Estimating the Probability of Failure for Financial Institutions: The Brazilian Case[Ψ]

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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. The model performs quite well. 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. Nonetheless, for individual major banks the probability of failure has decreased monotonically after the Russian crisis with the adoption of a floating exchange rate regime, an inflation targeting framework and the introduction of the new payment systems.

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

JEL: G21, G33.

[Ψ] 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 estimated 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[1].

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[2].

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

[1] See also Frydl (1999).
[2] Basically if banks know that if they experience difficulties some financial authority is going to rescue them then they would be willing to take more risks than they would otherwise do.

major banks which have traded shares in the São Paulo Stock Exchange, namely, Banco do Brasil, Unibanco, Itau and Bradesco. We also use an index for the entire banking system as a measure of financial instability.

The innovation of the paper is that it uses a model that has been used for assessing failure probabilities for particular institutions or banks and we propose 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.

This modeling has been used to the best of our knowledge only to Norway and the U.K. We test whether it can be useful for a highly volatile emerging market such as Brazil, which has undergone banking problems in the beginning of the year of 1999 with the abandonment of the fixed exchange rate. We show that the model developed in this paper can be of use for regulators as it serves as an analytical tool for assessing systemic risk. Additionally, we analyze whether the introduction of the new payment systems in Brazil has decreased systemic risk. Our results suggest that this modeling works quite well in assessing systemic risk as it captures increases in systemic risk.

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 has 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 these institutions[3]. One should use the variability in actual market valuations to estimate the market perception of volatility of the financial institution underlying portfolio.

Clare (1995) use 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.

We analyze the banking sector measure of financial failure probability, which we propose as a market measure of financial stability (or instability). This is the first paper to use this approach to study an emerging market. There is much to learn from this 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 and the implementation of 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

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

[3] An important assumption that is made is that markets are efficient.

where I_k stands for a k-th factor that impacts the return on stock i (the unexpected component of this factor), ζ_i is a random error term that has a normal distribution with zero mean and variance $\sigma^2_{\zeta_i}$, 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

$$E(R_i) = R_f + \sum_{k=1}^{K} b_{ik}\lambda_k \tag{2}$$

where the λ_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_{ik}'s and market prices of risk λ_k's[4]. Two 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, Schor 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

[4] The reader is referred to Admati and Pfleiderer (1985), Burmeister and McElroy (1988) and Clare and Thomas (1994).

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 Schor 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 components. 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 Schor 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:

$$y_t = \mu_t + \varphi_t + \omega_t + \varepsilon_t \tag{3}$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{4}$$

where the y_t stands for the growth rate in industrial production, μ_t is a stochastic level with a fixed slope β_t , φ_t represents a deterministic cycle, ω_t accounts for seasonality and ε_t and η_t are normally distributed white noise residuals with zero mean and variances given by σ_ε^2 and σ_η^2, respectively[5].

[5] The reader is referred to Harvey (1989) and Koopman et al (1995) for more details.

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. Then we built the one step ahead forecast for August 1994. We then include the realized observation for August 1994 and make a one-month ahead forecast of unexpected industrial production for September 1994. Following this procedure until August 2002 we have built a series of unanticipated growth rate of industrial production from August 1994 to August 2002[6]. 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 inflation rate π_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

[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.

the difference between this forecast and realized inflation as the unexpected inflation component[7].

2.1.3. Real Interest Rate

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 this regression.

[7] We used the IGP-DI as a measure for inflation.

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 Banco do Brasil, Unibanco, Itau e Bradesco 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. In order to assess systemic risk we use a sector index for the banking system, which includes most of the banks that have traded shares[8]. 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. The Model

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:

$$S_{it} = \frac{\sum_{l=1}^{N} P_{lt} X_{lt}}{N} \tag{7}$$

[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.

where the number of issued ordinary shares is given by N, P_l is the price of asset/liability l and X_l represents asset/liability l.

Thus, we have that the expected value of firm capital can be written as

$$E_{t-1}(S_t)N = S_{t-1}N\left\{1 + r_{ft} + \sum_{j=1}^{k} \lambda_j \beta_{ij}\right\} \tag{8}$$

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

$$S_t N = S_{t-1}N\left\{1 + r_{ft} + \sum_{j=1}^{k} \lambda_j \beta_{ij} + \zeta_{it}\right\} \tag{9}$$

$$E_{t-1}\left(S_t N - E_{t-1}(S_t N)\right)^2 = \left(S_{t-1}N\right)^2 \sigma_{\zeta_{it}}^2 \tag{10}$$

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).

$$\frac{S_{t-1}N}{\sqrt{\left(S_{t-1}N\right)^2 \sigma_{\zeta_{it}}^2}} = \frac{1}{\sigma_{\zeta_{it}}^2} \tag{11}$$

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 three for expression (11) would represent a probability of firm failure of one in one thousand. 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 December 2002.

3. Empirical Results

All empirical results in this section were derived using SAS 8.0[9]. 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 wasn't 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 at all equations. In this case, OLS and SUR provide the same results (Greene, 1997). Nonetheless, this test is necessary when estimating the factor risk premium for different banks. The formulation of the test is given by the null that both OLS and SUR are

[9] To build our factors using structural models that feed into our APT estimations we have used Stamp 6.0.

consistent but only SUR is efficient against the alternative that only OLS is consistent.

Table 1. Hausman Specification Test

Competing Models		Degrees of Freedom	Wald Statistic	Prob > χ^2
OLS	SUR	5	1.13	0.951

We compare results using both methods OLS and SUR and found a Wald statistic around 1.13 (Table 1). Asymptotically this statistic has a χ^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 2. 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.

Table 2. Factor Sensibilities - Brazilian Banks

Bank	Parameter	Estimate	Standard Error	t value	Prob > | t|
Banco do Brasil	β_{14} - Real Int. Rate	-2.743	0.739	-3.71	0.0003
	β_{15} - Market Port.	0.727	0.092	7.86	<.0001
Unibanco	β_{24} - Real Int. Rate	-2.778	0.537	-5.17	<.0001
	β_{25} - Market Port.	1.015	0.087	11.57	<.0001
Itau	β_{34} - Real Int. Rate	-1.923	0.372	-5.17	<.0001
	β_{35} - Market Port.	0.764	0.057	13.31	<.0001
Bradesco	β_{44} - Real Int. Rate	-2.490	0.425	-5.85	<.0001
	β_{45} - Market Port.	0.907	0.057	15.67	<.0001

In table 3 we present our results for the risk premium estimation.

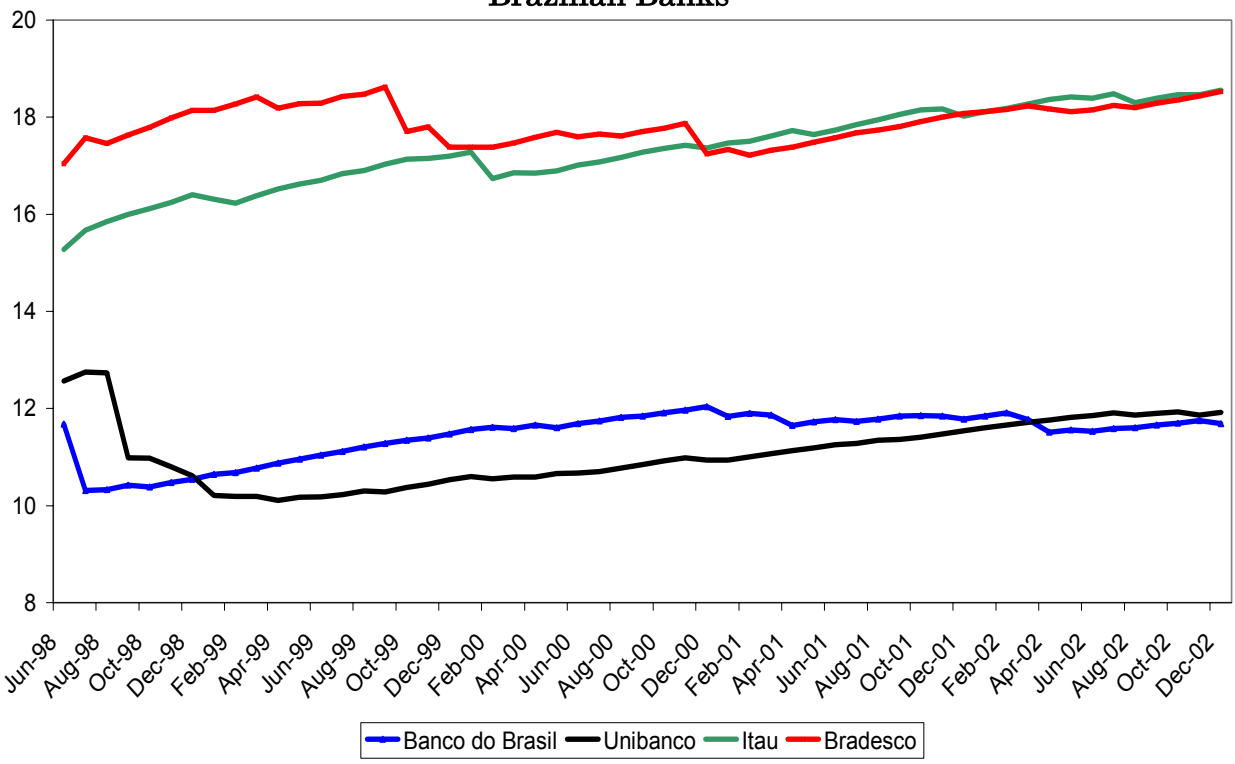
Table 3. Factor Risk Premium - Brazilian Banks

Parameter	Estimate	Standard Error	t value	Prob > | t |
λ_4 - Real Interest Rate	2.744	1.777	1.54	0.125
λ_5 - Market Portfolio	7.129	4.824	1.48	0.142

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[10].

Figure 1. Inverse of the Probability Measure of Failure

Brazilian Banks



So far we have presented results for single banks. In tables 4 and 5 we present results for the banking system. Both the real interest rate and

[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 $1/\sigma_\zeta^2$.

market portfolio are significant factors as we have seen before for individual banks.

Table 4. Factor Sensibilities - Banking System

Parameter	Estimate	Standard Error	t value	Prob > | t |
β_{54} - Real Interest Rate	-2.150	0.346	-6.20	<.0001
β_{55} - Market Portfolio	0.579	0.043	13.40	<.0001

Regarding the risk premiums we have had a change in our results. Now industrial production with credit risk play a role in explaining returns as we can see from table 5.

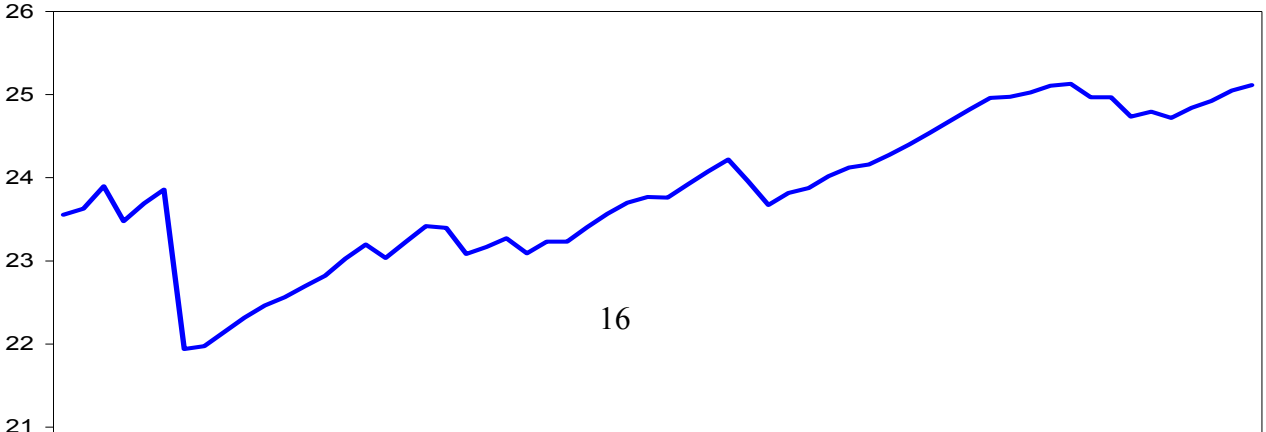
Table 5. Factor Risk Premium - Banking System

Parameter	Estimate	Standard Error	t value	Prob > | t |
λ_5 - Market Portfolio	0.672307	0.2162	3.11	0.0025

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 while the Argentinean crisis hasn't affected this measure.

Figure 2. Inverse of the Probability Measure 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 the domestic crisis with the devaluation of the Real[11] (February and March 1999).

Two banks failed after the devaluation of the Real after January 1999 due to their expositions to currency risk[12]. Nonetheless, our model indicates that systemic risk has increased for that period. One of the arguments that the Brazilian Central Bank's authorities have used to defend the rescue of two banks which have incurred in serious problems due to the devaluation was that the failure of these banks could trigger a systemic risk event[13]. The evidence presented by the model seems to suggest that the Central Bank was right in it's assessment of a systemic risk event.

[11] Brazilian official currency.

[12] Marka and Fonte Cindam believed that the Central Bank of Brazil would maintain the currency peg and sold currency futures in the futures market providing hedge for the market. With the fast devaluation in mid January in 1999 they became insolvent.

[13] The model should respond more quickly if we have used daily data. However, the use of daily data incur in the problem that macro variables are not available at this high frequency. An interesting alternative would be to model a CAPM and test this model using daily data.

Also in December 2001 with the Argentinean default on US$ 95 billions of debt these probabilities were not affected and thus contagion has not been an issue 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 where 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 little 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 seems to be diminished after the Russian crisis.

In 22 April 2002 a reserves transfer system was put in operation as part of the new payment system, which should reduce interbank settlement risk and therefore, mitigate systemic risk. Since the payment system is the main channel through which shocks may be transmitted in the financial system an efficient payment system is a major concern for financial stability. As we can see from figure 2 systemic risk has indeed continued a decreasing trend after this episode until June 2002 (but we are not able to see a major jump

in these probabilities). As the introduction of this system has been widely discussed within the financial system this behavior should be expected if we believe that agents would behave rationally.

Finally, the elections were an event that increased financial instability but not on the preceding Russian crisis scale. As banks in Brazil have huge holdings of domestic debt there were some concerns regarding default of government debt. After the elections these probabilities continued their downward trend as these concerns shown to be **unfundamented.**

4. Conclusions

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 four financial institutions, namely Banco do Brasil, Unibanco, Itau e Bradesco. 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 (December, 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. This could be due to the introduction of a floating exchange rate regime and the inflation targeting framework for monetary policy, which has enhanced substantially expectations regarding the future of the economy.

With the introduction of the payment system the trend in decreasing systemic risk has persisted until the vicinity of the presidential elections, which have increased financial institutions probability of default as these are net holders of public debt and there were some concerns regarding the payment of this debt by the leftist party. However, after the elections systemic risk has decreased.

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