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Measuring Integrated Market and Credit Risks in Bank Portfolios: An Application to a Set of Hypothetical Banks Operating in South Africa

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Abstract

The banking crises of the 1990s emphasize the need to model the connections between volatility and the potential losses faced by financial institutions due to correlated market and credit risks. We present a simulation model that explicitly links changes in the financial environment and the distribution of future bank capital ratios. This forward-looking quantitative risk assessment methodology allows banks and regulators to identify risks before they materialize and make appropriate adjustments to banks' portfolios. This model was applied to the study of the risk profile of the largest South African banks in the context of the Financial System Stability Assessment (FSSA) (1999).

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I. INTRODUCTION

The banking literature and practice have devoted a considerable amount of work to study bank risk. From the standard probit/logit analysis to the more sophisticated VaR models, most of the effort has been addressed to the identification of the sources of vulnerability, to the assessment of the probability of scenarios of financial distress and, more recently, to the measurement of market risk. The banking crises that developed in the late 90's in many emerging markets have brought a new emphasis to the issue and have reminded us of the importance of credit risk. They also created a need to examine the connections between the financial environment and the potential losses faced by financial institutions due to client defaults or downgradings. For example, Federal Reserve Board Chairman Alan Greenspan recently noted that "...the present practice of modeling market risk separately from credit risk, a simplification made for expediency, is certainly questionable in times of extraordinary market stress. Under extreme conditions, discontinuous jumps in market valuations raise the specter of insolvency, and market risk becomes indistinct from credit risk.[2]"

We present here a model that measures both market and credit risk, and proposes an explicit link between changes in the relevant variables that characterize the financial environment and changes in the value of a bank's capital ratio.[3] The model has the following features:

- Correlated market risk and credit risk are measured and analyzed.
- The future financial environment in which the bank assets and liabilities are valued and the credit rating of bank clients are simulated.
- Both loans to corporations and to households (mortgages) are modeled within an integrated framework.
- The correlated evolution of the credit quality of the bank loan portfolio is simulated in the context of the financial environment. The link between the financial environment and the credit quality of bank clients is provided by a continuous variable that moves in a correlated fashion with changes in the financial environment. In the case of corporate clients that variable is the debt to value (debt plus equity) ratio. In the case of the mortgage loans, that variable is the loan to property value ratio.

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[2] Speech by Chairman Alan Greenspan at the 36th annual conference on bank structure and competition of the Federal Reserve Bank of Chicago, Chicago, Illinois, May 4, 2000.

[3] For further discussion on this type of model applied to the analysis of bond portfolios see Barnhill and Maxwell (2000).

- The model deals with stylized bank portfolios. Approximately 500 individual assets and liabilities are simulated, which is found to be adequate to produce results that are statistically similar to much larger bank portfolios that may contain several million financial instruments.

We apply the model to various hypothetical banks operating in the South African financial environment as of June 1999. The financial characteristics of the South African aggregate banking system with respect to size, original capital ratio, and non-performing loans ratio were used to define all hypothetical banks. We start by applying the model to a base case where the bank operates in an environment of low market risk (i.e., low volatility and correlations), its loan credit quality distribution is compatible with the return on equity reported by the aggregate South African banking system, its loan portfolio is well diversified across business and personal lending, economic sectors, and geographic regions and its interest bearing assets and liabilities have the same maturity (e.g., one-year). We then study the effects of higher volatility, varying loan credit quality distribution, different degrees of portfolio concentration, and asset/liability maturity mismatches on the distribution of the banks' potential future capital ratios.

The paper is organized as follows: Section 2 describes the model. Section 3 describes the low versus the higher market risk scenarios under which the model was calibrated. Section 4 presents the characteristics of the hypothetical banks. Section 5 presents the results of the model with respect to the various cases. Section 6 discusses limitations and future extensions. Section 7 concludes.

II. The Model

The model that we present in this paper simulates the future financial environment as a distribution of possible scenarios. Changes in prices are simulated as a multivariate distribution using the specifications described below. Each scenario is represented by specific changes in a set of correlated environmental variables and by a specific credit quality for each of the bank's clients. In this way the model deals with correlated market and credit risk in an integrated fashion.

The future financial environment, under which the bank's assets and liabilities will be revalued, is represented by eight domestic correlated arbitrage-free interest rate term structures (T-Bill, AAA… B-CCC); three foreign interest rate arbitrage-free term structures (U.S., U.K., and Japan T-Bills); three FX rates (U.S. dollar, pound sterling, and Japanese yen); a set of 20 equity market indices representing various sectors of the economy; a set of twenty regional real estate price indices; the gold price; and the South African inflation rate,[4]

[4] In practice any number of interest rate term structures, FX rates, equity and real estate indices, commodities and economic indicators could be simulated. For the purpose of this exercise the total number of correlated environmental variables used in the model is 57.

all of which are modeled as correlated random variables. The correlated evolution of the market value of equity for business clients, their debt to value (debt plus equity) ratio, credit rating, and periodic defaults are then simulated in the context of the simulated financial environment. Similarly, the correlated value of real estate underlying mortgage loans, the loan to (property) value ratio, and periodic defaults are also simulated. The structure of the methodology is to select a time step (Δt) over which the stochastic variables are allowed to fluctuate in a correlated random process. Firm specific equity returns have one portion related systematically to the returns on an equity market index and a second portion, which is uncorrelated with other stochastic variables. Default recovery rates on loans are also assumed to be uncorrelated with each other and the other stochastic variables. For each simulation run a new financial environment (interest rate term structures, FX rates, market equity and real estate indices, etc.) as well as credit ratings, default rates, and default recovery rates are created. This information allows the market value of the bank's assets, liabilities, equity, and capital ratio to be calculated for each simulation run.

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

where:

MVE_t = The simulated market value of the bank's equity at time t,

$A_{i,t}$ = The market value of the i'th asset at time t, which reflects 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,

$L_{i,t}$ = The market value of the i'th liability at time t which reflects the simulated financial environment variables (e.g., interest rates, exchange rates, etc.).

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

Changes in the bank capital reflect changes in the value of assets and liabilities. The simulated prices are used to recalculate the value of the bank capital under each 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 Rand 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 simulated value of the loan under each simulated scenario.

The final and main outcome of the model after many simulation runs is an estimated distribution of the bank's capital[5] 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 may fall below certain thresholds. 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.

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

where:

$Capital\_Ratio_t$ = The simulated bank capital ratio at time t.

Modeling the financial environment

The environmental variables were simulated using the following models:

- Modeling changes in Interest Rates and Interest Rate Spreads :

Changes in interest rates were simulated using the Hull and White (1990a, 1993, and 1994) extended Vasicek model where interest rates are assumed to follow a mean-reversion process with a time dependent reversion level:[6]

$$\Delta r = a(\frac{\theta(t)}{a} - r)\Delta t + \sigma \Delta z$$

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

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[5] For the purpose of this paper, capital is tier 1 and 2, as defined by the Basle Banking Committee. Assets are defined as total assets.

[6] The simulation model is robust to the use of other interest rate models.

For each simulated spot interest rate an entire arbitrage-free term structure can be simulated and used to value all risk-free instruments in a portfolio. Once the risk-free term structure has been estimated then the AAA term structure is modeled as a stochastic lognormal spread over risk-free, the AA term structure is modeled as a stochastic spread over AAA, 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., AAA). This procedure insures that all simulated credit spreads are always positive and that the simulated term structures are approximately arbitrage free. These simulated risky term structures are used to value assets and liabilities that are not risk-free.

- Modeling changes in equity indices, real estate prices, exchange rates, commodity prices, and the inflation index

The equity indices, real estate price indices, FX rates, commodity prices, and the inflation index are simulated as stochastic variables correlated with the simulated spot interest rates and each other. For a discrete time step Δt:

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

where

S = asset spot price (i.e., equity indices, etc.),

μ = the expected growth rate,

σ = volatility,

Δt = a discrete time step, and

ε = a random sample from a standardized normal distribution.

The asset spot price (S) is assumed to follow geometric Brownian motion where the expected growth rate (m) and volatility (σ) are constant[7]. The expected growth rate is equal to the expected return on the asset (μ) minus its dividend yield (q).

- Modeling multiple correlated stochastic variables

Modeling multiple correlated stochastic variables requires a modification to the methods described above. Hull (1997) describes a procedure for working with an n-variate normal distribution. This procedure requires the specification of correlations between each of the n stochastic variables. Subsequently n independent random samples ε are drawn from standardized normal distributions. With this information the set of correlated random error

[7] See Hull, J. Options, Futures, and Other Derivative Securities, Prentice Hall, 1997, p.362.

terms for the n stochastic variables can be calculated. For example for a bivariate normal distribution,

$$\varepsilon_1 = x_1$$

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

where

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

ρ = the correlations between the two stochastic variables, and

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

Modeling bank securities

Once the model generates future multivariate distributions of changes in prices using the specifications described above, each security (i.e., loans, bonds and other bank assets and bank liabilities) is repriced using the simulated values. For those assets and liabilities that do not bear any credit risk, valuation is based on a present value approach where the cash flows are discounted using the simulated interest rates of the risk-free term structure and the simulated values for the correlated exchange rates, in the case of securities denominated in foreign currency (i.e., the model measures correlated market risk). With respect to loans that are subject to credit risk, an additional issue is to estimate how the credit risk of each issuer shifts under each of the simulated scenarios (i.e., the model measures correlated market and credit risk). Credit risk is defined as the potential loss that can be suffered by the bank due to client default and/or client downgrading. In our model, credit risk is modeled differently for loans to corporations and loans to individuals which were modeled as mortgage loans.

Corporate loans

The new value of each corporate loan under each simulation is calculated by discounting the future cash flows with the simulated interest rates that correspond to the simulated credit rating of the corporate client[8] (i.e., AAA,..BBB, BB, B, etc.) under that scenario.

In the event of default the pay-off on a loan is given by its recovery value net of transaction costs. The default recovery rate depends on the seniority of the loan, the existence and quality of collateral, and the efficiency of the legal system. Given that there is no

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[8] Shifts across credit ratings during a given risk horizon (e.g. one-year) are described by a credit transition matrix. We estimated two credit transition matrices for South African bank clients to account for scenarios with different volatility and correlation assumptions. (See Section 4).

research on this topic in South Africa, typical recovery values for defaulted business loans were provided to us by South African banks, based on their own experience. In this study business loan default recovery rates were modeled as a beta distribution with a mean of 0.45 and a standard deviation of 0.25.

The conceptual basis used for the estimation of the stochastic changes in business loan credit quality is the contingent claims analytical framework (Black, Scholes, Merton)[9] where a firm's credit quality is a function of its debt to value ratio (i.e., the firm's leverage) and the volatility of its asset value. In the present model, debt to value ratios are dependent on the simulated scenario, i.e., each of the simulated scenarios implies a unique debt to value ratio for each bank client. This means that credit ratings in this model are stochastic and are correlated with changes in the simulated financial environment.

The estimation of the debt to value ratios for each client in each scenario follows several steps:

- First, the returns on 20 sectorial stock indices for companies that trade in the Johannesburg Stock Exchange (JSE) index are simulated as part a correlated multivariate distribution of changes in all of the financial environment variables (i.e., interest rates, foreign exchange rates, real estate indices, etc.).

- The return on equity for each firm included in the portfolio is calculated using the following one-factor model:[10]

$$K_i = R_F + Beta_i\,(R_m - R_F) + \sigma_i \Delta z$$

where

K_i = The return on equity for the $firm_i$,

R_F = the risk-free interest rate,

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

R_m = the simulated return on the equity index,

σ_i = the firm specific volatility in return on equity, and

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

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[9] See e.g. Black, F. and M. Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy* 81, 637-659 and Merton, R., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449-470. This general approach is also followed by KMV and CreditMetrics™

[10] Multi-factor models could be used as well.

- Having simulated the firm's return on equity, the firm's simulated market value of equity can be calculated (i.e., simulated market value of equity = initial equity value + change in equity value).

- The firm's simulated debt to value ratio is constructed [i.e., total liabilities /(total liabilities + simulated market value of equity)].

- Finally, the simulated debt to value ratios are mapped into new credit ratings. Given that only 30 South African companies are formally rated by rating companies, we asked a large South African bank to use the S&P credit rating categories to rate a subset of traded South African companies. Using this private credit rating we developed estimates of betas, firm specific risk levels, and typical debt to value ratios for firms with various credit ratings. This information was used to assign new credit ratings to the hypothetical bank's business loan clients based on their simulated debt to value ratios11.

Loans to individuals

Loans to individuals were modeled entirely as a portfolio of mortgage loans.[12] The value of the mortgage loan is the appropriately discounted value of its future pay-offs.[13] If the household defaults, the value of the loan is replaced by its recovery rate net of transaction costs, which is modeled as a stochastic variable drawn from a beta distribution.

The variable used to estimate the credit quality of a mortgage loan and to predict defaults is the loan to value ratio (i.e., the remaining notional value of the loan to the value of the property). Loan to value ratios were linked to the financial environment through the

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[11] In the case of bank clients whose stock is not publicly traded we assume that their equity values fluctuate even if this cannot be observed (since the companies are not traded). We also assume that privately held companies have similar financial characteristics (i.e. betas and firm specific volatilities) to publicly traded companies with the same credit rating. (e.g. a BBB privately held company in a particular scenario will have similar systematic equity increases or decreases as a BBB publicly held company that belongs to the same sector, since both are assumed to have the same beta).

[12] The hypothetical banks to which this model is applied are based on the characteristics of the South African banking sector where mortgage loans comprise 90% of all loans to individuals. Consequently, modeling all loans to individuals as mortgage loans is a good approximation.

[13] Given that most mortgage loans in South Africa are based on floating rates, they lack significant optionalities, thus the present value of the future cash flows is close to the remaining face value of the loan.

simulated returns on the South African regional real estate price indices.[14] Specifically the returns on individual properties were assumed to have a beta of 1.0 relative to simulated returns on regional real estate price indices and a total return volatility (i.e., systematic plus unsystematic) of 15 percent. These assumptions are consistent with observations by banks regarding real estate price volatility during periods of financial stress. This link assures that the model captures the fact that large defaults in the real estate sector are typically caused by macroeconomic conditions, specifically high interest rates and low property prices. The model leaves out household credit score (i.e., specific risks) due to data limitations. Based on conversations with South African banks we made the following assumptions: (i) the typical loan to value ratio at which households default is above 1.10; and (ii) the recovery rate on loans to individuals net of transaction costs has a mean of 70 percent of the value of the loan and a standard deviation of 15 percent. In addition, any defaults that may occur at lower loan to value ratios will result in much smaller losses due to the high value of collateral.

Bank deposits, equity and bond holdings, and real estate assets were also repriced. Approximately 200 business loans, 200 mortgage loans, 15 other fixed income securities, 20 equity securities, 20 real estate assets, and gold were used to model the banks' asset and liability portfolios.

Finally, fee income plus other income less operating expenses was added to the simulated value of the bank portfolio in each scenario. Fee income plus other income less operating expenses is assumed to be constant across scenarios and was calculated as the average over the last three years. Data for this calculation was taken from the consolidated statement of profits and losses for all South African banks.

III. MODEL CALIBRATION

For the purpose of calibrating the model to undertake an integrated market and credit risk assessment of the hypothetical banks we studied two historical distributions of changes in prices and other environmental variables: January 1996-June 1999; and January 1998-June 1999. The characteristics of both distributions are described below together with an analysis of the business loan credit transition matrices that the model produced for each environment.[15]

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[14] All South African banks agreed that the conditions of the real estate market vary considerably across regions. This statement is consistent with the volatility and correlation analysis of Section 3.

[15] Appendix 1 shows the similarity between historical and simulated distributions of changes in prices. Because more observations (monthly time-series) are available for that period, we used the 1980-1999 period to make this comparison more intuitive.

Characteristics of the distributions of changes in environmental variables

Risk depends on the volatility of the environment and consequently, the following analysis focuses on the distributions of percentage changes in the environmental variables. Tables 1 and 2 show the historical means, medians, standard deviations and correlations of percentage changes in selected environmental variables for 1996–99 and for 1998–99. The following observations can be made:

- The 1998–99 period can be characterized as a period of higher volatility since, in general, standard deviations of changes in prices are larger than for the 1996–99 period. This is the case for changes in the T-Bill yield, the exchange rate of the Rand vis-a vis the U.S. dollar, the South African overall stock market index[16], the prime spread, the gold price and the inflation rate. It is important to notice that the correlations between variables are also higher during the 1998–99 period. This, together with evidence provided by other studies,[17] suggests that periods of higher volatility are usually periods of higher correlations (i.e., periods when the value of diversification is lower).

- There is, as expected, a clear positive correlation between changes in interest rates and percent changes in the exchange rate in both periods (0.61 in the 1996–99 period and 0.62 in the 1998–99 period) and a clear negative correlation between changes in interest rates and percent changes in the stock market aggregate index (-0.64 in the 1996–99 period and -0.71 in the 1998–99 period).

- The correlations between changes in interest rates and percent changes in real estate prices are small and negative in the 1996–99 period but become larger and negative during the 1998-99 period of higher volatility. Alternatively over the 1980 to 1999 period the correlation between interest rate changes and real estate returns was positive. These changing correlations are not specific of South Africa and have also been observed in other markets, such as the U.S. and Japan. A possible explanation for this behavior is that real estate assets reflect replacement cost in the long run. Consequently they are more valuable when inflation is high—and likely interest rates are high too. Its inflation hedge characteristic is less valuable when inflation is low (or expected to be low) and interest rates are low. This behavior predicts a positive correlation between interest rates and real estate returns, i.e., real estate prices will

[16] This is the case even for other stock market indices such as the S&P 500.

[17] See for example the very interesting paper by Andersen, Bollerslev, Diebold and Labys, "The Distribution of Exchange Rate Volatility," The Wharton School, Financial Institutions Center, 99-08. In particular, notice that Figure 4 shows that increasing volatility in the Yen and DM markets are associated with higher correlation between changes in the prices of both currencies.

tend to go up when inflation and interest rates go up and go down when inflation and interest rates go down. However when interest rates reach very high values, this relationship breaks down and real estate prices may decline. This negative correlation may be due to difficulties of borrowers to pay high mortgage rates, lower demand for housing due to economic recession, and an increasing stock of foreclosed assets. Real estate price declines may be substantial if a large number of borrowers default and a large amount of repossessed assets must be sold (e.g., the U.S. in 1989–91[18] and Japan in the 1990s).

- Aggregate and regional real estate prices in South Africa display interesting differences in behavior. During some periods the volatility of regional real estate prices may be as much as three times the volatility of the overall real estate prices. Most regions have experienced high negative correlations between real estate returns and interest rate changes in the 1998-1999 period such as Johannesburg (-0.43), Eastern Cape (-0.59), Vaal Triangle (-0.38), Northern Cape (-0.35), and Pretoria (-0.34), but in some areas the correlations were less negative and or even positive, although small. As a consequence, the aggregate index displays a lower negative correlation with interest rates (-0.19).

- The percent change in interest rates (e.g., prime rate) is more volatile than the exchange rate in both periods, possibly reflecting the fact that interest rate moves (more than the exchange rate) bear in the short term the burden of the financial market pressures. Interest rates are also more volatile than gold prices.

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[18] The commercial real estate market in the U.S. offers a good example of the risks of mortgage lending in an environment moving from higher to lower inflation rates. During the 1960's and 1970's increasing inflation rates resulted in appreciation in real estate prices which combined with substantial financial leverage, resulted in very attractive returns on invested equity. This environment also contributed to the perception that commercial mortgage loans were a "safe" investment. In late 1979 and the early 1980's the Federal Reserve Board moved aggressively to control the growth rate of the money supply and reduce inflation. This resulted in a deep recession, slower inflation rates, and deteriorating credit quality for business loans. Nevertheless due to the perception that real estate lending was low risk and to various tax advantages, a high level of commercial real estate developments continued through the mid 1980's. However the U.S. tax act of 1986 reduced many of the tax advantage of owning real estate. By the late 1980's and early 1990's commercial real estate prices declined sharply due to lower inflation rates, recession, over building, reduced tax incentives, and a large supply of repossessed properties. In some areas such as Washington DC (which had its own unique problems associated with a reduction in government employment) prices of some properties fell by 40 percent or more. The Resolution Trust Corporation set up to deal with failed saving and loan institutions frequently sold properties at less than one-half the amount of the outstanding first mortgage loan.

Credit transition matrix

One of the main consequences of the use of different volatility and correlation assumptions is that the simulations generate different credit transition matrices.[19]

Tables 3 and 4 present the two generated credit transition matrices for South Africa.[20] These tables summarize the distributions of credit rating changes i.e., they collect shifts across credit rating categories from each of the simulated scenarios.[21] A historical U.S. one-year credit transition matrix[22] (i.e., based on actual data on migrations and defaults that took place between the 1920-1996 period) is also presented in Table 5 to be used as a benchmark.[23]

As in the case of the US, the simulated credit transition matrices for South Africa have the bulk of the probability mass in the diagonal, which means that there is always a very high probability (more than a 50 percent) that securities do not migrate during one year and remain in the same credit category. There are however some differences between the two countries. Specifically: (i) the percentages in the diagonal are lower for the simulated

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[19] A credit transition matrix describes the process by which credit quality changes over time. In the framework of the proposed methodology the credit transition matrix is stochastic (i.e. dependent on the state of the economy).

[20] Barnhill, T. and Maxwell, W (2000) show that this model produces reasonable credit transition probabilities and prices for U.S. bonds with credit risk

[21] I.e. Over 8000 scenarios, loans initially rated as A, remain A in 84.93% of all scenarios, become Baa in 14.74% of all scenarios, Ba in 0.21% and Aa in 0.12% of all scenarios. Because the simulations have a one-year risk horizon, this is a one-year simulated transition matrix. An alternative procedure would be to sort the simulation results by some environmental variable (e.g. interest rate) and derive credit transition matrices contingent on assumed levels or changes in that environmental variable. This would allow keeping track of relationship between the (simulated) environmental variables (e.g. interest rates, exchange rate, gold price, etc) and the (simulated) credit risk of loans.

[22] Unfortunately, there is not enough information available in South Africa to estimate a historical credit transition matrix. On the other side, the simulated transition matrix has the advantage over a historical matrix that it makes credit migration a function of the environmental financial variables that define each of the simulated scenarios.

[23] The U.S. credit transition matrix should be read as follows: Between 1920 and 1996, in the U.S., 89.41% of bonds that at the beginning of the year were rated as Baa, remained rated as Baa bonds at the end of the year, while 4.19% of Baa bonds became A, 0,26% became Aa , 0.03% became Aaa, 5.07% became Ba, 0.66% became Ba, 0.66% became B, 0.07% became Caa-C and 0.30% defaulted. Notice that rows add up to one.

South African matrix; (ii) there are higher probabilities that a security migrates to the immediately higher or the immediately lower credit quality category in the South African matrix; and (iii) the two lowest categories (i.e., CCC and B) have a higher probability of default in the South African matrix. These differences are due to the fact that the historical volatility that prevailed in South Africa, and was used in the simulations, is much higher than the actual U.S. volatility between 1920 and 1996. As a consequence, the bulk of the probability mass in the simulated matrices for South Africa is spread out across the diagonal and its immediate entries; i.e., a more volatile environment produces higher credit risk from defaults and downgradings. As expected, credit ratings are more variable for the simulations based on the 1998–99 period of higher financial market volatility.

Mapping debt to value ratios

The South African credit transition matrices were constructed by mapping simulated debt to value ratios into credit ratings. We discuss in this section typical debt to value ratios or South African firms and their relationship with credit ratings.[24] We use the U.S. as a benchmark.

The private corporate sector in South Africa typically operates with a low level of long and short-term debt. The analysis of 244 companies that belong to 8 different sectors of production and trade their stock in the JSE reveals that the median debt to value ratio is 0.19 (i.e., 19 percent of asset values are funded with debt and the rest with equity) with a standard deviation of 0.24 and a maximum of 0.87.[25]

Table 6 presents a percentile analysis of the debt to value ratios for South African firms as well as typical debt to value ratios of U.S. firms ranked by their credit rating. According to the U.S. results, high debt to value ratios seem to be ratios of around 0.5, which corresponds to low credit quality corporations (B and below). Based on that cut point, we found 44 South African companies in our sample with high (i.e., 0.5 or above) debt to value ratios. As we move towards lower credit classes debt to value ratios tend to increase.

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[24] Very few South African firms issue publicly rated debt. In order to establish the typical debt to equity ratios of South African companies, we used two sources of information. First, we collected, from Bloomberg, debt to value ratios on all the South African companies that are publicly traded in the JSE. Then we asked one of the largest South African banks to provide their credit evaluation for each of those companies using the S&P credit rating categories.

[25] Twenty-five companies in the sample were found to have a debt to value ratio equal to zero. Since companies with a zero debt ratio cannot be bank clients, we excluded them from the analysis.

Size does not seem to be particularly related to the highest debt to value ratios and there are only a few cases that may be viewed as potential problems (i.e., large companies with large debt ratios).

In general, debt to value ratios are lower for South Africa when compared with the U.S. ratios, for the higher credit quality categories. For the lower credit rating categories the debt to value ratios of South African and U.S. firms become more compatible.

IV. THE HYPOTHETICAL BANKS

We use the characteristics of the South African aggregate banking sector as of June 1999, together with some additional assumptions, to construct 30 hypothetical banks.

Specifically, the 30 hypothetical banks, based on the aggregate South African banking sector, have the following common features (Tables 7a and 7b):

- Net loans represent 82 percent of total net assets.
- The proportion of defaulted loans is proxied by the South African aggregate non-performing loan ratio.[26]
- Trading income plus fee income minus operating expenses is assumed to be equal to the average over the 1995-June 1999 period for the system.

We start our analysis of the hypothetical banks by applying the model to a case chosen so as to be our "base" for comparison. In addition to the characteristics defined above the hypothetical bank of the "base" case also assumes the following features:

- The bank operates in an environment of low market risk.
- Individual loans account for 30 percent of total loans (similar to the aggregate South African banking sector) and are modeled entirely as mortgage loans.
- The corporate loan portfolio (including interbank loans) comprises the remaining 64 percent of the loan portfolio (similar to the aggregate South African banking sector).
- The loan credit quality distribution is such that it is compatible with the return on equity of the aggregate South African banking system. We call this credit quality "typical."

[26] The SARB provided total non-performing loans and non-performing mortgage loans. We estimated corporate non-performing loan ratios as a residual.

- The hypothetical bank is well diversified with loans allocated across ten economic sectors and seventeen geographic regions (Table 8). We call this portfolio allocation "diversified."

- The bank's interest bearing assets and liabilities have the same maturity (e.g., one-year).

We then construct twenty-nine additional hypothetical banks and perform several sensitivity analyses to study the effects of different assumptions on market risk, loan credit quality distribution, degree of portfolio concentration, and asset and liability maturity mismatches on potential future capital ratios.

When the bank was assumed to operate under low market risk, historical distributions of changes in prices for the period 1996-99 were used to calibrate the model (i.e., volatilities and correlations). Under the higher market risk scenarios, the model was calibrated using volatilities and correlations for the 1998-99 period.

Four different credit quality distributions were used to define different degrees of credit risk: "typical," "low," "medium" and "high" credit risk. They all have in common the amount of defaulted loans, which was proxied by the non-performing loan ratio for the aggregate South African banking system. The exact breakdown of loans by credit ratings in each distribution can be found in Table 9.

Five types of portfolio concentration were analyzed: "diversified," "diversified mortgages," "diversified business," "business one-sector," and "mortgages one-region." A "diversified" bank has the portfolio diversification of the aggregate South African system. Banks with "diversified mortgage" portfolios are assumed not to lend to the corporate sector. Their portfolios consist entirely of mortgage loans diversified across seventeen South African geographic regions. Banks with "diversified business" portfolios are assumed not to make mortgage loans. Their portfolios consist entirely of business loans diversified across ten economic sectors. Banks with "business one-sector" portfolios are assumed not to make any mortgage loans and to allocate their business loan portfolios in one economic sector (e.g., finance). Finally, banks with "mortgages one-sector" portfolios are assumed not to lend to the corporate sector and to allocate their entire portfolio in one geographic region (e.g., Kwazulu/Natal).[27]

We also study the effects of asset and liability maturity mismatches in the determination of bank risk levels by analyzing three maturity gaps: one year positive maturity gap (i.e., the maturity of the bank assets is greater than the maturity of its liabilities by one-year), one year negative maturity gap (i.e., the maturity of the bank assets is less than

[27] The choice of the single sector or region was based on the allocation characteristics of the South African banking system and the relative return volatility of that sector or region.

the maturity of its liabilities by one-year), and a zero maturity gap (i.e., the maturity of the bank's assets is equal to the maturity of its liabilities).

The description of the base case and the twenty-nine additional hypothetical banks are presented in Table 10. Appendix 2 summarizes all the data required by the estimation of the model.

V. Simulation Results: The Hypothetical Banks' Simulated Capital Ratios

The results of the simulations are shown in Table 11. All hypothetical banks are first sorted by market risk and then by the 99 percent VaR results.[28] The histograms in Figure 1 show the distribution of the simulated capital ratios produced by the model for the safest and the riskiest banks. Figures 2, 3, and 4 give comparative displays of the 99 percent VaR capital ratios for banks operating under low and high market risk, typical and high credit risk, and zero, positive and negative maturity gaps. The main results of the model show:

- The hypothetical bank of our "base" case in Table 11 is the strongest one. It operates in an environment of low market risk, has a credit quality distribution that produces a mean simulated return on equity similar to those reported by large south African banks, and is well-diversified across business and mortgage lending, economic sectors and geographic regions. The mean simulated capital ratio for the base case is 10.22 percent (versus an initial capital ratio of 8.4 percent), while the return on equity is approximately 21 percent. The VaR analysis predicts no bank failure under relatively extreme financial conditions (e.g., a 1 percent probability of risk-free interest rates of around 19 percent, gold prices of around $254/oz, a Rand devaluation of approximately 14 percent, a decline in the stock market index of around 52 percent, and an inflation rate of 7 percent). At the 99 percent VaR defined within an environment of low volatility, the bank's capital ratio is found to be almost the same as the initial capital ratio of 8.4 percent. The histogram of base case presented in Figure 1 shows a very symmetric distribution of the capital ratio around the mean.

- Remarkably strong results are also shown for the hypothetical banks in cases, 1 and 2 which assume portfolios consisting entirely of either business or mortgage loans concentrated in one economic sector or one geographic region. Using the same low market risk and the "typical" credit quality distribution assumptions, we find that the hypothetical banks are almost as safe. Their simulated mean capital ratios are around 10 percent and they project strong capital ratios at the 99 percent VaR level.

- Under the same financial environment of low market risk, it is only when the mass of the bank loan portfolio is concentrated in the lower credit rating categories (i.e., B,

[28] The 99% VaR indicates the level the capital ratio falls below 1% of the time.

CCC) that we see risk levels deteriorate significantly (see Cases 3, 4, and 5). Comparative results of simulated bank risk levels under typical and high credit risk distributions are given in Figure 2.

- The combination of high credit risk and extreme sectorial/geographical concentration in the loan portfolio leads to a considerably riskier distribution of future capital ratios. In Cases 6 and 7 market risk is still low but the majority of the loans are allocated in the two lowest credit rating categories, and the entire bank portfolio is concentrated in one economic sector (case 6), or in one geographic region (case 7). This translates into simulated mean capital ratios below initial levels, and an increased probability of failure. We find that the hypothetical bank in case 7 fails (i.e., has a negative capital ratio) at the 97.5 percent VaR risk level, while the bank in case 6 fails with a probability of less than 1 percent.[29]

- It can be seen that under the high market risk scenario all banks become riskier (see Figure 3). However, the hypothetical bank with a typical credit quality and a well-diversified portfolio does not fail (case 9). The mean capital ratio for Case 9 is 9.6 percent, with a standard deviation of 0.01, and a minimum capital ratio of 0.045. At the 1 percent VaR level the bank's capital ratio lies at 5.8 percent. One can observe similar results for the hypothetical bank in case 14 where the bank is simulated using the high market risk environmental assumptions, and has a well-diversified portfolio with loans spread evenly across all credit qualities.

- This is not the case however for banks with loan portfolios concentrated in the lower credit rating categories. In the context of a highly volatile financial environment, banks with loan portfolios that are well diversified across sectors and regions but concentrated in non-investment grade categories are likely to face significant risks. The hypothetical banks in cases 19 and 25 fail 1 percent of the times and 5 percent of the times respectively. Thus, the outcome of the simulations suggests that systemic risk is important in South Africa.

- Cases 8, 10, 13, 16, 18, 21, 23, 24, 28 and 29 test the effects of high portfolio concentration and varying loan credit quality in an environment of high market risk. As expected, the best performing hypothetical banks are those with loan portfolios characterized by typical or low credit risk, not entirely concentrated in either one economic sector or geographic region (Cases 8, 10, 13, and 18). While these banks are much riskier than the base case they do not fail at the 99 percent VaR level.

- However, as the credit quality of the banks' loan portfolios deteriorates and the degree of sectorial/geographical concentration increases, the simulated mean capital

[29] The relationship between a bank's capital ratio and bank failure deserves additional study. In many cases banks effectively fail before they deplete their equity capital.

ratios decline (cases 21, 23, 24, 28, and 29) significantly. The hypothetical banks in cases 21, 23, and 24 all fail at the 99 percent VaR level, while at the 97.5 percent VaR level almost all the initial capital has eroded.

We introduce interest rate risk in our simulations in cases 11, 12, 15, 17, 20, 22, 26, and 27. A maturity gap of one year is added to the asset and liability structure of our hypothetical banks. Figure 4 shows graphically the effect of asset and liability maturity mismatches on bank risk levels. Cases 17, 22, 26, and 27 have a positive maturity gap as the assets maturity is assumed to be greater than the liabilities maturity. In cases 11 and 17 we isolate interest rate risk (i.e., credit risk is not simulated). Market risk is high and the banks' loan portfolios are well diversified across business and mortgage lending, economic sectors and geographic regions.

- We find that maturity mismatches in the asset and liability structure are quite important in terms of the riskiness of the bank portfolio. This is especially true for the hypothetical bank (case 17) with a one-year positive maturity gap, which has a 99 percent VaR capital ratio of only 0.0087.

- When credit risk is not simulated, the difference in results between the bank with a positive maturity gap and the bank with a negative maturity gap can be attributed to the fact that the amount of bank assets bearing interest rate risk is larger than liabilities bearing interest rate risk, as well as interest rate spread risk which is larger for bank assets.

- Cases 12, 15, 20, 26, and 27 combine credit risk with non zero maturity gaps. The degree of portfolio concentration is held constant. The results again show that the addition of interest rate risk makes the distribution of future capital ratios more risky (cases 12, 15, 26, and 27).

- However, it can be seen that under conditions of high market risk, a bank with high credit risk and a negative maturity gap performs better than the same bank with zero maturity gap (case 20 versus case 25). This result comes about because of a positive correlation between credit losses and interest rate levels. In a rising interest rate environment, banks with significant credit risk exposure are less (more) risky if the maturity of their liabilities is greater (less) than the maturity of their assets. That is during periods of very high (low) interest rates the increase (decrease) in earnings resulting from a negative maturity gap offsets higher (lower) credit losses. Such outcomes illustrate the importance of undertaking correlated market and credit risk analyses.

- The riskiest cases are those where all elements of bank risk are elevated (Cases 28 and 29). Market risk is high, credit risk is high, and loans are allocated in either one economic sector or geographical region. The simulated mean capital ratios for these two banks are around 5.4 percent meaning that during the simulation horizon (e.g., one-year) the banks have lost on average 35 percent of their initial capital. The hypothetical banks fail 10 percent of the time. The relevant histogram in figure 1 shows the distribution of the simulated capital ratios of the hypothetical bank in case 29. The histogram has the typical skewed shape that characterizes the large losses that occur periodically in concentrated loan portfolios having high credit risk.

VI. Limitations and Extensions

While the paper presents a substantial new methodology for modeling the effects of financial environment volatility and bank portfolio factors on the capital ratio risk of South African banks several limitations and areas for future extension should be noted.

In the area of modeling volatility the well-known "fat-tail" problem is a concern. In the present paper the possibility of extreme moves in stochastic variables was handled by looking at alternative market risk environments. Still occasional extreme moves in stochastic variables may not be modeled as well as would be hoped. The application of alternative stochastic models such as jump diffusion process is an important area for future extension.

In the area of modeling the correlations between stochastic variables it was noted that correlations tend to increase in absolute amount during periods of market stress. This tends to systematically reduce the benefits of portfolio diversification. Again in the present paper the possibility of shifts in correlation structures was handled by estimating such variables during both "normal" and "stressful" periods. An alternative approach that deserves exploration would be to model the correlations between stochastic variables as a function of the level or change in some important environmental factor (e.g., interest rates).

The current risk analysis looked at a one-year time horizon. Bankers have noted that the impact of a strong financial shock may take effect with different time lags. Such concerns are handled in the current model by estimating borrower credit quality and defaults on a monthly basis. Thus to a significant extent lags in impacts are captured. It would also be feasible to extend the analysis for longer time horizons and research reported by Barnhill and Maxwell (2000) support the belief that the simulated credit transition probabilities are reasonable for longer periods. Nevertheless future research on the lag structure of the impact of financial market volatility on bank risk levels is an area deserving careful analysis, as the data become available.

The mean and standard deviations of the recovery rates on defaulted business and mortgage loans used in the simulations were estimated from conversations with South African Bankers. These numbers represent an estimate for portfolios of loans with various seniority and security characteristics, smaller and larger companies, and companies operating in various industries. If better data were available improved estimates of default recovery rates on various specific types of loans would improve the model's accuracy.

The methodology used to estimate defaults on mortgage loans was to similar to that used to model defaults on business loans. In particular if the simulated loan to value ratio exceeded 1.1 then the mortgage loan was assumed to default. This critical loan to value ratio was again based on conversations with South African bankers. It is recognized that the loan to value ratio at which default actually occurs is likely to vary from borrower to borrower depending on their particular credit standing and other factors. Extension of the mortgage default model to include such other factors is another area of important extension. Also the loan to value ratio at which default is assumed to occur is a variable having a significant impact on the simulated risk levels for the bank. Table 12 shows that changing the assumed loan to value ratio at which mortgage loans default from 1.1 to 1.15 has a significant marginal impact on the distribution of simulated bank capital ratios. Again better data would allow improved risk analyses.

The overall reliability of the bank risk analysis is a very important issue. It has been shown that the simulations produce financial environment volatilities and correlations that are close to the assumed values based on two historical periods. It has also been shown that the credit transition probabilities seem reasonable. Further qualitatively the results are reasonable (i.e., the riskiest cases are those where all elements of market and bank portfolio risk are elevated). Nevertheless back testing the model against observed bank failure rates and comparisons with other risk assessment methodologies are important future areas of research.

Finally the current paper focuses on a risk assessment for an individual bank. However the methodology is extendable to modeling multiple banks simultaneously. In this way the correlated impacts of market and credit risk on multiple banks with various portfolio structures could be evaluated. Thus in principle a systemic risk analysis giving the probability of correlated failures among multiple banks is an important further extension.

VII. Conclusions

We have presented a model that allows for the integration of market and credit risk and applied it to hypothetical banks that operate in South Africa as of June 1999. It is shown that the global financial environment can be modeled as a set of correlated random variables, and that correlated credit risk for portfolios of business and mortgage loans can be modeled as a function of both environmental variables and firm specific factors. Our study illustrates the ability of the model to capture the impact of correlated market risk and credit risk on the potential losses that the bank can suffer due to interest rate, foreign exchange rate, equity price and real estate price changes as well as client defaults and downgradings. It also demonstrates the limitations of methodologies that separate market and credit risk analysis or rely on subjective assessments.

In the empirical section of the paper we find that:

1. During periods of financial stress the volatility and correlations between important financial environment variables increase in absolute terms. This reduces the benefits of diversification and magnifies the risk of holding a concentrated portfolio.

2. Taken individually, market risk, credit risk, portfolio concentration, and asset and liabilities maturity mismatches are all important risk factors. However, they are clearly not additive and need to be evaluated as a set of correlated risks (see Figures 2, 3, and 4).

3. Market risk is not likely to cause a bank with a high credit quality, well-diversified portfolio to fail (see Figure 3).

4. However, higher market risks significantly increase bank risk levels, particularly so for banks with higher credit risk and more concentrated portfolios (see Figures 2 and 3). This is an important argument for assigning different ratings to two otherwise identical banks, one of which operates in a more volatile emerging market subject to periodic shocks, and the other in a more stable, developed market.

5. The credit quality of the bank's loan portfolio is the most important risk factor. Banks with high credit risk and concentrated portfolios are shown to have a significant risk of failure during periods of low volatility and a high risk of failure during periods of financial stress. Alternatively banks with lower credit risk and broadly diversified loan portfolios across business and mortgage lending are unlikely to fail even during very volatile periods (see Figure 2).

6. In most cases asset and liability maturity gaps increase bank risk levels. However, with a positive correlation between credit losses and interest rate levels banks with significant credit risk exposure are less (more) risky if the maturity of their liabilities is greater (less) than the maturity of their assets. This occurs because rising (falling) net interest rate income resulting from rising (falling) interest rates offsets rising (falling) credit losses (see Figure 4).

This forward-looking quantitative risk assessment methodology allows banks and regulators to identify potential risks before they materialize and make appropriate adjustments on a bank-by-bank basis. In particular it provides a base for evaluating potential changes in a bank's asset/liability portfolio composition (e.g., credit quality, sector/geographic concentration, maturity structure, currency structure, etc.) as well as its capital ratio. The model has the potential to be extended so as to assess the risk of correlated failures among a group of financial institutions (i.e., systemic risk analyses). This could be accomplished by modeling multiple banks (e.g., ten) simultaneously and analyzing the frequency with which multiple banks (e.g., two, three,..., ten) fail simultaneously.

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Table 1. Historical Volatilities, Means, Medians

	Standard Deviation*	Mean**	Median**
1996–99			
Change RSA t-bill (delta)	0.033	-0.00058	-0.0011
Percent ch prime	0.153	-0.0026	0
Percent ch del prime-t-bill	0.168	0.002841	0.009031
Percent ch rand/US$	0.109	0.0011687	0.007939
Percent change in RSA t-bill-US t-bill	0.287	-0.006984	-0.02107
Percent ch gold prices	0.078	-0.009344	-0.00676
Percent ch overall RSA stock index	0.268	0.002371	0.006623
Percent ch S&P500	0.152	0.017381	0.02499
Percent ch CPI	0.018	0.005811	0.005282
Percent ch total RSA R. Estate prices	0.017	0.005801	0.004377
Percent ch Johannesburg R. Estate prices	0.045	0.005491	0.004353
1998–99			
Change RSA t-bill (delta)	0.046	-00.00157	-0.0065
Percent ch prime	0.224	-0.007708	-0.02484
Percent ch del prime-t-bill	0.183	0.00419	0.00243
Percent ch rand/US$	0.141	0.0114	0.0094
Percent change in RSA t-bill-US t-bill	0.403	-0.017	-0.0543
Percent ch gold prices	0.078	-0.0056	-0.00591
Percent ch overall RSA stock index	0.376	0.0056	0.03553
Percent ch S&P500	0.191	0.0153	0.0383
Percent ch CPI	0.022	0.0053	0.0038
Percent ch total RSA R. Estate prices	0.010	0.004	0.004078
Percent ch Johannesburg R. Estate prices	0.038	0.006243	0.006155

* Annualized based on monthly time series.
** Monthly.

Table 2. Historical Correlations

Historical Correlations 1998–99	Change in T-Bill (delta)	Percentage Ch Prime-T-Bill	Percentage Change Rand/US$	Percentage Change Gold Prices	Percentage Change S&P500	Percentage Change RSA all Shares	Percentage Change R. Estate Prices Total RSA	Percentage Change Johannesburg R. Estate
Change RSA t-bill (delta)	1							
Percent ch prime-t-bill	-0.351292	1						
Percent ch rand/US$	0.624447	-0.1602851	1					
Percent ch gold prices	-0.363492	0.4892881	-0.065695	1				
Percent ch S&P500	-0.614876	0.56905824	-0.304589	0.2879288	1			
Percent ch RSA all shares	-0.713193	0.37032541	-0.179168	0.4432976	0.7788135	1		
Percent ch R. Estate prices total RSA	-0.192015	-0.124202	-0.044985	-0.130383	0.0050551	0.3250453	1	
Percent ch Johannesburg R. Estate	-0.42803	-0.1383054	-0.06915	0.1383084	0.272957	0.4241443	0.532321907	1

Historical Correlations 1996–99	Change in T-Bill (delta)	Percentage Ch Prime-T-Bill	Percentage Change FX Rate	Percentage Change Gold Prices	Percentage Change S&P500	Percentage Change Overall Stock Index	Percentage Change Total R. Estate Prices	Percentage Change Regional R. Estate Prices
Change in t-bill (delta)	1							
Percent ch prime-t-bill	-0.369764	1						
Percent ch forex rate	0.612104	-0.1801376	1					
Percent ch gold prices	-0.221826	0.24554273	-0.019363	1				
Percent ch S&P500	-0.464705	0.47842678	-0.238582	0.0930393	1			
Percent ch overall stock index	-0.647996	0.37293801	-0.189574	0.3271548	0.6286245	1		
Percent ch total R. Estate prices	-0.129673	-0.0443084	-0.059497	-0.222237	0.046632	0.0286285	1	
Percent ch Johannesburg R. Estate	-0.284756	-0.0659603	0.064567	-0.003278	0.1688844	0.1452197	0.716653729	1

Table 3. Simulated South African Transition Matrix Calibrated for the 1998-99 Period

	Probability of Rating After One Year (In percent)							
Initial rating	Aaa	Aa	A	Baa	Ba	B	Caa-C	Default
Aaa	95.94	4.04	0.02	0	0	0	0	0
Aa	12.35	60.75	26.90	0	0	0	0	0
A	0	0.12	84.93	14.74	0.21	0	0	0
Baa	0	0	17	52.34	30.17	0.49	0	0
Ba	0	0	1.2	13.93	57.80	27.01	0.03	0
B	0	0	0.02	0.65	14.28	69.31	8.31	7.43
Caa-C	0	0	0	0.18	6.23	8.81	64.54	20.24

Table 4. Simulated South African Transition Matrix Calibrated for the 1996–99 Period

	Probability of Rating After One Year (In percent)							
Initial rating	Aaa	Aa	A	Baa	Ba	B	Caa-C	Default
Aaa	98.49	1.51	0	0	0	0	0	0
Aa	8.51	71.65	19.84	0	0	0	0	0
A	0	0	90.61	9.39	0	0	0	0
Baa	0	0	12.16	64.89	22.94	0.01	0	0
Ba	0	0	0.22	10.40	68.74	20.64	0.03	0
B	0	0	0	0.07	10.25	79.71	7.14	2.83
Caa-C	0	0	0	0.01	3.42	8.12	76.70	11.75

Table 5. Moody's Transition Matrix Adjusted for Withdrawn Ratings, 1920–96

To examine if credit transitions are Markov and as benchmark for the transition probabilities generated using a contingent claims analysis, Moody's historical transition probabilities are reported (Carty and Lieberman, 1996). Carty and Lieberman find no bias in the withdrawn category. Thus, the transition probabilities are adjusted for bonds that have had their ratings withdrawn by Moody's.

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

Table 6. Distributions of Debt to Value Ratios by Credit Rating

Firm Rating	Percentile	SA Debt to Values Ratios*	U.S. Debt to Values Ratios** (High volatility firms)
Default	25	N/A	0.699
Default	50	N/A	0.851
Default	75	N/A	0.940
CCC	25	N/A	0.615
CCC	50	N/A	0.819
CCC	75	N/A	0.931
B	75	0.767	0.702
B	50	0.722	0.525
B	25	0.656	0.324
BB	75	0.472	0.554
BB	50	0.356	0.386
BB	25	0.204	0.226
BBB	75	0.305	0.431
BBB	50	0.152	0.305
BBB	25	0.061	0.198
A	75	0.163	0.340
A	50	0.065	0.212
A	25	0.029	0.131
AA	75	0.010	0.204
AA	50	0.010	0.127
AA	25	0.005	0.077
AAA	75	N/A	0.157
AAA	50	N/A	0.101
AAA	25	N/A	0.048

* The debt to value ratios presented here are based on an analysis of 87 South African Firms. Financial firms, firms with zero debt to value ratios, as well as firms with equity betas that were not found significant in the 95 percentile were excluded from the analysis.

** Barnhill, T. and W. Maxwell, 2000, Modeling Correlated Interest Rate, Exchange Rate and Credit Risk for Fixed Income Portfolios. Working Paper. The George Washington University,

Table 7a. South African Banking Sector.
Balance Sheet as of June 1999

	SA Rands (in thousands)	% of Total Assets
TOTAL ASSETS	**704,132,918**	**100.00**
Total Gross loans (+)	**588,084,862**	**83.52**
Individuals	211,209,371	30.00
Mortgage Loans	190,222,589	27.02
Credit Cards	11,081,962	1.57
Other individual loans	9,904,820	1.41
Interbank	29,361,068	4.17
Corporate (2-3-4)	347,514,423	49.35
Specific Provisions	**10,504,280**	**1.49**
Money	**14,724,326**	**2.09**
Trading Portfolio	**21,593,486**	**3.07**
Investment Porftolio	**46,847,409**	**6.65**
Fixed Assets	**10,783,371**	**1.53**
Other (++)	**32,603,724**	**4.63**

(+) Out of which, R 34,153,014 are in foreign currencies.
(++) Other includes: clients' liabilities for debt outstanding, deferred taxes, remittances in transit and properties in possession.

LIABILITIES	**644,796,296**	**91.57**
Interbank	37,746,813	5.36
Deposit in rands	475,547,332	67.54
Dep in foreign currency	45,381,732	6.45
Other Liabilities*	86,120,419	12.23
CAPITAL	**59,336,618**	**8.43**
Tier 1 - equity	5,266,800	0.75
Tier 1-reserves	38,134,119	5.42
All tier 1	**43,400,919**	**6.16**
Tier 2 equity	20,005	0.00
Tier 2 reserves	3,821,718	0.54
Tier 2 debt	14,958,622	2.12
All tier 2	**18,800,345**	**2.67**
Other (**)	(2,864,647)	-0.41

(*) Other liabilities comprise: loans received under repurchased agreements and other funding liabilities, acknowledgements of debt endorsed and rediscounted, trade creditors, impairements and tax liabilities
(**) Other comprises: Impairements, profits not formally appropriated by board resolution and no qualifying capital including revaluations and other reserves.

Table 7b. South African Banking Sector
Trading Income + Fee Income - Operating Expenses (in thousands of Rands)

1995	(7,280,117)
1996	(8,517,474)
1997	(8,726,305)
1998	(8,885,666)
annualized 1999	(7,479,858)

Table 8. South African Banking Sector.
Corporate Loans by Economic Sector (%)

Agriculture	3.1731
Mining	1.7293
Manufacture	9.8207
Construction	2.0149
Electricity and Water	0.6346
Trade and accomodation	5.2039
Transport and communication	2.5543
Finance, Real Estate and Business Services	38.2834
Other financial services	10.0746
Other services	26.5429
Total	100

TABLE 9: Description of Assumed Portfolio Credit Risk Distributions

Business Loans		Credit Risk			
		Typical	Low	Medium	High
Credit Class	AAA	0	13.76%	9.76%	5.76%
	AA	0	13.76%	9.76%	5.76%
	A	24.09%	13.76%	9.76%	5.76%
	BBB	24.09%	13.76%	9.76%	5.76%
	BB	24.09%	13.76%	9.76%	5.76%
	B	24.09%	13.76%	23.76%	43.76%
	CCC	0	13.76%	23.76%	23.76%
	Default	3.6%	3.6%	3.6%	3.6%
	Total	100.00%	100.00%	100.00%	100.00%

Mortgage Loans		Credit Risk			
		Typical	Low	Medium	High
Credit Class	LTV=0.5	0	13.33%	9.33%	5.33%
	LTV=0.6	0	13.33%	9.33%	5.33%
	LTV=0.7	23.33%	13.33%	9.33%	5.33%
	LTV=0.8	23.33%	13.33%	9.33%	5.33%
	LTV=0.9	23.33%	13.33%	9.33%	5.33%
	LTV=1	23.33%	13.33%	23.33%	43.33%
	LTV=1.075	0	13.33%	23.33%	23.33%
	Default	6.7%	6.7%	6.7%	6.7%
	Total	100.00%	100.00%	100.00%	100.00%

TABLE 10: THE HYPOTHETICAL BANKS

Cases	Market Risk	Credit Quality	Portfolio Concentration[7]	Maturity Gap
Base	Low[1]	Typical[3]	Diversified	0
Case 1	Low	Typical	Mortgages/One Region	0
Case 2	Low	Typical	Business/One Sector	0
Case 3	Low	Low[4]	Diversified	0
Case 4	Low	Medium[5]	Diversified	0
Case 5	Low	High[6]	Diversified	0
Case 6	Low	High	Mortgages/One Region	0
Case 7	Low	High	Business/One Sector	0
Case 8	High[2]	Typical	Diversified Mortgages	0
Case 9	High	Typical	Diversified	0
Case 10	High	Low	Diversified Mortgages	0
Case 11	High	None	Diversified	-1 yr[8]
Case 12	High	Typical	Diversified	-1 yr
Case 13	High	Typical	Diversified Business	0
Case 14	High	Low	Diversified	0
Case 15	High	Low	Diversified	-1 yr
Case 16	High	Typical	Business/One Sector	No
Case 17	High	None	Diversified	+1 yr[9]
Case 18	High	Low	Diversified Business	0
Case 19	High	Medium	Diversified	0
Case 20	High	High	Diversified	-1 yr
Case 21	High	Low	Business/One Sector	0
Case 22	High	Typical	Diversified	+1 yr
Case 23	High	Typical	Mortgages/One Region	0
Case 24	High	Low	Mortgages/One Region	0
Case 25	High	High	Diversified	0
Case 26	High	Low	Diversified	+1 yr
Case 27	High	High	Diversified	+1 yr
Case 28	High	High	Mortgages/One Region	0
Case 29	High	High	Business/One Sector	0

1 Historical monthly data from the period 1996-1999 were used to simulate a financial environment of low market risk.
2 Historical monthly data from the period 1998-1999 were used to simulate a financial environment of high market risk.
3 Loans spread evenly over middle credit qualities. See Table 9.
4 Loans spread evenly across all credit qualities.
5 The amount of loans in the lowest two credit qualities increased by 10 percent relative to low credit risk case.
6 The amount of loans in the second lower credit quality (e.g. B) increased by 30 percent and the amount in the lowest credit quality increased by 10 percent relative to the low credit risk case.
7 Assets maturity < Liabilities maturity. Maturity gap = -1 year.
8 Assets maturity > Liabilities maturity. Maturity gap = 1 year.

TABLE 11:
SIMULATION RESULTS

All hypothetical banks were simulated for a period of one year. Simulations were run for 2000 times using 12 time steps.
The initial capital ratio at t=0 was 8.4%.

					Capital Ratio							% Change in Capital Ratio	
Cases	Market Risk	Credit Risk	Portfolio Concentration	Maturity Gap	Mean	Std. Deviation	Max	Min	99% VaR	97.5% VaR	95% VaR	Mean	Std. Deviation
Base	Low[1]	Typical[3]	Diversified	0	0.102242	0.0078798	0.13163315	0.0661124	0.0829	0.08611	0.08922	0.2132748	0.093508093
Case 1	Low	Typical	Mortgages/One Region	0	0.100561	0.0081942	0.13537021	0.06627794	0.08129	0.08549	0.08805	0.1933357	0.097238066
Case 2	Low	Typical	Business/One Sector	0	0.100714	0.0107741	0.13621698	0.01936008	0.06385	0.07263	0.08377	0.1951444	0.127853963
Case 3	Low	Low[4]	Diversified	0	0.092248	0.011662	0.12634386	0.03698249	0.05456	0.06567	0.07099	0.0946868	0.138390048
Case 4	Low	Medium[5]	Diversified	0	0.088917	0.0160531	0.12778617	0.0110612	0.03769	0.04735	0.05733	0.055158	0.190498149
Case 5	Low	High[6]	Diversified	0	0.089388	0.0184952	0.12864148	-0.0193583	0.02661	0.04064	0.05296	0.0607469	0.219477492
Case 6	Low	High	Mortgages/One Region	0	0.081589	0.0197747	0.13265731	-0.0105329	0.02036	0.03094	0.04234	-0.0318016	0.234661862
Case 7	Low	High	Business/One Sector	0	0.082687	0.0362626	0.13795112	-0.1491139	-0.0544	-0.02307	0.00462	-0.0187769	0.430319006
Case 8	High[2]	Typical	Diversified Mortgages	0	0.096818	0.0105474	0.14209828	0.05458903	0.06661	0.07471	0.08005	0.1489172	0.125163666
Case 9	High	Typical	Diversified	0	0.096166	0.0138014	0.14267589	0.04532513	0.05832	0.06443	0.07102	0.1411766	0.163777848
Case 10	High	Low	Diversified Mortgages	0	0.087377	0.0126288	0.15744089	0.02985374	0.05215	0.0603	0.06591	0.0368866	0.149862364
Case 11	High	None	Diversified	-1 yr[7]	0.097405	0.0160587	0.14028306	0.02548354	0.05004	0.06111	0.06893	0.1558846	0.190564897
Case 12	High	Typical	Diversified	-1 yr	0.0956	0.0165087	0.13977628	0.01600424	0.04399	0.0533	0.06478	0.1344637	0.195904669
Case 13	High	Typical	Diversified Business	0	0.095552	0.0174621	0.14773864	0.00381167	0.04121	0.0503	0.06161	0.1338951	0.207218452
Case 14	High	Low	Diversified	0	0.083062	0.0189949	0.14293071	0.00016555	0.03126	0.03847	0.04802	-0.0143239	0.225407575
Case 15	High	Low	Diversified	-1 yr	0.082844	0.0178291	0.12492771	-0.0031528	0.03079	0.04145	0.05002	-0.0169119	0.211573142
Case 16	High	Typical	Business/One Sector	0	0.094482	0.020586	0.15571467	-0.03673	0.02354	0.04217	0.05297	0.1211933	0.244288795
Case 17	High	None	Diversified	+1 yr[8]	0.094882	0.0330371	0.19432301	-0.023263	0.00868	0.02299	0.03553	0.1259352	0.392042611
Case 18	High	Low	Diversified Business	0	0.079728	0.0268275	0.14904002	-0.0295159	0.00291	0.01438	0.02969	-0.0538852	0.318354984
Case 19	High	Medium	Diversified	0	0.072979	0.0261226	0.13950358	-0.0462515	-0.00019	0.0122	0.0241	-0.1339717	0.309990984
Case 20	High	High	Diversified	-1 yr	0.068718	0.0252537	0.12460924	-0.0503066	-0.00121	0.01101	0.02084	-0.1845453	0.299678961
Case 21	High	Low	Business/One Sector	0	0.077564	0.03033	0.1662849	-0.0756954	-0.01243	0.00134	0.01718	-0.0795685	0.359919115
Case 22	High	Typical	Diversified	+1 yr	0.091915	0.0372608	0.20228625	-0.0514865	-0.01314	0.00794	0.02564	0.090734	0.442164673
Case 23	High	Typical	Mortgages/One Region	0	0.087929	0.0302844	0.14793373	-0.1123583	-0.02342	0.00219	0.02574	0.0434287	0.359377095
Case 24	High	Low	Mortgages/One Region	0	0.077535	0.0296042	0.14637077	-0.0932982	-0.02635	0.00599	0.01926	-0.0799115	0.351305713
Case 25	High	High	Diversified	0	0.067045	0.035308	0.14439744	-0.0899845	-0.04136	-0.02174	-0.0034	-0.204397	0.418991307
Case 26	High	Low	Diversified	+1 yr	0.077584	0.0437819	0.20795837	-0.1214018	-0.04437	-0.02543	-0.0014	-0.0793311	0.519549326
Case 27	High	High	Diversified	+1 yr	0.061736	0.0542643	0.19692326	-0.1683488	-0.09937	-0.06302	-0.0435	-0.2673903	0.643941209
Case 28	High	High	Mortgages/One Region	0	0.054176	0.0580025	0.14210585	-0.1828829	-0.12906	-0.08997	-0.0674	-0.3571048	0.688301104
Case 29	High	High	Business/One Sector	0	0.054499	0.0645636	0.15662233	-0.3404743	-0.1922	-0.12325	-0.0752	-0.3532747	0.766160748

[1] Historical monthly data from the period 1996-1999 were used to simulate a financial environment of low market risk.

[2] Historical monthly data from the period 1998-1999 were used to simulate a financial environment of high market risk.

[3] Loans spread evenly over middle credit qualities. See Table 9.

[4] Loans spread evenly across all credit qualities.

[5] The amount of loans in the lowest two credit qualities increased by 10 percent relative to low credit risk case.

[6] The amount of loans in the second lower credit quality (e.g. B) increased by 30 percent and the amount in the lowest credit quality increased by 10 percent relative to the low credit risk case.

[7] Assets maturity < Liabilities maturity. Maturity gap = -1 year.

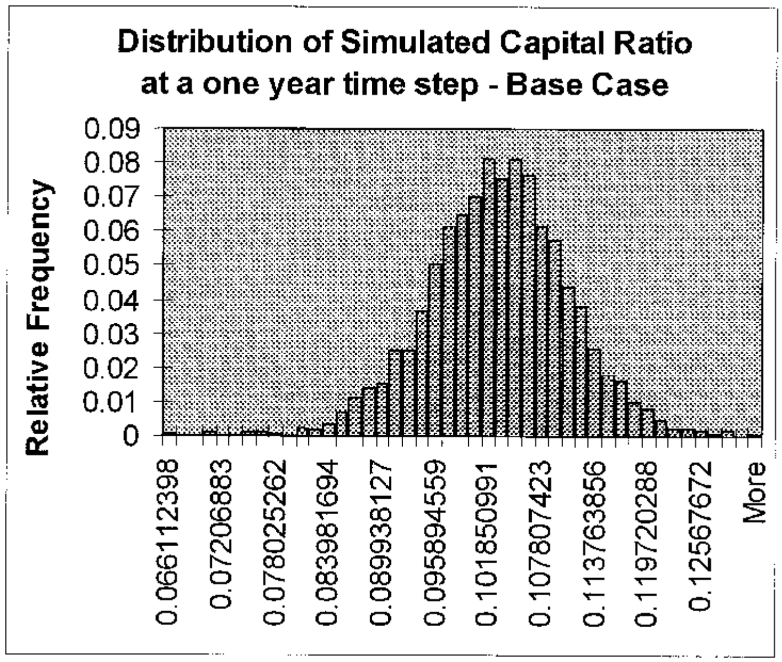
[8] Assets maturity > Liabilities maturity. Maturity gap = 1 year.

TABLE 12

SIMULATION RESULTS UNDER DIFFERENT ASSUMPTIONS OF MORTGAGE LOANS LTV ASSUMED DEFAULT POINT

Cases	Market Risk	Credit Risk	Portfolio Concentration	Maturity Gap	Mortgage Loans LTV Assumed Default Point	Capital Ratio							% Change in Capital Ratio	
						Mean	Std. Deviation	Max	Min	99% VaR	97.5% VaR	95% VaR	Mean	Std. Deviation
Case 9	High	Typical	Diversified	0	1.1	0.09617	0.013801	0.14268	0.04533	0.05832	0.06443	0.07102	0.14118	0.163778
Case 9*	High	Typical	Diversified	0	1.15	0.0987	0.013458	0.16887	0.02158	0.06015	0.06834	0.0758	0.17126	0.159705
Case 25	High	High	Diversified	0	1.1	0.06704	0.035308	0.1444	-0.08998	-0.0414	-0.02174	-0.0034	-0.2044	0.418991
Case 25*	High	High	Diversified	0	1.15	0.07405	0.031778	0.14498	-0.08519	-0.0259	-0.00404	0.00968	-0.1213	0.377102

Figure 1. Distribution of Simulated Capital Ratios (Base case, Case 29)



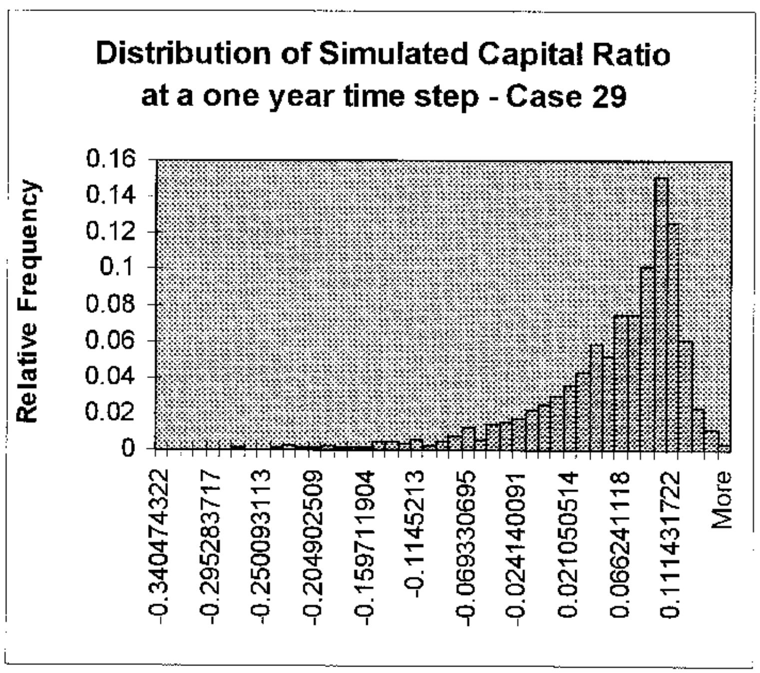
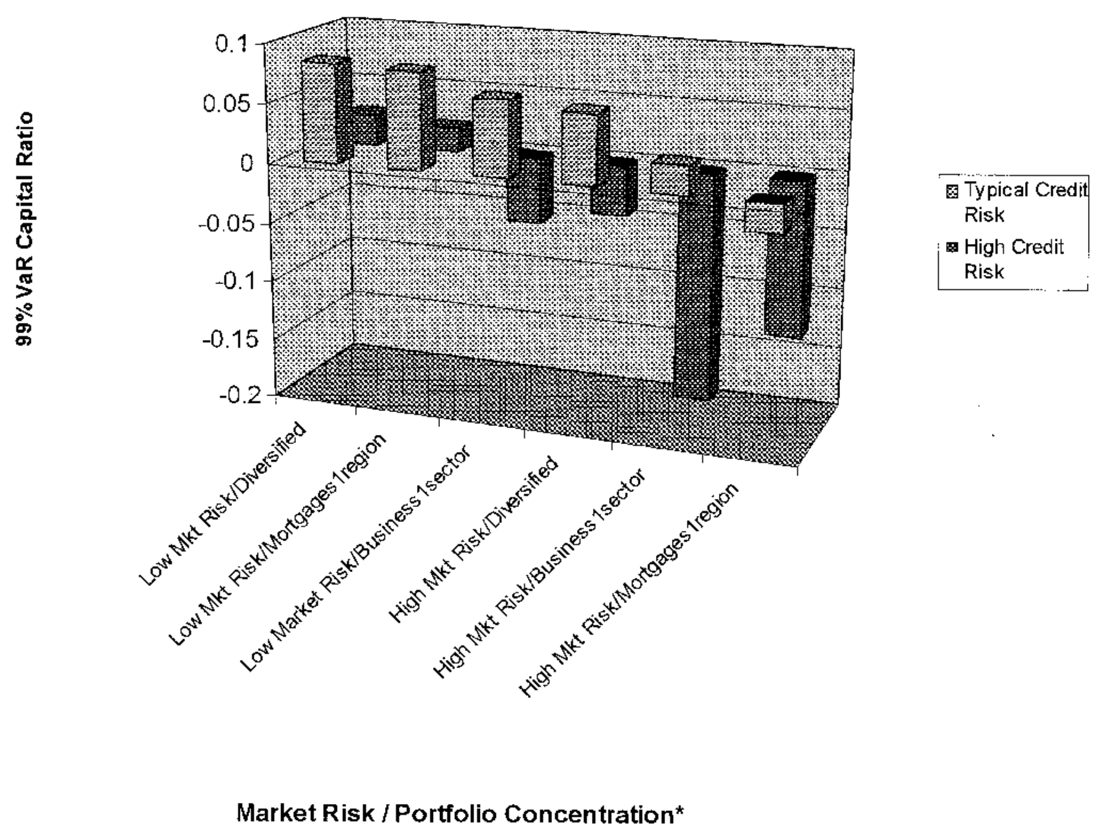
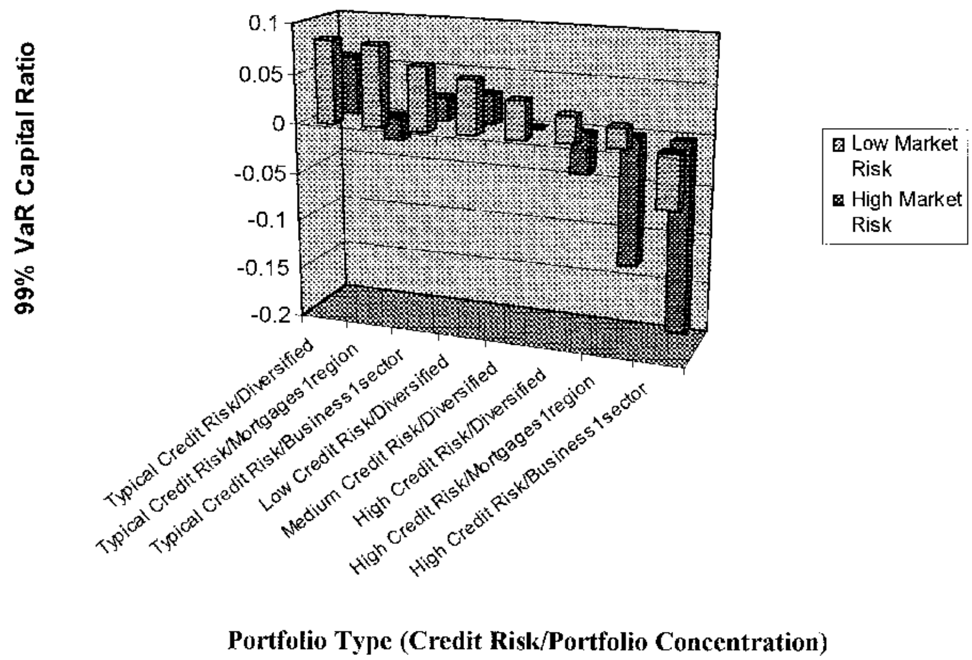


Figure 2: Bank Risk Levels under Typical and High Credit Risk



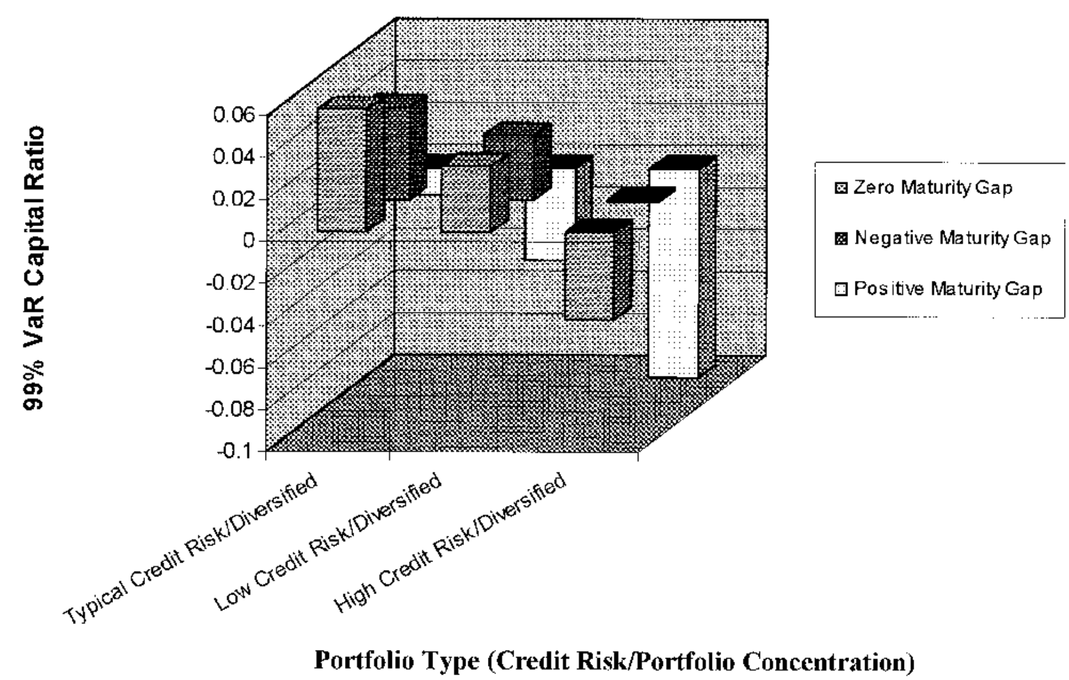
* All Portfolios have a maturity gap = 0

Figure 3: Bank Risk Levels under Low and High Market Risk Environments



* All portfolios have a maturity gap = 0.

Figure 4: Bank Risk Levels under Zero, Positive, and Negative Maturity Gaps for a High Market Risk Environment



Historical Versus Simulated Distributions

The model used in this paper is shown to produce simulated financial environments that match closely the assumed mean returns, volatilities and correlations for all of the input variables. In this section we present a comparison of historical and simulated distributions of changes in selected South African financial environment variables for the period 1980-1999:

Table A1. Annualized Period Volatility, 1980–99

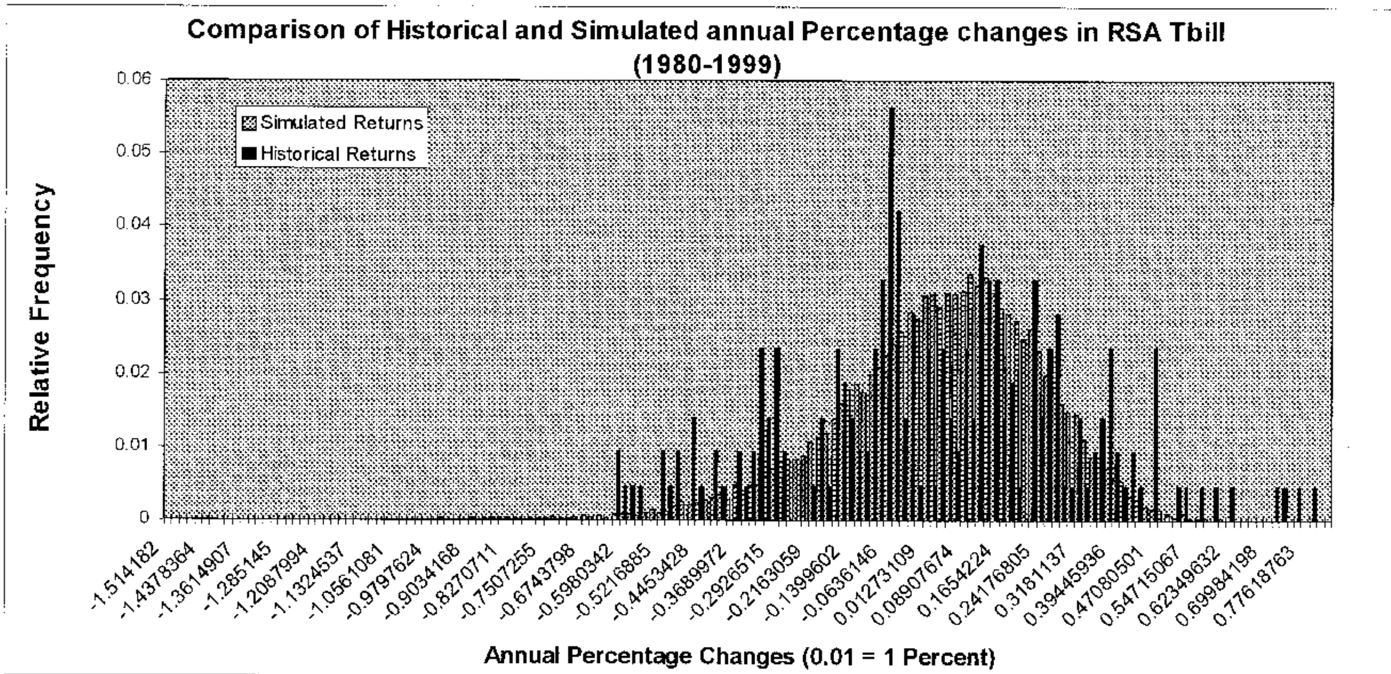
	Historical	Simulated	Sim - Hist
Change RSA t-bill (delta)	0.027033968	0.026455406	-0.0005786
Percent ch prime	0.147314304	0.133391729	-0.0139226
Percent ch prime-t-bill	0.264088068	0.244706538	-0.0193815
Percent changes in RSA t-bill-U.S. t-bill	0.436640172	0.46048863	0.0238485
Percent ch rand/US$	0.11857291	0.120641374	0.0020685
Percent ch gold prices	0.147170489	0.147050755	-0.0001197
Percent ch overall RSA stock Index	0.198208724	0.197311739	-0.000897
Percent ch S&P500	0.124143369	0.120908323	-0.003235
Percent ch CPI	0.018793196	0.018474558	-0.0003186
Percent ch total RSA R.Estate prices	0.032274539	0.032548107	0.0002736
Percent ch Johannesburg R.Estate prices	0.056613974	0.058485606	0.0588498

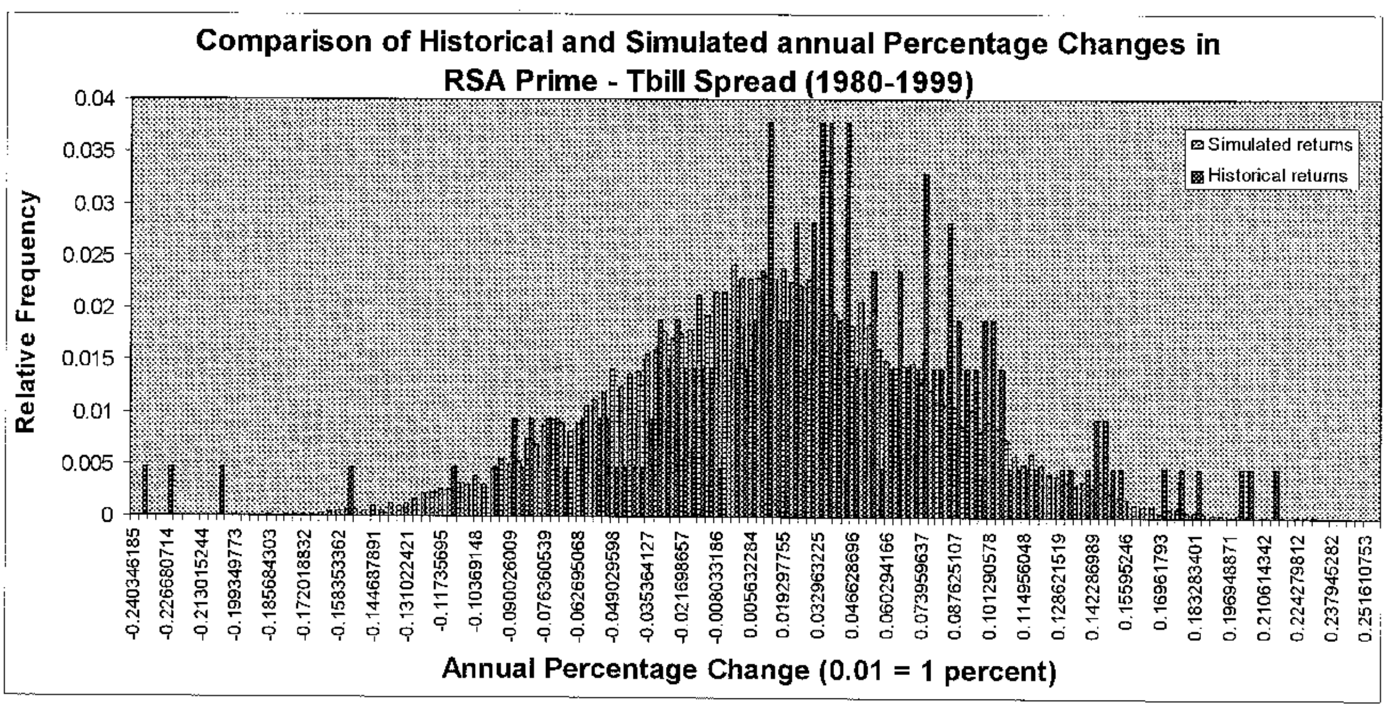
Table A2. Comparison of Historical and Simulated Correlations (1980-1999)

Simulated Correlations 1980-1999	Delta RSA T-Bill	Percent ch Prime-T-Bill	Percent ch Rand/US$	Percent ch Gold Prices	Percent ch S&P500	Percent ch RSA All Shares	Percent ch R.Estate Prices Total RSA	Percent ch Johannesburg R.Estate
Change RSA t-bill (delta)	1							
Percent ch Prime-t-bill	-0.409441	1						
Percent ch rand/US$	0.2232467	0.0745342	1					
Percent ch gold prices	-0.205825	0.1872278	-0.2447265	1				
Percent ch S&P500	-0.155735	0.1017783	-0.096958	-0.0627988	1			
Percent ch RSA all shares	-0.224282	0.0700847	-0.1862691	0.5067869	0.308881	1		
Percent ch R.Estate prices total RSA	0.1676506	-0.0924575	-0.012287	-0.13915	0.045282	-0.01521302	1	
Percent ch Johannesburg R.Estate	0.1434395	-0.0635339	0.03518057	-0.1215416	0.044048	0.03100018	0.773428464	1

Historical Correlations 1980–99	Delta RSA T-bill	Percent ch del Prime-TB	Percent ch Rand/US$	Percent ch Gold Prices	Percent ch S&P500	Percent ch RSA all Shares	Percent ch R.Estate Prices Total RSA	Percent ch Johannesburg R.Estate
Change RSA t-bill (delta)	1							
Percent ch del Prime-TB	-0.407294	1						
Percent ch Rand/US$	0.1754618	0.0346499	1					
Percent ch Gold Prices	-0.184752	0.1705394	-0.2680465	1				
Percent ch S&P500	-0.168501	0.0699528	-0.0667383	-0.0289682	1			
Percent ch RSA all Shares	-0.227074	0.0359627	-0.1589035	0.5078322	0.325106	1		
Percent ch R.Estate prices total RSA	0.1416545	-0.0955755	-0.0839384	-0.0869286	-0.030588	-0.03076612	1	
Percent ch Johannesburg R.Estate	0.1416069	-0.0627848	-0.0147793	-0.0860319	-0.037451	-0.00281019	0.743300156	1

Simulated-Historical Correlations 1980–99	Delta RSA T-Bill	Percent ch del Prime-TB	Percent ch Rand/US$	Percent ch Gold Prices	Percent ch S&P500	Percent ch RSA all Shares	Percent ch R.Estate Prices Total RSA	Percent ch Johannesburg R.Estate
Change RSA t-bill (delta)	0	0	0	0	0	0	0	0
Percent ch del Prime-TB	-0.002148	0	0	0	0	0	0	0
Percent ch rand/US$	0.0477849	0.0398843	0	0	0	0	0	0
Percent ch gold prices	-0.021073	0.0166885	0.02332006	0	0	0	0	0
Percent ch S&P500	0.0127661	0.0318254	-0.0302197	-0.0338306	0	0	0	0
Percent ch RSA all shares	0.0027925	0.034122	-0.0273656	-0.0010453	-0.016225	0	0	0
Percent ch R.Estate prices total RSA	0.0259961	0.003118	0.07165142	-0.0522214	0.07587	0.0155531	0	0
Percent ch Johannesburg R.Estate	0.0018325	-0.0007491	0.04995984	-0.0355097	0.081498	0.03381036	0.030128308	0


Comparison of Historical and Simulated annual Percentage changes in RSA Tbill (1980-1999)
Simulated Returns
Historical Returns
Relative Frequency
0.06
0.05
0.04
0.03
0.02
0.01
0
-1.514182
-1.4378364
-1.3614907
-1.285145
-1.2087994
-1.1324537
-1.0561081
-0.9797624
-0.9034168
-0.8270711
-0.7507255
-0.6743798
-0.5980342
-0.5216885
-0.4453428
-0.3689972
-0.2926515
-0.2163059
-0.1399602
-0.0636146
0.01273109
0.08907674
0.1654224
0.24176805
0.3181137
0.39445936
0.47080501
0.54715067
0.62349632
0.69984198
0.77618763
Annual Percentage Changes (0.01 = 1 Percent)


Comparison of Historical and Simulated annual Percentage Changes in RSA Prime - Tbill Spread (1980-1999)
Simulated returns
Historical returns
Relative Frequency
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
-0.240346185
-0.226680714
-0.213015244
-0.199349773
-0.185684303
-0.172018832
-0.158353362
-0.144687891
-0.131022421
-0.11735695
-0.10369148
-0.090026009
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-0.035364127
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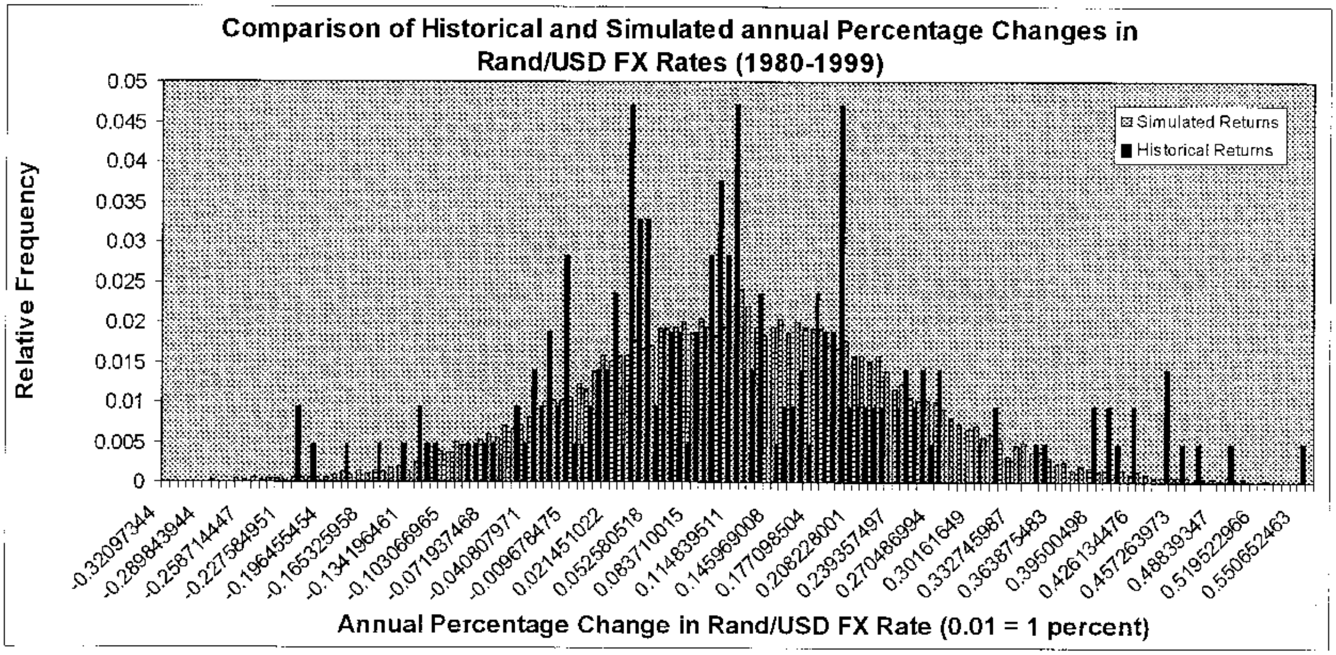
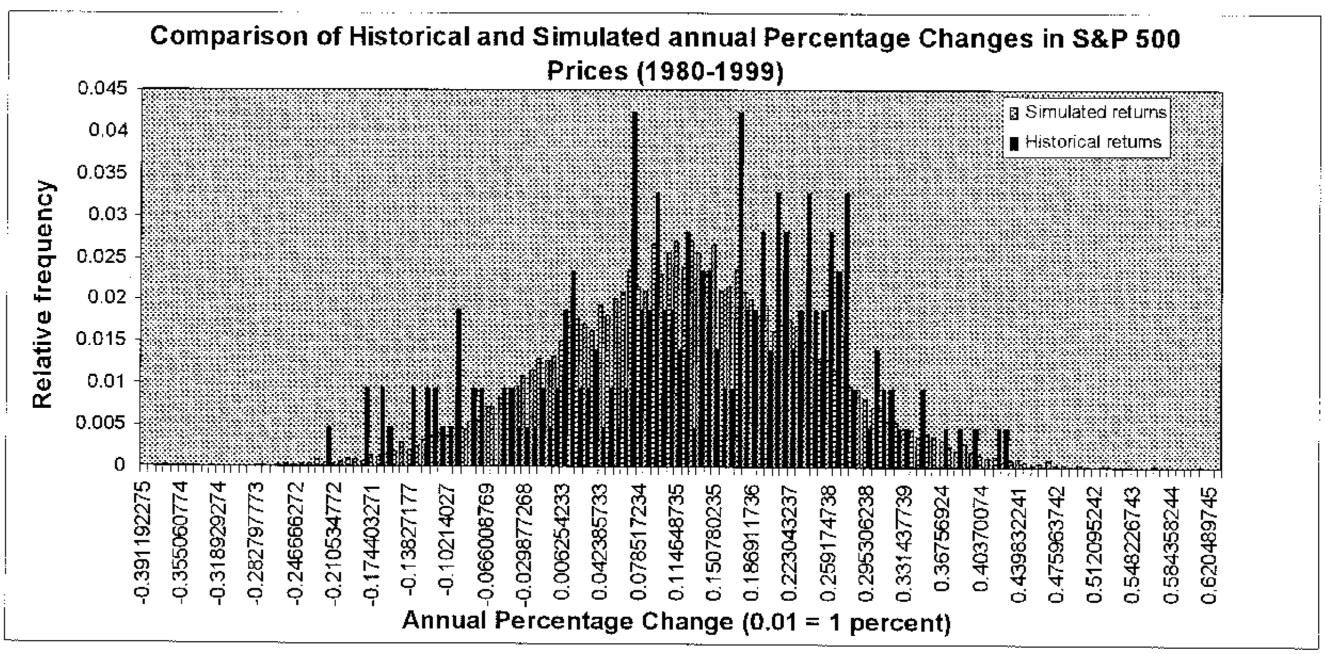
0.005632284
0.019297755
0.032963225
0.046628696
0.060294166
0.073959637
0.087625107
0.101290578
0.114956048
0.128621519
0.142286989
0.15595246
0.16961793
0.183283401
0.196948871
0.210614342
0.224279812
0.237945282
0.251610753
Annual Percentage Change (0.01 = 1 percent)


Comparison of Historical and Simulated annual Percentage Changes in Rand/USD FX Rates (1980-1999)
Relative Frequency
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Simulated Returns
Historical Returns
-0.32097344
-0.289843944
-0.258714447
-0.227584951
-0.196455454
-0.165325958
-0.134196461
-0.103066965
-0.071937468
-0.040807971
-0.009678475
0.021451022
0.052580518
0.083710015
0.114839511
0.145969008
0.177098504
0.208228001
0.239357497
0.270486994
0.30161649
0.332745987
0.363875483
0.39500498
0.426134476
0.457263973
0.48839347
0.519522966
0.550652463
Annual Percentage Change in Rand/USD FX Rate (0.01 = 1 percent)


Comparison of Historical and Simulated annual Percentage Changes in S&P 500 Prices (1980-1999)
Relative frequency
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Simulated returns
Historical returns
-0.391192275
-0.355060774
-0.318929274
-0.282797773
-0.246666272
-0.210534772
-0.174403271
-0.13827177
-0.10214027
-0.066008769
-0.029877268
0.006254233
0.042385733
0.078517234
0.114648735
0.150780235
0.186911736
0.223043237
0.259174738
0.295306238
0.331437739
0.36756924
0.40370074
0.439832241
0.475963742
0.512095242
0.548226743
0.584358244
0.620489745
Annual Percentage Change (0.01 = 1 percent)

Data Requirements

Modeling the financial environment:

The following data is needed to model the financial environment:

1. Time series of short-term interest rates or the credit spreads on various quality loans to undertake volatility and correlation analyses including:

   - Short-term interest rate for risk-free debt,
   - Short-term interest rate for AAA rated debt,
   - Short-term interest rate for AA rated debt,
   - Short-term interest rate for A rated debt,
   - Short-term interest rate for BBB rated debt,
   - Short-term interest rate for BB rated debt,
   - Short-term interest rate for B rated debt,
   - Short-term interest rate for CCC rated debt,

2. Specific estimates of the term structure of interest rates (short, medium, and long-term) for each currency, and credit risk level at the date the risk assessment is to be performed (i.e., June 30, 1999).

3. Prices for a set of interest rate options (e.g., Euro-currency caps, floors, and swaptions) for each currency on June 30, 1999.

Asset/liability portfolio structure:

The structure of an institution's asset and liability (A/L) portfolio plays and important role in determining the institution's risk level. Six crucial structural A/L portfolio factors are:

1. A/L maturity mismatches which create interest rate risk,

2. A/L currency mismatches which create foreign exchange rate risk,

3. Credit quality of governments, companies, and individuals to which the institution has loaned money which affects the risk of adverse rating changes and default,

4. The level of geographic and economic sector concentration (diversification) in the asset portfolio which greatly affects portfolio credit risk, and

5. The level of seniority and security for the loans in the portfolio that substantially affects the recovery rates on loans that may default.

6. "Off Balance Sheet" transactions that either reduce (i.e., hedge) or increase the institution's risk level.

Modeling business loans and securities:

To appropriately model business loan and corporate security risk levels it is necessary to have estimates of the number and amount (percentage) of each institution's business loans broken down for each currency by:

- sector (i.e., agriculture, construction, electricity, finance, mining, manufacture, trade, transportation, other)
- credit quality (e.g., AAA, …, default),
- seniority (e.g., senior secured, senior unsecured, senior subordinated, subordinated, discount and zero coupon),
- maturity (e.g., 0 to 3 months, etc.),
- yield range (e.g., 15% to 16%),
- optionality (e.g., callable).

To the extent that "audited" numbers are not available "expert" opinions will need to be used to fill in missing values for the following types of information (see attachment)

Currency Type		Credit Quality	Maturity	Sector (in Percent) Agriculture	Mining	Etc.	Total
1. Rand	90%						
				10	20	60	90
		AAA		0	1	5	6
			0-6 months	0	1	2	3
			6 months to 1 year	0	0	2	2
			1 year to 2 years	0	0	1	1
			Etc.				0
			Sub-total	0	1	5	6
			Percent non-callable				
			Percent callable				
			Percent putable				
			Percent senior secured				
			Percent senior unsecured				
			Percent senior subordinated				
		AA		1	5	5	11
			Detail				
		A		1	5	10	16
			Detail				
		BBB		2	5	15	22
			Detail				
		BB		2	1	10	13
			Detail				
		B		2	1	10	13
			Detail				
		CCC		1	1	3	5
			Detail				
		D		1	1	2	4
			Detail				
			Sub-total	10 0	2	60	90
2. Currency 2	10%						10
3. Etc.			Detail				
Total	100%						10 0

Modeling business loan credit quality:

Modeling the correlated stochastic credit quality of an institution's loan portfolio is a crucial part of the overall risk analysis. The approach taken is to first simulate the return on equity for each firm (actual or prototypical) in the institution's portfolio. These firm specific returns on equity are estimated as a function of a simulated return on an industry or economic sector plus a firm specific random term. The simulated return on the firm's equity is then used to estimate future firm specific debt to value ratios. The simulated debt to value ratio is then used to assign a simulated credit rating to the company. In order to implement this methodology the following data is needed:

A. Estimates of typical debt to value ratios for loans of various credit quality broken down by sector

	Range of Typical Debt to Value Ratios: Sector		
Credit Quality	Agriculture	Mining	Etc.
AAA	0-0.10	0-0.12	
AA	0.10-0.20	0.12-0.24	
A	0.20-0.30	0.24-0.36	
BBB	0.30-0.40	0.36-0.48	
BB	0.40-0.50	0.48-0.60	
B	0.50-0.60	0.60-0.72	
CCC	0.60-0.70	0.72-0.84	
D	0.70+	0.84+	

B. Balance sheets, income statements, and credit classification for all large exposure loans (10 percent of capital)

C. A time series of default rates on business loans by credit quality one year prior to default. If available credit ratings out to five years prior to default would also be useful.

D. Estimates of loan default recovery rates by sector and seniority of loan

	Typical Default Recovery Rates (Mean/Standard Deviation): Sector		
	Agriculture	Mining	Etc.
Seniority			
Senior Secured	.6/.2	.6/.2	
Senior Unsecured	.5/.2	.5/.2	
Senior Subordinated	.4/.3	.4/.3	
Subordinated	.3/.3	.3/.3	
Discount and zero coupon	.2/.3	.2/.3	

Modeling mortgage loans:

- The number and amounts of real estate loans broken down by loan to value ratios.
- The typical loan to value ratio at which mortgage loans default

Modeling other securities and money market deposits:

Other Securities include government securities, state and local government securities, equity securities, etc. The data required for other securities include *amounts* broken down for each currency by type, credit quality, maturity, rate range, and optionality:

Modeling liability structure:

To model the institution's liability structure we need the amount of each major liability type broken down by currency, maturity, rate range, and optionality.

Other information:

We also used estimates of the institution's *net* off balance sheet transactions and hedging transactions

Industry and Credit Quality Distribution of Loans as of June 30, 1999

	Portfolio Fractions	AAA	AA	A	BBB	BB	B	CCC
Business								
Agriculture	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Construction	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Electricity	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Finance	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Mining	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Manufacture	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Trade	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Transportation	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Other	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Subtotal	.45							
		AAA	AA	A	BBB	BB	B	CCC
Individual								
Mining	.05	.0025	.005	.01	.0125	.01	.0075	.0025
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Manufacturing	.1	.005	.01	.02	.025	.02	.015	.005
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Construction	.1	.005	.01	.02	.025	.02	.015	.005
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Trade	.1	.005	.01	.02	.025	.02	.015	.005
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Financial	.1	.005	.01	.02	.025	.02	.015	.005
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Government and other	.1	.005	.01	.02	.025	.02	.015	.005
Credit fractions		0.05	0.1	0.2	0.25	0.2	0.15	0.05
Subtotal	.55							