 and 5 respectively). We assess inter-bank exposure among three banks with same asset/liability structure, operating under the same financial/macroeconomic scenario, for different target capital ratio (capital ratio below which we consider the banks will default) and different degrees of inter-bank exposure (as fraction of total assets). The last case, no risk-free loans, is analyzed by removing the amount in the risk-free loan balance sheet account and adding it to the business and consumers' loans account. We have also assessed the impact of interest rate spreads on simulated Banks' capital ratios by constructing two hypothetical banks offering much lower interest rates (half of those

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

Using monthly observations resulted in the best estimations for betas (we obtained values in the range of 0.032 - 1.497).

²¹ 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.

reported by the Central Bank of Brazil) to business and consumers' loans and paying lower interest rates on deposits.

6.1. *The Impact of Credit Risk Exposure*

It is generally expected that banks with higher credit risk exposure will have higher probability of defaulting, *ceteris paribus*. We chose the asset/liability structure of the Bank 2 because of its smaller amount of risk-free government loans²² relative to other types of loans. As expected, when the credit quality of loans deteriorates, the simulated capital ratio does indeed decrease over one-year horizon. In Panel A of table 9, we can see that the simulated mean, maximum, and minimum values for capital ratio are slightly smaller for the bank with higher credit risk exposure (mean = 0.2003, max. = 0.3406, and min. = -0.0324) compared to the bank with a lower credit risk profile (mean = 0.2389, max. = 0.3813, and min. = 0.0710). In addition, the bank with the higher credit risk profile has a more volatile simulated capital ratio (std. deviation = 0.0496, against std. deviation = 0.0435 for bank with lower credit risk exposure). The VaR²³ results just confirm this figure. For example, it is expected that the bank with higher credit exposure have 10% probability of having its capital ratio falling below 0.1349. However, in the case of the bank with low credit risk profile, there is only 2.5% probability that simulated capital ratios will fall below a similar value: 0.1374. The 99% VaR simulated capital ratio levels show clearly that banks with a high credit risk loans portfolio distribution, have its capital ratios falling below a much lower value (0.0656), compared to banks with low credit risk profile (0.1168). These results are supportive to the view that the probability of bank default increases as its loans credit risk profiles deteriorate.

6.2. *The Impact of Inter-bank Credit Risk Exposure*

A next step in our analysis involved the assessment of the impact of inter-bank credit risk exposure. Our goal is to evaluate the probability of a cascade failure (probability that several banks will fail in a 'domino' sequence). We accomplished that in two phases: (i) we first estimated the simulated capital ratios for three banks with the same asset/liability structure and same credit risk exposure, operating simultaneously in the same financial/macro-economic environment, then (ii) we tested several degrees of inter-bank exposure (as a fraction of total assets), subtracted from Bank A capital ratio whenever Bank B and/or C's capital ratios fell below a threshold level (assumed to be a level such that the bank would default for some exogenous reasons).

Our simulated banks have same asset/liability structure as Bank 2. They also hold business and consumers' loans according to a higher credit risk profile, with loans distributed across different credit risk categories and across different business sectors and geographical regions as defined in table 5. Since this corresponds to one of the cases we have already discussed in the previous subsection, we do not report again descriptive statistics and VaR analysis, since they are basically the same as in table 9. We will rather report probabilities of default for different inter-bank credit exposure and for different (default) capital ratio threshold level (table 10).

As we can see in table 10, the probability of defaulting for these hypothetical banks does indeed decrease as the inter-bank exposure decreases, consistent to the results of Frank and Gale (2000). However the probabilities of default are very small, for different target capital ratio and inter-bank exposure. The extreme case of banks assumed to default when their capital ratio fall below 10%²⁴, resulted in only 6.8% of probability that at least one of the banks will default for all different degrees of

²² Bank 1 has almost twice more government loans (relatively to total assets) than bank 2. Since these government loans are assumed to be 'risk-free', this explains the smaller variability in the simulated capital ratio for bank1, compared to bank 2.

²³ We define the VaR as the level at which some percentage of simulated banks' capital ratios will fall below. For example, in table 10 the 99% VaR for simulated capital ratios of a bank operating with a higher credit risk portfolio profile is 0.0656, meaning that in 1% of the times, the simulated capital ratios fell below this value.

²⁴ See footnote 8.

inter-bank exposure tested (even with 10% of total assets in inter-bank transactions with each of the other banks, which means that the total inter-bank exposure amounts to 20% of total assets!). For more realistic target capital ratio such as 0.01, the probability of defaulting for Brazilian banks shrinks to practically zero.

These outcomes should not be so surprising, given (i) the large amount of government loans held by the banks (which are assumed to be risk-free), (ii) the impressive interest rate spread they earn on business and consumer loans (contrasted to the Central Bank referential interest rate and to the inflation rate), and (iii) the large initial capital ratios. In the next section, we will make some effort to shed light on determining the major factor responsible for the low default probabilities we found in these hypothetical banks.

6.3. *No 'Risk-Free' Loans and Lower Interest Rate Spreads*

We construct three sets of two hypothetical banks operating under the same financial and macroeconomic scenario we have been using so far. All banks have practically the same asset/liability structure as Bank 1, with few differences. In set one (our benchmark case), the two banks possess the same liability structure as the Bank 1, but one bank has a higher credit risk profile, while the other bank's business and consumers loans are distributed according to a lower credit risk rating. In the second set, we make an adjustment regarding the assets accounts of risk-free loans and business and consumers' loans. We imagine that the two banks do not hold any risk-free government loans at all. Our idea is to assess the size of protection these risk-free loans produce in the banks' portfolios, in the event part of the other business and consumers' loans default. To make the exercise a little more interesting, we add the amount invested in risk-free loans to the business and consumers' loans account²⁵. In the third set we make an interesting change: we assume that, for some exogenous reasons, the interest rates paid and received by the banks fall by half²⁶. We were particularly interested in the impact of a reduction in the interest rate spread earned by Brazilian banks on their probability of failing.

Some very interesting results were found and reported in table 11. For example, we initially thought that the large amount of risk-free loans would be responsible for balancing any default coming from other loans. However, simulated capital ratios for banks that do not hold any risk-free loan at all are reasonably higher. For example, the mean value for the high and low credit quality portfolios increases from 0.20497 and 0.23369 respectively (with 'risk-free' loans) to 0.24573 and 0.28614 (without 'risk-free' loans). Same pattern can be found for maximum, minimum, and VaR levels values. As expected, the standard deviations go up, as we remove the risk-free loans from the portfolio: 0.03420 and 0.03029 (with risk-free loans) to 0.04013 and 0.03150 (without risk-free loans), for high and low credit quality portfolios respectively). While this results seems counterintuitive, it is understandable, if we consider the magnitude of interest rate spread (it is more than 18% between risk-free and AA business loans) and the probability of defaults as estimated in the transition matrix²⁷ (table 7). Hypothetical banks holding riskier loans portfolios earn a high interest rate on such loans relative to the probability of those loans defaulting. Because of this result, we decided to implement one additional simulation set of two banks that are assumed to earn and pay much lower interest rates. We find that with lower interest rates and interest rate spreads simulated capital ratios shrink significantly. In the case of banks holding portfolios with higher credit risk profile, the mean value for the simulated capital ratio goes from 0.20497 (higher interest rate spread) to 0.10431 (when assumed interest rates are cut by half). Further in such a low interest rate spread

²⁵ The total assets account has not been changed. What changed relatively to the balance sheet presented in table 3 is the account domestic risk-free loans, which is all transferred to the business loans account.

²⁶ Perhaps some sort of strong regulatory event would force banks to lower interest rates, or perhaps an improvement in global and domestic macroeconomic scenarios jointly with a more competitive banking industry, would stimulate banks to charge a lower interest rate.

²⁷ It is estimated that 0% of AA loans will fall into the F category. In the case of A, B, C, D, and E loans categories these probabilities are 0.23%, 2.33%, 1.23%, 0.75%, and 7.30% respectively.

environment there is a substantial risk of bank failure (e.g. at a five- percent confidence the high credit risk bank's capital level falls to a negative 2.3 percent).

These numbers illustrate the substantial impact of the current large interest rate spreads earned by Brazilian banks. Should these spreads decline sharply, other things the same, bank failure probabilities would likely increase thus raising important bank management and regulatory policy questions (e.g. capital levels, loan portfolio credit quality, etc.). One potential offsetting factor would be the positive impact of lower interest rates on economic growth rates and borrower default rates.

6.4. Systemic Risk versus Interest Rate Spread

If interest rates spreads have such a big impact on the simulated capital ratios, some natural questions regarding systematic risk arise. What happens to the probability of multiple bank failures if interest rate margins fall substantially? Does inter-bank credit exposure have a more or less significant effect? In order to be able to answer these questions, we return to the exercise we made in subsection 6.2, when we assessed the inter-bank credit exposure effect. We simulate the same three banks, with the same asset/liability structure, operating under the same macroeconomic/financial environment, with one different detail: banks now are assumed to charge 50% lower interest rates than the three banks in subsection 6.2.

For the sake of comparison, we report the results for both two sets of three banks in table 12. The difference is evident: in panel A, the probability of the three banks falling below the target capital ratio of 0.01 simultaneously increases faster, as credit inter-bank exposure increases, for banks facing lower interest rates. More important, the risk of multiple bank failures increases to above five percent in some cases. For example, in Panel B, if we assume that the hypothetical banks in question would fail when their capital ratios reaches the critical level of 0.05, for a 0.03 inter-bank exposure, the probability that the three banks will fail simultaneously climbs from 1.06% (for banks earning higher interest rate margins) to 3.35%. When we set the critical bank capital ratio at 0.10 (i.e. Panel C), this increase in systemic risk becomes even more evident.

7. Extensions

It is quite possible to extend this analysis in at least three directions: (i) allow stochastic updates in the volatilities and correlations in each step of the simulation runs, (ii) utilize a different methodology for modeling the credit risk of consumers loans, (iii) assess the impact of government default on the Banks' portfolio.

We understand the limitations of using historical data in a forward-looking assessment methodology. Allowing volatilities and correlations to update stochastically in each simulation run will likely improve the realism of the risk analysis. For this purpose, we believe the DCC methodology developed by Engle (2002) will provide a very useful tool.

Regarding consumers' loans, we have assumed they can be modeled in the same way as business loans. Even though we were capable of estimating a transition matrix that is very similar to the historical matrix constructed by the Brazilian Credit Risk Bureau, consumers' loans represent a significant fraction of total loans usually held by Brazilian Banks. Developing a more precise model for consumers' loans would certainly improve our analysis.

Given the large amount of government loans held by banks the potential impact of a government default is in principle an important issue. However such an analysis is not an easy task. The simplest way of approaching this issue would be modeling Government loans in the same way as business loans and then assign some credit risk rating to these loans. In an alternative methodology, we could model government probability of default as a function of some macroeconomic factors such as debt/GDP or deficit/GDP. A more sophisticated alternative involves modeling government balance sheets in a similar way that we modeled banks' balance sheets. Along this line, Barnhill and Kopits (2003) have

implemented a methodology for modeling government default risk in a manner similar to that presented above for modeling the risk of bank failures. In principle both bank and government default risk could be modeled as correlated processes.

8. Conclusion

We present, in the current paper, a simulation framework (the Portfolio Simulation Approach – PSA) that allows for the modeling of integrated market and credit risk in bank asset and liability portfolios, with the main purpose of assessing the systemic risk of Brazilian commercial banks – defined as the probability of multiple bank failures occurring in a particular time period. We argue that our methodology have 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 our simulation methodology 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.

Our preliminary simulations indicated that the risk of the hypothetical banks studied failing is small, as is the level of systemic bank risk. Further systemic bank risk is not very sensitive to the level of inter-bank credit exposures and to the credit risk profile of loans held by banks. There are at least three potential explanations for this result: (i) the large amount of ‘risk-free’ loans held by banks, (ii) the high capital ratios with which the hypothetical banks operate, and (iii) the large interest rate spreads earned by banks, which are much larger than the default rates on business and consumer loans.

We found the large interest rate spreads to be the most important element on our analysis. When we analyze hypothetical banks earning much more modest (but perhaps typical) interest rate spreads, bank failure risk and systemic bank risk increase substantially. Under this circumstance both inter-bank credit exposure as well as the credit quality of bank loan portfolios become important risk factors.

Important future extensions of this paper, for which we have made significant progress, are the modeling of stochastic volatilities and correlations using the Dynamic Conditional Correlation approach proposed by Engle (2002), and the modeling of consumer loan default rates separately from business loans. In particular, the more realistic modeling of stochastic volatilities and correlations should improve our ability to account for periodic financial shocks that might have important impacts on emerging economies.

Appendix A

The Portfolio Simulation Approach

In this appendix we present the main body of the Portfolio Simulation Approach, as published in Barnhill and Maxwell (2002).

A.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:

$$Dr = a \left(\frac{q(t)}{a} - r \right) Dt + s Dz, \quad (\text{A.1})$$

where:

- Dr = 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,
- $q(t)$ = “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,
- Dt = a small increment to time,
- s = “sigma” the instantaneous standard deviation of r , which is assumed to be constant, and
- Dz = a Wiener process driving term structure movements with Dr being related to Dt by the function $Dz = e\sqrt{\Delta t}$.

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.

A.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 yield²⁸. For a discrete time step, Δt , it can be shown that

$$S + \Delta S = S \exp \left[\left(m - \frac{s^2}{2} \right) \Delta t + se\sqrt{\Delta t} \right], \quad (\text{A.2})$$

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),

²⁸ 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.

- q = dividend yield,
 s = volatility,
 e = 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

$$K_m = \ln((S + DS)/S) + q, \quad (\text{A.3})$$

where:

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

The return on equity for individual firms and individual real estate properties is simulated using a one-factor model²⁹.

$$K_i = R_F + \text{Beta}_i(K_m - R_F) + s_i D_z, \quad (\text{A.4})$$

where:

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

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.

A.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 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

²⁹ There are several articles stating that the CAPM single factor model does not capture the relation risk-return precisely (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 uses 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.

the set of correlated random error terms for the n stochastic variables can be calculated. For example, for a bivariate normal distribution,

$$\mathbf{e}_1 = x_1, \tag{A.5}$$

$$\mathbf{e}_2 = r x_1 + x_2 \sqrt{1 - r^2}, \tag{A.6}$$

where:

- x_1, x_2 = independent random samples from standardized normal distributions,
- r = the correlation between the two stochastic variables, and
- $\mathbf{e}_1, \mathbf{e}_2$ = 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.

A.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 rating³⁰. 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 recovery rate on the loan is estimated as a beta distribution³¹ with a specified mean value and standard deviation.

³⁰ 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.

³¹ Utilizing a beta distribution allows the recovery rate to fall within 0% and 100% while maintaining the same mean and standard deviation.

Appendix B

The Dynamic Conditional Correlation Model (Engle (2002))

The paper by Bollerslev, Engle, and Wooldridge (1988) was one of the first to model time-varying conditional variances and covariances. In this approach, conditional variances and covariances are modeled using the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model of Bollerslev (1986). Specifically, the first order GARCH in mean is used, i.e., GARCH (1,1)-M, and it is assumed that each covariance or variance does not depend on the past realizations of other covariances or variances. The latter assumption significantly simplifies estimation of the model. The authors apply their model to a conditional version of the Capital Asset Pricing Model (CAPM), in which the expected return of an asset is a function of the conditional covariance of that asset's returns with the market.

As in Bollerslev, Engle, and Wooldridge (1988), Bollerslev (1990) models each conditional variance and each conditional covariance using the GARCH process. To reduce the number of parameters to be estimated, Bollerslev (1990) assumes that conditional covariances are proportional to the square root of the product of the corresponding conditional variances, thereby making conditional correlations constant in time. This simplifying assumption significantly reduces the dimensionality of the problem and improves estimation results. Bollerslev (1990) applies this model to the analysis of five exchange rates following the adoption of the European Monetary System in March of 1979 and finds significantly higher comovements in the exchange rates after the system was adopted.

Other papers that employ multivariate conditional heteroskedasticity models in various contexts include Engle, Ng, and Rothschild (1990), Kroner and Claessens (1991), Bollerslev, Chou, Kroner (1992), Bollerslev, Engle, and Nelson (1994), Engle and Mezrich (1996), and Ding and Engle (2001). However, most of these papers study only a limited set of conditionally correlated variables due to the fact that large sets of variables require too many parameters, which makes the numerical estimation of these models rather challenging. To overcome this problem, Engle (2002) proposes a relatively simple model in which the number of variables does not affect the number of parameters in the correlation equation. This model can be viewed as a generalization of the model by Bollerslev (1990), such that conditional correlations are allowed to vary in time. The properties of Engle's (2002) model are further investigated in Engle and Sheppard (2001).

In our implementation of Engle's (2002) model, we assume that interest rates and similar variables follow the following discrete process:

$$r_{t+1} = \mathbf{k} - (\mathbf{k} - r_t) \cdot e^{-q} + \mathbf{h}_{t+1}, \quad \mathbf{h}_{t+1} \sim N(0, h_{t+1}), \quad (\text{B.1})$$

which resembles the solution to Vasicek's (non-risk-neutralized) diffusion with the unconditional mean of \mathbf{q} and the speed of mean reversion \mathbf{k} . Define the standardized residual:

$$\mathbf{e}_{t+1} = \frac{\mathbf{h}_{t+1}}{\sqrt{h_{t+1}}}. \quad (\text{B.2})$$

Then the variance of \mathbf{h}_{t+1} is modeled as in E-GARCH (1,1):

$$\ln h_{t+1} = \mathbf{w} + a \cdot (|\mathbf{e}_t| - \sqrt{2/p}) + c \cdot \mathbf{e}_t + b \cdot \ln h_t. \quad (\text{B.3})$$

For variables other than interest rates (e.g., for stock indices, exchange rates, etc.), the following model is estimated:

$$\ln S_{t+1} = \ln S_t + (d - h_t / 2) + \mathbf{h}_{t+1}, \mathbf{h}_{t+1} \sim N(0, h_{t+1}), \quad (\text{B.4})$$

which resembles the solution to (non-risk-neutralized) lognormal diffusion with the drift (net of any dividends) d . The variance of the residual is modeled via E-GARCH (1,1) in equation (B.3).

For two variables i and j , the correlation $\mathbf{r}_{i,j,t+1}$ at time $t+1$ between their standardized residuals $\mathbf{e}_{i,t+1}$ and $\mathbf{e}_{j,t+1}$ is modeled using Engle's (2002) Dynamic Conditional Correlation model:

$$q_{i,j,t+1} = \bar{\mathbf{r}}_{i,j} + \mathbf{a} \cdot (\mathbf{e}_{i,t} \cdot \mathbf{e}_{j,t} - \bar{\mathbf{r}}_{i,j}) + \mathbf{b} \cdot (q_{i,j,t} - \bar{\mathbf{r}}_{i,j}), \quad (\text{B.5})$$

$$\mathbf{r}_{i,j,t+1} = \frac{q_{i,j,t+1}}{\sqrt{q_{i,i,t+1} \cdot q_{j,j,t+1}}}. \quad (\text{B.6})$$

For each variable i , the following parameters are estimated: a , b , c , either \mathbf{k} and \mathbf{q} or d . For each pair of variables, the following parameter is estimated: $\bar{\mathbf{r}}_{i,j}$. Finally, \mathbf{a} and \mathbf{b} are estimated.

We use the maximum likelihood technique to estimate for each variable either equations (B.1) and (B.3), or equations (B.1) and (B.4). Then, we use maximum likelihood to estimate equations (B.5) and (B.6). Once these two stages are performed, our algorithm attempts to further improve on the solution by using hereto obtained estimates to simultaneously estimate equations (B.1), (B.3), (B.4), (B.5), and (B.6). Depending on application, the simultaneous estimation may or may not improve the results from the preceding two-stage estimation. Once the best possible estimates are obtained, we use them in our simulation.

Table 1
EWMA Volatilities

Volatilities for a set of Brazilian financial and macroeconomic variables were estimated via exponentially weighted moving average (RiskMetrics™) 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 (RiskMetricsTM) 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														
TIWire														
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™) 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, TIwire (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	TIWire	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
TIWire			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
Transition Probability Matrices

We contrast the historical credit rating transition probabilities, as assigned by Moody (adjusted for withdrawn ratings, period of 1992-1996) and by the Brazilian Credit Risk Bureau (for the Brazilian Financial System, adjusted for repayments, and averaged between the periods of June 2000 to June 2001, and June 2001 to June 2002). We suggest a mapping between the two agencies' transition matrices by comparing the probability that each of the credit risk rating will fall into the lowest credit category, before defaulting (Caa-C for Moody and F for Brazilian Credit Risk Bureau), as well as the probabilities that a particular credit rating will stay at a similar credit risk category.

Panel A: Moody's Transition Matrixes Adjusted for Withdrawn Ratings, in the period of 1920–1996, (probability of Rating after One Year).

Initial Rating	Aaa	Aa	A	Baa	Ba	B	Caa-C	Default
Aaa	92.28%	6.43%	1.03%	0.24%	0.02%	0.00%	0.00%	0.00%
Aa	1.28%	91.68%	6.09%	0.70%	0.17%	0.02%	0.00%	0.06%
A	0.07%	2.45%	91.59%	4.97%	0.67%	0.11%	0.02%	0.13%
Baa	0.03%	0.26%	4.19%	89.41%	5.07%	0.66%	0.07%	0.30%
Ba	0.01%	0.09%	0.43%	5.09%	87.23%	5.47%	0.45%	1.23%
B	0.00%	0.04%	0.15%	0.67%	6.47%	85.32%	3.44%	3.90%
Caa-C	0.00%	0.02%	0.04%	0.37%	1.38%	5.80%	78.78%	13.60%

Panel B: Brazilian Credit Risk Bureau's Transition Matrix Adjusted for Repayments, weighted average of June 2000 to June 2001, and June 2001 to June 2002).

	AA	A	B	C	D	E	F	G+H
AA	89.80%	4.95%	2.95%	0.75%	0.90%	0.10%	0.15%	0.50%
A	6.90%	77.30%	6.60%	4.50%	2.20%	0.45%	0.30%	1.80%
B	7.90%	10.25%	68.75%	4.70%	3.15%	1.40%	0.55%	3.30%
C	3.10%	8.50%	11.00%	64.05%	4.95%	1.25%	1.20%	5.95%
D	3.80%	7.70%	5.95%	9.85%	49.80%	2.75%	2.80%	17.25%
E	3.00%	5.60%	2.15%	2.75%	3.50%	48.85%	10.05%	24.10%
F	1.55%	1.30%	3.10%	1.90%	2.15%	2.60%	55.15%	32.20%
Mapping	Baa	Baa	Ba	Ba	B	B	Caa-C	Default

Table 4
Business and Consumers' Loans Distribution – Lower Credit Risk

The Central Bank of Brazil provided us with the business and consumers' loans distribution by credit risk rating, for a lower credit risk profile bank portfolio. Business loans are distributed across several business equity sectors, while consumers' loans are distributed across geographical regions.

	Total	AA	A	B	C	D	E	F	G-H
Other Sectors	0.25554	0.10437	0.05266	0.06297	0.00908	0.01363	0.00557	0.00238	0.00488
Banks	0.00230	0.00230	0	0	0	0	0	0	0
Basic Industry	0.00090	0	0.00020	0.00071	0	0	0	0	0
Beverage	0.00267	0.00242	0	0	0	0	0.00025	0	0
Chemicals	0.04122	0.03716	0.00201	0.00141	0	0	0	0	0.00063
General Industry	0.06564	0.01605	0.04321	0.00188	0.00296	0.00098	0	0.00004	0.00052
Metal	0.09173	0.03495	0.05446	0.00124	0.00001	0.00000	0.00105	0	0.00002
Mining	0.00596	0.00582	0.00014	0	0	0	0	0	0
Oil Equity Sector	0.01849	0.01847	0	0.00000	0.00003	0	0	0	0
Paper	0.03484	0.02428	0.00953	0.00056	0	0	0	0.00031	0.00016
Telecom Wireless	0	0.00000	0	0	0	0	0	0	0
Textile	0.02089	0.00157	0.00599	0.01232	0	0	0.00033	0.00010	0.00059
Tobacco	0.00900	0.00900	0	0	0	0	0	0	0
Utility	0.19417	0.14039	0.05004	0.00098	0.00276	0	0	0	0
Region 1 (North)	0.00454	0.00011	0.00098	0.00140	0.00030	0.00037	0.00020	0.00014	0.00105
Region 2 (North-East)	0.01378	0.00032	0.00298	0.00424	0.00090	0.00111	0.00060	0.00044	0.00318
Region 3 (Central-West)	0.01751	0.00041	0.00379	0.00539	0.00115	0.00141	0.00076	0.00056	0.00404
Region 4 (South-East)	0.16374	0.00384	0.03541	0.05041	0.01074	0.01318	0.00714	0.00520	0.03782
Region 5 (South)	0.05707	0.00134	0.01234	0.01757	0.00374	0.00459	0.00249	0.00181	0.01318
Total	1	0.40279	0.27374	0.16109	0.03167	0.03526	0.01840	0.01097	0.06607

Table 5
Business and Consumers' Loans Distribution – Higher Credit Risk

The Central Bank of Brazil provided us with the business and consumers' loans distribution by credit risk rating, for a higher credit risk profile bank portfolio. Business loans are distributed across several business equity sectors, while consumers' loans are distributed across geographical regions.

	Total	AA	A	B	C	D	E	F	G-H
Other Sectors	0.2059424	0.0125988	0.0464724	0.0152482	0.0073180	0.0032945	0	0.0447813	0.0750204
Banks	0	0.0046215	0	0	0	0.0008630	0	0	0.0003833
Basic Industry	0.0071376	0	0.0022266	0.0048691	0	0	0	0	0
Beverage	0.0047726	0.0046107	0	0	0	0	0.0001339	0	0
Chemicals	0.0265717	0.0059409	0.0161034	0.0033503	0.0000162	0	0.0002703	0	0.0007347
General Industry	0.0387532	0.0200292	0.0105298	0.0023986	0.0008638	0.0002680	0	0.0002758	0.0041606
Metal	0.0677511	0.0201477	0.0415661	0.0037555	0.0015234	0	0.0003604	0	0
Mining	0.0342590	0.0340512	0	0	0.0000069	0	0	0	0
Oil Equity Sector	0.0050048	0.0032910	0	0	0.0000339	0	0	0	0.0016505
Paper	0.0245144	0.0103142	0.0069921	0.0004158	0	0	0	0.0060111	0.0006373
Telecom Wireless	0	0	0	0	0	0	0	0	0
Textile	0.0177983	0	0.0050054	0.0094559	0	0	0.0008321	0.0000443	0.0023562
Tobacco	0	0	0	0	0	0	0	0	0
Utility	0.0885040	0.0663236	0.0200156	0.0016454	0	0	0	0	0
Region 1 (North)	0.0135804	0.0004006	0.0034585	0.0017411	0.0022140	0.0022539	0.0002970	0.0005976	0.0025380
Region 2 (North-East)	0.0854431	0.0025206	0.0217597	0.0109542	0.0139297	0.0141806	0.0018687	0.0037598	0.0159683
Region 3 (Central-West)	0.0384777	0.0011351	0.0097991	0.0049330	0.0062730	0.0063860	0.0008415	0.0016932	0.0071910
Region 4 (South-East)	0.2331296	0.0068774	0.0593709	0.0298884	0.0380069	0.0386914	0.0050988	0.0102586	0.0435692
Region 5 (South)	0.1083600	0.0031966	0.0275960	0.0138923	0.0176658	0.0179840	0.0023699	0.0047683	0.0202512
Total	1.0000000	0.1960590	0.2708955	0.1025478	0.0878516	0.0839215	0.0120733	0.0721901	0.1744612

Table 6
Distribution of Brazilian Companies' Debt Ratios 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.

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

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.

Panel A: 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%

Panel B: 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%

Panel C: 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 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 7.

Mean	0.00002
25 th percentile	-0.01169
50 th percentile	-0.00150
75 th percentile	0.01081
Maximum	0.10600
Minimum	-0.07175

Table 9
Simulated Capital Ratios – High versus Low Credit Risk Profile

We report in this table the simulated capital ratios for two banks with the same asset liability structure Bank 2, operating simultaneously under the same financial/macroeconomic environment, with two different credit risk exposure: high and low credit risk profile (as defined in tables 4 and 5). We also report some descriptive statistic for the two banks in Panel A, and VaR analysis in Panel B. VaR shows the percentage of simulated capital ratios that fall over a particular value. For example, VaR 99% = 0.0656 means that 99% of the simulated capital ratios are bigger than 0.0656. Results are based on 2000 simulation runs.

Panel A: Descriptive statistics for two banks' capital ratios.

<i>Credit Risk Profile</i>	<i>Initial Capital Ratio</i>	<i>Mean</i>	<i>Std. Deviation</i>	<i>Maximum</i>	<i>Minimum</i>
<i>Higher</i>	0.1478	0.2003	0.0496	0.3406	-0.0324
<i>Lower</i>	0.1743	0.2389	0.0435	0.3813	0.0710

Panel B: VaR Analysis for two banks' capital ratios.

<i>VaR</i>	<i>Credit Risk Profile</i>	
	<i>High</i>	<i>Low</i>
99.0%	0.0656	0.1168
97.5%	0.0931	0.1374
95.0%	0.1097	0.1573
90.0%	0.1349	0.1847
75.0%	0.1703	0.2131
50.0%	0.2041	0.2430
25.0%	0.2359	0.2682
10.0%	0.2587	0.2902
5.0%	0.2735	0.3048
2.5%	0.2831	0.3144
1.0%	0.2945	0.3249

Table 10
Simulated Capital Ratios: Varying Inter-bank Credit Exposure

We present here the simulated probability of default for three banks operating simultaneously under the same financial/macro-economic scenario (as described in section 5), with the same credit risk exposure (higher credit risk profile, as defined in table 5) and with the same asset/liability structure as Bank 2. For several different degrees of inter-bank exposure (as a fraction of total assets), we estimated the probability that at least one of the banks will fall below some particular target capital ratio, as well as the probability that the three banks will fall below the same specified target capital ratio. This target capital ratio represents the capital ratio below which banks are assumed to default.

Panel A: Target Capital Ratio = 0.01

<i>Inter-bank Exposure</i>	<i>Simulated Probabilities</i>	
	<i>At least one bank < target¹</i>	<i>All three banks < target²</i>
0.00	0.65%	0.15%
0.01	0.65%	0.25%
0.03	0.65%	0.35%
0.05	0.65%	0.40%
0.07	0.65%	0.50%
0.09	0.65%	0.60%
0.10	0.65%	0.65%

Panel B: Target Capital Ratio = 0.05

<i>Inter-bank Exposure</i>	<i>Simulated Probabilities</i>	
	<i>At least one bank < target¹</i>	<i>All three banks < target²</i>
0.00	1.55%	0.35%
0.01	1.55%	0.60%
0.03	1.55%	1.05%
0.05	1.55%	1.25%
0.07	1.55%	1.45%
0.09	1.55%	1.50%
0.10	1.55%	1.50%

¹ Probability that at least one of the banks' capital ratios will fall below target ratio. The inter-bank exposure will affect the probability of defaulting only when at least one of the banks has already fallen below the target capital ratio, given the way we set up this analysis (see pages 23 and 24), and this is why the probability of at least one bank falling below the target capital ratio does not change as the inter-bank credit exposure increases.

² Probability that all three banks' capital ratio will fall below target ratio simultaneously.

Table 10 (cont.)**Simulated Capital Ratios: Varying Inter-bank Credit Exposure**

We present here the simulated probability of default for three banks operating simultaneously under the same financial/macro-economic scenario (as described in section 5), with the same credit risk exposure (higher credit risk profile, as defined in table 5) and with the same asset/liability structure as Bank 2. For several different degrees of inter-bank exposure (as a fraction of total assets), we estimated the probability that at least one of the banks will fall below some particular target capital ratio, as well as the probability that the three banks will fall below the same specified target capital ratio. This target capital ratio represents the capital ratio below which banks are assumed to default.

Panel C: Target Capital Ratio = 0.10

<i>Inter-bank Exposure</i>	<i>Simulated Probabilities</i>	
	<i>At least one bank < target¹</i>	<i>All three banks < target²</i>
0.00	6.80%	1.65%
0.01	6.80%	3.10%
0.03	6.80%	4.40%
0.05	6.80%	5.55%
0.07	6.80%	6.45%
0.09	6.80%	6.70%
0.10	6.80%	6.80%

¹ Probability that at least one of the banks' capital ratios will fall below target ratio. The inter-bank exposure will affect the probability of defaulting only when at least one of the banks has already fallen below the target capital ratio, given the way we set up this analysis (see pages 23 and 24), and this is why the probability of at least one bank falling below the target capital ratio does not change as the inter-bank credit exposure increases.

² Probability that all three banks' capital ratio will fall below target ratio simultaneously.

Table 11
Simulated Capital Ratios: Varying Risk-Free Loans Levels and Interest Rate Spreads

In this table we show the distribution of simulated capital ratios for three sets of two hypothetical Brazilian commercial banks at a one-year time step. The sets involve: (i) banks' portfolio holding risk-free government loans with higher interest rate spread, as reported by the Central Bank of Brazil, (ii) banks' portfolio with no 'risk-free' loans (i.e. the reported risk-free loans distributed across business loans, using the same weights reported in tables 4 and 5) but with the same interest rate spread as in the first set, and (iii) banks' portfolios with no 'risk-free' loans as in the second set, earning half of the interest rate spreads in the previous two sets.

Risk Included in Analysis

Interest Rate Risk	yes	yes	yes	yes	yes	yes
Interest Rate Spread Risk	yes	yes	yes	yes	yes	yes
Credit Risk	yes	yes	yes	yes	yes	yes
FX Risk	yes	yes	yes	yes	yes	yes
Domestic Risk-Free Loans	yes	yes	no	no	no	no
Interest Rate ¹	-	-	-	-	Down 50%	Down 50%
Credit Risk Profile ²	High	Low	High	Low	High	Low
Initial Value	0.08214	0.12841	0.08214	0.12841	0.08214	0.12841
Mean Value	0.20497	0.23369	0.24573	0.28614	0.10431	0.16739
Std. Deviation	0.03420	0.03029	0.04013	0.03150	0.05193	0.03804
Maximum Value	0.35617	0.37333	0.41917	0.44331	0.32095	0.35557
Minimum Value	0.06342	0.12304	0.06144	0.14985	-0.17870	-0.03038

VaR Confidence Levels

99% Level	0.11949	0.16138	0.14585	0.20991	-0.03246	-0.05846
97.5% Level	0.13951	0.17711	0.16085	0.22139	-0.01140	-0.03674
95% Level	0.14953	0.18649	0.17808	0.23571	0.01397	-0.02333

¹ We imagined a hypothetical scenario where the interest rates charged and received by Brazilian banks are cut by half.

² Credit risk rating of business and consumers' loans follow the distribution among several risk categories and across business sectors and geographical regions, as defined previously in tables 4 and 5.

Table 12
Simulated Capital Ratios: Lower Interest Rate Spreads and Varying Inter-Bank Credit Exposures

We present here the simulated probability of default for three banks operating simultaneously under the same financial/macroeconomic scenario (as described in section 5), with the same credit risk exposure (higher credit risk profile, as defined in table 5) and with the same asset/liability structure as Bank 2. For several different degrees of inter-bank exposure (as a fraction of total assets), we estimated the probability that at least one of the banks will fall below some particular target capital ratio, as well as the probability that the three banks will fall below the same specified target capital ratio. This target capital ratio represents the capital ratio below which banks are assumed to default.

Panel A: Target Capital Ratio = 0.01

Inter-bank Exposure	Simulated Probabilities			
	At least one bank < target ¹		All three banks < target ²	
	lower interest rates	higher interest rates	lower interest rates	higher interest rates
0.00	1.95%	0.65%	0.15%	0.15%
0.01	1.95%	0.65%	0.65%	0.25%
0.03	1.95%	0.65%	0.90%	0.35%
0.05	1.95%	0.65%	1.35%	0.40%
0.07	1.95%	0.65%	1.75%	0.50%
0.09	1.95%	0.65%	1.90%	0.60%
0.10	1.95%	0.65%	1.95%	0.65%

Panel B: Target Capital Ratio = 0.05

Inter-bank Exposure	Simulated Probabilities			
	At least one bank < target ¹		All three banks < target ²	
	lower interest rates	higher interest rates	lower interest rates	higher interest rates
0.00	6.50%	1.55%	1.25%	0.35%
0.01	6.50%	1.55%	1.95%	0.60%
0.03	6.50%	1.55%	3.35%	1.05%
0.05	6.50%	1.55%	4.40%	1.25%
0.07	6.50%	1.55%	5.25%	1.45%
0.09	6.50%	1.55%	5.90%	1.50%
0.10	6.50%	1.55%	5.95%	1.50%

¹ Probability that at least one of the banks' capital ratios will fall below target ratio. The inter-bank exposure will affect the probability of defaulting only when at least one of the banks has already fallen below the target capital ratio, given the way we set up this analysis (see pages 23 and 24), and this is why the probability of at least one bank falling below the target capital ratio does not change as the inter-bank credit exposure increases.

² Probability that all three banks' capital ratio will fall below target ratio simultaneously.

Table 12 (cont.)
Simulated Capital Ratios: Lower Interest Rate Spreads and Varying Inter-Bank Credit Exposures

We present here the simulated probability of default for three banks operating simultaneously under the same financial/macro-economic scenario (as described in section 5), with the same credit risk exposure (higher credit risk profile, as defined in table 4) and with the same asset/liability structure as Bank 2. For several different degrees of inter-bank exposure (as a fraction of total assets), we estimated the probability that at least one of the banks will fall below some particular target capital ratio, as well as the probability that the three banks will fall below the same specified target capital ratio. This target capital ratio represents the capital ratio below which banks are assumed to default.

Panel C: Target Capital Ratio = 0.10

Inter-bank Exposure	Simulated Probabilities			
	At least one bank < target ¹		All three banks < target ²	
	lower interest rates	higher interest rates	lower interest rates	higher interest rates
0.00	20.20%	6.80%	6.05%	1.65%
0.01	20.20%	6.80%	9.30%	3.10%
0.03	20.20%	6.80%	13.80%	4.40%
0.05	20.20%	6.80%	16.55%	5.55%
0.07	20.20%	6.80%	18.70%	6.45%
0.09	20.20%	6.80%	19.55%	6.70%
0.10	20.20%	6.80%	19.75%	6.80%

¹ Probability that at least one of the banks' capital ratios will fall below target ratio. The inter-bank exposure will affect the probability of defaulting only when at least one of the banks has already fallen below the target capital ratio, given the way we set up this analysis (see pages 23 and 24), and this is why the probability of at least one bank falling below the target capital ratio does not change as the inter-bank credit exposure increases.

² Probability that all three banks' capital ratio will fall below target ratio simultaneously.

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