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Systemic bank risk in Brazil: an assessment of correlated market, credit, sovereign and inter-bank risk in an environment with stochastic volatilities and correlations

Theodore M. Barnhill, Jr.
(The George Washington University)

Marcos Rietti Souto
(International Monetary Fund)

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Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-1
Telex within Germany 41227, telex from abroad 414431

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

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Conference on the Interaction of Market and Credit Risk

6–7 December 2007, Berlin

Thursday, 6 December

8:30 – 9:00	Registration (Harnack Haus)
9:00 – 9:15	**Welcome Address by Hans Reckers (Deutsche Bundesbank)**
Session 1	**Banking and Securitization** **Chair: Myron Kwast (Federal Reserve Board)**
9:15 – 10:15	**Recent Financial Market Developments** **Keynote address by E. Gerald Corrigan (Goldman Sachs)**
10:15 – 11:05	**Banking and Securitization** Wenying Jiangli (Federal Deposit Insurance Corporation) Matthew Pritsker (Federal Reserve Board) Peter Raupach (Deutsche Bundesbank) Discussant: Deniz O. Igan (International Monetary Fund)
11:05 – 11:30	**Refreshments**
Session 2	**Integrated Modelling of Market and Credit Risk I** **Chair: Klaus Duellmann (Deutsche Bundesbank)**
11:30 – 12:10	**Regulatory Capital for Market and Credit Risk Interaction: Is Current Regulation Always Conservative?** Thomas Breuer (Fachhochschule Vorarlberg) Martin Jandačka (Fachhochschule Vorarlberg) Klaus Rheinberger (Fachhochschule Vorarlberg) Martin Summer (Oesterreichische Nationalbank) Discussant: Simone Manganelli (European Central Bank)

12:10 – 13:00	**An Integrated Structural Model for Portfolio Market and Credit Risk** Paul H. Kupiec (Federal Deposit Insurance Corporation) Discussant: Dan Rosen (R² Financial Technologies Inc.)
13:00 – 14:30	**Lunch**
Session 3	**Integrated Modelling of Market and Credit Risk II** **Chair: Til Schuermann (Federal Reserve Bank of New York)**
14:30 – 15:20	**The Integrated Impact of Credit and Interest Rate Risk on Banks: An Economic Value and Capital Adequacy Perspective** Mathias Drehmann (European Central Bank) Steffen Sorensen (Bank of England) Marco Stringa (Bank of England) Discussant: Jose A. Lopez (Federal Reserve Bank of San Francisco)
15:20 – 16:10	**An Economic Capital Model Integrating Credit and Interest Rate Risk** Piergiorgio Alessandri (Bank of England) Mathias Drehmann (European Central Bank) Discussant: Andrea Sironi (Bocconi University)
16:10 – 16:40	**Refreshments**
16:40 – 18:00	**Panel discussion** **Moderator: Myron Kwast (Federal Reserve Board)** **Panelists: Pierre Cailleteau (Moody's),** **Christopher Finger (RiskMetrics),** **Andreas Gottschling (Deutsche Bank),** **David M. Rowe (SunGard)**
20:00	**Conference Dinner (with Gerhard Hofmann, Deutsche Bundesbank)**

Friday, 7 December

Session 4	**Risk Measurement and Markets** **Chair: Thilo Liebig (Deutsche Bundesbank)**
9:00 – 9:50	**A Value at Risk Analysis of Credit Default Swaps** Burkhard Raunig (Oesterreichische Nationalbank) Martin Scheicher (European Central Bank) Discussant: Alistair Milne (Cass Business School)
9:50 – 10:40	**The Pricing of Correlated Default Risk: Evidence From the Credit Derivatives Market** Nikola Tarashev (Bank for International Settlements) Haibin Zhu (Bank for International Settlements) Discussant: David Lando (Copenhagen Business School)
10:40 – 11:10	**Refreshments**
11:10 – 12:10	**Structural Models and the Linkage between Equity and Credit Markets** **Keynote Address by Hayne Leland (The University of California, Berkeley)**
Session 5A	**Securitization, Regulation and Systemic Risk** **Chair: Hayne Leland (The University of California, Berkeley)**
12:10 – 13:00	**Solvency Regulation and Credit Risk Transfer** Vittoria Cerasi (Milano-Bicocca University) Jean-Charles Rochet (Toulouse University) Discussant: Loriana Pelizzon (University of Venice)
13:00 – 14:30	**Lunch**
14:30 – 15:20	**Determinants of Banks' Engagement in Loan Securitization** Christina E. Bannier (Frankfurt School of Finance and Management) Dennis N. Hänsel (Goethe University Frankfurt) Discussant: Gabriel Jimenez (Bank of Spain)

15:20 – 16:10	**Systemic Bank Risk in Brazil: An Assessment of Correlated Market, Credit, Sovereign and Inter-Bank Risk in an Environment with Stochastic Volatilities and Correlations** Theodore M. Jr. Barnhill (The George Washington University) Marcos Rietti Souto (International Monetary Fund) Discussant: Mathias Drehmann (European Central Bank)
Session 5B	**Credit Dependencies and Market Risk** **Chair: Kostas Tsatsaronis (BIS)**
12:10 – 13:00	**Interaction of Market and Credit Risk: An Analysis of Inter-Risk Correlation and Risk Aggregation** Klaus Böcker (UniCredit Group) Martin Hillebrand (Sal. Oppenheim) Discussant: Rüdiger Frey (University of Leipzig)
13:00 – 14:30	**Lunch**
14:30 – 15:20	**Market Conditions, Default Risk and Credit Spread** Dragon Tang (Kennesaw State University) Hong Yan (University of South Carolina) Discussant: Til Schuermann (Federal Reserve Bank of New York)
15:20 – 16:10	**The Effect of Seniority and Security Covenants on Bond Price Reactions to Credit News** David D. Cho (State University of New York at Buffalo) Hwagyun Kim (Texas A&M University) Jungsoon Shin (State University of New York at Buffalo) Discussant: Joerg Rocholl (European School of Management and Technology in Berlin)
16:10 – 16:30	**Final Remarks by Philipp Hartmann (European Central Bank)**
16:30 – 17:00	**Refreshments**

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

Theodore M. Barnhill, Jr. †
The George Washington University

Marcos Rietti Souto‡
International Monetary Fund

Abstract

In this study we develop and demonstrate a powerful and flexible 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 (i.e. 28 of the largest Brazilian banks) and groups of banks (i.e. the Brazilian banking system). The methodology importantly accounts for bank asset and liability maturity and currency mismatches and loan portfolio credit quality and sector and region concentrations. In a significant innovation, 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 bank 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 securities held by Brazilian banks, but also reflects the banks' adequate capitalizations and extraordinarily high interest rate spreads. Once sovereign risk is considered and losses in the market value of government securities reaches 10 percent (or higher), 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 also demonstrate the potential systemic risk impact of variation in average recovery rates on defaulted private sector loans which reflect, among other factors, bank lending policies, the efficiency of the legal system in resolving defaults, and aggregate levels of defaults. Our analysis also highlights the importance of accounting for the differential risk characteristics of various banks and for the inter-bank risk channel, through which a systemic crisis may propagate. It further indicates that, in the event of a sovereign default, the Government of Brazil would face constrained debt management alternatives. To the best of our knowledge no one else has put forward a systematic methodology for assessing correlated market and credit (sovereign, corporate and inter-bank) default risk for a financial system.

JEL Classification: G0
Keywords: Integrated Market and Credit Risk, Monte Carlo Simulation, Brazilian banks

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† Professor of Finance, Director Global and Entrepreneurial Finance Research Institute (GEFRI), The George Washington University, barnhill@gwu.edu
‡ Financial Sector Expert, Monetary and Capital Markets Department, International Monetary Fund, msouto@imf.org

Non-technical Summary

In this study we seek to develop a forward-looking methodology for assessing the systemic banking risk (the likelihood of multiple banks failures), that integrates market and credit risk using a Portfolio Simulation Approach (PSA), with an application to the Brazilian banking system. We have performed a large number of simulations using comprehensive data for 28 of the largest Brazilian banks, which invest heavily in government loans. In the first part we simulate the banks individually, considering two scenarios: (i) Brazilian government never defaults on its domestic debt; and (ii) Brazilian government can default at a rate comparable to the average default rate of sovereign debts rated in the same grade as Brazil, according to Fitch. Our results show that, while some banks do lose money even if government default is not accounted, none of the banks face significant default risks, over the 1-year simulation horizon. However, once the government default is factored in, then several simulated banks present default problems. These results combined show the perverse side of lending too much to the government. First, even if the government does not default, holding too much government debt preempts banks from earning higher (riskier) interest income from business and customers' loans. Second, it is possible to reduce the amount lent to the government and balance the portfolio in such a way that banks' will still produce profitable capital on average, even after accounting for government default. We also show that average and standard deviations of the return on average assets (ROAA) and the return on average equity (ROAE) are unbiased estimators for the same moments for historical ROAA and ROAE. While this result needs to be taken with caution, given the analysis limitations, it does show the simulation framework capability of reproducing banks' profitability ratios that are reasonably comparable to historical values

In the second part we use the results from these simulations and divide the banks in to three groups according to their default rates and to the average capital required to bail the banks out, so as to push their simulated capital ratios to a 0.08 capital level. Our categorization is generally consistent with Moody's and Standard and Poor's ratings, and departs slightly from Fitch ratings. Simulated groups also produce capital ratios, default rates, and bail-out cost that are on average very consistent with the credit risk categorization: average 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 groups simultaneously and include the risk component associated with interbank default (interbank propagation channel). 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 interbank propagation channel is very small.

Nichttechnische Zusammenfassung

In dieser Studie wollen wir eine vorausschauende Methodik zur Einschätzung des systemischen Bankrisikos (der Wahrscheinlichkeit von multiplen Bankausfällen) entwickeln, die das Markt- und das Kreditrisiko anhand eines Portfoliosimulationsverfahrens integriert. Die Methodik soll sodann auf das brasilianische Bankensystem angewendet werden. Wir haben zahlreiche Simulationen durchgeführt, die sich auf umfassende Daten für 28 der größten brasilianischen Banken mit starkem Engagement im Bereich der staatlichen Kredite stützten. Im ersten Teil simulieren wir die Banken einzeln, wobei zwei Szenarien unterstellt werden: 1) die brasilianische Regierung ist immer in der Lage, ihre Inlandsschulden zu bedienen, und 2) die brasilianische Regierung kann zahlungsunfähig werden, wobei die Ausfallrate in etwa der durchschnittlichen Ausfallrate von Staatsschulden mit demselben Fitch-Rating wie Brasilien entspricht. Unsere Ergebnisse zeigen, dass einige Banken zwar tatsächlich Verluste verzeichnen, auch wenn eine Zahlungsunfähigkeit der Regierung nicht berücksichtigt wird, dass aber keine der Banken in dem einjährigen Simulationszeitraum einem nennenswerten Ausfallrisiko unterliegt. Wird allerdings der Ausfall der Regierung miteinbezogen, weisen mehrere simulierte Banken Probleme bezüglich des Ausfallrisikos auf. Zusammen betrachtet offenbaren diese Ergebnisse die negativen Seiten einer zu starken Kreditvergabe an den Staat. Erstens hindert ein zu hoher Bestand an Staatspapieren, selbst wenn die Regierung nicht zahlungsunfähig wird, die Banken daran, höhere (risikoreichere) Zinserträge aus Unternehmens- und Kundenkrediten zu erzielen. Zweitens ist es möglich, den der Regierung gewährten Kreditbetrag zu verringern und das Portfolio derart auszurichten, dass die Banken im Durchschnitt selbst dann noch gewinnbringendes Kapital erwirtschaften, wenn eine Zahlungsunfähigkeit der Regierung einbezogen wird. Wir weisen zudem nach, dass durchschnittliche und standardmäßige Abweichungen von der durchschnittlichen Gesamtkapitalrendite und der durchschnittlichen Eigenkapitalrendite für dieselben Momente unverzerrte Schätzwerte für die entsprechende historische Gesamtkapital- und Eigenkapitalrendite darstellen. Diese Erkenntnis ist aufgrund der Einschränkungen der Analyse zwar mit Vorsicht zu betrachten, doch zeigt sie, dass das Simulationsverfahren imstande ist, Ertragskennziffern der Banken nachzubilden, die hinlänglich mit den historischen Werten vergleichbar sind.

Im zweiten Teil verwenden wir die Ergebnisse dieser Simulationen und ordnen die Banken in drei Gruppen ein; dies geschieht nach Maßgabe der jeweiligen Ausfallrate und des durchschnittlichen Kapitals, das zur Rettung der Banken erforderlich ist, um ihre simulierte Eigenkapitalquote auf einen Wert von 0,08 anzuheben. Unsere Einteilungen stimmen im Wesentlichen mit den Ratings von Moody's sowie Standard and Poor's überein, weichen aber geringfügig von den Fitch-Ratings ab. Für die simulierten Gruppen werden ebenfalls Eigenkapitalquoten, Ausfallquoten und Rettungskosten ermittelt, die im Durchschnitt deutlich der Klassifizierung der Kreditrisiken entsprechen: Wenn das

Kreditrisiko steigt, gehen die durchschnittlichen simulierten Eigenkapitalquoten zurück und die Ausfallraten sowie die Rettungskosten nehmen zu.

Abschließend bewerten wir die systemischen Risiken des brasilianischen Finanzsystems auf verschiedene Weise. Zunächst untersuchen wir eine einzelne Bank, die einer Kombination aus allen 28 Banken entspricht, und danach simulieren wir die drei Gruppen gleichzeitig unter Berücksichtigung der mit Interbank-Ausfällen zusammenhängenden Risikokomponente (Interbank-Ausbreitungskanal). Unsere Ergebnisse zeigen, dass – verglichen mit der gleichzeitigen Simulation – bei der Zusammenfassung aller Banken in einer einzelnen Bank die Kosten, die sich aus einer Krise infolge eines systemischen Risikos ergeben, stark unterzeichnet werden; allerdings ist das Risiko eines gleichzeitigen Ausfalls aller Banken durch den Interbank-Ausbreitungskanal sehr gering.

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 credit quality (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). There is also reason to believe that bank market risk is driven systematically by the same future financial and economic conditions. These correlated market and credit risks have significant impacts on individual bank risk and banking system risk and need to be accounted for systematically, to produce more useful integrated risk assessments.[1]

The 80's and 90's have witnessed a number of systemic banking crises[2], sometimes with transnational contagion effects. 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."*

Forward-looking risk assessment methodologies can be of central importance in quantifying the potential magnitude of the risk and, more importantly, in 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.

[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 default on sovereign balance sheet. We look forward to addressing this future research topic.

Barnhill and Maxwell (2002) developed 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 Brazilian bank loans[4]. These studies have demonstrated that the PSA methodology produces:

1. simulated financial environments that match 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 reflecting correlated market and credit risk.

To the best of our knowledge no one else has put forward a systematic methodology for assessing *correlated* market and credit (sovereign, corporate, and inter-bank) default risk for a financial system.

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[5]. 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

[4] Section 2 provides 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.

[5] 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.

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 (i.e. may also impact multiple banks simultaneously. Sixth, various factors including bank lending policies, the efficiency of the legal system in resolving loan defaults, and the aggregate level of defaults can impact substantially on bank risk through variations in the recovery rates on defaulted loans. Finally, sovereign defaults may simultaneously impose direct losses on banks through a reduction in the market value of their Government securities 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. A combination of correlated 'bad draws' for these macroeconomic/financial state variables will eventually impact the banks with negative effects comparable to those provoked by a large macroeconomic shock. Indeed, we have modeled volatilities and correlations as stochastic variables in our simulation, in an attempt to increase the mass towards the distributions' tails (see Barnhill and Souto (2007)). This approach not only allows us to capture the influences of macroeconomic forces[6] 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 GDP 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. Barnhill and Souto (2007) provide a comprehensive examination of stochastic process for volatilities and correlations and its 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 corresponding decay factor 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 allows us to capture correlations

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

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.

The reliability of the model is demonstrated in various ways. First, Barnhill, Souto, and Tabak (2003), and Barnhill and Souto (2007) have shown that the model can produce simulated credit rating transition probabilities and default rates for business loans that are very similar to those reported by Brazilian Banks. Second, by simulating a set of 11 private domestic Brazilian banks we show that the models produce means and standard deviations of return on average equity and assets[7] (ROAE and ROAA respectively) that are unbiased predictors of banks' historical means and standard deviations of ROAE and ROAA. Finally we show that our risk assessments for individual banks are generally consistent with the ratings provided by Moody's and Standard and Poor's.

We then proceed to simulate the banks at different levels: (i) individual, (ii) groups, and (iii) simultaneously. 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 percent probability which is consistent with the average default probability of countries rated by Fitch in the same grade as Brazil (B rating), as of December 2004.

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 percent of their total assets. In this study we model government default in a relatively simplistic way, as a very large 'corporate borrower' whose known default probability is systematically related to returns on the Brazilian equity market index plus an idiosyncratic component. 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[8]. For this purpose, we first aggregate the 28 banks into three groups according to their individual risk characteristics and then simulate them simultaneously[9]. It is important to keep in mind the significance of modeling all of the correlated risks above. In particular during times of economic stress it is likely that default losses on private sector loans will increase, market volatility

[7] These returns on assets and equity reflect changes in the values of assets and liabilities, interest income and expenses, other net operating expenses, and taxes over the simulation period.

[8] 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.

[9] 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.

and risk will also likely increase, and so 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 are varied, hard to predict in advance, and will be very dependent on the contemporaneous policies adopted by the Government at the time of any such default. For the present application we will use a matrix of potential additional losses on banks' portfolios, through two different channels. First, even if banks face no losses on government securities, they may face additional losses on their business and consumer loans, as these sectors of the economy are impacted by major disruptions in the economy due to the sovereign default event. Second we assess the direct impacts of various potential declines in the market value of the banks' government debt portfolio.

Our analysis finds that most Brazilian 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 securities 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 securities, then it could trigger a systemic banking system failure. In the particular case of GOB, in the event of government default, we show that losses of 10 percent or higher in the market value of government securities would create problems for a number of individual banks. Loss rates of 25 percent or higher on government securities could provoke a systemic banking crisis. Since the amount of GOB securities in Brazilian bank balance sheets is substantially larger than the amount of business and consumer (private sector) loans, the impact of incremental defaults on private sector loans has a smaller impact on banks' risk of failure. A less obvious impact is that holding a very large amount of government debt preempts banks from earning higher interest income from business and consumer loans. It may be entirely possible to reduce the amount lent to the government and balance the portfolio in such a way that the banks 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. In this analysis we assume that a sovereign default imposes a 10 percent average loss on government securities and an incremental default rate on business and consumer loans equal to the average default rate for each credit category. Specifically, we categorize Brazilian banks into three groups, based on their capital ratio at the 99% VaR level (meaning that the bank has 1 percent probability of having its capital ratio falling below this number). We find that our categorization is generally consistent with Moody's and Standard and Poor's ratings. Simulated capital ratios, default rates, and potential 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 the systemic risk of the Brazilian financial system, in different ways. We first consider a single bank that is a combination of all 28 banks. Subsequently we simulate three aggregate banks (based on the above risk categories) 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. Our 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 risk 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 a 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 consumer 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 (as opposed to the current method of modeling operating expense as a constant percentage of assets). 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 as a correlated stochastic variable. In spite of all the identified data and other limitations we believe the model has 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 describes the portfolio simulation model we use to undertake the various integrated risk assessments. In Section 3 we present and discuss the risk assessments for Brazilian banks and the Brazilian banking system. Concluding remarks and final comments are given in Section 4.

2. An Integrated Model of Correlated Market, Credit, Sovereign, and Inter-Bank Risk in an Environment with Stochastic Volatilities and Correlations

An integrated analysis of correlated market risk, and private sector, sovereign, and inter-bank default risk on both individual banks (i.e. 28 of the largest Brazilian banks) and groups of banks (i.e. the Brazilian banking system) requires a powerful and flexible forward-looking risk assessment methodology. Portfolio simulation is the methodology we have identified as being capable of undertaking such an analysis.

Our models are based on the observation that at any future time all entities existing in a particular economic environment will experience the same financial and economic conditions. We propose that it is possible to identify a set of correlated financial and economic variables, for example sector equity returns and regional unemployment rates[10], which *systematically* impact the credit quality and produce correlated default rates among various groups of borrowers (e.g. businesses in various sectors, and individuals in various regions). We also model many uncorrelated borrower specific risk factors. We find such detailed individual borrower and portfolio modeling necessary to assess the risk level of portfolios of loans with varying credit quality distributed across various sectors and regions. In particular it allows for explicit modeling of loan portfolio concentration and diversification impacts on bank risk levels.

We further propose that the identified set of correlated financial and economic variables can include ones which have *systematic* impacts on the market values of securities, loans, and other assets. Examples of such variables are interest rates, interest rate spreads, FX rates, equity index returns, and commodity prices. Also in a significant innovation financial and economic environment variables are modeled with stochastic volatilities and correlations.

The structure of the systemic bank risk simulation model is as follows:

– Simulate the future financial environment (e.g. 1 year) as a set of correlated stochastic variables that systematically impact each bank's market risk (interest rates, interest rate

[10] In circumstances where banks hold significant mortgage loans it is useful to model regional real estate prices as a systematic credit risk driver (see Barnhill, Papapanagiotou, and Schumacher, 2003 and Barnhill, Papapanagiotou, and Souto, 2004). Most Brazilian banks hold very few mortgage loans thus we did not model Brazilian real estate prices.

spreads, FX rates) and credit risk (sector equity returns, regional real estate prices, regional unemployment rates, etc.).

– Simulate the correlated evolution of the credit rating (default) for each borrower in each bank's loan portfolio as a function of the simulated financial environment.

– Simulate the correlated evolution of the credit rating (default) for the Government of Brazil as a function of the simulated financial environment.

– Revalue each asset and liability in each bank's balance sheet as a function of the simulated financial environment and credit ratings. Note that for each run of the simulation the simulated value of each bank's assets and liabilities reflect correlated market and credit risk.

– Estimate each bank's pre-tax income, operating costs, taxes, and after-tax income over the simulation period.

– Calculate financial performance measures for each bank (e.g. economic capital ratio, rate of return on assets, etc.) under the simulated conditions. Estimate if the bank will fail or not.

– Estimate each bank's potential losses on defaulted inter-bank loans.

– Recalculate financial performance measures for each bank (e.g. economic capital ratio, rate of return on assets, etc.) under the simulated conditions. Re-estimate if each bank will fail or not.

– Repeat the simulation a large number of times.

– Analyze the distributions of simulated bank financial performance measures (e.g. economic capital ratio) to determine individual bank and banking system systemic risk levels[11].

2.1. Modeling the Financial Environment

2.1.1. Simulating Stochastic Term Structures

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

[11] In the present study the bank portfolio is assumed to be constant over the risk horizon of the exercise (e.g., one-year) and is repriced in each run of the simulation using the simulated prices and credit quality of the borrowers. Simulations were run for 2000 times using monthly (i.e. 12) time steps.

The model for r is:

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

where Δr is the risk-neutral process by which r changes, a is the rate at which r reverts to its long term mean, r is the instantaneous continuously compounded short-term interest rate, $\theta(t)$ is "Theta", an unknown function of time which is chosen so that the model is consistent with the initial term structure and is calculated from the initial term structure as:

$$\theta(t) = F_t(0,t) + \alpha F(0,t) + \frac{\sigma^2}{2a}(1 - e^{-2at}), \tag{2}$$

$F(0,t)$ is the forward interest rate at time t as calculated at time 0, $F_t(0,t)$ is the derivative of the forward interest rate with respect to time, Δt is a small increment to time, σ is "sigma", the instantaneous standard deviation of r, which is assumed to be constant, and Δz is 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. In this study they are estimated from a time series of short-term interest rates over the 1995-2004 period. Given a simulated future value of r, the initial term structure, and the other parameters of the model a complete term structure of risk-free interest rates can be calculated and financial assets can be re-valued at time step Δt.

Once the risk-free term structure has been estimated then the AA term structure is modeled as a stochastic lognormal spread over risk-free, the A term structure is modeled as a stochastic spread over AA, etc. The mean value of these simulated credit spreads are set approximately equal to the forward rates implied by the initial term structures for various credit qualities (e.g. AA). This procedure insures that all simulated credit spreads[12] are always positive and that the simulated risky term structures are approximately arbitrage free.

2.1.2. Simulating Asset Returns

The model utilized to simulate the value of the equity market indices and FX rate (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

[12] Different credit spreads for borrowers with different ratings estimated for each bank so as to account for the average default rate in each category and match the historical net interest income of each bank.

$$S + \Delta S = S \exp\left[\left(m - \frac{\sigma^2}{2}\right)\Delta t + \sigma\varepsilon\sqrt{\Delta t}\right], \tag{3}$$

where ε is a random sample from a standardized normal distribution.

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

$$K_m = (\Delta S/S) + q. \tag{4}$$

2.1.3. Simulating an n-variate Normal Distribution

In the current 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 (the Cholesky decomposition). 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,

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

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

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

2.1.4. Stochastic Volatilities and Correlations

Variances and covariances are updated for each simulation time step via the following model:

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\sigma_{ij,t-1}v_t, \tag{7}$$

where $v_t \sim N(0,1)$. Initial variances and covariances at the start of each simulation run are estimated as the average realized variances and covariances over the entire Jul/94 to Dec/03 period. 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.

Barnhill and Souto (2007) show that by changing the decay factor (λ) appropriately this approach increases the probability mass of index returns in the tails of simulated distributions and matches reasonably well the historical evolution of volatilities. This model is implemented to simulate the credit transition matrix for Brazilian bank loans and it is shown that this methodology has the potential to improve simulated transition probabilities as compared to the constant volatility case. In particular, it increases the simulated probability of default in lower credit risk categories to values closer to observed historical levels.

2.2. Modeling Banks' Assets, Liabilities and Income

2.2.1. 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[13] and then properly linked to different correlated 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) Government of Brazil securities[14]; (iii) business loans; (iv) consumer 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) who model residential mortgage loans for South African banks, and Barnhill, Papapanagiotou, and Souto (2004) who model both residential and commercial mortgage loans for Japanese banks. Equity and real estate investments are separately modeled through multiple one-factor models, with systematic and unsystematic risk components.

Unlike state variable returns that are estimated for each time-step in each simulation path, all balance sheet accounts are recalculated only at the end of each simulation period[15]. In Table 3 we

[13] Based on the data we obtained, we categorized the liabilities into the following three maturity groups: < 1-year, between 1 and 3 years, and > 3 years. The simulation methodology, however, is flexible enough to handle multiple maturities for both liabilities and assets as well as multiple currency denominations.

[14] We initially assume the government securities have no risk of default risk. 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.

[15] 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.

present some descriptive statistics on the stylized balance sheet for 28 Brazilian banks. This data was obtained from BankScope and the web site of the Brazilian central bank[16].

2.2.2. Banks' Loan Portfolio Composition

Absent other information, loans (which usually comprise the biggest fraction of most banks portfolios) are typically modeled as bonds. We allocate business and consumer loans separately across eight credit risk categories defined by Banco Central do Brasil (AA ,…, H). In the case of business loans, we also distribute them across 10 business sectors, while loans to individuals are distributed across 6 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. In total we use approximately 450 stylized securities to model each bank. While a larger number of currencies and securities could have easily been modeled, we believe that this number is adequate to capture statistically much of the impact of bank asset and liability portfolio maturity, currency, credit quality and sector and region concentration characteristics.

2.2.3. Banks' Operating Expenses, Taxes, and Income

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) to estimate pre-tax income. We also estimate taxes paid by banks as an assumed percentage of taxable income over the simulation period. After-tax income is estimated as pre-tax income less estimated taxes.

2.3. Modeling Bank Loan Portfolio Credit Risk

The methodology used to model business loan credit transition probabilities and defaults starts with an extensive empirical analysis of all publicly traded companies in Brazil and all bank loans made to those firms by all Brazilian banks. The purpose of this analysis is to identify typical debt to value ratios, beta coefficients, and firm specific equity return volatilities for Brazilian firms with various bank assigned credit ratings. We use this information to develop stylized firms for each

[16] It is possible to model a great variety of other financial instruments (e.g. bonds, zero coupon bonds, variable rate loans, forward contracts, swaps, options, etc.) within our simulation framework.

credit rating (i.e. target debt to value ratio, and assumed beta and firm specific risk factors). For each run of the simulation the return on each borrowing firm's equity is estimated as 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[17].

2.3.1. Modeling Bank Borrowers' Return on Equity

The return on equity for individual firms is simulated using a one-factor model.

$$K_i = R_F + Beta_i\,(Km\text{-}R_F) + \sigma_i \Delta z, \tag{8}$$

where K_i is the return on equity for the firm$_i$, R_F is the risk-free interest rate, $Beta_i$ is the systematic risk of firm$_i$, K_m is the simulated return on the equity index from equation 6, σ_I is the firm specific volatility in return on equity, and Δz is a Wiener process with Δz being related to Δt by the function $\Delta z = \varepsilon\sqrt{\Delta t}$.

After simulating the market return, the return on equity for an individual firm is estimated in the CAPM framework (equation 8). The first step in calculating the expected return on equity for a "typical" firm in a particular rating class (e.g. B) is to estimate appropriate beta coefficients and the unsystematic component of equity return risk.

2.3.2. Estimating Betas for a set of Brazilian Companies

In order to implement the single-factor CAPM model[18] it is necessary to estimate betas and firm specific volatilities for Brazilian companies. Estimating betas for Brazilian companies was not an easy task, since many of them trade infrequently. As several stocks lack liquidity, price series tend to have artificial rigidities that might lower the estimated betas, misleading empirical evidence.

Using 12 equity sector indices for Brazil (banks, basic industry, beverage, chemicals, general industry, metal, mining, oil, paper, telecommunication wireless, textile, tobacco, utility), betas for 543

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[17] We were unable to obtain the data required to develop a separate credit risk model for consumer loans. Thus in this study we also model consumer loans as business loans. For this purpose we model a systematic risk factor for each region which has the return and volatility characteristics of the Ibovespa stock index but which has correlations with other financial and economic environment variables equal to those of the regional unemployment rates. This model allows us to generate credit transition probabilities and default rate similar those reported by Brazilian banks and also account for some of the diversification benefits of lending to different types of borrowers (i.e. businesses in various sectors, and consumers in various regions).

[18] We opted for the CAPM single-factor model to evaluate the systematic and unsystematic portions of risk, because of its simplicity to implement and its appealing intuition of the risk/return relationship. However, multi-factor models could be used as well.

companies were estimated accordingly to their respective industry sector[19]. Data on prices for sector indices and individual stocks were collected from DataStream. We assume that the debt to value ratios, betas, and firm specific risk volatilities for these 543 firms will be representative of those for other bank borrowers with similar bank assigned credit ratings.

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

$$\beta_U = \frac{\beta_L}{1+\left(1-\tau_c\right)\frac{D}{S}}, \tag{9}$$

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

Monthly observations produced the most consistent estimations for betas. Final results for estimated betas and firm-specific risk for firms in various credit rating categories as assigned by Brazilian banks[20], are given in Table 1. As would be expected both the betas and firm specific risk levels increase as company bank loan ratings decline.

2.3.3. Mapping Debt Ratios into Credit Ratings

The above simulated equity returns are then used to estimate a distribution of possible future equity market values and debt ratios[21]. The simulated debt ratios are then mapped into credit ratings. This methodology assumes a deterministic relation between the firm's debt ratio and its credit rating[22]. In a contingent claims framework this is equivalent to assuming a constant volatility for the value of the firm.

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[19] Estimating betas using sector indices instead of a broad market index allows us to capture the diversification benefit, as banks lend to companies in different sectors of the economy.

[20] More details on the simulated banks and on the transition probability matrix employed in this paper can be found in Barnhill, Souto, and Tabak (2003).

[21] The debt-to-value ratio is defined as book value of debt divided by book value of debt plus market value of equity. We then assume that the firm has an expected growth rate and target debt-to-value ratio. Fluctuations in realized company returns around trend returns result in fluctuations in simulated future debt-to-value ratios. While a case can be made for using the market value of debt to define debt-to-value ratios we did not have this information for Brazilian companies.

[22] 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.

To implement this method an empirical analysis of the distribution of debt ratio[23] by rating class is performed on all publicly traded non-financial firms that borrow from all Brazilian banks[24]. Debt ratio distributions are then analyzed by rating category. The results are also found in Table 1. As expected, debt ratio increases as company bank loan ratings decline. For simulation runs reported later in this study, we assume that debt ratios start at the midpoint between the maximum and minimum values for the assumed initial credit rating category. Credit ratings are generally assumed to change when simulated debt ratios cross the min-max boundaries. However due to the fact that the distribution of debt to value ratios of G and H companies is very similar, the debt to value ratio at which firms are assumed to default is set at 0.96. This level is approximately equal to the mean for defaulting firms. Increasing (decreasing) this critical debt to value ratio reduces (increases) simulated loan default rates.

2.3.4. Banks' Recovery Rate on Defaulted Private Sector Loans

The recovery rate on defaulted business and consumer loans ("private sector loans") is an important risk factor. Variables affecting the recovery rate include the seniority and security of the loans, the asset and liability structure of the company, the potential to reorganized a defaulted business into a profitable going concern, the industry, bank lending policies, bank collection policies, the aggregate volume of defaulted loans that must be resolved[25], and importantly the efficiency of the legal system in resolving loan defaults.

In the case of Brazil historically the legal system was viewed as taking an exceptionally long time to resolve loan defaults and bankruptcies and that the recovery rate on defaulted loans was low. For the current study when we wish to model historical distributions of bank returns or model potential extreme systemic banking system problems we will assume an average recovery rate on defaulted bank loans of 15 percent.

In June 2005 a decade long effort to modernize Brazil's bankruptcy laws came into effect. This change is projected to improve the recovery prospects for defaulted Brazilian bank loans (see Eccles, 2005). Thus for the current study when we undertake forward looking risk assessments for Brazilian banks and the banking system our base case assumption is that the recovery rate on

[23] Merton (1974) defined leverage ratio as debt over equity. To simplify, for comparison purpose, the algebraically equivalent debt over total market capitalization (i.e. debt ratio), is defined as [book value of debt/(book value of debt + market value of equity)], is utilized in this study.

[24] This information is compiled by the Central Bank of Brazil and the results presented in Table are published in Barnhill, Souto, and Tabak (2003).

[25] For example in the case of Japanese financial system problems during the 1990's and early 2000's, when a very large volume of loans defaulted, the recovery rate was estimated to be in the 20 to 30 percent range (See Barnhill, Papapanagiotou, and Souto (2004).

defaulted private sector loans is drawn from a beta distribution[26] with a mean value of .45 and a standard deviation of .25. However we will also report simulation results based on an assumed recovery rate of 15 percent to illustrate the potential impacts of a lower recovery rate on systemic banking system risk levels.

2.3.5. Valuing the Bank's Loan Portfolio

After simulating the loans' future credit rating their values are calculated using the simulated term structure of interest rates appropriate for each risk class. If the loan is simulated to default, the recovery rate on the loan is set at either the higher (45 percent) or lower (15 percent) levels discussed above. If the loan is denominated in a foreign currency then its numeraire currency value is calculated by multiplying the simulated loan value by the simulated foreign exchange rate that by construction is also a correlated stochastic variable.

2.4. Simulated Credit Transition Matrix

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

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. In order to provide a more precise measure of how close one transition matrix is to the other, we use the metrics proposed by Jafry and Shuermann (2004), defined as:

$$M_{SVD}(P) \equiv \frac{\sum_{i=1}^{N} \sqrt{\lambda_i \left(\tilde{P}' \tilde{P} \right)}}{N}, \tag{10}$$

where P is the transition matrix, $\tilde{P} \equiv P - I$, I is the identity matrix, λ_i is the i^{th} eigenvalue of P and N is the order of the matrix P.

For the historical CTM, $M_{SVD} = 0.3294$, while for the simulated CTM, $M_{SVD} = 0.3306$, resulting in $\Delta M_{SVD} = 0.0012$. As compared to values provide in Jafry and Shuermann (2004) for

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

bootstrapped SVDs, this value is a strong indicator that the two CTMs are indeed very similar to one another[27].

2.5. Modeling Bank Capital Ratios

The previous analysis allows the market value of the bank's assets, liabilities, equity, and capital ratio to be calculated for each simulation run:

$$MVE_t = \sum_{i=1}^{n} A_{i,t} - \sum_{i=1}^{n} L_{i,t} \ , \tag{11}$$

where MVE_t is the simulated market value of the bank's equity at time t, $A_{i,t}$ is the simulated market value of the i'th asset at time t which reflect the simulated financial environment variables (e.g., interest rates, exchange rates, equity prices, and etc.) and where appropriate, the simulated credit rating of the borrower, $L_{i,t}$ is the simulated market value of the i'th liability at time t which reflect the simulated financial environment variables (e.g., interest rates, exchange rates, etc.).

The bank's simulated capital ratio reflect changes in the value of assets and liabilities as well as bank net interest income, operating costs, and taxes over the simulation period. The simulated prices are used to recalculate the value of the bank capital under each simulation run (i.e. scenario). If for example, the bank made a loan in a foreign currency and the loan will be repaid in full in a year, the value of the loan will be given by the discounted value of the equivalent Real amount of the loan. In order to recalculate the value of the loan under each scenario, the simulated interest rate for that scenario is used in the present value formula and the simulated value of the exchange rate for that scenario is used to convert the simulated value of the loan into the domestic currency. This produces a new simulated value of the loan for each scenario.

The final outcome of the model after many simulation runs is an estimated distribution of the bank's capital[4] to asset ratio, characterized by a mean, a standard deviation, a maximum and a minimum value, as well as a Value-at-Risk output indicating how frequently the bank's capital to asset ratio fall is below certain thresholds (e.g. 3 percent) which is used to estimate the banks' default probability. Declines in the capital ratio (i.e., potential losses) under each simulation run are estimated as the difference between the initial bank capital and the simulated capital ratio[28].

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[27] In Jafry and Shuermann (2004), average ΔM_{SVD} ranged from -0.03491 to 0.01071, for transition probability matrices estimated using different methods, but over the same dataset of S&P ratings histories.

[28] It is important to note that we are modeling banks' tier-1 (equity) capital ratio.

$$Capital\_Ratio_t = MVE_t / \sum_{i=1}^{n} A_{i,t} \text{ ,} \tag{12}$$

where $Capital\_Ratio_t$ is the simulated bank capital ratio at time t.

2.6. Modeling Sovereign Risk

The Government of Brazil is modeled as a large business borrower with an assumed debt to value ratio and an assumed market value of equity. The government's market value of equity 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 market value of equity and 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, beta, and idiosyncratic risk components are selected to produce a targeted average sovereign default rate of 4.5 percent. The simulated sovereign defaults are thus systematically related to returns on the Brazilian equity market (and other correlated state variables) 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[29] which are also correlated with simulated financial and economic variables (e.g. equity returns, interest rates, foreign exchange rates, etc.).

The impacts of a Government default on the banking system are varied, hard to predict in advance, and will be 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 securities 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 explicitly default on its domestic debt, the banks may ultimately incur losses on the market value of its government debt portfolio. To be able to model such potential sovereign default impacts 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

[29] 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).

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 securities, they may face additional losses on their business and consumer loans, as these sectors of the economy are impacted by major disruptions in the economy due to 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, 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 securities, by assuming that banks may lose 0 percent, 10 percent, or 25 percent of the market value of their government securities. 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[30]. In addition to study the importance of the recovery rate on defaulted private sector loans in systemic risk assessments we repeat the above analysis for both the higher (45 percent) and lower (15 percent) assumed recovery rates.

2.7. Modeling Inter-Bank Default Risk

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[31]. For this purpose, we first aggregate the 28 banks into three groups according to their individual risk characteristics and then simulate them simultaneously[32]. Since we do not have precise information on inter-bank

[30] 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.

[31] 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.

[32] 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.

borrowers/lenders identities, we assume inter-bank lending to be proportional to the three aggregate banks total assets. We then assume, in a second lance, that if one bank falls below a 3 percent capital ratio[33], then it becomes incapable of honoring its inter-bank obligations and defaults on them. Only 50 percent of these inter-bank obligations are 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 above. In particular during times of economic stress it is likely that default losses on private sector loans will increase, market volatility and risk will also likely increase, and so 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.

2.8. Modeling Systemic Bank Risk

Finally, we assess the 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 percent average loss in the market value on government securities and an incremental default rate on business and consumer loans equal to two times the average simulated default rate per risk category, then the single-bank default rate is 2.2 percent, 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 percent, 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 securities, 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.

[33] Anecdotal evidence suggests that banks generally start having solvency problems when their capital ratio (total asset minus total liabilities, over total assets) falls below 3 percent.

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 banking system risk. In the first set of simulations 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 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 for a single aggregate bank and subsequently three aggregate banks with different risk levels to assess systemic banking system risk (i.e. the likelihood of multiple banks defaults) reflecting market, credit, sovereign, and inter-bank risk. These correlated market and credit risk assessments are based on analyses of the output from 2,000 simulation runs.

3.1. Individual Banks, No Government Default, Higher Volatilities

The first set of our risk simulations focus on 11 Brazilian private domestic banks[34], which we will use for model validation purpose. The idea is to compare means and standard deviations for simulated return on average equity (ROAE) and return on average assets (ROAA), with historical distributions of reported ROAE and ROAA. 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 provides 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 11 banks, over a 1-year period (December 2004 to December 2005) assuming that the GOB does not default. As the 2000-2004 period precedes the change in Brazilian bankruptcy laws we assume a 15 percent recovery rate on defaulted private sector loans.

To make this simulation exercise as consistent as possible, we have estimated a new set of volatilities and correlations, using monthly data for all stochastic financial environment variables and over the same 2000-04 period. Both volatilities and correlations are substantially different than the

[34] These are hypothetical banks constructed using publicly available data in the Brazilian Central Bank website. It is an effort to replicate main Brazilian banks characteristics and to make this exercise as close to reality as possible.

ones estimated for the 2003-04 period which are used in all of the other simulations reported in this paper. In general, using data for 2000-2004 increases the volatility significantly, which is not surprising, 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 integrated market and credit risk capabilities of the simulation methodology we utilize.

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

$$ROAAavg_{h,i} = \beta_1 \cdot ROAAavg_{s,i} + \varepsilon_1 \tag{13}$$

$$ROAAsd_{h,i} = \beta_2 \cdot ROAAsd_{s,i} + \varepsilon_2 \tag{14}$$

$$ROAEavg_{h,i} = \beta_3 \cdot ROAEavg_{s,i} + \varepsilon_3 \text{ and} \tag{15}$$

$$ROAEsd_{h,i} = \beta_4 \cdot ROAEsd_{s,i} + \varepsilon_4, \tag{16}$$

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 4. 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 1.61); (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 0.47); (iii) in all regressions, the Wald Statistics fail to reject the null, $\beta = 1$, at 95 percent confidence level.

While encouraging, these results need to be taken with care for several reasons. First, historical means and standard deviations 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) [35]. Simulation results for this group are presented in Table 5, and a few comments are in order. First, reported VaR levels indicate the percentage of time that simulated bank capital ratios fall above a certain threshold. For example, Bank 20 VaR at 99% level is 0.154, indicating that 1 percent of the time the simulated capital ratio for Bank 20 fell 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 ratios 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 7, 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 simulation 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 percent 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 a 0.08

[35] 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 percent on average in the past 10 years, according to Klaar, Rawkins, and Riley (2004).

capital ratio on an economic capital basis (e.g. Bank 5 with minimum capital ratio of 0.043, Bank 7 with 0.050, and Bank 21 with 0.057, among others). Finally, simulated capital ratios have a 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 securities held by these banks, this result is not surprising at all. Bank 9 holds a more modest fraction of government securities. However, the credit quality of its portfolio is fairly high, with a corresponding small default rate.

3.3. Individual Banks, Government Default[36]

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 can still 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 6). The definition of government default itself is neither simple nor consensual[37]. 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. We believe the Fitch study provides useful guidelines as to the estimated default rates. We present in Table 3 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 Billion (sovereign foreign currency bonds), in 2001, and was downgraded from BB to DDD (recovery expected to be around 90 percent - 100 percent). The other is Moldova, which

[36] This study was conducted when Brazil was rated as B. Currently Brazil is being rated as BB+ by most rating agencies. With this higher credit rating (and consequently lower expected sovereign default probability) if this study we repeated today then our bank and systemic banking system risk estimates would be expected to be lower.

[37] 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 percent) consistent with what Klaar, Rawkins, and Riley (2004) report for sovereign debt default for countries graded by Fitch as B level (like Brazil).

defaulted on US$ 75 million of Eurobonds (later restructured and followed by a Paris Club deal), in 2002, and was downgraded from CC to DD (50 percent - 90 percent 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, 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 GOB to default at an average rate of 4.5 on foreign currency loans, consistent with Klaar, Rawkins, and Riley (2004). In the event of such a default, we assume the value of domestic debt may also be adversely affected.

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 securities, by assuming that banks may lose 0 percent, 10 percent, or 25 percent of the market value of their government securities. Such losses may result from increases in required market interest rates and interest rate 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 an increase in their default rates equal to the average default of that credit risk category[38], 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. As indicated earlier in cases where we assess systemic banking system risk we will evaluate these 9 potential loan loss scenarios for two assumed private sector defaulted loan recovery rates (15 percent and 45 percent).

In Tables 7 to 9 we report the average simulated bank default rate[39], 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 percent probability of having their capital ratios falling below this level). Given that banks hold a significant amount of government securities, bank default rates start to appear significant only when there is some degree of losses on government securities. For example, if banks lose an average of 10 percent in the market value of their government debt, then 6 banks (e.g. Bank 5 and Bank 16) will have a default rate of around 4 percent to 5 percent. If banks lose 25 percent of the market value of their government securities, then 15 banks (e.g. Bank 3, Bank 8, Bank 10, etc.) will have a default rate of around 4 percent to 6 percent. In either of these cases (i.e. 10 percent or 25 percent 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 percent of the market value of government securities 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 securities, or they have a balance between government, business, and consumer 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 on business and

[38] See Table 2, which provides the average one-year historical default rate on Brazilian bank loans with various credit qualities.

[39] Based on anecdotal evidence, we consider banks to default whenever its simulated capital ratio equals 0.03 or less. The methodology, however, is flexible enough to deal with different default thresholds.

consumer loans. 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 percent of the market value of their government securities, this 'bail-out' cost ranges from 0.055 of total assets (Bank 13) to 0.278 (Bank 22). Again, the large amount of government securities 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 percent of the market value of government securities, capital ratios may range from 0.248 (Bank 6) to -0.199 (Bank 22).

While having the previously noted limitations, 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 securities. 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)[40]. Thus, government securities 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[41]. We will focus our attention on a single output derived from the simulations 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 percent of the market value of their government securities, experience an incremental increase in defaults on their private sector loans equal to twice the average default rate, and have a 45 percent average recovery rate on defaulted private sector loans. 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 sets

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

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

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 compared in Table 10, with the ratings from Moody's and Standard and Poor's. Our ratings are generally consistent with Moody's and Standard and Poor's. For example, we rate 12 of the 16 banks in the intersection set similarly to Moody's and 7 of the 10 banks in the intersection set similarly to Standard and Poors, while we only rate 9 of the 18 banks in the intersection set similarly to Fitch.

We want to stress that our results should be taken only as an additional piece of evidence to evaluate the reliability of the portfolio simulation risk assessments. 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' 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 provides 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 Banking System Risk

For assessing systemic banking system risk, 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 11 and Table 12) are consistent with what we have obtained for individual banks. When we model correlated market and private sector loan credit risk, but do *not* consider government default, simulated capital ratios are comfortably above an assumed 0.08 target capital level, with small standard deviation (0.003). This result is intuitive given the substantial amount of government securities 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 securities of 10 percent. Table 12 indicates that a 25 percent loss rate on Government securities, in the event of a sovereign default, the default rate on the single aggregate bank may reach 3 percent (3.6 percent) with assumed average recovery rates on private sector loans of 45 percent (15 percent). The associated cost to bring the single-bank capital back to a 0.08 level averages 5.7 percent (6.1 percent) of the bank's total assets. The 99% VaR capital ratio also deteriorates substantially. Under the no-government- default assumption it is 0.147, while it drops to 0.021 (0.016) under the above sovereign default scenario when the average recovery rates on defaulted private sector loans are 45 percent (15 percent).

While used frequently, modeling systemic risk via a single aggregate bank has significant limitations. First it masks the fact that under certain conditions (e.g. 10 percent loss rate on government securities) a number of individual banks could fail simultaneously[42]. Second this approach does not account for inter-bank exposures that can trigger sequential failures. 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[43]. 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

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

[43] 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.

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 13), show that all three groups of banks are profitable and on average have increasing capital ratios. When sovereign risk is considered (Table 14), then only Group 3 survives all our simulated scenarios (same as for the individual banks). Group 1 has a small non-zero default probability at a 10 percent loss rate on government securities. Group 2 also has a non-zero default rate when the assumed losses in the market value of Government debt increases from 10 percent to 25 percent. Under the scenario of 25 percent average losses on government securities and a 45 percent average recovery rate on defaulted private sector loans, Group 1 defaults at an average rate of 0.048 and Group 2 defaults at rates in the range of 0.1 percent to 1.8 percent. The average cost of 'bailing-out' these banks is large, for Group 1 it surpasses the 12 percent 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 5 to 6 percent of its total assets. Under the assumption of a lower 15 percent recovery rate on defaulted private sector loans, group 1's and group 2's default probabilities and bailout costs increase.

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 percent of market value then the 99% VaR capital levels for Groups 1, 2, and 3 falls to the range of -0.049 (-0.056), 0.035 (0.024), and 0.11 (0.105) respectively for the 45 percent (15 percent) assumed recovery rates on defaulted private sector loans.

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 and assuming that the groups borrow money from others proportionately to their total assets. For example, Group 1 lends 3.6 percent 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.

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[44]. Then, we assume that when one group defaults, the other groups will recover at the same average as the other types of loans, 50 percent 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 each group's 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 15A and 15B which assume a 45 percent and 15 percent recovery rate on defaulted private sector loans respectively. A few comments are in order. First, in Table 15A, as expected, the inter-bank propagation channel moves from the riskier groups to the less risky groups. 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 securities. Group 3 starts having solvency problems only when a sovereign default imposes a high average loss of 40 percent or more on the market value of government securities. This reveals another nocive facet of banks holding exceedingly large concentrations of government securities. 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 securities, 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 securities of 10 percent could create significant solvency problems for 5 or 6 out of 28 banks analyzed. Higher loss rates would of course create even 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 securities in Brazilian balance sheets is much larger than the amount of business and consumer loans, the impact of incremental defaults on business and households has much smaller effects 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. For example at a 10% loss rate on government securities there is a zero probability of both Group 1 and Group 2 defaulting simultaneously. At a 25% loss rate on government securities the probability of

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

both Group 1 and Group 2 defaulting at the same time reaches 3.0 percent (3.9 percent) for average recovery rates on private sector loans of 45 percent (15 percent). 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 percent of its total capital under the scenario of a 25 percent average loss on government securities. Under the same scenario, the two riskier groups default at a rate in the range of 1.6 percent to 3.9 percent, with the average cost to bring their capital level back to 0.08 level equal to over 10 percent of their total assets. A comparison of Tables 15 A and Table 15B which assume the higher (45 percent) and lower (15 percent) recovery rates on defaulted private sector loans illustrate the potential significance of this variable on systemic risk levels.

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. We have simulated the banks individually, considering two different scenarios. In one we access correlated market and business loan credit risk, but assume the Brazilian government will never default on its debt obligations. With few exceptions Brazilian banks perform very well in these simulations increasing their capital on average over the 1-year simulation horizon.

Regressions of simulated means and standard deviations of bank ROAE and ROAA on historical ROAE and ROAA means and standard deviations indicate that the simulated values are unbiased predictors of the historical ones. While this result needs to be taken with caution, it does show the capability of the PSA framework for modeling bank portfolio correlated market and credit risk and for simulating bank profitability distributions that are comparable to historical values.

In a second set of risk assessments we model correlated market, credit and sovereign risk. When the possibility of government default is considered the bank risk level 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 percent, which is the average rate for sovereign rated debts in the same rating category of Brazil (B), according to a study done by Fitch. Our simulated 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 the simulated private sector loan defaults as well.

When 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 percent to 25 percent on the government securities held by banks. At a 10 percent loss rate on government securities in the event of a sovereign default 6 of the 28 banks could fail. At a 25 percent loss rate on Government securities over half of the 28 banks could fail. One exception is Bank 9, which continued to produce reasonable simulated capital ratios even after considering sovereign risk. Bank 9 is a bank with a much smaller fraction of total assets invested in government securities. Thus, balancing better the portfolio between government, business, and consumer 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 concentration risk.

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 securities is 25 percent or higher and that the cost to bail the system (to bring the average capital ratio to 0.08 level) is about 5.7 percent 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 on bank failure rates. 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 to a systemic failure of the Brazilian financial system). Even though the three banks may default only when facing much heavier losses on government securities (40 percent or more), the cost associated with such event reaches the range of 16 percent - 18 percent of total assets, for a recovery rate on business and customers' loans around 45 percent (or in the range of 19 percent - 20 percent of total assets for a recovery rate of 15 percent). Our analysis also reveals another nocive facet of banks holding very large concentrations of government securities. 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 securities, 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 percent or higher on government securities could have significant systemic banking system impacts. Since the amount of GOB securities in Brazilian balance sheets is much larger than the amount of business and consumer loans, the impact of incremental defaults on business and households have smaller impacts on banks' default rates and monetary losses. We also consider the impact of higher (45 percent) and lower (15 percent) average recovery rates on defaulted private sector loans. We find in extreme events (sovereign defaults) should loan recovery rates on private sector loans be systematically depressed then banking system systemic risk increases significantly.

It is important to note 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 consumer 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 (and feasible) to model bank operating expenses as an additional correlated stochastic variable within the PSA framework.

Modeling correlated market, credit, sovereign, and inter-bank risk is a challenging task. All methodologies which might be used have limitations. In spite of the limitations we have identified above, we believe that the portfolio simulation methodology has been demonstrated to be able to deal with all of these correlated risks and to have the potential to provide important insights into individual bank and systemic banking system risk levels.

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Table 1[45]

Debt Ratios, Betas and Unsystematic Risk used in the Portfolio Simulation Risk Assessments

This table provides results for distributional analysis of equity return risk characteristics, debt-to-value ratios, and internal bank credit ratings for all publicly traded Brazilian companies.

	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	-

[45] From Barnhill, Souto, and Tabak (2003).

Table 2[46]
Credit Transition Matrices

Comparison of historical credit transition matrices (CTM) for 2 large Brazilian banks with simulated CTM using stochastic volatilities and correlations.

Panel A: Historical bank loan 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 bank loan CTM using stochastic volatilities 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

[46] From Barnhill and Souto (2007).

Table 3
Brazilian Banks Balance Sheets – Main Statistics

This table provides statistics on the stylized balance sheets used in the simulation to describe the main assets and liabilities accounts for Brazilian Banks, as of December 2004.

	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.

Notes:

1. Public Funding, Debt Capital, Government Securities, and Foreign Loans are allocated to three different maturity buckets.
2. Domestic Business and Consumer Loans are spread over 10 sectors and 6 regions and each loan can be assigned a unique maturity.
3. In total approximately 450 stylized securities and loans are used to model each bank.

Table 4
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	0,95	0,90	3,46
	(9,79)		
St. Dev.	1,26	0,70	3,73
	(4,89)		
Panel B: ROAA Regressions			
Mean	1,25	0,89	3,58
	(8,99)		
St. Dev.	1,61	0,47	3,34
	(3,12)		
Panel C: Pooled Observations			
All	0,96	0,90	3,22
	(19,13)		

Table 5
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 capital ratio levels indicate the percentage of time that simulated values fall below a certain threshold. For example, BANK 1 VaR at 99% level is 0.191, indicating that 1 percent of the times simulated capital ratios for BANK 1 fell below 0.191. The assumed recovery rate on defaulted private sector loans is 45 percent in these simulations.

	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 5 (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 5 (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 6
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 7
Simulated Default Probabilities: Individual Banks, Government Default

Simulated default probabilities on individual banks. 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, 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 securities, by assuming that banks may lose 0 percent, 10 percent, or 25 percent of the market value of their government securities for a variety of reasons. The assumed recovery rate on defaulted private sector loans is 45% in these simulations.

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	0.047	0.047	0.047	0.047	0.047	0.047
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

Table 8
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 the 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, 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 securities, by assuming that banks may lose 0 percent, 10 percent, or 25 percent of the market value of their government securities for a variety of reasons. The assumed recovery rate on defaulted private sector loans is 45% in these simulations.

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	0.077	0.078	0.080	0.197	0.198	0.200
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

Table 9
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 percent 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, 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 securities, by assuming that banks may lose 0 percent, 10 percent, or 25 percent of the market value of their government securities for a variety of reasons. The assumed recovery rate on defaulted private sector loans is 45% in these simulations.

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

Table 10
Individual Banks – Credit Rating

Brazilian banks are classified in to 3 credit risk categories, from Group 1 (less risky) to Group 3 (more risky), according to their 99% VaR capital ratios. 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. The size of the intersection set is represented in the parenthesis.

Panel A: Ratings distributions by rating grade.

	Fitch	Moody's	Standard and Poor's	Barnhill and Souto
Investment Grade	18	1	0	9
Speculative Grade	0	15	10	19

Panel B: Ratings intersection.

	Fitch	Moody's	Standard and Poor's	Barnhill and Souto
Fitch	-	1	0	9
		(12)	(7)	(18)
Moody's			10	12
			(10)	(16)
Standard and Poor's				7
				(10)
All 4 ratings methodologies	0			
	(7)			

Table 11
Simulated Capital Ratios: All 28 banks as One Single Bank
No Government Default

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 percent of the time simulated capital ratios for the single bank have fell below 0.147. Assumed average recovery rate on defaulted private sector loans = 45 percent.

		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 12
Simulated Default Probabilities, Bail-Out Costs, and 99% Capital Ratios
Government Default Risk Considered
All 28 banks Modeled as a Single Bank

This table presents simulated default probabilities on groups of banks, average 'bail-out' cost as 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), and the 99% VaR simulated capital ratio is the threshold below which banks capital ratio will fall 1 percent 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, 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 percent, 10 percent, or 25 percent of the market value of their government loans for a variety of reasons.

Panel A: All 28 - Government default, 45 percent recovery rate on business and customers' loans.

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	0,017	0,022	0,030
Bail-Out' Cost:									
All 28 banks	0,000	0,000	0,000	0,000	0,000	0,000	0,055	0,057	0,057
99% VaR Level:									
All 28 banks	0,143	0,143	0,143	0,110	0,108	0,105	0,027	0,024	0,021

Panel B: All 28 - Government default, 15 percent recovery rate on business and customers' loans.

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	0,025	0,033	0,036
Bail-Out' Cost:									
All 28 banks	0,000	0,000	0,000	0,000	0,000	0,000	0,058	0,059	0,061
99% VaR Level:									
All 28 banks	0,142	0,141	0,141	0,106	0,103	0,101	0,022	0,019	0,016

Table 13
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. The assumed recovery rate on defaulted private sector loans is 45 percent in these simulations.

	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 14
Simulated Default Probabilities, Average 'Bail-Out' Cost, and 99% Capital Ratios: Individual Aggregate Banks, Government Default

This table presents simulated default probabilities on groups of banks, average 'bail-out' cost as 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), and the 99% VaR simulated capital ratio is the threshold below which banks capital ratio will fall 1 percent 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, 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 securities, by assuming that banks may lose 0 percent, 10 percent, or 25 percent of the market value of their government securities for a variety of reasons.

Panel A: Recovery rate on defaulted private sector loans = 45%.

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	0,001	0,001	0,001	0,048	0,048	0,048
Group 2	0,000	0,000	0,000	0,000	0,000	0,000	0,001	0,004	0,018
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	0,054	0,055	0,055	0,122	0,123	0,124
Group 2	0,000	0,000	0,000	0,000	0,000	0,000	0,051	0,054	0,057
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	0,087	0,087	0,086	0,046	0,046	0,045	-0,048	-0,049	-0,049
Group 2	0,132	0,130	0,126	0,109	0,103	0,096	0,045	0,035	0,025
Group 3	0,211	0,211	0,211	0,186	0,184	0,183	0,112	0,110	0,108

Panel B: Recovery rate on defaulted private sector loans = 15%.

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	0,002	0,002	0,002	0,048	0,048	0,048
Group 2	0,000	0,000	0,000	0,000	0,000	0,000	0,007	0,017	0,034
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	0,058	0,057	0,057	0,128	0,129	0,130
Group 2	0,000	0,000	0,000	0,000	0,000	0,000	0,057	0,060	0,063
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	0,081	0,081	0,081	0,040	0,039	0,038	-0,055	-0,056	-0,057
Group 2	0,125	0,123	0,119	0,103	0,095	0,086	0,034	0,024	0,013
Group 3	0,208	0,208	0,207	0,182	0,180	0,178	0,106	0,105	0,103

Table 15-A
Systemic Risk: Simultaneously Simulated Aggregate Banks
Recovery Rate on Defaulted Private Sector Loans = 45 percent

This table presents simultaneously simulated default probabilities on groups of banks, average 'bail-out' cost as 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), and the 99% VaR simulated capital ratio is the threshold below which banks capital ratio will fall 1 percent of the time.

Recovery rate = 45%

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	0,021	0,030
		(0,109)	(0,110)	(0,111)
	40%	0,048	0,048	0,048
		(0,239)	(0,251)	(0,258)
	50%	0,048	0,048	0,048
		(0,358)	(0,362)	(0,366)

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
		(0,168)	(0,177)	(0,182)
	50%	0,048	0,048	0,048
		(0,271)	(0,275)	(0,279)

Table 15-B
Systemic Risk: Simultaneously Simulated Aggregate Banks
Recovery Rate on Defaulted Private Sector Loans = 15 percent

This table presents simultaneously simulated default probabilities on groups of banks, average 'bail-out' cost as 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), and the 99% VaR simulated capital ratio is the threshold below which banks capital ratio will fall 1 percent of the time.

Recovery rate = 15%

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%	0,034	0,036	0,039
		(0,114)	(0,117)	(0,119)
	40%	0,048	0,048	0,048
		(0,259)	(0,267)	(0,274)
	50%	0,048	0,048	0,048
		(0,369)	(0,373)	(0,378)

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
		(0,183)	(0,189)	(0,195)
	50%	0,048	0,048	0,048
		(0,280)	(0,284)	(0,289)

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