Examining the Probability of Financial Institution Failure: The Brazilian Case

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Abstract
In this paper we use the Arbitrage Pricing Theory to infer the probability of financial institution failure for banks in Brazil. We build an index of financial stability for Brazilian Banks. We analyze four of the major publicly traded banks on an individual basis and an index that include all banks with traded shares in the domestic market. Empirical results seem to provide evidence that after the Russian crisis in 1998, systemic risk has increased in the country but this risk has decreased over time through 2002, with some temporary increases in the beginning and the end of 2001. Nonetheless, for individual major banks the probability of failure has decreased monotonically after the Russian crisis.

Keywords: financial institutions, probability of failure, banks, arbitrage pricing theory, systemic risk.

JEL: G21, G33.

* The views expressed in this paper are those of the authors and do not necessarily reflect those of the Central Bank of Brazil.  
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1. Introduction

In the past years financial stability has been in the top of the agenda for many central banks and financial supervisor authorities around the world. The dramatic increase in the number of banking crisis in recent years in both developed and underdeveloped countries seems to be one of the main reasons. The avoidance of such events is of particular importance for central banks or financial supervisors which are responsible for assessing systemic risks and preventing systemic crises.

One of the reasons that financial stability has received a special attention from central banks is that the costs of financial stability can be sizeable due to spillover effects from the banking sector to the real economy. Besides, the loss of confidence in the banking system and subsequent bank runs within a specific country may lead the economy to a recession and into a vicious circle in which a plunge in GDP may also deepen problems within the banking industry.

In some recent papers the costs of financial instability and banking crisis have been estimated and they are found to be quite large. In an International Monetary Fund (IMF, 1998) study of 53 countries (using both developed and underdeveloped countries) it is found that the cumulative output losses from 54 banking crises averaged 11.6%. Furthermore, if there were both a banking and a currency crises then this average rose to 14.4%. Hoggarth et al. (2001) using a cross-section of developed and underdeveloped countries estimate that output losses during banking crisis are on average around 15% to 20% of annual GDP. Furthermore, they found
that these losses are much larger if the country experiences both a banking
and currency crisis, particularly in emerging market countries.

Since the costs of financial instability could be large there is some room
for policy action from authorities. Crockett (1997) argues that the banking
system has a capacity to generate systemic contagion and thus securing
stability should be a concern of public authorities. Nonetheless, the author
also reminds us that although the costs of financial crisis may be large too
much support can lead to moral hazard problems.

In summary most central banks and financial supervisors authorities are
concerned with financial stability due to the high costs that financial
instability my cause. This motivates the development of analytical tools for
predicting crises.

Miles and Hall (1988) have developed a model which uses asset prices
from banks or financial institutions to infer the probability of failure of
these firms. These probabilities are then analyzed over time and regulators
could use them to assess systemic risk within a particular economy. Clare
(1995) and Clare and Priestley (2002) have done some work assessing
failure probabilities in the same spirit as Miles and Hall (1988).

In this paper we follow along the lines of Miles and Hall (1988), Clare
(1995) and Clare and Priestley (2002). We use the Arbitrage Pricing Theory
in order to infer the probability of failure of banks within the Brazilian
banking system for the period from 1998 to 2002. We analyze four of the
major banks which have traded shares in the São Paulo Stock Exchange,

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1 See also Frydl (1999).
namely, A, B, C and D. We also use an index for the entire banking system as a measure of financial instability.

The innovation of the paper is that it estimates a model that has been used for assessing failure probabilities for particular institutions or banks and proposes a financial stability index for the entire banking system. Furthermore, it would be important also to assess these probabilities for large banks as well as they have more potential for contagion across the financial system.

The paper is divided as follows. The next section presents the methodology that will be used throughout the paper. In section 3 empirical results are discussed and section 4 concludes the paper and gives directions for further research.

2. Methodology

Miles and Hall (1988) use the Capital Asset Pricing Model (CAPM) to assess probability of failure of Barclays, Midland, National Westminster and Lloyds over the period from June 1975 and September 1987. They found that there have been a significant variation in risk for their sample period. The main idea is that regulators would want to assess the risk of the value of assets and liabilities for banks and financial institutions, which is a difficult task, to define capital adequacy. To overcome these difficulties they propose to focus on share prices that should reflect the market value of

\footnote{2 Basically if banks know that if they experience difficulties some financial authority is going to rescue}
these institutions. One should use the variability in actual market valuations to estimate the market perception of volatility of the financial institution underlying portfolio.

Clare (1995) uses the Arbitrage Pricing Theory (APT) to calculate the probability of financial institution failure for securities houses in the U.K. in the same spirit as Miles and Hall (1988). We follow his approach and analyze measures of financial institution failure for an emerging market country, namely, Brazil.

In this paper we study the impact of recent crisis on major banks in Brazil assessing their measure of financial failure probabilities in the sense described by Clare (1995) as these banks would be the most likely to have spillover effects over the entire financial system.

Clare and Priestley (2002) found an increase in these probability measures in Norway for commercial banks after the financial deregulation that took place in the mid 1980s. This trend continued until the crisis that happened in 1991. Therefore, their results corroborate the use of these forward-looking measures of probability of failure by regulators to assess systemic risk.

The main innovation in our paper regards the use of these probability measures. We analyze the banking sector measure of financial failure probability, which we propose as a market measure of financial stability (or instability). To the best of our knowledge this is the first paper to use this approach to study an emerging market. There is much to learn from this them then they would be willing to take more risks than they would otherwise do.
study as Brazil has had a significant volatility in the equity market in the past years as consequence of domestic and international turbulence, specially after the adoption of the floating exchange rate regime with an inflation targeting framework in the first semester of 1999. Thus, we analyze failure probabilities for banks and the banking system for that period and beyond, through 2002.

In the next section we present the APT model that we have used in our estimations and we also discuss Clare's (1995) model for calculating financial institutions failure probabilities.

2.1. APT model for Brazil

Arbitrage Pricing theory assumes that financial asset returns are related to an unknown number of factors. Let the return generating process be expressed as

\[ R_i = a_i + \sum_{k=1}^{K} b_{ik} I_k + \zeta_i \]  

(1)

where \( I_k \) stands for a k-th factor that impacts the return on stock i (the unexpected component of this factor), \( \zeta_i \) is a random error term that has a normal distribution with zero mean and variance \( \sigma_{\zeta_i}^2 \), and \( b_{ik} \) corresponds to the sensitivity of stock i to factor k. The APT model that emerges from this return generating process is given by

\[ R_i = a_i + \sum_{k=1}^{K} b_{ik} I_k + \zeta_i \]

An important assumption that is made is that markets are efficient.

\[ \sigma_{\zeta_i}^2 \]
\[ E(R_i) = R_f + \sum_{k=1}^{K} b_{ik} \lambda_k \]  

where the \( \lambda_k \) is the extra expected return due to the sensitivity to factor \( k \), \( R_f \) stands for the risk-free interest rate, and \( E(\cdot) \) is the expectations operator.

Testing the APT requires defining the factors that influence stock returns and estimating the \( b_{ij} \)'s and market prices of risk \( \lambda_i \)'s. To the best of our knowledge two main papers have been written using the APT for Brazil. In one hand, we have Bonomo and Garcia (2001), which have tested a conditional APT model for the period 1976-1992. The authors have used one factor in addition to the market portfolio to capture large inflation risk for that period. The authors have found that inflation risk plays a crucial role in the pricing of portfolios for the Brazilian economy for their sample.

In the other hand, Bonomo et al. (2002) found several intuitively macroeconomic variables which could be used to price stocks in the Brazilian stock market and test an APT model for Brazil. One of the main criticisms of the APT modeling regards the choice of macroeconomic variables (factors that would influence stock returns) that enter the model. In this paper we follow Bonomo et al. (2002) and use industrial production, inflation, the real interest rate and credit risk since they argue that these variables affect in one way or the other asset prices. We also use a proxy for the market portfolio (the Index for the São Paulo Stock Exchange - IBOVESPA).
In order to build the variables that enter the APT we need to model these variables as we have to extract their non anticipated component. In the following we describe how these variables were built and used in the model in order to estimate the APT.

2.1.1. Industrial Production

In the same sense as Bonomo et al. (2002) we use a structural model for the industrial production growth rate released by IBGE, without seasonal adjustment. We estimate the following equation:

\[ y_t = \mu_t + \varphi_t + \omega_t + \varepsilon_t \]  \hspace{1cm} (3)

\[ \mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \]  \hspace{1cm} (4)

where the \( y_t \) stands for the growth rate in industrial production, \( \mu_t \) is a stochastic level with a fixed slope \( \beta_t \), \( \varphi_t \) represents a deterministic cycle, \( \omega_t \) accounts for seasonality and \( \varepsilon_t \) and \( \eta_t \) are normally distributed white noise residuals with zero mean and variances given by \( \sigma^2_{\varepsilon} \) and \( \sigma^2_{\eta} \), respectively.\(^4\)

The unanticipated growth rate for industrial production is then calculated as the difference between the observed variable and the forecast produced by the model. We first fit this model for the period beginning in January 1980 to July 1994 and then we built the one step ahead forecast for August 1994. We then use the realized observation for August 1994 and make a one-month ahead forecast of unexpected industrial production. We

\( ^4 \) The reader is referred to Admati and Pfleiderer (1985), Burmeister and McElroy (1988) and Clare and Thomas (1994).
follow this procedure until August 2002. We then have a series of unanticipated growth rate of industrial production from August 1994 to August 2002. We also use the number of working days as an explanatory variable for industrial production since the index may be lower only because in a particular month there are less working days.

2.1.2. Inflation

The unanticipated inflation rate \( \pi_t \) is modeled using a structural model:

\[
\pi_t = \mu_t + \varepsilon_t \tag{5}
\]

\[
\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{6}
\]

In this case we had to include many dummies for inflation since Brazil has had a highly inflationary regimes in the 1980s and in the beginning of the 1990s and thus we had to model these structural changes accounting for both changes in level and slope. As we did for industrial production we run the model from 1980 to 1994 and we did a one-step ahead forecast. We use the difference between this forecast and realized inflation as the unexpected inflation component.

2.1.3. Real Interest Rate

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5 The reader is referred to Harvey (1989) and Koopman et al (1995) for more details.
6 Since each month has a different number of working days we used the number of working days as an explanatory variable for industrial production.
7 We used the IGP-DI as a measure for inflation.
As a proxy for this variable we use the difference between interest rates and the unexpected inflation rate for that particular month. The latter was obtained as described in section 2.1.2. We use the interest rate on the Certificado de Depósito Interbancário (CDI) as our measure for the interest rate.

2.1.4. Credit Risk

The difference between the interest rate charged for working capital and the CDI interest rate accumulated for a particular month is used to measure credit risk. Since this spread has a non zero mean this series has been normalized.

2.1.5. Market Portfolio

In order to include in the model systematic risk a proxy of the market portfolio is also considered. It was constructed regressing the difference between the Index for the São Paulo Stock Exchange (IBOVESPA) and CDI on the previous macroeconomic variables. We use as a factor the resultant error obtained in the previous regression.

As one of the assumptions that we have to do in order to run the APT is that the factors have zero mean, the unexpected inflation rate, credit risk and real interest rates were standardized.
2.1.6. Data

We use closing prices for A, B, C and D which are amongst the largest banks in Brazil and were the group of banks that had continuously traded share prices for the time period considered in this paper. Other banks had many missing observations as they are not traded frequently and were not used in this study.

In order to assess systemic risk we also use a sector index for the banking system, which includes most of the banks that have traded shares. All returns were calculated using the difference in natural logs. Finally, in order to reduce noise in our data sample we built monthly returns using average prices for a particular month instead of using prices for the end of the month.

2.2. A measure of financial institution failure probability

From the APT we have that returns on asset i should be compensated in addition of the risk-free interest rate for the risk factors that are relevant. This is given in equation (2).

The share price of a firm can be written as:

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8 As we're using an index to assess systemic risk and we have monthly observations the negative effects of infrequent trading on our estimations should be minimized.
\[
S_a = \frac{\sum_{i=1}^{N} P_i X_i}{N} \tag{7}
\]

where the number of issued ordinary shares is given by \(N\), \(P_i\) is the price of asset/liability \(i\) and \(X_i\) represents asset/liability \(i\).

We then have that the expected value of firm capital can be written as

\[
E_{t-1}(S_i)N = S_{t-1}N \left\{ 1 + r_f + \sum_{j=1}^{k} \lambda_j \beta_{xy} + \xi_{xy} \right\} \tag{8}
\]

we have also the actual value and the conditional variance of firm capital is

\[
S_iN = S_{t-1}N \left\{ 1 + r_f + \sum_{j=1}^{k} \lambda_j \beta_{xy} + \xi_{xy} \right\} \tag{9}
\]

\[
E_{t-1}(S_iN - E_{t-1}(S_iN))^2 = (S_{t-1}N)^2 \sigma_{\xi_{xy}}^2 \tag{10}
\]

Expression (10) gives the conditional variance of the value of capital at time \(t\) as measured at time \(t-1\). This is the variability in the market value of the bank's capital around it's expected value. We can derive our probability of failure as the number of standard deviations the value of capital represents at time \(t-1\). This is given in expression (11).

\[
\frac{S_{t-1}N}{\sqrt{(S_{t-1}N)^2 \sigma_{\xi_{xy}}^2}} = \frac{1}{\sigma_{\xi_{xy}}} \tag{11}
\]
Thus, we will estimate through an APT the standard deviation of the errors using equations (1) and (2) in order to invert them and calculate expression (11). A value of 10 for the variance would represent a probability of firm failure of 10/100 and thus the lower expression (11) (See Clare, 1995).

Regulators should be concerned not only with the actual value of these probabilities but with sudden changes in these probabilities. Thus in the following section we will estimate these probabilities for the period of January 1998 to May 2002.

3. Empirical Results

All empirical results in this section were derived using SAS 8.0. We use a two step procedure in order to run the APT. In the first step, one estimates the betas for all four banks using ordinary least squares (OLS). Finally, with the betas one can run a multivariate equation model, considering as observational units the four brazilian banks, to estimate the risk premiums (λ’s).

It was not necessary to apply the Hausman specification test to decide between Ordinary Least Squares (OLS) and Seemingly Unrelated Regressions (SUR) when estimating the factor sensibilities. We have identical independent variables in all equations. In this case, OLS and SUR provide the same results (Greene, 1997). But when estimating the factor risk premium for different banks this test is necessary. The formulation of
the test is given by the null that both OLS and SUR are consistent but only SUR is efficient against the alternative that only OLS is consistent.

<table>
<thead>
<tr>
<th>Comparing</th>
<th>Degrees of Freedom</th>
<th>Wald Statistic</th>
<th>Prob &gt; $\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>SUR</td>
<td>5</td>
<td>9.2081</td>
</tr>
</tbody>
</table>

We compare results using both methods OLS and SUR and found a Wald statistic around 9.2081. Asymptotically this statistic has a $\chi^2$ distribution with 5 degrees of freedom and with a 95% level of confidence we cannot reject the null. In this case, we conclude that we should adjust the model using SUR.

Results for the first step for all banks are given in table 1. As we can see some of these factors are not significant. Industrial production and inflation were not significant for all banks. However, both the real interest rate and the market portfolio were significant for most of them.

\[9\] To build our factors using structural models that feed into our APT estimations we have used Stamp 6.0.
### Table 1. Factor Sensibilities - Brazilian Banks

<table>
<thead>
<tr>
<th>Bank</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t value</th>
<th>Prob &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_{11}$ - Ind. Production</td>
<td>0.006</td>
<td>0.235</td>
<td>0.027</td>
<td>0.978</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{12}$ - Inflation</td>
<td>2.502</td>
<td>1.570</td>
<td>1.594</td>
<td>0.115</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{13}$ - Credit Risk</td>
<td>-1.789</td>
<td>1.380</td>
<td>-1.297</td>
<td>0.198</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{14}$ - Real Int. Rate</td>
<td>-2.886</td>
<td>1.736</td>
<td>-1.662</td>
<td>0.100</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{15}$ - Market Port.</td>
<td>0.875</td>
<td>0.136</td>
<td>6.416</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{21}$ - Ind. Production</td>
<td>0.170</td>
<td>0.263</td>
<td>0.647</td>
<td>0.519</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{22}$ - Inflation</td>
<td>-0.993</td>
<td>1.755</td>
<td>-0.566</td>
<td>0.573</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{23}$ - Credit Risk</td>
<td>0.018</td>
<td>1.542</td>
<td>0.012</td>
<td>0.991</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{24}$ - Real Int. Rate</td>
<td>-3.420</td>
<td>1.941</td>
<td>-1.762</td>
<td>0.082</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{25}$ - Market Port.</td>
<td>0.886</td>
<td>0.153</td>
<td>5.810</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{31}$ - Ind. Production</td>
<td>0.166</td>
<td>0.207</td>
<td>0.803</td>
<td>0.424</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{32}$ - Inflation</td>
<td>0.853</td>
<td>1.386</td>
<td>0.616</td>
<td>0.540</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{33}$ - Credit Risk</td>
<td>-0.274</td>
<td>1.218</td>
<td>-0.225</td>
<td>0.822</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{34}$ - Real Int. Rate</td>
<td>-2.151</td>
<td>1.532</td>
<td>-1.404</td>
<td>0.164</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{35}$ - Market Port.</td>
<td>0.490</td>
<td>0.120</td>
<td>4.068</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{41}$ - Ind. Production</td>
<td>-0.073</td>
<td>0.218</td>
<td>-0.335</td>
<td>0.738</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{42}$ - Inflation</td>
<td>1.117</td>
<td>1.458</td>
<td>0.766</td>
<td>0.446</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{43}$ - Credit Risk</td>
<td>-0.121</td>
<td>1.281</td>
<td>-0.095</td>
<td>0.925</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{44}$ - Real Int. Rate</td>
<td>-3.187</td>
<td>1.613</td>
<td>-1.976</td>
<td>0.051</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{45}$ - Market Port.</td>
<td>0.745</td>
<td>0.127</td>
<td>5.881</td>
<td>0.000</td>
<td></td>
</tr>
</tbody>
</table>

In table 2 we present our results for the risk premium estimation. As we can see only inflation and credit risk were significant at the 90% level.
### Table 2. Factor Risk Premium - Brazilian Banks

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t value</th>
<th>Prob &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$ - Industrial Production</td>
<td>-6.244</td>
<td>5.788</td>
<td>-1.079</td>
<td>0.286</td>
<td></td>
</tr>
<tr>
<td>$\lambda_2$ - Inflation</td>
<td>-1.812</td>
<td>0.989</td>
<td>-1.831</td>
<td>0.073</td>
<td></td>
</tr>
<tr>
<td>$\lambda_3$ - Credit Risk</td>
<td>-3.384</td>
<td>2.013</td>
<td>-1.682</td>
<td>0.099</td>
<td></td>
</tr>
<tr>
<td>$\lambda_4$ - Real Interest Rate</td>
<td>-0.197</td>
<td>1.359</td>
<td>-0.145</td>
<td>0.885</td>
<td></td>
</tr>
<tr>
<td>$\lambda_5$ - Market Portfolio</td>
<td>-1.939</td>
<td>5.416</td>
<td>-0.358</td>
<td>0.722</td>
<td></td>
</tr>
</tbody>
</table>

In figure 1 we present our measure of probability of financial failure. As we can see there is a jump in the probability of failure in the Russian crisis and these probabilities tend to lower through 2002 for all banks.

**Figure 1. Inverse of the probability of failure - Brazilian Banks**

![Figure 1](chart.png)

10 The variances of the errors are used as proxies for the probabilities of failure for banks and the inverse of these variances is plotted in figure 1. The higher this variance the higher the probability of failure and the lower the inverse $1/\sigma^2$. 

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10
So far we have presented results for single banks. In tables 3 and 4 we present results for the banking system. Both the real interest rate and market portfolio are significant factors as we have seen before for individual banks.

**Table 3. Factor Sensibilities - Banking System**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t value</th>
<th>Prob &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{51}$ - Industrial Production</td>
<td>0.041</td>
<td>0.142</td>
<td>0.291</td>
<td>0.772</td>
<td></td>
</tr>
<tr>
<td>$\beta_{52}$ - Inflation</td>
<td>0.762</td>
<td>0.950</td>
<td>0.801</td>
<td>0.425</td>
<td></td>
</tr>
<tr>
<td>$\beta_{53}$ - Credit Risk</td>
<td>0.064</td>
<td>0.835</td>
<td>0.077</td>
<td>0.939</td>
<td></td>
</tr>
<tr>
<td>$\beta_{54}$ - Real Interest Rate</td>
<td>-2.844</td>
<td>1.051</td>
<td>-2.705</td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td>$\beta_{55}$ - Market Portfolio</td>
<td>0.460</td>
<td>0.083</td>
<td>5.572</td>
<td>0.000</td>
<td></td>
</tr>
</tbody>
</table>

Regarding the risk premiums we have had only one change in our results. Now Industrial production along with inflation and credit risk also plays a role in explaining returns as we can see from table 4.

**Table 4. Factor Risk Premium - Banking System**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t value</th>
<th>Prob &gt;</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_1$ - Industrial Production</td>
<td>-75.238</td>
<td>26.605</td>
<td>-2.828</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>$\lambda_2$ - Inflation</td>
<td>17.638</td>
<td>8.286</td>
<td>2.129</td>
<td>0.038</td>
<td></td>
</tr>
<tr>
<td>$\lambda_3$ - Credit Risk</td>
<td>-78.852</td>
<td>17.698</td>
<td>-4.455</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>$\lambda_4$ - Real Interest Rate</td>
<td>-5.572</td>
<td>5.031</td>
<td>-1.108</td>
<td>0.274</td>
<td></td>
</tr>
<tr>
<td>$\lambda_5$ - Market Portfolio</td>
<td>-51.718</td>
<td>38.346</td>
<td>-1.349</td>
<td>0.184</td>
<td></td>
</tr>
</tbody>
</table>
In figure 2, we present results for the probability of failure for the banking system. As we can see, the Russian crisis seems to have affected these probabilities in a more pronounced way than the Argentinean crisis. Nonetheless, we have some increases of these probabilities.

Figure 2. Inverse of the probability of failure - Banking System

It is important to note that although we have had some increases in these probabilities due to crisis (both external and domestic) which have affected the equity market, these probabilities are very low. This is true for both individual banks and the banking system. This result is similar to that obtained by Clare (1995) and Miles and Hall (1988). We found two main episodes which have witnessed a huge increase in the probabilities of failures, the Russian crisis (August 1998) and December 2000.
Furthermore, we have a small increase in these probabilities in January 1999, with the devaluation of domestic currency. Two banks failed in that period due to their expositions to currency risk\textsuperscript{11}.

Also in December 2001 with the Argentinean default on US$ 95 billions of debt these probabilities get higher but contagion has not been as pronounced as in the Russian crisis. There is one main difference on the domestic side that we need to consider when comparing these probabilities. In August 1998 market concerns were related to the sustainability of the currency crawling peg regime and thus international reserves went down from around US$ 70 billions until January 1999 to approximately US$ 36 billions, when the Central Bank had to devaluate the currency and introduced a floating exchange regime.

In the recent Argentinean crisis there seems to be small evidence of contagion to domestic banking system. A possible explanation for this phenomenon is that the exposure of domestic banks to Argentina was very small. Moreover, the decrease in foreign capital inflows that could be a consequence of Argentinean default could be compensated by the depreciation in domestic currency, since the country had adopted a floating exchange regime. Therefore, contagion seem to be diminished after the Russian crisis.

\textsuperscript{11} Marka and Fonte Cindam believed that the Central Bank of Brazil would maintain the currency peg and
4. Conclusions

To the best of our knowledge this is the first paper that addresses banking failure in the Brazilian economy from a market price perspective. Most papers that discuss and model banking failures generally use banks accounts.

In this paper we have derived an APT model which has been used to build probabilities of failure of 4 financial institutions, namely A, B, C and D. Furthermore, we have used a banking sector index to build these probabilities and we interpret the latter as a systemic risk index.

Our findings suggest that the Russian crisis has had a major impact on failure probabilities for all individual banks. Afterwards these probabilities seem to lower smoothly until the end of our sample (May, 2002).

However, when one analyzes the systemic risk index we find that we have more spikes than for individual banks. The main increase in this probability was due to the Russian crisis and thereafter international crisis such as the recent Argentinean crisis failed in increasing these probabilities evidencing that contagion has decreased since 1998.

sold currency futures in the futures market providing hedge for the market. With the fast devaluation in mid January in 1999 they became insolvent.
References


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