Systemic Bank Risk in Brazil: An Assessment of Correlated Market, Credit, Sovereign, and Inter-Bank Risk in an Environment with Stochastic Volatilities and Correlations

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Synopsis

In this study we develop a forward-looking portfolio simulation methodology for assessing the *correlated* impacts of market risk, and private sector, Sovereign, and inter-bank default risk on both individual banks and groups of banks (i.e. a banking system). This risk assessment methodology produces estimates of the probability of individual and multiple banks failing as well as the estimated monetary costs of recapitalizing the banking system. We find a number of variables have important impacts on individual bank risk and systemic bank risk including the: (1) Sovereign default rate, (2) bank loan portfolio credit risk distributions, (3) loan portfolio sector, region, and Sovereign concentrations, (4) initial bank capital ratios, (5) economic environment volatilities and correlations, (6) asset and liability maturity and currency mismatches, (7) banks' net interest margins, and (8) banks' operating expense ratios.

We apply the portfolio simulation model to 28 of the largest Brazilian banks. A significant innovation is that financial and economic environment variables are modeled with stochastic volatilities and correlations. We demonstrate the reliability of the models by comparing simulated and historical credit transition probabilities, simulated and historical rates of return, and simulated versus actual bank credit ratings.

When omitting Sovereign risk our analysis indicates that none of the banks face significant default risk over a 1-year horizon. This low default risk stems primarily from the large amount of government loans held by Brazilian banks, but also reflects the banks' adequate capitalizations and extraordinarily high interest rate spreads. A decline in spreads to more normal levels would likely reduce bank profitability and increase bank and systemic bank default risk. We model Sovereign defaults to be systematically related to returns on an equity market index with an idiosyncratic component as well. This simple model is calibrated to produce an average Sovereign default rate consistent with that estimated by Fitch for a B rated Government credit. The impacts of a Government default is difficult to predict and will be very dependent on the contemporaneous policies adopted. In this initial effort we consider a range of direct losses in the market value of Government loans and incremental default rates on private sector loans. Once Sovereign risk is considered, then several banks present potential default problems. In particular, once losses in the market value of government loans reaches 10% (or hgher) of banks total assets, several banks face potential solvency problems. These results demonstrate the well known risk of concentrated lending to a borrower which has a non-zero probability of default (e.g. Government of Brazil).

We assess systemic risk of the Brazilian financial system in different ways. We first consider a single aggregate bank that is a combination of all 28 banks. Second we divide the banks into three groups according to our estimated default risk and aggregate their balance sheets. We then simulate the three aggregate banks simultaneously and estimate the risk that one or more of the banks will default due to correlated market, credit, Sovereign, and inter-bank default risk. Our results show that aggregating the banks in one single bank heavily underestimates the cost associated with a systemic risk crisis, when compared to the simultaneous simulation case, albeit the risk of all banks defaulting at the same time, through the inter-bank propagation channel becomes significant only when banks suffer substantial losses in the market value of government loans. Our analysis also reveals another nocive facet of banks holding exceedingly large concentrations of government loans. In the event of a Sovereign default, the government has constrained debt management alternatives. Should the government take actions that significantly reduce the market value of government loans, then it may trigger a systemic risk financial system failure.

A less obvious impact of banks holding a very large amount of government debt is that it preempts them from earning higher interest income from business and customers' loans. It may be entirely possible to reduce the amount lent to the government and balance the portfolio in such a way that the bank's expected profitability and risk profiles both improve, after accounting for Sovereign risk. This suggests that the development of global markets for sovereign debt denominated in local currency could have the dual benefits of allowing Sovereigns to diversify their borrowing sources and banks to diversify their loan portfolios and default risk.

These results are put forward to demonstrate a methodology and thus should be taken as illustrative rather than definitive measures for Brazilian bank risk. Nevertheless we believe that these types of models have good potential to be applied systematically by off-site bank supervisors to identify bank and systemic bank risks before they materialize and to assist in the formulation of effective risk management policies.

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1. Introduction

At any future time individuals, businesses, banks, groups of banks, and the Government of Brazil (GOB) will all face the same financial and economic environment (for better or worse). There is every reason to expect that the default probability for each of the above entities is non-zero, stochastic, and correlated with future financial and economic environment conditions (e.g. default rates will go up during periods of economic stress). These correlated default rates for individuals, businesses, banks, groups of banks, and the GOB have a significant impact on individual bank risk and banking system risk and need to be accounted for systematically[1].

The 80's and 90's have witnessed a number of systemic banking crises[2], sometimes with transnational contagion effects. In some cases these events were triggered by Sovereign defaults (e.g. Argentina and Russia). The importance of developing tools for assessing *ex-ante* the probability of a systemic failure of the banking sector and their large associated monetary cost is obvious. For emerging economies the government may have difficulty in accessing adequate funds to resolve this type of crisis[3]. In addition, as noted by Demirgüç-Kunt and Detragiache (1998), banking crises might also spread to other sectors of the economy, as the availability of credit may be disrupted, *"[r]educing investment and consumption, and possibly forcing viable firms into bankruptcy."* It can be equally harmful to *"[t]he functioning of the payment system, as banks failure undermines confidence in financial institutions, reducing domestic savings and producing a large-scale capital outflow. Finally, a systemic crisis may force otherwise-sound banks to close their doors."*

Even though systemic failure events are not restricted to the banking sector, financial systems are particularly vulnerable to contagion effects (the financial fragility hypothesis; De Bandt and Hartmann (2000)). Banks take cash deposits that are subject to be withdrawn at any time. Since it is unlikely that deposits will be withdrawn all at the same time, banks invest this money in longer-term contracts, notably loans to individuals and corporations, keeping only a small fraction of these deposits in liquid reserves. In order to be willing to leave their money in the bank, depositors need to be confident on the bank's ability to pick profitable investment opportunities and to be confident that other depositors will also keep their money deposited in the bank. Thus, banks are particularly vulnerable to liquidity shocks, if an event causes depositors to run on the bank. Secondly, banks are highly interconnected through a large and complex network of financial contracts (more than any other sector of the economy), making one bank significantly exposed to the one another in the event of bank defaults.

Forward-looking risk assessment methodologies can be of central importance in quantifying the potential magnitude of the risk and, more importantly, allowing for the identification and evaluation of proactive steps that may be undertaken to manage such risks. The current practice is to undertake market and credit risk assessments separately (e.g. Basel Accord (1988, 1996, and 2001)). Combining such separate risk measures into one overall portfolio risk measure is not easily accomplished (see, for example, Jarrow and Turnbull (2000) and Barnhill and Maxwell (2002)). The absence of reliable overall portfolio risk measures creates problems for 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. To the best of our knowledge no one else has put forward a systematic methodology for assessing *correlated* market, credit, Sovereign, and inter-bank default risk for a financial system.

[1] The ValueCalc Global Portfolio and Credit Risk software, copyright FinSoft, Inc. 1996-2005, was used to undertake the risk analyses reported in this study.

[2] See Lindgren, Garcia, and Saal (1996) and Caprio and Klingebiel (1996).

[3] This, of course, suggests the need to also model the impact of systemic banking system risk on Sovereign risk. We look forward to addressing this future research topic.

In this study we construct a portfolio simulation model that undertakes such an integrated risk assessment, in the same spirit of Barnhill and Maxwell (2002), and apply the model to the Brazilian financial system[4]. In order to be able to do that, we first need to understand the potential venues through which a systemic banking failure can propagate. The literature has identified several channels. First, banks are directly interdependent through a nexus of financial inter-bank contracts. One insolvent bank might become unable to honor their contracts, provoking financial distress to its counterparts (e.g. Rochet and Tirole (1986) and Elsinger, Lehar, and Summer (2003)). Second, banks' assets have some degree of correlation as banks might invest in the same industries or geographical regions. If a shock affects one or more particular industry (or geographical region), then banks with exposure to that industry (or geographical region) will be systematically affected (e.g. Acharya (2001) and Lehar (2003)). Third, the news of one bank failure can provoke depositors from other banks to withdraw their funds (bank run), depleting banks' capital (Diamond and Dybvig (1983)) and Gorton (1985)). Fourth, a downward business cycle may cause companies' distress, rendering many loans delinquent and causing banks to further reduce business lending. This can deepen the business cycle, worsening the financial crises and affecting more banks (e.g. Gorton (1988)). Fifth, correlated interest rate, exchange rate and equity price risk may also impact multiple banks simultaneously. Sixth, Sovereign defaults may simultaneously impose direct losses on banks through a reduction in the market value of their Government debt and indirect loses brought about by economic and contract disruptions that incrementally increase the default rates on private sector loans.

We model the financial and economic environment under which banks are assumed to operate as a set of correlated stochastic processes describing various macroeconomic/financial state variables. While we do not model explicitly a big macroeconomic shock smashing the banking sector, it is possible that a combination of 'bad draws' can eventually impact the banks with negative effects comparable to those provoked by a large macroeconomic shock. This approach not only allows us to capture the influences of macroeconomic forces[5] on banks performance, but also potentially the influences from variations in interest rates, exchange rates, and other factors. We deem this step to be very important. Several authors have stressed the importance of macroeconomic factors such as cyclical downturns, interest rate increases, or exchange rate devaluations on banks performance (e.g. Gorton (1988) and Lindgren, Garcia, and Saal (1996), among others). In order to properly characterize the dynamic nature of the correlated stochastic processes, we model volatilities and correlations as stochastic variables by updating them in each Monte Carlo step using an exponentially weighted moving average (EWMA) methodology. Barnhill and Souto (2005) provide a comprehensive examination of EWMA properties and performance, when incorporated within a Monte Carlo simulation. In that study they were able to simulate distributions of changes in volatilities that are reasonably close to historical distributions, by adjusting the EWMA decay factors appropriately. We will use their study as a basis for setting up the decay factors for the current bank simulation.

Banks' asset and liability portfolios (loans, equity and real estate investments, government securities, etc.) are modeled with considerable detail. For example, we use the credit quality distribution of private sector loans, as well as the distribution of such loans by different industries and geographical regions as model inputs. This feature of our simulation is very important because it allows us to capture correlations in default rates in a bank's private sector loan portfolio (one of the main channels of systemic crises, according to Acharya (2001)) at different levels: (i) if banks lend to similar industries or to similar geographical regions; (ii) if banks have similar loan portfolio credit qualities; and (iii) if banks have similar portfolio composition with respect to asset and liability maturities and currencies. Information on the structure of the banks' portfolios is also needed to model correlated Sovereign default risk, and inter-bank default risk.

[4] Brazilian financial system is a very interesting case to be studied because of some interesting features shared by many Brazilian banks: (i) huge exposure to government default; (ii) high interest rate spreads; and (iii) substantial inefficiencies.

[5] It is possible to include proxies such as unemployment rates, GDP, etc.

The reliability of the model is demonstrated in various ways. First, Barnhill, Souto, and Tabak (2003), and Barnhill and Souto (2005) have shown that the models produce simulated credit rating transition probabilities and default rates for business loans that are very similar to those reported by Brazilian Banks. The methodology used to model business loan credit transition probabilities and defaults starts with an extensive empirical analysis of publicly traded companies in Brazil to identify typical debt to value ratios, beta coefficients, and firm specific equity return volatilities for firms with various credit ratings. For each run of the simulation the return on a firm's equity is estimated to be a function of the simulated return on an equity market index plus a firm specific random change. This simulated equity return allows the estimation of a new debt to value ratio and credit rating (including default) for each firm in the bank's loan portfolio (see Appendix 1 for a comparison of the historical and simulated credit transition probabilities for Brazilian bank loans). Second, by simulating a set of 13 private domestic Brazilian banks we show that the models produce means and standard deviations of returns on equity and assets that are unbiased predictors of banks' historical means and standard deviations of returns. Finally we show that our risk assessments for individual banks are generally consistent with the ratings given by Moody's and Standard and Poor's.

For our individual bank risk assessments we simulate 28 of the largest Brazilian banks for two different cases: (i) GOB is assumed to never default; and (ii) GOB can default on its debt with a 4.5% probability which is consistent with the average default probability of countries rated by Fitch in the same grade as Brazil (B rating).

The issue of government default is central for assessing banking risk in Brazil, as Brazilian banks hold a significant amount of government securities, sometimes above 80% of their total assets. In this study we model government default in a relatively simplistic way. In particular we model the GOB as a very large corporate borrower. This borrower has an assumed debt to value ratio. The value of the GOB's net worth, and thus its debt to value ratio, is assumed to be systematically related to returns on the Brazilian equity market index and to also have an idiosyncratic component. On each run of the simulation we estimate a new debt to value ratio for the GOB and if this value exceeds some critical level, then the GOB is assumed to default. The initial debt to value ratio and other factors are selected to produce a targeted average Sovereign default rate (e.g. 4.5%). The simulated Sovereign defaults are thus systematically related to returns on the Brazilian equity market which are also systematically related to simulated defaults on private sector loans. Through this mechanism we end up modeling correlated Sovereign and private sector loan defaults[6] which are also correlated with simulated financial and economic variables (e.g. equity returns, interest rates, foreign exchange rates, etc.).

The impact of inter-bank exposure is modeled, in a second step after the Monte Carlo simulations are done, and the initial bank risk assessments completed[7]. For this purpose, we first aggregate the 28 banks into three groups according to their individual risk characteristics and then simulate them simultaneously[8]. Since we do not have precise information on inter-bank borrowers/lenders identities, we assume that inter-bank lending to be proportional to the three aggregate banks total assets. We then assume, in a second stage analysis, that if one bank falls below a 3% capital ratio, then it becomes incapable of honoring its inter-bank obligations and defaults on them. Only 50% of these inter-bank obligations is assumed to be recovered, with subsequent impact on other banks' capital ratios. Eventually, one bank's failure can induce other banks to become insolvent as well, depending upon the size of inter-bank exposure, combined with other factors, as mentioned above. It is important to keep in mind the significance of modeling all of the correlated risks

[6] For more elaborate alternatives to the above method of modeling Sovereign default risk, which could also be used in this type systemic bank risk assessment model, see Barnhill and Kopits (2004) and Barnhill (2006).

[7] Each simulation run produces a random path over a certain time-period (e.g. one year). To minimize computational effort and time, balance sheet accounts are recalculated only at the end of the time-period.

[8] The current version of the ValueCalc programs only allows for simulating three banks simultaneously (for computer memory reasons), although it has the potential to simulate any number of banks simultaneously.

above. In particular during times of economic stress it is likely that default losses on private sector loans will rise, market volatility and risk will also likely increase, and so too will the risk of Sovereign default. Thus should a Sovereign default occur it will likely be at a time when many banks are already being adversely impacted by other risk factors. This is just the time when the failure of several banks could, through inter-bank credit defaults, precipitate a number of additional bank defaults and a systemic banking crisis.

The impacts of a Government default on the banking system will be varied, hard to predict in advance, and very dependent on the contemporaneous policies adopted by the Government at the time of any such default. It may be that the government would wish to expand its monetary base in order to repay domestic loans; this practice has well-known nocive effects on the economy, which might, eventually spill-over to the banking system. On top of that, such default events are usually associated with major disruptions in the whole economy, affecting all sectors, and banks' borrowers may become incapable of repaying some of their debts. It is also possible that banks will suffer losses on Government loans due to increases in the market's required risk premium on Government debt, because the government may defer the payment of certain debts, or may force banks to accept new debt instruments with a lower market value (e.g. longer maturities, fixed rates, etc.). In any instance, even if the government does not fully default on its domestic debt, the banks may ultimately incur market value losses. To be able to model this explicitly is not an easy task. No one knows for sure which set of actions will be taken by the government during such events. There are then innumerous possible outcomes for banks holding government debt, each of which will impact banks' portfolios differently. Modeling the impact of Sovereign defaults on banks and banking systems is clearly a topic on which we wish to conduct substantial additional research.

For the present application we will use a matrix of some potential government default implications that will provoke additional losses on banks' portfolios, through two different channels. First, even if banks face no losses on government loans, they may face additional losses on their business and customers' loans, as these sectors of the economy are impacted by major disruptions in the economy provoked by the Sovereign default event. We conjecture that these events will impacts firms with different credit worthiness differently. That is, we assume that firms with higher credit quality are better prepared to handle these crisis events. The way we capture this differential impact is by imposing an increment in the default rate on private sector loans in each credit category. We assume three different scenarios: (i) businesses and individuals have a zero increment to their default rates; (ii) businesses and individuals in each credit risk category have an increase in their default rates equal to the average default rate of that credit risk category[9], and (iii) businesses and individuals in each credit risk category have an increase in their default rates equal to two times the average default rate of that credit risk category. The second channel incorporates losses directly on the government loans, by assuming that banks may lose 0%, 10%, or 25% of the market value of their government loans. The combination of all these possible outcomes lead to 9 potential scenarios banks may face in the event of a government default. While these scenarios are far from exhausting the innumerous alternatives, they do provide what we believe to be a reasonable range for the incremental losses banks may face due to a Government default[10].

Our analysis finds that most banks have reasonably high simulated capital ratios so long as the government does not default. However in the event of a Sovereign default a number of Brazilian banks face potential solvency problems and could, if customers lose confidence, face liquidity problems as well. These results illustrate the well known risk of concentrated lending to an entity with a non-zero default rate. It also reveals another nocive facet of banks holding exceedingly large concentrations of government loans with a non-zero default probability. In the event of a Sovereign default, the government has constrained debt management alternatives. Should the government take actions that significantly reduce the market value of government loans, then it could trigger a systemic financial system failure. In the particular case of GOB, in

[9] Appendix 1 gives the average one-year historical default rates on Brazilian bank loans with various credit qualities.

[10] Development of a systematic methodology for modeling the correlated distributions of direct losses on government debt and incremental losses on private sector loans is a high priority for future research.

the event of government default, we show that losses of 10% or higher in the market value of government loans would create problems for a number of individual banks. Loss rates of 25% or higher on government loans could provoke a systemic banking crisis. It is important to emphasize, however, that this number should be taken as illustrative, rather than definitive, given the limitations of the data we have utilized in this study and given its stylized framework. Since the amount of GOB loans in Brazilian balance sheets dwarfs the amount of business and customers' loans, the impact of incremental defaults on business and households has only a marginal effect on banks' default rates and monetary losses. A less obvious impact is that holding a very large amount of government debt preempts banks from earning higher interest income from business and customers' loans. It may be entirely possible to reduce the amount lent to the government and balance the portfolio in such a way that the bank's expected profitability and risk profiles both improve, after accounting for Sovereign risk. This suggests that the development of global markets for sovereign debt denominated in local currency could have the dual benefits of allowing Sovereigns to diversify their borrowing sources and banks to diversify their loan portfolios and default risk.

Our simulations also provide a way of grouping the banks, based on their credit worthiness, under an integrated risk framework. Specifically, we categorize Brazilian banks into three groups, based on their capital ratio at the 99% VaR level (meaning that the bank has 1% probability of having its capital ratio falling below this number) and also assuming that the government can default imposing a 10% average loss on government loans and an incremental default rate on business and customers' loans that is equal to the average default rate per each credit category. We find that our categorization is generally consistent with Moody's and Standard and Poor's ratings, while slightly departing from Fitch ratings. Simulated capital ratios, default rates, and bail-out costs are on average very consistent with the credit risk categorization: the 99% VaR simulated capital ratios degrades as credit risk increase and default rates and bail-out cost increase as credit risk increases.

Finally, we assess systemic risk of the Brazilian financial system, in different ways. We first consider a single bank that is a combination of all 28 banks, then we simulate the three aggregate banks simultaneously and include the risk component associated with inter-bank default (inter-bank propagation channel). Our results show that aggregating the banks into one single bank underestimates the cost associated with a systemic risk crisis, when compared to the three-bank simultaneous simulation case. For example, if we assume the government to default and banks suffer a 25% average loss in the market value on government loans and an incremental default rate on business and customers' loans equal to two times the average simulated default rate per risk category, then the single-bank default rate is 2.2%, with an associated average cost to bring its capital ratio back to 0.08 of 0.055 of total assets. Under the same scenario, the probability of having the two groups with the lower credit profile defaulting at the same time is 2.9%, with an associated cost of 0.111 of the two banks' total assets. Because one of the three groups is very well-capitalized, it will only default when it incurs even larger losses on government loans, should the government default. While the above assumptions are somewhat arbitrary the analysis highlights the danger of modeling the financial system as one single financial institution and not accounting for the differential risk characteristics of various banks and for the inter-bank channel, through which a systemic crisis may propagate.

It is important to emphasize that our results should be taken as illustrative rather than definitive measures for Brazilian banks risk. This is so for several reasons. First, from a data standpoint, we have not had access to the most detailed (and specific) information on banks portfolios and on interest rate spreads charged by Brazilian banks. This information is protected by a confidentiality law in Brazil and could not be provided to us. Second, there are some methodological shortcomings on our analysis that can be improved further in future work. One of them would be modeling the GOB's asset and liability structure and default risk in more detailed manner (e.g. see Barnhill and Kopits (2004), or Barnhill (2006)). Such an approach would potentially yield more accurate Sovereign default estimates results. It would also be interesting to improve further the methodology for modeling customers' loans in contrast to our approach of considering these loans to behave similarly to corporate loans. Finally, considering the significant operational expense ratio incurred by Brazilian banks, it would be quite interesting to build operational expenses variations in to the simulation model. A simplistic way of capturing this risk facet could be through fitting a stochastic process in to the operational expense ratio time series and simulating it within the PSA framework. In spite of all the identified data and other limitations we believe the model have demonstrated substantial potential for measuring and managing the risk level of banks and banking systems. Clearly there are opportunities to improve and extend both the methodologies and the data used in the analysis.

The remainder of this paper proceeds as follows. Section 2 gives a brief overview of the framework for simulating banks. In Section 3 we present and discuss the simulation results for individual, aggregate, and simultaneously simulated banks. Concluding remarks and final comments are given in Section 4. Appendix 1 gives additional detail on the analytical models utilized. Appendix 2 describes the data used in the various analyses.

2. A Conceptual Framework for Simulating Banks

Given the correlated nature of credit and market risk (see Fridson *et al.* (1997) and Jarrow and Turnbull (2000)), the importance of an integrated risk assessment methodology seems apparent. Barnhill and Maxwell (2002) 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, equity market and credit risk – the Portfolio Simulation Approach (PSA). This approach was later extended by Barnhill, Papapanagiotou, and Schumacher (2003) to undertake financial institution asset and liability risk assessments for South African banks and by Barnhill, Papapanagiotou, and Souto (2004) to estimate potential losses associated with banking default in the Japanese financial system. Barnhill, Souto, and Tabak (2003) utilize the PSA approach to simulate credit transition matrix for two large Brazilian banks[11]. These studies have demonstrated that the PSA methodology produces:

1. simulated financial environments 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, and
4. simulated value at risk measures for bond portfolios very similar to historical value at risk measures.

The simulations are constructed over an Excel platform, which allows a very rich specification of banks balance sheet accounts, portfolio credit quality and distribution across geographic regions and business sectors, interest rate term structures, volatilities and correlations between assets returns, etc[12]. A Monte Carlo exercise is then conducted, over a selected time period, with the credit quality and market value of each balance sheet account been updated accordingly to correlated underlying stochastic processes governing interest rates, equity market indices, FX rates, etc.

2.1. Modeling the Financial and Economic Environment

The financial and economic environment under which banks operate is modeled as a set of correlated state variables, such as domestic interest rates (for different credit risk grades[13]), foreign interest rate, foreign exchange rates, equity indices, commodity prices (particularly gold and oil), unemployment rates and CPI. In

[11] Appendix 1 gives additional technical details regarding the simulation model formulation as well as a comparison of the simulated and historical credit transition probability matrices (and default rates) for Brazilian business loans.

[12] This feature of the simulation framework proves very useful in capturing correlation between asset returns at different levels: (i) if banks lends to similar industries or to similar geographical regions; (ii) if banks have similar credit quality of portfolio; and (iii) if banks have similar portfolio composition with respect to different financial instruments available in the market. As stressed by Acharya (2001), correlation between asset returns might play a significant role in propagating a banking crisis.

[13] Because we model interest rates for different credit risk categories, an important piece of information for banks simulation is the interest rate spread between different credit risk categories. In the case of Brazil, where banks are known to charge huge interest rate spreads, this information becomes even more important.

this particular exercise we do not model mortgage loans[14], but it is possible to do that, in which case real estate indices would also be part of the state variables list.

These variables are assumed to follow correlated stochastic processes[15]. The stochastic processes parameters are typically estimated from historical data. Selection of the time period for parameter estimation is done based on some knowledge of the recent and past history of events that have occurred in the country. Stochastic processes shock components are then drawn, for the Monte Carlo exercise, via Cholesky decomposition, as weighted by variables correlations. The decomposition process starts off the most exogenous variable in the simulation, usually the domestic interest rate, moving to the more endogenous variables.

Volatilities and covariance's are also modeled as stochastic, via EWMA model. Barnhill and Souto (2005) have shown that, in spite of some limitations, EWMA can reproduce reasonably well volatilities evolution and is more appropriate for modeling banks operating in more volatile economies such as Brazil. Similar to modeling stochastic returns, volatility shocks are also modeled via Cholesky decomposition and are thus affected by the correlation structure of the state variables.

2.2. Banks' Balance Sheets

Banks' balance sheets are modeled with some degree of detail. On the liabilities side, we have (i) domestic funding, which includes inter-bank, demand, savings, and fixed deposits, NCD's, repos, and others; (ii) foreign funding (in foreign currency); (iii) debt; (iv) non-interest bearing liabilities; (v) capital and reserves; and (vi) equity. Domestic and foreign funding and debt can be broken down, in the simulation framework, in up to three different maturities and then properly linked to different stochastic interest rates (domestic or foreign) and foreign exchange rates. As we shall see, some asset accounts can also be modeled through multiple maturities and this structure allows us to incorporate asset and liability maturity and currency mismatches (i.e. market risk) as a component of banks' integrated risk assessments.

On the asset side, the main accounts are (i) money (cash and gold reserves); (ii) domestic risk free loans[16]; (iii) business loans; (iv) customers loans; (v) foreign loans; (vi) equity investments; (vii) real estate investments; and (viii) non-interest earning assets. Money and non-interest earning assets are not updated in the course of the simulations (we thus assume that the bank does not change the amount of money and non-interest earning assets it holds, over the course of the simulation). Because they are usually the main risk elements in any bank's portfolio, loans are modeled in more details and will be discussed in the next section. Like some of the liabilities accounts, it is also possible to model multiple loans maturities. As mentioned above, however, we are not modeling mortgage loans for Brazilian banks, but it is possible to be done. For examples of this application, see Barnhill, Papapanagiotou, and Schumacher (2003) on South African banks, and Barnhill, Papapanagiotou, and Souto (2004) on Japanese banks. Equity and real state investments are separately modeled through multiple one-factor models, with systematic and unsystematic risk components.

In addition to the bank's assets and liabilities we also model net non-interest income. Net non-interest income is defined as fee income plus other non-interest income minus operating expenses. This sum is typically divided by total assets. We use historical information on this ratio to estimate, as of the end of simulation period, how much the bank will have spent on operations. This amount is then deducted from the bank's simulated net interest income plus (minus) capital gains (losses). Unlike state variable returns that are

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[14] Mortgage loans in Brazil are mostly concentrated in the hands of one single government bank: Caixa Economica Federal. Commercial banks hold just a tiny fraction, if any, of mortgage loans. For this exercise, we will allocate any amount of mortgage as business loans (because they have collateral).

[15] More detailed information on the stochastic processes formulation underlying the simulation framework can be found in Barnhill and Maxwell (2002).

[16] We initially include the government loans in this category (no risk of default). There is a simple way of simulating the risk that the government might default on its debt, which will be discussed in more details below.

estimated for each time-step in each simulation path, all balance sheet accounts are recalculated only at the end of each simulation period[17].

2.3. Banks Portfolio Composition

It is possible to model a great variety of financial instruments (e.g. bonds, zero coupon bonds, variable rate loans, forward contracts, swaps, options, etc.) within our simulation framework. Absent other information, loans (which usually comprise the biggest fraction of most banks portfolios) are typically modeled as bonds. We allocate business and customers loans separately across various credit risk categories. In the case of business loans, we also distribute them across business sectors, while loans to individuals are distributed across regions. This break down is important for capturing the portfolio diversification or concentration aspects of the risk analysis as well as the integrating of market and credit risk[18]. The data used in the application of the model to the Brazilian banks and banking system is discussed more fully in Appendix 2 and Tables 1 - 9[19].

3. Simulation Results

Our risk assessments relate to four sets of Monte Carlo simulations: (i) individual banks, with no government default, with volatilities and correlations estimated over the 2000-2004 period, (ii) individual banks, with no government default; (iii) individual banks, with government default; and (iv) systemic risk. In the first set of simulation our goal is to compare simulated and historical rates of return on bank equity and assets. In the second and third sets of simulations we wish to compare individual bank risk with and without Sovereign default risk. We also compare the risk assessment produced by our portfolio simulations with the bank credit ratings provided by Fitch, Moody's, and Standard and Poor's. Using the risk assessments from the third set of simulations we group banks into three risk categories and construct three aggregate banks. In the fourth set of simulations we undertake a simultaneous risk analysis these three aggregate banks to assess systemic bank risk (i.e. the likelihood of multiple banks defaults) reflecting market, credit, Sovereign, and inter-bank risk.

3.1. Individual Banks, No Government Default, Higher Volatilities

The first set of our simulations comprises 13 Brazilian private domestic banks, which we will use for model validation purpose. The idea is to compare averages and standard deviations for simulated ROAE and ROAA, with values estimated over historical data. Given that this data is not available for a long period in Bank Scope (generally just the previous 8 eight years), and considering the set of events that have recently occurred in Brazil, in particular the aftermath of Russian crisis (1999) that culminated on government authorities dropping the currency peg that was the main anchor of the stabilization plan put forth in 1994, we will focus our analysis on the 2000-2004 period, which gives 5 years of annual historical data on ROAE and ROAA. Since in this period the GOB has not experienced any default on its debt obligations, we will simulate these 13 banks, over 1-year period (December 2004 to December 2005) assuming that the GOB does not default.

To make this simulation exercise as consistent as possible, we have estimated a new set of volatilities and correlations (Table 9), using monthly data for the same variables and over the same 2000-04 period.

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[17] We also specify the time-horizon and the time steps over which price paths and balance sheet accounts will be simulated, and the number of simulation runs.

[18] Our approach to modeling loan credit quality migrations and defaults is discussed more fully in Appendix 1.

[19] In total ValueCalc's portfolio simulation models approximately 450 different securities for each bank. This level of detail is needed to adequately capture correlated market and credit risk for asset and liability portfolios with loans spread across different credit categories, sectors, and regions.

Both volatilities and correlations are substantially different than the ones estimated for the 2003-04 period. In general, using data for 2000-2004 increases the volatility reasonably, which is not totally surprising at all, given the Argentina default in 2001 and the election in Brazil in 2002, which both had a significant impact on the volatilities of the underlying state variables as discussed above. Higher equity volatility broadens the distribution of simulated company D/V ratios and, subsequently, increases simulated default rates impacting banks portfolios, balance sheets, and, ultimately, simulated ROAE and ROAA.

We focus on ROAE and ROAA ratios, because they are intuitive and widely used measures of banks' profitability. To be able to simulate distributions for these ratios that are reasonably close to historical values, is an important achievement in the context of our simulation framework and highlights the capabilities of the methodology in place. Simulated ROAA and ROAE are reported in Tables 10 and 11 and, at a first glance, they seem strikingly close to historical values, for some banks. For example, average simulated ROAA is 0.020 for Bank

8, while historical mean is 0.019. Likewise, Bank 27 has a simulated average ROAA of 0.019 against a historical mean of 0.018. Other banks simulated values depart more from historical averages and standard deviations, in particular Bank 9 and Bank 7. Looking closer at these banks balance sheet structure, we find out that not only are they fast-growing banks (having increased their total assets by almost 500%, during the 2000-04 period), but their portfolio composition also has changed substantially. It is noteworthy that our simulation framework does not allow for such dynamic portfolio rebalancing, which makes it difficult to replicate historical values in such cases. Bank 9 and Bank 7 are then excluded from the analysis that follows.

In order to investigate further whether simulated means and standard deviations for ROAA and ROAE are unbiased estimators for historical means and standard deviations, we perform the following regressions:

$$ROAAavg_{h,i} = \beta_1 \cdot ROAAavg_{s,i} + \varepsilon_1 , \tag{1}$$

$$ROAAsd_{h,i} = \beta_2 \cdot ROAAsd_{s,i} + \varepsilon_2 , \tag{2}$$

$$ROAEavg_{h,i} = \beta_3 \cdot ROAEavg_{s,i} + \varepsilon_3 , \text{ and} \tag{3}$$

$$ROAEsd_{h,i} = \beta_4 \cdot ROAEsd_{s,i} + \varepsilon_4 , \tag{4}$$

where $ROAAavg_{h,i}$, $ROAAsd_{h,i}$, $ROAEavg_{h,i}$, $ROAEsd_{h,i}$ are averages and standard deviations for ROAA and ROAE, using annual historical data during the 2000-04 period, for each bank i in our validation sample, and $ROAAavg_{s,i}$, $ROAAsd_{s,i}$, $ROAEavg_{s,i}$, $ROAEsd_{s,i}$, are averages and standard deviations for ROAA and ROAE using the 2000 simulated values generated as of December 2005. We then use a Wald type-statistics for testing the null $\beta = 1$. (If $\beta = 1$ the simulated return means and standard deviations are unbiased predictors of the historical return means and standard deviations). We also performed one more regression using all observations for both ROAA and ROAE, averages and standard deviations (pooled observations). Results for these regressions are presented in Table 13. These results show that the: (i) beta coefficient is usually close to one (exception is beta for ROAA standard deviation regression, which is equal to 1.75); (ii) adjusted R^2 is quite high in all regressions (again, the smallest one is the adjusted R^2 for ROAA standard deviation regression, which is equal to 0.53; (iii) in all regressions, the Wald Statistics fail to reject the null, $\beta = 1$, at 95% confidence level.

While encouraging, these results need to be taken with care for several reasons. First, historical averages and means are calculated using only 5 annual observations (from to 2000 to 2004). Thus, adding or dropping one observation can make a significant difference in estimating averages and standard deviations, particularly if we consider that these banks operate in a volatile environment and that Brazil has experienced some acute shocks recently (e.g. the fear of contagion from Argentina default). Second, we use observations for only 11 banks to run the regressions (only pooled regression uses 44 observations). Adding or dropping banks from the sample will likely affect the results (for the better or for the worse) as well. Finally, we are using means and standard deviations for historical ROAA and ROAE, estimated on the temporal direction, to regress against means and standard deviations for simulated ROAA and ROAE, generated for a slice of time (as of December 2005). The underlying assumption is that historical ROAA and ROAE are stationary and thus it makes sense to compare the different measures. It is virtually impossible to test whether ROAA and ROAE are stationary or not, with such small time series.

3.2. Individual Banks, No Government Default, Lower Volatilities

The second set of our simulations comprises all 28 banks, simulated individually, assuming that the GOB will never default on its domestic debt over the simulation horizon (1-year) [20]. Simulation results for this group are presented in Table 13, and a few comments are in order. First, reported VaR levels indicate the percentage of time that simulated values fall above a certain threshold. For example, Bank 20 VaR at 99% level is 0.154, indicating that 1% of the time simulated capital ratios for Bank 20 have fallen below 0.154. Second, with a few exceptions, Brazilian banks are well capitalized. For example, Bank 12 has a 0.252 capital ratio and Bank 6 has 0.382. Banks with capital ratio below 0.07 are Bank 5 (0.059), Bank 14 (0.062), Bank 16 (0.065), Bank 21 (0.067), and Bank 23 (0.063). Third, in general, *if* we do not factor government default into the simulations, Brazilian banks are profitable and have an increasing capital ratio on average over the 1-year simulation period. The exception is Bank 6, which has an average simulated capital ratio of 0.372, against an initial capital ratio of 0.382. Bank 6 is the bank with smallest interest rate spreads after we adjust the spreads so as to match historical reported net interest margin. Bank 12, Bank 7, and Bank 19 have a drop of only 0.01 relatively to the initial capital ratio, which we still consider to be within the sampling error range. None of the banks produce simulated capital ratios that would indicate significant default risk problems over a one-year time step. Even the minimum simulated capital ratios are well above the 3% level which we have set as the critical bank capital level at which banks begin to default. Although in several cases the simulated capital ratios are below the 0.08 threshold often used to evaluate banks (e.g. Bank 5 with 0.043, Bank 7 with 0.050, and Bank 21 with 0.057, among others). Finally, simulated capital ratios have a very small standard deviation for all banks, ranging from 0.001 (Bank 19) to 0.007 (Bank 13 and Bank 24). Given the substantial amount of government loans held by these banks, this result is not surprising at all. Bank 9 holds a more modest fraction of government loans. However, the credit quality of its portfolio is fairly high, with corresponding small default rate.

3.3. Individual Banks, Government Default

Since Brazilian banks hold a significant amount of GOB debt, it is very important to assess the impact of correlated Sovereign risk on banks' default probabilities. For this exercise, we propose to model government default in a relatively simplistic way, which we claim still can provide reasonable insights on banks' exposure to Sovereign risk. In particular in the current study we model the GOB as if it were a large corporate borrower, subject to systematic and idiosyncratic risk factors. When determining these parameters, we need to be able to reproduce reasonably closely the rate at which a sovereign country like Brazil is expected to default, given its current macroeconomic conditions. We also wish to capture appropriately the correlations between market risk, private sector loan defaults, and Sovereign defaults.

For this purpose we draw heavily from a recent study published by Klaar, Rawkins, and Riley (2004) on Sovereign Rating and default rates, by surveying the government default cases that have been witnessed in the past 10 years, for the countries they assign sovereign rating (Table 14). The definition of government

[20] In fact as we shall see in the next section, countries at the same sovereign rating as Brazil (B) have a one-year default rate of 4.5% on average in the past 10 years, consistent with Klaar, Rawkins, and Riley (2004).

default itself is neither simple nor consensual[21]. Fitch defined default as a failure to make timely payment of principal and/or interest on either: (i) rated foreign currency debt; or (ii) other material foreign currency debt obligations, such as Paris or London Club liabilities. Even though we are more concerned with government default on domestic debt, we believe the Fitch study provides useful guidelines as to estimated default rates. We present in Table 16 the government default cases studied by Fitch, after 1998. Of 6 cases, only two countries have been downgraded to a D category, after the default event. One case is Argentina, which defaulted on over US$ 70 Billions (sovereign foreign currency bonds), in 2001, and was downgraded from BB to DDD (recovery expected to be around 90%-100%). The other is Moldova, which defaulted on US$ 75 millions of Eurobonds (later restructured and followed by a Paris Club deal), in 2002, and was downgraded from CC to DD (50%-90% expected recovery rate). Other countries, even though they fitted in the default definition above, were not downgraded to D categories. Indonesia was downgraded from BB+ to B- after rescheduling payments to Paris and London Clubs in 1998, while Uruguay was downgraded from B to B-, after a distressed debt episode (over US$ 5 billion of foreign currency sovereign debt) in 2003. Russia was more severely downgraded, from BB+ to CCC, in 1998, with a default on its domestic debt that quickly spilled over to foreign currency debt as well. Ukraine defaulted on Eurobonds in 1999, prior to the first public Fitch rating. However, Fitch has maintained a shadow rating of B before the episode and B- after the episode. The importance of these ratings go beyond potential interest rates charged on sovereign debt for these countries, or giving potential investors a sense of country risk level. For the present study, using the model discussed earlier (see Appendix 1 for more technical details), we chose to produce GOB average default rates that are comparable to the average default rates of countries sovereign debt rated at the same risk level as Brazil (B). We assume the government to default at an average rate of 4.5%, consistent with Klaar, Rawkins, and Riley (2004).

An important issue in the event of a sovereign default on its foreign debt is the government's willingness/ability to honor its domestic debt obligations. While the government may want to expand its monetary base in order to repay domestic loans, this practice has well-known nocive effects on the economy, which might, eventually spill-over into the banking system. It is also possible that the government may force debt holders to change their contracts for something that has a lower market value than the original ones. In any instance, even if the government does not fully default on its domestic debt, the banks may ultimately incur market value losses. To be able to model this explicitly is not an easy task. No one knows for sure which set of actions will be taken by the government during such events. There are then innumerous possible outcomes for banks each of which will impact banks' portfolios differently. Given this limitation, we propose to construct a matrix of some potential government default implications that will provoke additional losses on banks' portfolios, through two different channels. The first channel incorporates losses directly on the government loans, by assuming that banks may lose 0%, 10%, or 25% of the market value of their government loans. Such losses may result from increases in required market risk spreads, because the government may defer payment of the debt, or may force banks to change the terms of the debt in ways that reduce its value.

In addition government default events are usually associated with major disruptions in the whole economy, affecting all sectors, and banks' borrowers may become incapable of repaying some of their debts. We conjecture that these events will impact firms with different credit worthiness differently. That is, we assume that firms with higher credit quality are better prepared to handle these crisis events. The way we capture the differential impact of a Sovereign default is by imposing an increase on the default rate on private sector loans in different credit categories. We assume three different scenarios: (i) businesses and individuals have a zero increment to their default rates; (ii) businesses and individuals in each credit risk category have

[21] Indeed, considering that governments have the option to issue money to pay domestic debt, it is even more troublesome to define government default on domestic debt. In this study we keep the matters simple and simulate government default at an average rate (4.5%) consistent with what Klaar, Rawkins, and Riley (2004) report for sovereign debt default for countries graded by Fitch as B level (like Brazil).

an increase in their default rates equal to the average default of that credit risk category[22], and (iii) businesses and individuals in each credit risk category have an increase in their default rates equal to two times the average default of that credit risk category.

The combination of all these possible outcomes lead to 9 potential Government and private sector incremental loan loss scenarios bank may face in the event of a government default. While these scenarios are far from exhausting the innumerous alternatives, they do provide a reasonable range for incremental bank loan losses.

In Tables 15 to 17 we report the average simulated default rate[23], the associated average cost to bring banks' capital ratio back to a 0.08 level (estimated only for the times when the bank defaults), and the 99% VaR capital level (banks have 1% probability of having their capital ratios falling below this level). Given that banks hold a significant amount of government loans, default rates start to appear significant only when there is some degree of losses on government loans. For example, if banks lose an average of 10% in the market value of their government debt, then 5 banks (e.g. Bank 5 and Bank 16) will default around 4%-5% of the time. If banks lose 25% of the market value of their government loans, then 15 banks (e.g. Bank 3, Bank 8, Bank 10, etc.) will default around 4%-5% of the time. In either of these cases (i.e. 10% or 25% loss rates) the bank failures would result from a Sovereign default and thus would be highly correlated and could precipitate a systemic banking system problem. Interestingly, some banks will not default at all (e.g. Bank 1 and Bank 2), even in the worst case scenario that we analyze in this paper (losing 25% of the market value of government loans and suffering incremental defaults on business and individual loans equal to twice their average historical default rates). These banks either are highly capitalized, and thus capable of absorbing a larger shock on the government loans, or they have a balance between government, business, and customers' loans that allows them to diversify the risk of a potential government default, along with a high net interest margin stemming from large interest rate spreads. The average cost (as percentage of total assets) to bring the banks back to a 0.08 capital level whenever they default is usually pretty high. For example, if the GOB defaults and the banks lose 25% of the market value of their government loans, this 'bail-out' cost ranges from 0.052 of total assets (Bank 3) to 0.278 (Bank 22). Again, the large amount of government loans held by Brazilian banks make them quite vulnerable in the event of a Sovereign default, potentially requiring large amounts of capital to bail them out. The simulated 99% VaR capital ratios just reinforce the size of the losses these banks face in the event of government default. If banks lose 25% of the market value of government loans, capital ratios may range from 0.245 (Bank 6) to -0.199 (Bank 22).

While relatively simplistic, this approach to modeling correlated market, credit, and sovereign risk highlights the danger of the exposure of many Brazilian banks to very high levels of GOB loans. It is true that Brazil has been implementing more responsible fiscal and monetary policies, controlling the inflation, and obtaining important positive balance in exports/imports, among other positive indicators. However, Brazil is still an emerging economy, vulnerable to flow of capitals, with a huge stock of debt (both domestic and foreign)[24]. Thus, government loans are not free of risk, and the correlated risk of government default should be accounted for.

3.4. Rating Brazilian Banks

We now will compare the simulated results obtained in the previous section with rating agency ratings of Brazilian banks[25]. We will focus our attention on a single output derived from the simulations

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[22] See Table A1. 2 in Appendix 1 which gives the average one-year historical default rate on Brazilian bank loans with various credit qualities.

[23] We consider the bank to default whenever its simulated capital ratio equals 0.03 or less.

[24] Total debt to GDP is around 55%, as of December 2004 (source: Government Financial Statistics, IMF).

[25] Since business and customers' loans, as well as 90% of government loans are modeled with 1-year maturity, we use the ratings for the short-term debt instruments that these banks hold.

including the risk of a Sovereign default. In particular we will look at the 99% confidence level capital ratio (99% VaR level) for the scenario where in the event of a Sovereign default banks lose 10% of the market value of their government loans and experience an incremental increase in defaults on their private sector loans equal to twice the average default rate. This measure embeds both the default probability and the size of associated monetary loss and is consistent with what the rating agencies also utilize for rating banks, businesses, and Sovereigns. For this purpose, we will divide our sample of banks into three groups, according to their 99% VaR capital level. Group 1 will be comprised by banks with 99% VaR capital ratios less than 0.07, Group 2 with banks with 99% VaR capital ratios between 0.07 and 0.13, and Group 3 with 99% VaR capital ratios above 0.13. Since the 99% VaR gives the threshold below which banks capital ratio will fall 99% of the time, the lower the 99% VaR level, the closer the bank is to the critical 0.03 level and the higher the probability of default (thus the riskier the bank).

Results from our credit classification are provided in Table 18, along with the ratings from Fitch, Moody's, and Standard and Poor's. Our ratings are generally more consistent with Moody's and Standard and Poor's than with Fitch. For example Fitch rates Bank 28 as AA (investment grade), while we place it in the riskier group 1. Bank 28 is rated as B3 or BB- by Moody's and Standard and Poor's (not investment grade anymore), respectively. However we rate Bank 27 in the group 3, consistent with Fitch that rates it as AA-, while Moody's and Standard and Poor's rate them in the B3 or BB- categories.

We want to stress that our results should be taken only as an additional piece of evidence when interpreting the ratings for several reasons. First, there are some data limitations underlying our analysis, since we have not obtained all the information that would be desirable for this study. Importantly, detailed information on banks' portfolio (for example, the distribution by business sectors) and on interest rate spreads (an important component in Brazilian banks risk assessment) have not been made available to us. Second, our classification only takes into account the 99% VaR level capital ratio. We do not combine this piece of information with any other information on banks' balance sheet and portfolio composition, as the rating agencies do. Finally, we have modeled government default in a relatively simplistic way. Barnhill and Kopits (2004), and Barnhill (2006) have shown the possibility of modeling government balance sheets in more detail using a similar PSA methodology. In spite of these limitations, we believe our methodology presents a plausible approach for assessing correlated market, credit, and Sovereign risk for individual banks. As we will discuss in the next section we believe it also provide an opportunity to assess systemic banking system risk, which includes all of the above correlated risks in a simultaneous analysis for multiple banks plus the risk of correlated inter-bank defaults.

3.5. Systemic Risk

For assessing the risk of multiple banks failures, we will consider two cases. First, we aggregate the 28 banks into one single bank. Second we aggregate banks according to their risk rating, in the three groups described above. Aggregated balance sheet accounts were obtained by simple addition from all banks in each group, while loan credit quality distributions and assets and liability maturity structures were obtained by a weighted average (size of each category relatively to total assets, in each bank).

3.5.1. One Single Aggregate Bank

The simulation results for a single aggregate bank (Table 19) are consistent with what we have obtained for individual banks. When we do not consider government default, simulated capital ratios are comfortably above an assumed 0.08 target capital level, with small standard deviation (0.003), given the substantial amount of government loans that are collectively held by the 28 banks in our simulation sample. Because the single aggregate bank has a 0.154 initial capital ratio it does not face solvency problems when a Sovereign default imposes market value losses on government loans of 10%. At a 25% loss rate on Government loans, in the event of a Sovereign default, the default rate on the single aggregate bank may reach 2.2% and the associated cost to bring the single-bank capital back to a 0.08 level averages 5.5% of the bank's total assets. The 99% VaR also deteriorates substantially. Under the no-government-default assumption it is 0.147, while it drops to 0.024 under the above Sovereign default scenario.

Modeling systemic risk via a single aggregate bank has significant limitations. First it masks the fact that under certain conditions (e.g. 10% loss rate on government loans) a number of individual banks could fail simultaneously[26]. Second this approach does not account for inter-bank exposures that can trigger sequential failures, as discussed above. Still, the simulated results do show the importance of modeling correlated Sovereign risk not only at an individual bank level, but also, and perhaps most importantly, at a systemic level.

3.5.2. Multiple Aggregate Banks

So far we have simulated the banks individually and taken account of correlated market, credit, and Sovereign risk. However we have not taken into account one important channel for propagating a systemic crisis, through inter-bank credit exposures. For this purpose, we will simulate the 3 aggregated banks (Groups 1, 2, and 3) simultaneously, under the same financial and economic environment[27]. Then we will examine the simulated capital ratios for all three banks to determine if one or more banks fail. In that event we will then calculate the default impacts on other banks as the failed banks become incapable of repaying their inter-bank debts. This exercise will be explained in more detail in section 3.5.2.2. Before we get there, however, it is useful to describe the groups separately and to simulate them individually, to have a more precise understanding of their default risk.

3.5.2.1. Individual Aggregate Banks

Simulated capital ratios, without Sovereign risk (Table 22), show that all three groups of banks are profitable and on average have increasing capital ratios. When Sovereign risk is considered (Table 23), then only Group 3 survives all our simulated scenarios (same as for the individual banks). Groups 1 and 2 have non-zero default rates when their assumed losses in the market value of Government debt increase from 10% to 25%. Under the scenario of 25% average losses on government loans, Group 1 defaults at an average rate of 0.047 and Group 2 defaults at rates in the range of 3.1% to 4.6%. The average cost of 'bailing-out' these banks is large, for Group 1 it surpasses the 12% of total assets required to bring its capital ratio back to a 0.08 level. For Group 2 the average bail-out cost it is around 6% of its total assets.

Another important risk measure, the 99% VaR capital level, provides an even more distinct picture. All banks have their 99% VaR capital level deteriorate when a Sovereign default results in market value losses on government loan. If such loses reach 25% of market value then the 99% VaR capital levels for Groups 1, 2, and 3 falls to the range of -0.05, 0.02, and 0.12 respectively.

3.5.2.2. Simultaneous Aggregate Banks

For assessing systemic risk, we simulate correlated market, credit and Sovereign risk for the three groups of aggregate banks simultaneously, under the same financial and economic environment. Then, in a second analytical step, we introduce the inter-bank propagation channel by adjusting each group's simulated capital ratio whenever one of the other two groups' simulated capital ratios fall below 0.03, using the information on inter-bank lending (Table 20) and assuming that the groups borrow money from others proportionately to their total assets. For example, Group 1 lends 3.6% of its total assets or equivalently R$5,503.60 Millions. Since Group 2 has total assets of R$551,250.10 Millions and the sum of Group 2 and Group 3 total assets is R$878,571.10 Millions, we assume that R$551,250.10/R$878,571.10 = 0.63 of Group 1's total inter-bank lending is lent to Group 2. The remaining 1 – 0.63 = 0.37 is lent to Group 3.

[26] Also, we are simulating only 28 Brazilian banks (70% of financial system total assets). Including more banks would certainly push the cost for bailing the financial system out to a higher level.

[27] The choice of using three banks as opposed to all 28 banks was made primarily because of memory limitations in the Excel spreadsheet application of the ValueCalc software. Relieving such memory is an area of current work.

For estimating the impact of inter-bank lending, when banks default, we assume inter-bank lending to be risk-free in the first step of the simulation[28]. Then, we assume that when one group defaults, the other groups will recover at the same average as the other types of loans, 50% of the defaulted inter-bank loans. Obviously, higher recovery rates would certainly diminish the impact of inter-bank default. We then recalculate simulated total assets and simulated capital ratios, after deducting the defaulted amounts that are not recovered. With new simulated capital ratios, we replicate the same VaR analysis and also estimate default rates and the monetary cost to bring groups' capital ratios back to 0.08 capital level. We also estimate the default rates and monetary cost when two banks and three banks default simultaneously. These results are presented in Tables 23 and 24 and few comments are in order. First, as expected, the inter-bank propagation channel moves from the riskier categories to the less risky categories. Second, because Group 3 is very well capitalized and has the highest credit profile, it only defaults when incurring a much bigger loss on the government loans. Group 3 starts having solvency problem only when a Sovereign default imposes a high average loss of 40% or more on the market value of government loans. This reveals another nocive facet of banks holding exceedingly large concentrations of government loans. In the event of a Sovereign default, the government has constrained debt management alternatives. Should the government take actions that result in a heavy loss on the market value of government loans, then it may trigger a systemic risk default in the financial system. In the particular case of GOB, our analysis suggests that losses on government loans of 10% could create significant solvency problems for 5 or 6 out of 28 banks analyzed. Higher loss rates would of course create eve larger systemic banking system risks. It is important to emphasize, however, that this number should be taken as illustrative, rather than definitive, given the limitations of the data we have utilized in this study and given its stylized framework. Since the amount of GOB loans in Brazilian balance sheets dwarfs the amount of business and customers' loans, the impact of incremental defaults on business and households has little effect on banks' default rates and monetary losses. Third, when we integrate the inter-bank risk into our framework, systemic default rates (i.e. risk of multiple bank failures in the same time period) are smaller compared to the individual banks default rates. However, when the systemic event takes place, it is a lot more costly (as a percent of the assets of the defaulting banks) than previously assessed when simulating all 28 banks as a single bank. We have estimated the average cost to 'bail-out' the single-bank to be 5.5% of its total capital under the scenario of a 25% average loss on government loans. Under the same scenario, the two riskier groups default at a rate in the range of 1.6% to 2.9%, with the average cost to bring their capital level back to 0.08 level equal to 10% of their total assets.

4. Concluding Remarks

We examine a sample of 28 of the largest Brazilian banks, in an effort to assess and quantify the risk of a systemic failure. 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, particularly for countries that may not have the necessary financial resources to deal with the scope of this type of event. Even though the number of banks we simulate in our sample is fairly small as compared to the total number of financial institutions in Brazil (1882), we believe these 28 banks are large and representative enough to provide a reasonable measure for the systemic risk of Brazilian financial system.

The fact that Brazil is a leading emerging economy in Latin America and has a developed financial system with some peculiar features (like the size of government loans held by banks and the interest rate spreads that are charged from business and customers' loans), make this a very interesting exercise. Indeed, it is exactly because of that that we have simulated the banks individually, considering two different scenarios. In one, the Brazilian government is assumed never to default on its debt obligations and with few exceptions, Brazilian banks perform very well, increasing their capital on average over the 1-year simulation horizon.

After regressing average and standard deviations for ROAE and ROAA between simulated and historical values, for a set of private domestic banks, we find that moments for simulated values are unbiased

[28] This is to avoid 'double-counting' the effect of inter-bank default. Initially, inter-bank loans were lodged as loans to the banking sector.

estimators for historical averages and standard deviations. While this result needs to be taken with a lot of caution, it does show the capability of the PSA framework for simulating banks portfolios and balance sheets and produce profitability ratios distributions that are reasonably comparable to historical values.

In a second set of risk assessments we factored government default in and the picture changed substantially. For this purpose, we modeled the government as a large 'corporate' borrower impacted both by systematic risk in the form of stochastic equity market returns but also idiosyncratic return risk. We calibrate this model to produce an assumed average sovereign default rate of approximately 4.5%, which is the average rate for sovereign rated debts in the same rating category of Brazil (B), according to a study done by Fitch. Such defaults are systematically related to the returns on the Brazilian equity market and are thus correlated with general economic and financial conditions in Brazil and thus private sector loan defaults as well.

We also compared our bank risk assessment to the ratings given by Moody's, Standard and Poor's and Fitch. We find our ratings to be generally consistent with those of the rating agencies. This suggests to us that, given the needed data, it would be possible for off-site bank supervision departments to implement a systematic forward looking bank portfolio risk assessment methodology for all banks operating in a particular country as well as a systemic risk analysis for the entire banking system. Such analytical approaches also allow the testing of alternative policy actions (e.g. bank capital levels, portfolio concentration levels, etc.) to help manage such risks before they materialize.

Considering Sovereign risk, virtually all Brazilian banks generated simulated capital ratios that are much lower at a 99% confidence level, under the scenario of GOB imposing losses of 10% to 25% on the government loans held by banks. At a 10% loss rate on government loans in the vent of a Sovereign default 5 or 6 of the 25 banks could fail. At a 25% loss rate on Government loans over half of the 28 banks could fail. One exception is BANK 9, which continued to produce favorable simulated capital ratios even after considering sovereign risk. Bank 9 is a bank with a much smaller fraction of total assets invested in government loans. Thus, balancing better the portfolio between government, business, and customers' loans may not only yield more profitable loans portfolios, but also hedge the banks against a potential government default. GOB debt is not free of risk. Concentrated lending to an entity with a non-zero default probability creates well known portfolio risks.

For conducting the systemic risk analysis, we grouped the banks in three categories. For this purpose, we used the results from the individual banks simulations (with government default) and have categorized banks in to three credit risk groups, based on their default risk. Once the groups have been created, we utilize two different approaches to measure systemic risk. First we aggregate all the banks in one single bank and simulate it individually, with the possibility of government default. Results for this approach show that the financial system might be dragged down by a government default only when the average loss on government loans is 25% or higher and that the cost to bail the system (to bring the average capital ratio to 0.08 level) is about 5.5% of the total assets, under this scenario.

In the second approach we simulate the three groups separately and simultaneously, under the same financial and economic environment. In this first pass we assess the impact of correlated market, credit, and Sovereign risk to assess bank failures. In a second pass we assess the impact of inter-bank defaults on the remaining banks' capital ratios to determine is they may also fail. Our results show that if a bank has heavy inter-bank credit exposure as compared to its initial capital then correlated inter-bank default losses may become "the straw that breaks the camel's back". More important, however, was the estimated bail-out cost when the three groups defaulted simultaneously (which amounts for a systemic failure of Brazilian financial system). Even though the three banks may default only when facing much heavier losses on government loans (40% or more), the cost associated with such event reaches the range of 16%-18% of total assets. Our analysis also reveals another nocive facet of banks holding very large concentrations of government loans. In the event of default, the government has limited debt management alternatives. Should a government action cause significant loss in the market value of government loans, then it may trigger a systemic risk default in the financial system. In the particular case of GOB, in the event of government default, losses of 10% or higher on government loans could have significant systemic banking system impacts. It is important to emphasize, however, that this number should be taken as illustrative, rather than definitive, given the limitations of the data we have utilized in this study and given its stylized framework. Since the amount of

GOB loans in Brazilian balance sheets dwarfs the amount of business and customers' loans, the impact of incremental defaults on business and households has little effect on banks' default rates and monetary losses.

It is important to emphasize that our results should be taken as illustrative rather than definitive assessment of Brazilian bank risk. This is so for two main reasons. First, from a data standpoint, we have not succeeded to obtain more detailed (and specific) information on banks portfolios and on interest rate spreads charged by Brazilian banks. This information is protected by a confidentiality law in Brazil and could not be provided to us because we have to map this information with public information such as banks' financial statements, making it difficult to maintain bank confidentiality. Second, there are some methodological shortcomings on our analysis that can be improved with further work. A potentially significant limitation of the study is its assumption of an average Sovereign default rate based on the Fitch rating. An attractive alternative would be to model the government's balance sheets in a more complete manner (e.g. see Barnhill and Kopits (2004), or Barnhill (2006)) simultaneously with the country's banking system. We believe this approach could improve both the average Sovereign default rate estimation and the correlations between Sovereign defaults and other risk factors. It may also give important new insights into optimal policy decisions to manage the risks of both Sovereign defaults and systemic banking crises. It would also be interesting to improve further the methodology for modeling customers' loans in contrast to our approach of considering these loans to behave similarly to corporate loans. Finally, considering the significant operational expense ratio incurred by Brazilian banks, it would be quite interesting to build operational expense variations into the simulation model. A simplistic way of capturing this risk facet could be through fitting a stochastic process into the operational expense ratio time series and simulating it within the PSA framework. In spite of all the limitations we believe that the portfolio simulation methodology has been demonstrated to have the potential to provide important insights into bank and systemic banking system risk levels.

Appendix 1: A Conceptual Framework for Fixed Income Portfolio Integrated Market and Credit Risk Assessment[29]

Financial environment simulation modeling combined with portfolio theory offers a very promising integrated risk assessment approach. In general, 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. Combining such separate risk measures into one overall portfolio risk measure is not easily accomplished. The absence of reliable overall portfolio risk measures creates problems for determining capital adequacy requirements, capital-at-risk measures, hedging strategies, etc.

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 returns (as distinct from economic sector index) 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, market equity returns, etc.) as well as firm 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.

A1.1. Simulating Interest Rates

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

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

where

Δr = the risk-neutral process by which r changes,

a = the rate at which r reverts to its long term mean,

r = the instantaneous continuously compounded short-term interest rate,

$\theta(t)$ = "Theta" is an unknown function of time that is chosen so that the model is consistent with the initial term structure and is calculated from the initial term structure,

Δt = a small increment to time,

σ = the instantaneous standard deviation of r, which is assumed to be constant, and

Δz = a Wiener process driving term structure movements with Δr being related to Δt by the function $\Delta z = \varepsilon\sqrt{\Delta t}$.

The above mean reversion and volatility rates can be estimated from a time series of short-term interest rates or implied from cap and floor prices. Credit spreads can either be modeled as correlated log normal variables or as fixed values.

[29] This appendix is drawn largely from Barnhill, Souto and Tabak (2003).

A1.2. Simulating Asset Prices and Returns

The model utilized to simulate the value of the equity market indices (*S*) assumes that (*S*) follows a geometric Brownian motion where the expected growth rate (*m*) and volatility (σ) are constant (Hull 1997, p. 362). The expected growth rate is equal to the expected return on the asset (μ) minus its dividend yield (*q*). For a discrete time step, Δt, it can be shown that

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

where:

ε = a random sample from a standardized normal distribution.

The return on the market index (K_m) is estimated as

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

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

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

where

K_i = the return for the $asset_i$,

R_F = the risk-free interest rate,

$Beta_i$ = the systematic risk of $asset_i$,

K_m = the simulated return on the equity or real estate index from equation 3,

σ_i = the asset specific return volatility, and

Δz = a Wiener process with Δz being related to Δt by the function $\Delta z = \varepsilon\sqrt{\Delta t}$.

The parameters needed to implement the above model were estimated from historical data on the Brazilian financial market.

A1.3. 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 the set of correlated random error terms for the *n* stochastic variables can be calculated. For example, for a bivariate normal distribution,

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

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

where

x_1, x_2 = independent random samples from standardized normal distributions,

ρ = the correlation between the two stochastic variables, and

ε_1, ε_2 = the required samples from a standardized bivariate normal distribution.

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

A1.4. Mapping Debt Ratios into Credit Ratings

The above-discussed simulated equity returns are then used to estimate a distribution of possible future firm equity values and debt ratios. The simulated debt ratios are then mapped into credit ratings. This methodology assumes a deterministic relation between a firm's or property's debt ratio and its credit rating[30]. In a contingent claims framework this is equivalent to assuming a constant volatility for the value of the firm.

After simulating the bond's or loan's future credit rating its value is calculated using the simulated term structure of interest rates appropriate for that risk class. If the bond or loan is simulated to default, the recovery rate on the bond is simulated as a beta distribution[31] with a specified mean value and standard deviation.

A1.5. Model Calibration for Brazil

A very important piece of information in the business credit risk modeling concerns the estimation of risk of companies in the economy. Using 12 sector indices for Brazil, betas for over 500 companies were estimated. Based on this analysis and experience in similar modeling efforts in the U.S., Japan, and South Africa, Barnhill, Souto and Tabak (2003) estimated the following ranges for debt ratios, beta, and unsystematic risk levels for Brazilian business firms with various credit ratings (using the credit risk scale established by Banco Central do Brasil).

Table A1.1: Debt Ratios, betas and Unsystematic Risk used in the Simulations

	AA	A	B	C	D	E	F	Default
Debt-to-Value ratios								
Lower bound	0.270	0.457	0.660	0.745	0.785	0.798	0.802	0.960
Target	0.405	0.620	0.810	0.838	0.890	0.902	0.894	0.960
Upper bound	0.516	0.706	0.865	0.917	0.922	0.935	0.940	0.960
Beta	0.67	0.85	1.00	1.10	1.20	1.30	1.36	-
Unsystematic risk	0.38	0.55	0.69	0.71	0.77	0.78	0.72	-

A1.2. Simulated Transition Matrix

With the above model calibration Barnhill, Souto, and Tabak (2003) simulated the credit transition matrix for Brazilian business loans (Table A1: 2) and compared this simulated transition matrix to the historical credit transition matrix for two large Brazilian banks (Table A1: 2).

[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.

Table A1.2: Simulated Credit Transition Matrix: Historical vs. Stochastic Volatility (Barnhill and Souto (2005)).

Panel A: Historical CTM for two large Brazilian banks.

	AA	A	B	C	D	E	F	Default
AA	0.901	0.064	0.021	0.005	0.002	0.000	0.000	0.007
A	0.119	0.690	0.102	0.047	0.021	0.003	0.004	0.014
B	0.033	0.110	0.719	0.092	0.020	0.005	0.006	0.016
C	0.033	0.042	0.153	0.674	0.047	0.009	0.013	0.031
D	0.011	0.019	0.040	0.051	0.602	0.039	0.054	0.184
E	0.001	0.078	0.005	0.008	0.041	0.558	0.040	0.268
F	0.008	0.006	0.012	0.023	0.031	0.076	0.568	0.276

Panel B: Simulated CTM for two large Brazilian banks, with stochastic volatility and covariances.

	AA	A	B	C	D	E	F	Default
AA	0.905	0.094	0.001	0.000	0.000	0.000	0.000	0.000
A	0.103	0.698	0.196	0.002	0.000	0.001	0.000	0.001
B	0.007	0.107	0.661	0.190	0.011	0.008	0.003	0.014
C	0.003	0.060	0.145	0.706	0.038	0.012	0.008	0.030
D	0.001	0.020	0.058	0.053	0.579	0.076	0.027	0.187
E	0.001	0.013	0.038	0.045	0.019	0.576	0.042	0.266
F	0.001	0.014	0.047	0.050	0.025	0.007	0.581	0.276

Panel C: Differences in probability between simulated and historical CTM's.

	AA	A	B	C	D	E	F	Default
AA	-0.004	-0.030	0.020	0.005	0.002	0.000	0.000	0.007
A	0.016	-0.008	-0.094	0.046	0.021	0.003	0.004	0.013
B	0.026	0.003	0.058	-0.098	0.009	-0.003	0.004	0.002
C	0.030	-0.018	0.009	-0.032	0.009	-0.003	0.005	0.001
D	0.010	-0.001	-0.018	-0.002	0.023	-0.037	0.027	-0.003
E	0.000	0.066	-0.033	-0.037	0.022	-0.018	-0.002	0.002
F	0.007	-0.008	-0.035	-0.027	0.006	0.070	-0.013	0.001

Historical and simulated credit transition matrices for these two banks are very similar to one another. The most important difference being that the simulated default rates on AA and A rated loans is zero or close to zero, while the historical default rates have a small positive value.

Appendix 2. The Data

All input information for the simulation exercise was set either as of December 2004, or over a period that ends on December 2004. This forward looking simulation is run over a one-year time step to December 2005. All risk analyses (both individual banks and banking system) utilize 2000 simulation runs.

A2.1. Financial and Economic Environment

By the end of 2004, Brazil had overcome most of the uncertainties and concerns about potential contagion from the Argentinean crisis as well as the uncertainties regarding the fiscal and monetary policies that would be implemented by the new left of center government. As discussed by Barnhill and Souto (2005), the uncertainties associated with these events have led to substantial volatility in Brazil, with special impact on foreign exchange rates, equity indices, and interest rates. Indeed, after global investors realized that Brazil would not be dragged down by Argentina and after the new government showed clearly its disposition to continue in the path of pursuing responsible fiscal and monetary policies, many economic indicators have dropped back to lower and more stable levels (see Barnhill and Souto (2005) for a better description of the main macroeconomic time series dynamics in Brazil).

For estimating initial volatilities[32] and correlations, we use the period of January 2003 to December 2004 (Table 1). While somewhat arbitrary, we believe this period to be representative for the forward-looking analysis for Brazilian banks, incorporating what we believe to be most of the recent time series dynamics that can be observed for the state variables. The state variables selected are: Brazilian short-term domestic nominal interest rate, U.S. nominal interest rate, Brazilian FX rate, Gold, Oil, Brazilian CPI level, Ibovespa (the broad Brazilian equity market index), ten more business sector equity indices[33] (basic industry, construction material, chemicals, cyclical services, food production, food retail, forest and paper, telecommunications, and utilities), and the unemployment rates for five big cities in Brazil (Recife, Belo Horizonte, Salvador, Rio de Janeiro and Sao Paulo, and Porto Alegre). We present in Table 1 spot prices (as of December 2004), volatilities (annualized) and correlations for these variables[34]. For equity, we report average volatilities and correlations for all equity indices (Ibovespa plus the other ten sectors). For unemployment rates we report the average correlations for all cities. The annualized volatility used for unemployment rate was the same as the Ibovespa broad market index. The reason for that relies on the way we model customers' loans, similarly to business loans. These models utilize the simulated returns on equity market indices to generate future debt-to-value ratios which allow an assessment of credit transition probabilities and defaults. For these models to produce default rates comparable to historical levels the volatility of the reference market index (e.g. unemployment rates) needs to be consistent with that of equity market indices.

A2.2. Banking Sector

Brazil has a well-developed financial system with 1,882 financial institutions (including the credit cooperatives), with total assets of 1.45 trillions of Reais (or about 550 Billions of US dollars) as of December 2004 (Table 2), corresponding to 82.67% of nominal GDP. Most of the assets are concentrated in the hands of the 50 largest Brazilian banks, responding for 82.7% of the total assets of the entire financial system, 92.6% of deposits, and 88.3% of net income. When we add all tier-I and tier-II banks (total equal to 140 banks), total assets are 97.8% of the financial system, deposits are 98.2% and net income is 95.2%. These numbers give an idea of the degree of concentration in the Brazilian financial system.

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[32] By volatility we mean the standard deviation of return time series.

[33] The choice for these sectors obeyed the information we have on the banks' business loans distribution by business sectors. Those are the sectors for which this information was made available to us.

[34] Volatilities and correlations have been estimated using returns time series.

For this study we will focus our attention on 28 of the largest Brazilian banks. While somewhat modest compared to the total number of financial institutions in Tier-I and Tier-II, these banks represent a significant fraction of the Brazilian financial system (almost 70% of total assets, 74% of deposits, and 53% of net income). Further, these banks form a quite heterogeneous sample. There are 5 domestic government owned banks, 12 domestic privately owned banks, and 11 banks that have foreign ownership. With respect to the type of bank, the vast majority is comprised by commercial banks. There are 3 investments banks that even though they do not lend money to individuals, they do engage in corporate lending activities. As we shall see later, the heterogeneity in the sample pervades banks' balance sheet structure and portfolio composition. We thus feel comfortable that this sample provides a reasonable representation of the Brazilian banking system.

A2.3. Interest Rate Spreads

One final and very important characteristic of the Brazilian banking sector refers to the huge interest rate spreads charged by banks. The Central Bank of Brazil is undergoing an effort to collect and compile data on interest rate spreads from all Brazilian banks. Unfortunately, this information has not been made available to us. Barnhill, Souto, and Tabak (2004) have estimated interest rate spreads based on the average interest rate that is charged from Business and Consumers loans. Spreads (over the domestic 'risk-free' interest rate) were calculated so as to produce simulated net interest margins[35] that are compatible with reported values as available in Bank Scope. They assumed spreads to form a profile across different risk categories, consistent with stylized facts observed in the banking industry of other countries and that produces average interest rates comparable to those for the Brazilian banking system[36] (51% per year for business loans and 85% for customers' loans). In spite of all these assumptions, their estimated spreads have come reasonably close to what the Off-Site Supervision Department in the Central Bank of Brazil believes is being charged by Brazilian banks. Estimating bank-specific spreads, consistent with reported net interest margin, is crucial for our analysis as historical net interest margins vary quite a bit across Brazilian banks (Table 5), from 0.027 to 0.707. These are average net interest margins calculated over a 5 year period (2000-2004)[37].

A2.4. Banks Ratings

There are three large rating agencies – Fitch, Standard and Poor's, and Moody's – that provide credit rating for countries, companies, and banks. Their rating scales (see Table 3) are very similar, with some few distinguishable features. For example: the rating scales for Fitch and Standard and Poor's are extremely similar. The difference comes about the way Fitch classifies various obligations in default, according to their expected recovery value. While Standard and Poor's have only the category 'D' for default, Fitch has the categories 'DDD', with expected recovery value of 90% or more of the outstanding amounts and accrued interest, 'DD', with expected recovery value in the range of 50%-90%, and 'D', with expected recovery value below 50%. Both agencies utilize '+' and '-' to show relative standing within major categories AA to CCC. Moody's rating is slightly different in its form, although with very similar major categories as Standard and Poor's. However, Moody's offer more graduations within the major categories Aa to B, assigning numerical modifiers '1', indicating that the counterparty is in the higher end of the major category, '2' if it is in the middle range, and '3' if it is in the lower end of its letter rating category. Also common to the three rating scales are the investment and speculative grade grouping. Investment grade represent the rating categories with little or no credit risk, while the speculative grade groups rating categories with significant credit risk or default risk. The Central Bank of Brazil utilize a different rating scale, going from AA to H,

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[35] Equal to net interest income in year t divided by the average (arithmetic) interest earning assets in years t and $t-1$.

[36] Average interest rates provided by the Central Bank of Brazil, also reported in Barnhill, Souto, and Tabak (2004).

[37] We believe the average net interest margin over 2000-04 provides a better measure of how much banks accrue on interest earning assets. It will also serve for model validation, when we compare historical vs. simulated ROA and ROE.

where G and H can be placed in the one single category, with the lowest credit quality. Beyond that, loans are assumed to default. Only AA, A, and B, can be considered investment grade, although we would consider B to be in the shadow region between the two grades[38].

In Table 4 we present the ratings that are provided by Fitch, Standard and Poor's, and Moody's to Brazilian banks for some of the banks in our sample and few comments are in order. First, only a few banks are rated by all three agencies and they represent some of the largest banks in Brazil (Bank 12, Bank 3, Bank 25, Bank 26, Bank 28, and Bank 27). Second, Fitch is the agency that provides the most ratings to the banks in our sample (19 banks), while Moody's provide ratings for 16 banks and Standard and Poor's to 10 banks. Third, Fitch appears to be more 'generous' in rating Brazilian banks. All banks in our sample that are rated by Fitch can be placed in the investment grade group (from BBB to AA). The opposite occurs with the other two agencies: Moody's rates only one bank in the investment grade (Bank 21), while Standard and Poor's rates none in the investment grade. Fourth, ratings by Standard and Poor's and Moody's are in general much more consistent with each other, and somewhat conflicting with Fitch. For example, Fitch rates Bank 16 as BBB+ (investment grade), while the same bank receives a B1 rate (speculative grade) from Moody's. Bank 27 is rated as AA- (again investment grade) by Fitch, while Moody's rates it as B3 and Standard and Poor's as BB- (both speculative grade). For the eight banks that are rated by the three agencies, they either receive single or double B grades from Moody's and Standard and Poor's, while they receive AA type of grades from Fitch.

The rating methodologies utilized by agencies such as Moody's are generally designed to measure not only the likelihood of a company defaulting on its debt obligation, but also the potential monetary loss associated with this default. For this purpose, comprehensive ratio and financial statements analysis are usually combined with risk measurement techniques. The case of banks is even more complex, as these financial institutions commonly possess an intricate portfolio, with different financial instruments diversified across business sectors and geographical regions, and with different maturities and payoff structures.

A2.5. Banks' Balance Sheets

Data on 28 Brazilian banks' balance sheet and income statement have been collected from Bank Scope, as of December of 2004, and then translated into the simplified version as in Table 5, which is the format used in the Monte Carlo simulation. A few important features appear to be common in our banks sample. Public funding accounts for the biggest fraction in the liability side, with domestic funding being the most important account. Percentages for domestic funding vary from 26% to 85.2%. However, 22 banks have more than 50% of their liabilities in domestic funding. Foreign funds account for much minor fractions with few exceptions (mainly foreign banks), ranging from 0% to 54.5%. This shows that Brazilian banks typically have small exposure to FX rate movements in the liabilities side. Non-interest bearing liabilities vary a lot, ranging from 4% to 50.2%. The higher the percentage in this account, the lower the exposure of banks' liabilities to interest rate movements, and the higher the net interest margin earned by the bank, *ceteris paribus*. Equity and reserves account for minor fractions as well, varying from 5% to 22.8%. Banks have virtually zero debt.

On the asset side, banks generally hold very little in liquid assets such as money and gold. Indeed, Brazilian banks hold 0% in gold reserves and 0% to 9.4% in cash. A striking feature of Brazilian banks' balance sheets is the amount of government debt they hold in their portfolios[39]. Percentages can go from 25% to 89.1%. As we shall see later, a major analytical issue is the potential market value losses on bank portfolios with concentrated government loan positions in the event of Sovereign default. Brazilian banks

[38] Barnhill, Souto, and Tabak (2003) have done the mapping between the one utilized in Brazil and other international agencies' ratings, based on default rates and transition probabilities of loans for 2 large Brazilian banks. The mapping present here in Table 5 reflects their analysis.

[39] In the Bank Scope balance sheet format, government debt held by banks is accounted mainly in two large accounts, according to Central Bank of Brazil officials: open market transactions and trading securities.

also hold a significant amount of business loans, some with as much as 55.6% of its total assets in business loans, while others lend as little as 1.0% of its total assets to businesses. Brazilian banks hold a much more modest fraction of customers' loans, ranging from 0% to 37.6% of total assets. Foreign loans, equity and real estate investments represent very minor percentages of total assets for all banks. One final important comment on the asset side regards the other assets account, which comprises all non-interest earning assets. Many Brazilian banks hold a significant fraction of their total assets as non-interest earning assets, with several banks having more than 10% of their total assets as non-interest earning assets[40]. Non-interest earning assets are dead-weights for banks. Ideally, banks should invest as much as possible of their assets, leaving only marginal fractions as non-interest earning. With such high percentage of assets not earning interest, banks likely feel pressure to earn higher rates on other bank assets. We conjecture that this is one of the factors behind the high interest rate spreads. Brazilian banks also have relatively high operating expenses. Our ratio of net non-interest income over total assets gives a measure of how much the banks are making/spending operationally, that is not coming from interest. These numbers are fairly for Brazilian banks, and can reach as much as -0.080. With such high operational expense, banks operating in Brazil perhaps feel pressure to earn high interest rate spreads on business and consumer loans. A significant fraction of this operational expense comes from overheads. Brazil has a heavy legal/tax burden associated with personnel. Implementing policies that will allow banks to diminish this cost can potentially allow them to charge smaller interest rate spreads.

On the liability/maturity structure, we provide the distributions of domestic and foreign funding across different maturities. This information is available for all banks in the Central Bank of Brazil website, for a variety of maturities. Our simulation framework however just permits using three different maturities. We have combined funding on three different maturities categories: (i) 1 year, encompassing all funding that is maturing at 1 year or less; (ii) 2 years, for funds maturing between 1 and 3 years; and (iii) 5 years, for funds maturing after 3 years. These numbers generally correspond to the average maturity in each of the categories, as provided in Central Bank of Brazil website. Distribution of domestic and foreign funding, for different maturities, is provided in Table 6. Most of the banks concentrate their funding on short-term maturity (1 year or less), with few exceptions. The median percentage of domestic funding allocated in 1-year maturity is 77.8% against 21.2% for 2-years maturity and 0.5% for 5-years. For foreign funding percentages are 88.5%, 10.4%, and 0.0% respectively.

On the asset side, the only account for which we explicitly model maturities is the 'risk-free' loans (government debt) account. Since we do not obtained information for each bank on their specific maturity structure for this account, we conjecture that banks on average hold these securities in the same proportion as the government overall debt distribution. Information on all government debt is available in the Brazilian Treasury Website. For determining the distribution, we allocate as 1-year maturity all government debt that matures in 1-year or less plus all floating rate debt. The remaining debt is allocated as with 3-years maturity, because this is the average maturity reported by the Brazilian Treasury. We provide the final distribution used in the simulation in Table 6, Panel B. Almost 90% of all risk-free loans are considered 1-year maturity or less, while the remaining 10% is allocated as 3-years maturity loans.

A2.6. Banks Portfolio Composition

On the sector distribution of business loan, due to the lack of more detailed data we had to use average numbers distributions provided by the Central Bank of Brazil. Ideally, we would use specific bank information and specific distributions for each sector and each credit risk category. The values we used in the simulations are presented in Table 7. Business loans are considered to be distributed across 10 main business

[40] Bank 11 has 44% of non-interest earning assets. A closer look into their balance sheet (from Central Bank of Brazil website) reveals that a significant fraction of this account is indeed comprised by FX currency (non-interest) instruments.

sectors: Basic Industries (36.6%), Construction Material (11%), Chemicals (2.5%), Cyclical Services (9.3%, Food Production (9.3%), Food Retail (18.2%), Forestry and Paper (2.3%), Telecom (3.8%), and Utilities (2.2%). The tenth sector represents all other industries (4.7%), as proxied by the Brazilian broad equity market index – IBOVESPA.

Customers' loans are distributed across geographical regions (Table 8). Brazil has five major geographical regions: (i) North, where the Amazon forest is located, with the smallest population concentration in the country; (ii) Northeast, considered the poorest region in Brazil; (iii) Central region, where Brazilian capital is located, and which is a medium point between the poorest regions and the richest (and more industrialized) regions; (iv) Southeast; and (v) South. Southeast is the richest and most industrialized region in Brazil, with the highest concentration of population, followed by the South region. Distribution of customers' loans across regions varies a lot from bank to bank although they are mostly concentrated in the Southeast region.

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Table 1
Historical Volatilities and Correlations – 2003-2004

Spot prices, annualized volatilities, and correlations for equity and unemployment rates are averages of all equity indices and unemployment rates for all five big cities, respectively. Mean reversion rates were obtained from Hull and White (1990) model. Mean reversion rate $(\hat{\beta})$ is obtained from the regression $\Delta r_t = \alpha + \beta r_t + \varepsilon_t$, with $\Delta r_t = r_t - r_{t-1}$. The annualized standard deviation is equal to $\hat{\sigma}_\varepsilon \sqrt{12}$, for monthly data.

Panel A: Spot Prices (As Of December 2004).

	BR rate	US rate	FX rate	CPI	Gold	Oil	Equity	Un. rates
	17.8%	2.2%	2.66	146.6	37500	43.4	3442	10.2%

Panel B: Annualized Volatilities.

	BR rate	US rate	FX rate	CPI	Gold	Oil	Equity	Un. rates
	5.63%	0.56%	13.50%	1.67%	20.36%	31.86%	28.64%	21.56%

Panel C: Correlations.

	BR rate	US rate	FX rate	CPI	Gold	Oil	Equity	Un. rates
BR rate	1	-0.22	0.53	-0.80	-0.48	-0.57	-0.85	0.25
US rate		1	-0.26	0.62	0.34	0.78	0.50	-0.67
FX rate			1	-0.72	0.31	-0.26	-0.61	-0.05
CPI inflation				1	0.28	0.78	0.85	-0.41
Gold					1	0.58	0.42	-0.57
Oil						1	0.67	-0.59
Equity							1	-0.42
Unemp. rates								1

Panel D: Interest Rates Mean Reversion Rates.

BR rate	US rate
54.0%	37.8%

Table 2
Brazilian Financial Sector by Total Assets

Financial figures for several groups of Brazilian banks, as of December of 2004, in thousands of Brazilian currency and in percentages, relatively to the Brazilian Financial System.

	N.o of Banks	Total Assets	%	Deposits	%	Net Income	%
50 largest banks	50	$1,199,428,044	82.7%	$529,876,584	92.6%	$11,198,000	88.2%
Simulated banks sample[2]	28	$1,037,118,800	71.5%	$424,690,694	74.2%	$6,774,438	53.4%
Tier I[3]	108	$1,224,015,699	84.4%	$537,765,610	94.0%	$11,393,976	89.8%
Tier II	32	$194,526,209	13.4%	$23,848,860	4.2%	$680,569	5.4%
			97.8%		98.2%		95.2%
Brazilian Financial System[4]	1882	$1,450,625,745		$572,124,524		$12,689,279	
(as % of nominal GDP)		82.67%		32.60%		0.72%	

Nominal GDP[5]: $1,754.77

1. In thousands of Brazilian currency.
2. 28 banks simulated in this study (they are among the 50 largest banks).
3. Includes the 50 largest banks.
4. Includes all credit cooperatives.
5. In billions of national currency (source: World Economic Outlook - IMF).
6. Source: Central Bank of Brazil Website.

Table 3
Credit Rating Scales Used by Rating Agencies

This table provides a mapping for rating scales provided by Fitch, Moody's, Standard and Poor's, and the ones utilized by the Central Bank of Brazil. While the mapping between Fitch, Moody's, and Standard and Poor's rating scales is easier to be done, for the Brazilian rating scale we rely on the work of Barnhill, Souto, and Tabak (2004), who considered default rates and credit transition probabilities for loans in the portfolios of 2 large Brazilian banks, to do the mapping.

	Fitch[1, 2]	S & P[1]	Moody's[3]	Brazil
Investment Grade	AAA	AAA	Aaa	
	AA	AA	Aa	AA
	A	A	A	A
	BBB	BBB	Baa	B
Speculative Grade	BB	BB	Ba	C
	B	B	B	D
	CCC	CCC	Caa	E
	CC	CC	Ca	F
	C	C	C	G-H
Default	DDD	D	D	
	DD			
	D			

1. The ratings from AA to CCC may be modified by the addition of a plus or minus sign to show relative standing within the major rating categories.

2. Various default degrees relates to their recovery prospects. 'DDD' obligations have 90%-100% expected recovery of outstanding amounts and accrued interest, while 'DD' indicates potential recoveries in the range of 50%-90% and 'D' below 50%.

3. Moody's applies numerical modifiers 1, 2, and 3 in each generic rating category from Aa to B. The modifier 1 indicates that the counterparty is in the higher end of its letter-rating category; the modifier 2 indicates a mid-range ranking; and the modifier 3 indicates that the counterparty is in the lower end of its letter-rating category.

Table 4
Brazilian Banks Credit Rating

Ratings provided by Fitch, Moody’s, and Standard and Poor’s that are available to some of the 28 banks in our sample. Highlighted are the banks for which rating is available from all three rating agencies.

Bank	Fitch	Moody's	Standard and Poor's
Bank 1		B3	
Bank 2	A+		
Bank 3	AA	Ba3	BB-
Bank 4	AA	B3	
Bank 6	A+		
Bank 7	A-		
Bank 8	BBB		
Bank 9	BBB+		
Bank 10		B3	BB-
Bank 12	AA	Ba3	BB
Bank 13		B3	BB-
Bank 16	BBB+	B1	
Bank 17		B3	BB-
Bank 18	AA	B3	BB-
Bank 20	BBB		
Bank 21	A+	A3	
Bank 22	A+	B3	
Bank 24	BBB	B2	
Bank 25	AA-	B3	BB
Bank 26	AA	B3	BB-
Bank 27	AA-	B3	BB-
Bank 28	AA	B3	BB-
Total →	18	16	10

Source: Fitch, Moody's, and Standard and Poor's website.

Table 5
Brazilian Banks Balance Sheet

Simplified balance sheet for the 28 banks in our sample in percentages of total assets, as of December 2004. Domestic Funding includes inter-bank, demand, savings, and fixed deposits, NCD's, repos, and others. Domestic 'risk-free' loans are federal government loans. Net non-interest income over total assets, a measure of banks operational performance, is equal to (operating income + other non-interest income – operating expenses)/total assets.

	Min.	Median	St. Dev.	Max.
Capital and Liabilities				
Public Funding				
Domestic funding	26.0%	59.8%	17.9%	85.2%
Foreign Funding	0.9%	7.3%	12.7%	54.5%
Capital and Other Liabilities	0.0%	0.0%	0.0%	0.0%
Non-interest bearing	3.9%	12.2%	12.4%	50.2%
Equity and reserves less impairments	5.0%	10.1%	7.4%	38.4%
Debt	0.0%	0.0%	1.3%	4.0%
Total	100.0%	100.0%	0.0%	100.0%
Assets				
Money	0.0%	1.3%	2.1%	9.4%
Gold	0.0%	0.0%	0.0%	0.0%
Domestic Risk-Free Loans	25.0%	54.2%	18.3%	90.5%
Domestic business loans	1.0%	21.2%	13.9%	55.6%
Domestic Individual loans	0.0%	3.5%	11.3%	57.0%
Foreign Loans	0.0%	0.0%	0.0%	0.0%
Equity Investments	0.0%	0.4%	0.8%	3.8%
Real Estate Investments	0.0%	1.1%	1.2%	3.6%
Other Assets	2.5%	10.6%	9.1%	44.4%
Total	100.0%	100.0%	0.0%	100.0%
Net Interest Margin	0.027	0.075	0.042	0.203
Net Non-Interest Income/Total Assets	-0.080	-0.032	0.031	0.040

Source: BankScope and Central Bank of Brazil website.

Table 6
Assets and Liabilities Structure

This table provides distributions of domestic and foreign funding across three different maturities, as percentages of total domestic and foreign funding, for each of the 28 banks in our simulation sample, as of December 2004. Maturities categories are: (i) 1 year, encompassing all funding that is maturing at 1 year or less; (ii) 2 years, for funds maturing between 1 and 3 years; and (iii) 5 years, for funds maturing after 3 years. These numbers generally correspond to the average maturity in each of the categories, as provided in Central Bank of Brazil website. Since we did not obtained information for each bank on their specific maturity structure for this account, we conjecture that banks on average hold these securities in the same proportion as the government overall debt distribution. Information on all government debt is available in the Brazilian Treasury Website. For determining the distribution, we allocate as 1-year maturity all government debt that matures in 1-year or less plus all floating rate debt. The remaining debt is allocated as with 3-years maturity, because this is the average maturity reported by the Brazilian Treasury.

Panel A: Liability Side.

	Domestic Funding			Foreign Funding		
	1 year	2 years	5 years	1 year	2 years	5 years
Min.	37.2%	0.0%	0.0%	14.4%	0.0%	0.0%
Median	77.8%	21.2%	0.4%	88.5%	10.4%	0.0%
St. Dev.	16.5%	14.7%	4.4%	22.3%	14.8%	12.1%
Max.	100.0%	55.2%	22.2%	100.0%	59.6%	58.6%
All 30 Banks:						
Average	77.5%	20.7%	1.7%	82.8%	13.6%	3.7%
St. Dev.	16.5%	14.7%	4.4%	22.3%	14.8%	12.1%

Panel B: Asset Side.

	'Risk-Free' Loans	
	1 year	3 years
All banks	89.2%	10.8%

Sources:

- Domestic and foreign funding: Central Bank of Brazil website.
- 'Risk-Free' loans: Brazilian Treasury website.

Table 7
Brazilian Banks Business Loans: Sectors Distribution

Distribution of business loans across business sectors for 2 large Brazilian banks, as of December 2003. Under Ibovespa we allocate all loans that are from borrowers in industries other than the nine listed below. Utilities does not include Telecommunications, placed separately.

Ibovespa	4.7%
Basic Industries	36.6%
Construction Material	11.0%
Chemicals	2.5%
Cyclical Services	9.3%
Food Production	9.3%
Food Retail	18.2%
Forestry and Paper	2.3%
Telecom	3.8%
Utilities	2.2%

Source: Barnhill, Souto, and Tabak (2004).

Table 8
Brazilian Banks Customers Loans: Geographical Distribution

Distribution of consumers' loans across the five geographical regions in Brazil, for all 28 banks in our simulation sample, as of December 2004. Percentages were estimated relatively to total amounts of customers' loans for each bank.

	Min.	Median	St. Dev.	Max.
North Region	0.0%	0.0%	14.4%	76.5%
Northeast Region	0.0%	1.7%	19.3%	90.5%
Southeast Region	0.0%	81.1%	34.5%	100.0%
Central Region	0.0%	0.3%	2.9%	9.3%
South Region	0.0%	2.8%	19.3%	98.3%

Source: Central Bank of Brazil website.

Table 9
Historical Volatilities and Correlations – 2000-2004

Spot prices, annualized volatilities, and correlations for equity and unemployment rates are averages of all equity indices and unemployment rates for all five big cities, respectively.

Panel A: Annualized Volatilities.

	BR rate	US rate	FX rate	CPI	Gold	Oil	Equity	Un. rates
	0.88%	0.21%	22.29%	1.89%	23.08%	32.88%	35.13%	29.94%

Panel B: Correlations.

	BR rate	US rate	FX rate	CPI	Gold	Oil	Equity	Un. rates
BR rate	1	-0.08	-0.09	0.43	-0.08	0.00	-0.14	-0.01
US rate		1	-0.08	-0.02	-0.08	0.21	0.05	-0.03
FX rate			1	-0.07	0.81	0.14	-0.29	0.05
CPI inflation				1	-0.05	-0.03	0.08	0.16
Gold					1	0.24	-0.18	0.07
Oil						1	-0.02	0.06
Equity							1	-0.10
Unemp. rates								1

Table 10
Individual Banks ROE: simulated versus historical

This table presents statistics on historical and simulated Return on Average Equity (ROAE) for the 13 Brazilian banks in the validation sample. Historical values were obtained from Bank Scope for the 2000-2004 period to calculate averages and standard deviations. Simulated values were obtained for the end of 2005, where ROAE is net income divided by average equity (beginning- and end-of-period), consistent with Bank Scope definition.

	Bank 2		Bank 7		Bank 8		Bank 9		Bank 12	
	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.
N. Obs.	5	2000	5	2000	5	2000	5	2000	5	2000
Mean	0.109	0.171	0.261	0.120	0.182	0.331	0.323	0.355	0.213	0.151
St. Dev.	0.015	0.026	0.139	0.059	0.060	0.028	0.180	0.016	0.023	0.017
Median	0.115	0.172	0.283	0.123	0.183	0.333	0.282	0.356	0.212	0.153
Max.	0.121	0.270	0.433	0.342	0.253	0.429	0.631	0.417	0.242	0.198
Min.	0.085	0.051	0.057	0.089	0.111	0.198	0.191	0.284	0.187	0.072

	Bank 16		Bank 18		Bank 20		Bank 22		Bank 24	
	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.
N. Obs.	5	2000	5	2000	5	2000	5	2000	5	2000
Mean	0.133	0.234	0.298	0.210	0.085	0.154	0.201	0.150	0.237	0.296
St. Dev.	0.065	0.032	0.021	0.016	0.019	0.030	0.092	0.029	0.054	0.038
Median	0.108	0.237	0.303	0.210	0.089	0.155	0.162	0.149	0.213	0.300
Max.	0.236	0.338	0.322	0.264	0.102	0.257	0.346	0.256	0.321	0.408
Min.	0.081	0.064	0.273	0.123	0.052	0.027	0.121	0.041	0.194	0.118

	Bank 25		Bank 27		Bank 28	
	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.
N. Obs.	5	2000	5	2000	5	2000
Mean	0.231	0.281	0.159	0.173	0.283	0.274
St. Dev.	0.024	0.027	0.007	0.021	0.021	0.014
Median	0.230	0.285	0.159	0.174	0.279	0.275
Max.	0.256	0.358	0.169	0.248	0.308	0.358
Min.	0.194	0.175	0.149	0.084	0.258	0.198

Table 11
Individual Banks ROA: simulated versus historical

This table presents statistics on historical and simulated Return on Average Asset (ROAA) for the 13 Brazilian banks in the validation sample. Historical values were obtained from Bank Scope for the 2000-2004 period to calculate averages and standard deviations. Simulated values were obtained for the end of 2005, where ROAA is net income divided by average total assets (beginning- and end-of-period), consistent with Bank Scope definition.

	Bank 2		Bank 7		Bank 8		Bank 9		Bank 12	
	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.
N. Obs.	7	2000	8	2000	7	2000	8	2000	8	2000
Mean	0.021	0.013	0.043	0.005	0.019	0.020	0.071	0.041	0.018	0.020
St. Dev.	0.002	0.002	0.028	0.002	0.007	0.002	0.024	0.002	0.003	0.003
Median	0.021	0.013	0.042	0.005	0.023	0.020	0.058	0.041	0.017	0.021
Max.	0.022	0.023	0.073	0.016	0.024	0.029	0.111	0.051	0.021	0.028
Min.	0.018	0.004	0.013	0.001	0.011	0.011	0.054	0.030	0.015	0.009

	Bank 16		Bank 18		Bank 20		Bank 22		Bank 24	
	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.
N. Obs.	8	2000	8	2000	8	2000	5	2000	8	2000
Mean	0.014	0.009	0.030	0.027	0.011	0.014	0.026	0.006	0.029	0.025
St. Dev.	0.006	0.001	0.002	0.002	0.004	0.003	0.012	0.001	0.008	0.004
Median	0.015	0.009	0.029	0.027	0.010	0.014	0.019	0.006	0.025	0.025
Max.	0.020	0.014	0.033	0.035	0.016	0.026	0.043	0.011	0.039	0.038
Min.	0.006	0.002	0.027	0.014	0.006	0.002	0.016	0.001	0.021	0.008

	Bank 25		Bank 27		Bank 28	
	Hist.	Sim.	Hist.	Sim.	Hist.	Sim.
N. Obs.	8	2000	8	2000	7	2000
Mean	0.017	0.015	0.018	0.019	0.024	0.015
St. Dev.	0.003	0.002	0.001	0.003	0.004	0.001
Median	0.017	0.016	0.019	0.019	0.025	0.015
Max.	0.021	0.021	0.020	0.030	0.029	0.021
Min.	0.015	0.009	0.017	0.009	0.019	0.010

Table 12
ROAA and ROAE Regressions

This table provides results for regressions performed over historical and simulated ROAA and ROAE means and standard deviations ($ROx_{h,i} = \beta_x \cdot ROx_{s,i} + \varepsilon_x$), with observations for 11 Brazilian private domestic banks. Between brackets we report the t-statistic for the beta coefficient. We also report the Wald statistics for testing the null $\beta = 1$ (last column).

	β	Adj. R^2	Wald Stat.
Panel A: ROAE Regressions			
Mean	0.84	0.89	2.97
	(9.32)		
St. Dev.	1.48	0.74	3.39
	(5.71)		
Panel B: ROAA Regressions			
Mean	1.13	0.88	1.03
	(8.88)		
St. Dev.	1.75	0.53	2.48
	(3.67)		
Panel C: Pooled Observations			
All	0.90	0.83	2.98
	(15.95)		

Table 13
Simulated Capital Ratios: Individual Banks, No Government Default

This table provides statistics and VaR values at different percentage levels, using 2000 simulated capital ratios, for each of the 28 banks in our Simulation sample, assuming that the GOB does not default on its domestic debt. Reported VaR levels indicate the percentage of time that simulated values fall below a certain threshold. For example, BANK 1 VaR at 99% level is 0.210, indicating that 99% of the times simulated capital ratios for BANK 1 have felt below 0.210.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10
Initial	0.189	0.141	0.083	0.149	0.059	0.382	0.073	0.096	0.184	0.091
Mean	0.201	0.144	0.093	0.163	0.075	0.372	0.072	0.114	0.227	0.102
St. Dev.	0.004	0.004	0.003	0.004	0.006	0.002	0.004	0.004	0.005	0.007
Maximum	0.214	0.164	0.103	0.174	0.094	0.383	0.087	0.133	0.242	0.122
Minimum	0.183	0.123	0.080	0.143	0.043	0.363	0.050	0.098	0.208	0.070
VaR Levels:										
99.0%	0.191	0.132	0.086	0.152	0.058	0.367	0.062	0.105	0.215	0.083
97.5%	0.193	0.136	0.087	0.156	0.061	0.368	0.064	0.107	0.217	0.088
95.0%	0.195	0.137	0.089	0.157	0.063	0.368	0.066	0.108	0.219	0.090
90.0%	0.197	0.139	0.090	0.159	0.066	0.369	0.067	0.110	0.221	0.093
75.0%	0.199	0.142	0.092	0.161	0.071	0.370	0.070	0.112	0.224	0.098
50.0%	0.201	0.144	0.094	0.164	0.075	0.372	0.072	0.115	0.227	0.102
25.0%	0.204	0.147	0.095	0.166	0.079	0.374	0.075	0.117	0.229	0.106
10.0%	0.206	0.149	0.097	0.168	0.082	0.375	0.077	0.119	0.232	0.110
5.0%	0.207	0.151	0.098	0.169	0.084	0.376	0.079	0.120	0.234	0.112
2.5%	0.208	0.153	0.098	0.170	0.085	0.377	0.080	0.122	0.235	0.114
1.0%	0.210	0.155	0.099	0.171	0.087	0.379	0.082	0.123	0.237	0.117

Table 13 (Cont.)
Simulated Capital Ratios: Individual Banks, No Government Default

	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18	Bank 19
Initial	0.091	0.252	0.132	0.062	0.103	0.065	0.094	0.200	0.201
Mean	0.110	0.251	0.150	0.074	0.150	0.070	0.112	0.240	0.200
St. Dev.	0.003	0.004	0.007	0.002	0.004	0.002	0.007	0.004	0.001
Maximum	0.121	0.266	0.181	0.081	0.167	0.078	0.140	0.257	0.209
Minimum	0.096	0.235	0.123	0.068	0.136	0.060	0.083	0.215	0.196
VaR Levels:									
99.0%	0.103	0.242	0.136	0.070	0.142	0.064	0.096	0.227	0.197
97.5%	0.104	0.244	0.137	0.071	0.144	0.065	0.098	0.231	0.198
95.0%	0.106	0.245	0.139	0.072	0.145	0.066	0.101	0.232	0.198
90.0%	0.107	0.246	0.141	0.072	0.146	0.067	0.104	0.234	0.199
75.0%	0.108	0.249	0.145	0.073	0.148	0.069	0.108	0.237	0.199
50.0%	0.110	0.252	0.149	0.074	0.150	0.070	0.112	0.240	0.200
25.0%	0.111	0.254	0.154	0.075	0.152	0.072	0.116	0.242	0.201
10.0%	0.113	0.256	0.159	0.076	0.155	0.073	0.120	0.245	0.202
5.0%	0.114	0.257	0.162	0.077	0.156	0.074	0.122	0.246	0.203
2.5%	0.115	0.258	0.166	0.077	0.158	0.075	0.124	0.248	0.203
1.0%	0.116	0.260	0.170	0.078	0.160	0.076	0.127	0.250	0.204

Table 13 (Cont.)
Simulated Capital Ratios: Individual Banks, No Government Default

	Bank 20	Bank 21	Bank 22	Bank 23	Bank 24	Bank 25	Bank 26	Bank 27	Bank 28
Initial	0.174	0.067	0.073	0.063	0.139	0.092	0.161	0.206	0.090
Mean	0.168	0.069	0.077	0.122	0.160	0.104	0.172	0.209	0.102
St. Dev.	0.005	0.003	0.002	0.003	0.007	0.003	0.003	0.005	0.002
Maximum	0.189	0.079	0.087	0.135	0.196	0.113	0.184	0.225	0.114
Minimum	0.148	0.057	0.066	0.107	0.127	0.092	0.162	0.192	0.094
VaR Levels:									
99.0%	0.154	0.060	0.070	0.114	0.141	0.096	0.165	0.198	0.097
97.5%	0.158	0.062	0.072	0.115	0.145	0.098	0.166	0.200	0.098
95.0%	0.159	0.063	0.073	0.116	0.148	0.099	0.167	0.202	0.099
90.0%	0.162	0.065	0.075	0.118	0.151	0.100	0.168	0.204	0.100
75.0%	0.165	0.067	0.076	0.120	0.155	0.102	0.170	0.207	0.101
50.0%	0.169	0.069	0.077	0.122	0.160	0.104	0.172	0.210	0.103
25.0%	0.172	0.071	0.079	0.124	0.165	0.106	0.174	0.212	0.104
10.0%	0.175	0.073	0.080	0.126	0.169	0.108	0.176	0.215	0.105
5.0%	0.177	0.074	0.081	0.127	0.172	0.109	0.177	0.217	0.106
2.5%	0.179	0.075	0.082	0.128	0.174	0.110	0.178	0.219	0.107
1.0%	0.181	0.076	0.084	0.129	0.177	0.111	0.179	0.220	0.108

Table 14
Government Default Cases in the Period of 1998-2003

This table provides information on the government default cases as in the Klaar, Rawkins, and Riley (2004) study. Government default is defined as a failure to make timely payment of principal and/or interest on either: (i) rated foreign currency debt; or (ii) other material foreign currency debt obligations, such as Paris or London Club liabilities.

	First Rating		Default Event			
					Grade	
Country	Date	Grade	Description	Date	Before	After
Argentina	1997	BB	Defaulted on over US$ 70 billions of sovereign foreign currency bonds.	2001	BB	DDD
Indonesia	1997	BBB-	Rescheduled Paris and London Club operations in 1998. Further reschedules in 2000 and 2002.	1998	BB+	B-
Moldova	1998	B+	US$75 millions of Eurobonds restructured, followed by a Paris Club deal.	2002	CC	DD
Russia	1996	BB+	Default on local currency debt in 1998, and quickly began to incur in arrears on foreign currency debt.	1998	BB+	CCC
Ukraine	2001	B+	Default on Eurobonds (event prior to the first rating[2]).	1999	B+	B+
Uruguay	1995	BB+	Distressed debt exchange affecting over US$ 5 billions of foreign currency sovereign debt.	2003	B	B-

1. Source: Fitch Ratings website.
2. Even though this event is anterior to the first public sovereign rating, Fitch maintained a shadow rating during this period.

Table 15
Simulated Default Probabilities: Individual Banks, Government Default

Simulated default probabilities on individual banks (probability that the banks' capital ratio fall below 0.03). We assume various different scenarios. On the business and individuals loans, we assume that: (i) businesses and individuals have a zero increment to their default rates; (ii) businesses and individuals in each credit risk category have an increase in their default rates equal to the average default of that credit risk category[41], and (iii) businesses and individuals in each credit risk category have an increase in their default rates equal to two times the average default of that credit risk category. The second channel incorporates losses directly on the government loans, by assuming that banks may lose 0%, 10%, or 25% of the market value of their government loans for a variety of reasons.

Losses on Government Loans	0%	0%	0%	10%	10%	10%	25%	25%	25%
Incremental Defaults on Business and consumer Loans	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates
Banks:									
Bank 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 3	0.000	0.000	0.000	0.001	0.001	0.001	0.046	0.046	0.046
Bank 4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002
Bank 5	0.000	0.000	0.001	0.038	0.045	0.048	0.048	0.048	0.048
Bank 6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 8	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.038	0.041
Bank 9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 10	0.000	0.000	0.000	0.005	0.007	0.007	0.060	0.060	0.060
Bank 11	0.000	0.000	0.000	0.000	0.000	0.000	0.045	0.045	0.045
Bank 12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 13	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.004	0.005
Bank 14	0.000	0.000	0.000	0.050	0.050	0.050	0.050	0.050	0.050
Bank 15	0.000	0.000	0.000	0.000	0.000	0.000	0.045	0.045	0.045
Bank 16	0.000	0.000	0.000	0.041	0.041	0.041	0.041	0.041	0.041
Bank 17	0.000	0.000	0.000	0.000	0.000	0.000	0.034	0.035	0.037
Bank 18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 19	0.000	0.000	0.000	0.000	0.000	0.000	0.049	0.049	0.049
Bank 20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 21	0.000	0.000	0.000	0.050	0.050	0.050	0.050	0.050	0.050
Bank 22	0.000	0.000	0.000	0.050	0.050	0.050	0.050	0.050	0.050
Bank 23	0.000	0.000	0.000	0.000	0.000	0.000	0.051	0.051	0.051
Bank 24	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 25	0.000	0.000	0.000	0.000	0.000	0.000	0.048	0.048	0.048
Bank 26	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Bank 27	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 28	0.000	0.000	0.000	0.000	0.000	0.000	0.046	0.046	0.046

[41] Appendix 1gives the average one-year historical default rate on Brazilian bank loans with various credit qualities.

Table 16
Simulated Average 'Bail-Out' cost: Individual Banks, Government Default

Average 'bail-out' cost is the average capital (as percentage of total assets) necessary to bring banks' capital ratio back to 0.08 level, whenever they fall below 0.03 (assumed default). We assume various different scenarios. On the business and individuals loans, we assume that: (i) businesses and individuals have a zero increment to their default rates; (ii) businesses and individuals in each credit risk category have an increase in their default rates equal to the average default of that credit risk category[42], and (iii) businesses and individuals in each credit risk category have an increase in their default rates equal to two times the average default of that credit risk category. The second channel incorporates losses directly on the government loans, by assuming that banks may lose 0%, 10%, or 25% of the market value of their government loans for a variety of reasons.

Losses on Government Loans	0%	0%	0%	10%	10%	10%	25%	25%	25%
Incremental Defaults on Business and consumer Loans	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates
Banks:									
Bank 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 3	0.000	0.000	0.000	0.051	0.054	0.056	0.102	0.105	0.108
Bank 4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.052
Bank 5	0.000	0.000	0.053	0.064	0.068	0.074	0.163	0.170	0.178
Bank 6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 8	0.000	0.000	0.000	0.000	0.000	0.000	0.059	0.060	0.062
Bank 9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 10	0.000	0.000	0.000	0.059	0.059	0.061	0.150	0.153	0.156
Bank 11	0.000	0.000	0.000	0.000	0.000	0.000	0.073	0.076	0.076
Bank 12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 13	0.000	0.000	0.000	0.000	0.000	0.000	0.055	0.055	0.055
Bank 14	0.000	0.000	0.000	0.061	0.061	0.061	0.173	0.173	0.173
Bank 15	0.000	0.000	0.000	0.000	0.000	0.000	0.158	0.158	0.158
Bank 16	0.000	0.000	0.000	0.084	0.085	0.086	0.233	0.234	0.234
Bank 17	0.000	0.000	0.000	0.000	0.000	0.000	0.060	0.062	0.062
Bank 18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 19	0.000	0.000	0.000	0.000	0.000	0.000	0.083	0.083	0.084
Bank 20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 21	0.000	0.000	0.000	0.088	0.091	0.094	0.239	0.243	0.248
Bank 22	0.000	0.000	0.000	0.095	0.095	0.095	0.278	0.278	0.278
Bank 23	0.000	0.000	0.000	0.000	0.000	0.000	0.085	0.086	0.087
Bank 24	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 25	0.000	0.000	0.000	0.000	0.000	0.000	0.065	0.068	0.070
Bank 26	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.050
Bank 27	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank 28	0.000	0.000	0.000	0.000	0.000	0.000	0.168	0.168	0.168

[42] Appendix 1gives the average one-year historical default rate on Brazilian bank loans with various credit qualities.

Table 17
Simulated 99% VaR Capital Ratio: Individual Banks, Government Default

The 99% VaR simulated capital ratio is the threshold below which banks capital ratio will fall 1% of the time. We assume various different scenarios. On the business and individuals loans, we assume that: (i) businesses and individuals have a zero increment to their default rates; (ii) businesses and individuals in each credit risk category have an increase in their default rates equal to the average default of that credit risk category[43], and (iii) businesses and individuals in each credit risk category have an increase in their default rates equal to two times the average default of that credit risk category. The second channel incorporates losses directly on the government loans, by assuming that banks may lose 0%, 10%, or 25% of the market value of their government loans for a variety of reasons.

Losses on Government Loans	0%	0%	0%	10%	10%	10%	25%	25%	25%
Incremental Defaults on Business and consumer Loans	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates
Banks:									
Bank 1	0.189	0.189	0.189	0.175	0.174	0.173	0.126	0.124	0.122
Bank 2	0.129	0.129	0.129	0.115	0.114	0.113	0.051	0.050	0.050
Bank 3	0.085	0.085	0.084	0.051	0.048	0.045	-0.026	-0.029	-0.032
Bank 4	0.152	0.151	0.151	0.128	0.125	0.122	0.058	0.055	0.052
Bank 5	0.058	0.056	0.053	0.011	0.005	-0.002	-0.092	-0.100	-0.108
Bank 6	0.365	0.364	0.364	0.335	0.334	0.333	0.248	0.247	0.245
Bank 7	0.065	0.064	0.063	-0.001	-0.002	-0.003	-0.121	-0.123	-0.124
Bank 8	0.103	0.103	0.102	0.084	0.083	0.080	0.018	0.016	0.013
Bank 9	0.213	0.213	0.213	0.210	0.208	0.206	0.190	0.188	0.186
Bank 10	0.077	0.077	0.077	0.040	0.038	0.035	-0.081	-0.085	-0.088
Bank 11	0.102	0.102	0.102	0.077	0.077	0.077	0.003	0.003	0.003
Bank 12	0.238	0.238	0.238	0.213	0.211	0.210	0.134	0.131	0.129
Bank 13	0.132	0.132	0.132	0.108	0.107	0.106	0.038	0.036	0.035
Bank 14	0.080	0.080	0.080	0.018	0.018	0.018	-0.094	-0.094	-0.094
Bank 15	0.147	0.147	0.147	0.086	0.086	0.086	-0.080	-0.080	-0.080
Bank 16	0.067	0.067	0.067	-0.006	-0.007	-0.008	-0.156	-0.157	-0.158
Bank 17	0.094	0.094	0.094	0.081	0.080	0.079	0.017	0.015	0.014
Bank 18	0.225	0.225	0.225	0.208	0.207	0.206	0.137	0.134	0.132
Bank 19	0.196	0.196	0.196	0.135	0.135	0.134	-0.005	-0.006	-0.006
Bank 20	0.155	0.154	0.154	0.139	0.137	0.134	0.087	0.084	0.081
Bank 21	0.061	0.061	0.060	-0.012	-0.015	-0.019	-0.164	-0.169	-0.173
Bank 22	0.076	0.076	0.076	-0.016	-0.016	-0.016	-0.199	-0.199	-0.199
Bank 23	0.110	0.110	0.110	0.080	0.079	0.079	-0.011	-0.012	-0.013
Bank 24	0.140	0.139	0.139	0.136	0.134	0.133	0.113	0.110	0.107
Bank 25	0.095	0.095	0.095	0.073	0.071	0.069	0.010	0.007	0.005
Bank 26	0.161	0.161	0.161	0.132	0.131	0.130	0.046	0.045	0.043
Bank 27	0.196	0.196	0.196	0.177	0.175	0.173	0.112	0.110	0.107
Bank 28	0.092	0.092	0.092	0.040	0.040	0.040	-0.095	-0.095	-0.095

[43] Appendix 1gives the average one-year historical default rate on Brazilian bank loans with various credit qualities.

Table 18
Individual Banks – Credit Rating

The quartile values are in Table 13 are used to classify Brazilian banks in to 3 credit risk categories, from Group 1 (less risky) to Group 3 (more risky). Banks with 99% confidence level capital ratios less than 0.07 were put in group 1, banks with 99% confidence level capital ratios between 0.07 and 0.13 were put in group 2, and Banks with 99% confidence level capital ratios over 0.13 put in Group 3.

	Bank Name	PSA Group	Fitch	Moody's	Standard and Poor's
1	Bank 1	3		B3	
2	Bank 2	2	A+		
3	Bank 3	1	AA	Ba3	BB-
4	Bank 4	2	AA	B3	
5	Bank 5	1			
6	Bank 6	3	A+		
7	Bank 7	1	A-		
8	Bank 8	2	BBB		
9	Bank 9	3	BBB+		
10	Bank 10	1		B3	BB-
11	Bank 11	2			
12	Bank 12	3	AA	Ba3	BB
13	Bank 13	2		B3	BB-
14	Bank 14	1			
15	Bank 15	2			
16	Bank 16	1	BBB+	B1	
17	Bank 17	2		B3	BB-
18	Bank 18	3	AA		
19	Bank 19	3	AA	B3	BB-
20	Bank 20	3	BBB		
21	Bank 21	1	A+	A3	
22	Bank 22	1	A+	B3	
23	Bank 23	2			
24	Bank 24	3	BBB	B2	
25	Bank 25	2	AA-	B3	BB
26	Bank 26	3	AA	B3	BB-
27	Bank 27	3	AA-	B3	BB-
28	Bank 28	1	AA	B3	BB-

Sources: Fitch, Moody's, and Standard and Poor's websites, and authors calculation.

Table 19
Simulated Capital Ratios: All 28 banks as One Single Bank

This table provides statistics and VaR values at different percentage levels, using 2000 simulated capital ratios, for a hypothetical single bank that aggregates all 28 banks in our Simulation sample. Aggregated balance sheet accounts were obtained by simple addition from all banks in each group, while loans distribution and assets and liabilities maturities structured were obtained by weighted average of each category in each bank relatively to total assets). In Panel A we present results for the case when the Brazilian Federal Government is assumed never to default, while in Panel B results are presented for the various scenarios, assuming the government may default on its domestic debt. Reported VaR levels indicate the percentage of time that simulated values fall above a certain threshold. For example, for the no government default case, VaR at 99% level is 0.147, indicating that 1% of the times, simulated capital ratios for the single bank have felt below 0.147.

	All 28 No_Gov. Default
Initial Value	0.154
Mean	0.154
St. Dev.	0.003
Maximum	0.163
Minimum	0.144
VaR Levels:	
99.0%	0.147
97.5%	0.148
95.0%	0.149
90.0%	0.150
75.0%	0.152
50.0%	0.154
25.0%	0.156
10.0%	0.158
5.0%	0.159
2.5%	0.160
1.0%	0.161

Table 19 (Cont.)
Simulated Capital Ratios: All 28 banks as One Single Bank

Panel B: Government default.

Losses on Government Loans	0%	0%	0%	10%	10%	10%	25%	25%	25%
Incremental Defaults on Business and consumer Loans	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates
Default Probabilities:									
All 28 banks	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.015	0.022
Bail-Out' Cost:									
All 28 banks	0.000	0.000	0.000	0.000	0.000	0.000	0.055	0.055	0.055
99% VaR Level:									
All 28 banks	0.147	0.147	0.146	0.113	0.111	0.108	0.030	0.027	0.024

Table 20
Aggregate Banks Balance Sheets

Simplified balance sheet for the 3 aggregated banks by credit risk, as of December 2004. Domestic Funding includes inter-bank, demand, savings, and fixed deposits, NCD's, repos, and others. Domestic 'risk-free' loans are federal government loans. Net non-interest income over total assets, a measure of banks operational performance, is equal to (operating income + other non-interest income – operating expenses)/total assets.

	Group1	Group 2	Group 3
Capital and Liabilities			
Public Funding			
Domestic funding	72.2%	59.7%	56.1%
Foreign Funding	6.3%	12.2%	6.6%
Capital and Other Liabilities			
Non-interest bearing	13.1%	17.0%	15.1%
Equity and reserves less impairments	6.5%	9.9%	19.9%
Debt	1.9%	1.1%	2.3%
Total	100.0%	100.0%	100.0%
Assets			
Money	4.5%	4.1%	1.6%
Gold	0.0%	0.0%	0.0%
Domestic Risk-Free Loans	56.2%	46.0%	51.7%
Domestic business loans	22.4%	28.6%	20.9%
Domestic Individual loans	5.0%	7.3%	10.2%
Foreign Loans	0.0%	0.0%	0.0%
Equity Investments	0.3%	1.2%	0.5%
Real Estate Investments	1.4%	1.5%	2.4%
Other Assets	10.3%	11.4%	12.7%
Total	100.0%	100.0%	100.0%
Net Interest Margin	0.066	0.080	0.109
Interbank Lending	3.6%	8.4%	0.8%
Net Non-Interest Income/Total Assets	-0.025	-0.026	-0.041

Source: BankScope and Central Bank of Brazil website.

Table 21
Aggregate Banks Liability Maturity Structure and Customers' Loans Geographical Distribution

This table provides distribution of domestic and foreign funding across three different maturities, as percentages of total domestic and foreign funding, for each of the 3 aggregated banks in our simulation sample, as of December 2004. Maturities categories are: (i) 1 year, encompassing all funding that is maturing at 1 year or less; (ii) 2 years, for funds maturing between 1 and 3 years; and (iii) 5 years, for funds maturing after 3 years. These numbers generally correspond to the average maturity in each of the categories, as provided in Central Bank of Brazil website. Groups' percentages are weighted averages of banks in the sample by their total assets.

Panel A: Public funding maturity structure.

	Domestic Funding			Foreign Funding		
	1 year	2 years	5 years	1 year	2 years	5 years
Group 1	90.3%	9.1%	0.6%	74.9%	10.0%	15.2%
Group 2	71.2%	28.2%	0.6%	75.8%	20.3%	3.8%
Group 3	76.6%	19.7%	3.7%	83.5%	16.5%	0.0%

Panel B: Customers' loans geographic distribution

	Group 1	Group 2	Group 3
North Region	2.6%	3.4%	2.2%
Northeast Region	13.1%	8.3%	8.2%
Southeast Region	55.7%	58.7%	75.2%
Central Region	6.6%	5.6%	3.7%
South Region	21.9%	23.9%	10.8%

Table 22
Simulated Capital Ratios: Individual Aggregate Banks, No Government Default

This table provides statistics and VaR values at different percentage levels, using 2000 simulated capital ratios, for the three hypothetical aggregate banks, by credit rating, for the case when the GOB is assumed never to default.

	Group 1	Group 2	Group 3
Initial	0.081	0.106	0.219
Mean	0.094	0.128	0.227
St. Dev.	0.002	0.004	0.004
Maximum	0.101	0.143	0.241
Minimum	0.082	0.107	0.210
VaR Levels:			
1.0%	0.087	0.117	0.216
2.5%	0.089	0.119	0.218
5.0%	0.090	0.120	0.220
10.0%	0.091	0.122	0.221
25.0%	0.093	0.125	0.224
50.0%	0.095	0.128	0.227
75.0%	0.096	0.131	0.229
90.0%	0.097	0.133	0.232
95.0%	0.098	0.135	0.233
97.5%	0.098	0.136	0.235
99.0%	0.099	0.138	0.236

Table 23
Simulated Default Probabilities, Average 'Bail-Out' Cost, and 99% VaR Capital Ratio: Individual Aggregate Banks, Government Default

Average 'bail-out' cost is the average capital (as percentage of total assets) necessary to bring banks' capital ratio back to 0.08 level, whenever they fall below 0.03 (assumed default). We assume various different scenarios. On the business and individuals loans, we assume that: (i) businesses and individuals have a zero increment to their default rates; (ii) businesses and individuals in each credit risk category have an increase in their default rates equal to the average default of that credit risk category[44], and (iii) businesses and individuals in each credit risk category have an increase in their default rates equal to two times the average default of that credit risk category. The second channel incorporates losses directly on the government loans, by assuming that banks may lose 0%, 10%, or 25% of the market value of their government loans for a variety of reasons.

Losses on Government Loans	0%	0%	0%	10%	10%	10%	25%	25%	25%
Incremental Defaults on Business and consumer Loans	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates	0	+ 1 times the average historical default rates	+ 2 times the average historical default rates
Default Probabilities:									
Group 1	0.000	0.000	0.000	0.000	0.000	0.000	0.047	0.047	0.047
Group 2	0.000	0.000	0.000	0.000	0.000	0.000	0.031	0.038	0.046
Group 3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bail-Out' Cost:									
Group 1	0.000	0.000	0.000	0.000	0.000	0.000	0.123	0.126	0.128
Group 2	0.000	0.000	0.000	0.000	0.000	0.000	0.058	0.059	0.061
Group 3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
99% VaR Level:									
Group 1	0.088	0.087	0.086	0.047	0.045	0.043	-0.047	-0.049	-0.052
Group 2	0.116	0.116	0.115	0.093	0.090	0.087	0.021	0.017	0.014
Group 3	0.216	0.216	0.216	0.196	0.194	0.192	0.124	0.121	0.119

[44] Appendix 1gives the average one-year historical default rate on Brazilian bank loans with various credit qualities.

Table 24
Systemic Risk: Simultaneously Simulated Aggregate Banks

We report probability of two groups defaulting simultaneously (Panel A) and for the three groups defaulting simultaneously (Panel B). We report the average 'bail-out' cost (in parenthesis), only for the scenarios when the systemic default takes place with a non-zero probability. The average 'bail-out' cost is the average capital (as percentage of total assets) necessary to bring banks' capital ratio back to 0.08 level, whenever they fall below 0.03 (assumed default).

Panel A: Probability of Groups 1 and 2 defaulting at the same time and associated cost (given default), to bring both banks' capital ratios to 0.08.

		Incremental Defaults on Business and Consumers' Loans		
		0	+ 1 times the average historical default rates	+ 2 times the average historical default rates
Losses on Government Loans	0%	0.000	0.000	0.000
	10%	0.000	0.000	0.000
	25%	0.016	0.023	0.029
		(0.109)	(0.109)	(0.111)
	40%	0.048	0.048	0.048
		(0.234)	(0.246)	(0.256)
	50%	0.048	0.048	0.048
		(0.358)	(0.362)	(0.367)

Panel B: Probability of all groups defaulting at the same time and associated cost (given default), to bring all banks' capital ratios to 0.08.

		Incremental Defaults on Business and Consumers' Loans		
		0	+ 1 times the average historical default rates	+ 2 times the average historical default rates
Losses on Government Loans	0%	0.000	0.000	0.000
	10%	0.000	0.000	0.000
	25%	0.000	0.000	0.000
	40%	0.048	0.048	0.048
		(0.163)	(0.173)	(0.180)
	50%	0.048	0.048	0.048
		(0.270)	(0.274)	(0.278)