REPUTATIONAL RISK MEASUREMENT: BRAZILIAN BANKS

ABSTRACT:

This paper investigates the reputational risk measurement in banking using a simple model that integrates random effects and Logit models. The pricing theory is outlined to include risk determinant factors as well as negative news for banks. The environment under which the quantitative model is applied corresponds to the perfect macroeconomic storm of Brazil that represents its weak oil prices, faint domestic economic activity and huge political problems. These aspects can increase risk in Brazilian banks, particularly by creating rumors that may trigger bank runs or other reputational problems. The results indicate that the large banks in the sample have the capacity to absorb the problems related to reputational risk with small variance and probability. One large investment bank suffered reputational problems.

KEYWORDS: financial markets, asset pricing, risk management.

JEL: D53, G12, G32.
1. INTRODUCTION

The complex international financial system has its origin in the last decades and requires more regulation of financial institutions. This aspect comprises financial markets and financial intermediaries reinforcing the asset pricing theories that must join intermediation theories with risk management regulation.

In Brazil, the perfect macroeconomic storm implies that this Latin American country is suffering weak oil prices, weak domestic economic activity and political problems. The Petrobrás scandal, involving bribery schemes in the state-owned oil company, has touched many politicians, including lawmakers and state governors. This scandal has been called Lava Jato, or Car Wash, and has consequences of lowered investments in infrastructure and oil, with effects spilling over into economic sectors, paralyzing the Brazilian economy, and testing the soundness of Brazilian banks in facing rumors.

Bank runs are susceptible to bad news and underline the importance of managing and measuring reputational risk and establishing a contingency plan to burn assets and preserve bank liquidity against huge withdrawal of deposits.

Around the world, bank run crises share the aspect of negative rumors. For example, Jiangsu Shenyang Rural Commercial Bank faced negative rumors that it had reduced its liquidity and compromised its soundness. In Brazil, the current case is the BTG Pactual, whose CEO was arrested by the Brazilian Court during the Car Wash scandal investigations.

Although reputational risk is difficult to measure and often considered a secondary risk, the current Brazilian economic environment could trigger a bank run. This is highlighted by the risk management requirements of Basel II (1996 and 2006), particularly reputational risk management.

This paper proposes a model to measure the reputational risk level in the Brazilian banking system, applying an econometric framework that accounts for random effects and logit estimations with panel data to obtain the Value at Reputational Risk.

The results indicate an unprecedented and robust way to quantify the reputational risk level of banks linking the asset pricing theory and the intermediation theory. The results of this risk
measurement approach may contribute to risk management, banking regulation and financial stability.

The remainder of the paper is organized as follows. The next section describes the relevant literature about bank regulation, risk management and reputational risk measure. Next, we discuss the methodology used in the study. The date and results are presented in the following section. The paper closes with some concluding comments.

2. LITERATURE REVIEW

2.1 Bank regulation and risk management

The international financial system is complex, and this complexity has its origin in the last decades. Because of this and the crises in the globalized world, regulation of financial institutions has been increasing.

It is important to understand why banks raise funds in deposits if they are subject to bank runs, as shown by Diamond and Dybvig (1983). This is an important aspect associated with reputational risk because negative perception of a bank can anticipate this problem.

Another aspect of modern banking is that banking theory has exchanged traditional financial intermediation for many other activities. However, bank runs continue to be a common feature, with deposit withdrawals occurring because of customers’ expectations of bank failure. Financial intermediaries exist because of their capacities to reduce transaction costs and the higher quality of bank loans quality compared to other forms of credit.

Bhattacharya and Thakor (1993) formulated some questions, such as, why do we have financial intermediaries? Why do banks deny credit to some rather than charging higher prices? Why do banks finance illiquid assets with liquid liabilities? Why do banks hold some loans on their balance sheets and sell others? Why are some loans securitized? What is the role of financial intermediaries in capital allocation? In answer to the last question, the authors explained that borrowers face a variety of financing sources, ranging from venture capitalists to the capital market, and the borrower’s choice depends on their credit history and investment opportunities.
International bank regulations recognize the market risk amendment, establishing debates surrounding the introduction of internal measures that trigger mechanisms to ensure that banks manage their risk measures truthfully, see Basel (1996).

As a result, banks take deposits and make loans but find new possibilities to securitize loans without keeping their balance sheets. The fact that intermediaries dominate markets also has important implications for asset pricing theory. Allen and Santomero (1998) showed that current asset-pricing theories assume that investors choose optimal portfolios directly, and contemporary intermediation suggests that this approach may have important market features.

To highlight regulation types, Barth et al. (2000) analyzed the helping-hand approach (governments regulate to correct market failures) and the grabbing-hand approach (governments regulate to support political constituencies). Their evidence suggests that regulatory and supervisory strategies that focus on empowering the private sector and limiting adverse incentive effects from deposit insurance best promote bank performance and stability.

To understand international standards of capital regulation, Santos (2000) showed that the deposit insurance incentive increased risk of their leverage. This risk-shifting incentive has been one of the main reasons for bank capital regulation.

The new complexity of the financial system consists of both financial markets and financial intermediaries, reinforcing asset pricing theories, which need to be integrated with intermediation theories, see Allen and Gale (2004).

What is the causal relationship between risk and capital? Fiordelisi et al. (2011) found evidence for a bi-directional causal link that emphasizes the importance of attaining long-term efficiency gains to support financial stability. Therefore, the internal risk model can induce banks to separate capital to face specific risk exposure.

Prudential regulation of banks uses risk measures to produce financial stability. In this context, reputational risk, which is not easily quantified, contrary to credit risk, market risk and operational risk, appears.

Nevertheless, bank runs underline the importance of managing and measuring reputational risk and guiding the cost of a contingency plan, with actions for burning assets to preserve the bank’s liquidity against massive deposit withdrawal.
2.2 Reputational risk measure

The financial world has faced several bank run crises, including Banesto (1994) in Spain; Bank Negara Malaysia (1999) in Myanmar; Asia Wealth Bank (2003) and Yoma Bank Ltd (2003) in Myanmar; Northern Rock in Britain (2007); Bear Stearns (2008), IndyMac (2008), and Wachovia (2008) in USA; DSB Bank (2009) in the Netherlands; and Jiangsu Shenyang Rural Commercial Bank (2014) in China. Bank run crises can have different initial triggers, but a common aspect is negative rumors.

In this context, reputation is a reflection of how well or how badly different groups, denominated stakeholders, esteem a bank’s image, see Larkin (2003, p.1). Reputational risk represents losses in the bank’s value and has been a topic in academic literature, although evidence of reputation losses in banks tends to be limited and difficult to quantify.

Walter (2006) found the link between reputational risk and exploitation of conflicts of interest in financial intermediation, which is arguably one of the most important threats to the reputational capital of financial firms.

Lin and Paravisini (2011) showed that the risk of reputation loss can provide an informal enforcement mechanism when contracts are incomplete. Using within-firm estimators, they show that monitored banks increase their funding supply after a reputation loss caused by the discovery of fraud by one of its borrowers.

Fiordelisi et al. (2013) determined reputational loss following operational losses in banking, estimating the reputational risk for a large sample of banks in Europe and the US between 2003 and 2008. The authors provided evidence that the probability of reputational damage increases with high profit and size. They also showed a higher level of invested capital and intangible assets reduce the probability of reputational damage.

Soprano et al. (2009) showed that modeling reputational and operational risks is strictly related, as operational losses usually have an impact on reputation. However, the authors did not calculate reputational risk with their model.
2.3 Asset pricing and stock price reaction determinants

One of the most important seminal papers in asset pricing theory is Sharpe (1964), who analyzed the relationship between asset price and the components of its overall risk, focusing on the mean and variance framework and using the Capital Asset Pricing Model (CAPM).

Following his work and aiming to clarify the logical structure of these related issues, albeit under idealized conditions, Lintner (1965) showed the effects of risk and uncertainty on asset prices and rational decision rules for individuals and institutions to use in security portfolio selection. Mossin (1966) then established the concept of “price of risk” that can be explored in terms of slope of the market line.

The next seminal contribution to asset pricing, Ross’s (1976) Arbitrage Pricing Theory (APT), proposed an alternative to the mean variance capital asset pricing model introduced by Sharpe and Lintner. Ross observed that two portfolios with the same risk could not have different returns because the difference would be eliminated by arbitrage. Therefore, he built a model with multiple factors to incorporate various unspecified sources of risk. APT offers a testable alternative to the CAPM.

The problem became determining the number of factors necessary to model asset returns. Connor and Korajczyk (1993) developed a statistical test to identify the number of factors and found evidence for one to six factors. In addition, Cheng (1995) showed that the market index factor had higher significance in explaining monthly return of shares.

Almost at the same time, Fama (1993) identified five common risk factors that seem to explain average returns in the stock and bond markets. The stock market factors include an overall market factor and factors related to firm size and book-to-market equity. The bond-market factors are maturity and default risks.

Later, Haugen and Baker (1996) established that the determinants of expected stock returns – risk, liquidity, price-level, growth potential and stock price history – are stable in their influence from period to period and from country to country.

However, what happens to bank stock prices return in a case of illegal activity or other negative perceptions by stakeholders? The answer implies the overreaction hypothesis because of the effect of bad news on bank reputation.
De Bondt and Thaler (1985) suggested that most people tend to “overreact” to unexpected and
dramatic news events and investigated whether such behavior affects stock prices. Reichert et al.
(1996) found that public announcements of prosecution for major corporate crimes have a
significant and long-term negative impact on shareholder wealth. The results indicate that
indictments of larger firms have a smaller impact on excess returns.

Levitt (2000) showed that uncountable investors have suffered significant losses from
restatements of audited financial statements.

Murphy et al. (2004) examined the magnitude of market-imposed penalties experienced by
firms alleged to have committed illegal acts. Their results offer the strongest evidence to date
regarding a link between market-imposed penalties associated with allegations of misconduct and
the subsequent changes in the uncertainty of earnings.

Palmrose et al. (2004) studied market reaction and found substantial variance in the abnormal
returns, indicating that more severe reactions indicate management fraud, material dollar effects
and restatements attributed to auditors. Correction of misstatements may increase or decrease
previously reported income by small or large amounts.

Gillet et al. (2010) examined stock market reactions to the announcement of operational losses
by financial companies and observed that, in cases of internal fraud, the loss in market value is
bigger than the operational loss announced, a sign of reputational damage.

Therefore, when modeling reputational risk based on the stock price, it must consider multiple
factors that determine the stock price return and evaluate the negative news that will trigger a
negative reaction in the capital market.

3. METHODOLOGY

To model reputational risk, this paper put together the contributions of Haugen and Baker
(1996) and Soprano et al. (2009) to measure the impact of multiple risk factors and negative news
for the bank on the bank’s share price return. The model’s limitation is that it can only be applied
to banks listed on the stock exchange.
Therefore, this paper admits four assumptions. First, the market efficiency hypothesis, where the share price reflects each new reputational event announced. Second, reputational events will directly affect the bank’s market value. Third, the correlation between reputational risk and market value implies that the firm’s stock price is equal to the present discounted expected value of the cash flow. Fourth, shareholders will sell stock if they believe that future losses are imminent.

The reputational risk model has three stages. First, it estimates with panel data the bank’s stock price return following equation (1).

\[ y_{it} = X_{it} \beta + u_{it} \]  

where \( y_{it} \) is the stock price return of bank, the vector \( X_{it} \) is composed for systemic risk factor \( R_{SR} \), liquidity factor \( R_{LF} \), price level factor \( R_{PL} \), excess return in previous month factor \( R_{ER} \), and reputational risk factor \( R_{RR} \). The last variable represents a dummy variable that assumes one when a reputational event occurs to bank \( i \) at time \( t \), or zero otherwise.

Second, use a Logit model to obtain the probability of a reputational risk event. For that, estimates the reputational risk variable against the other variables that explain the bank’s stock price return.

\[ \delta = X'_{it} \hat{\beta} + \mu_{it} \]  

where \( X'_{it} = [R_{SRi} R_{LFi} R_{PLi} R_{ERi}] \), \( \delta = R_{RRi} \) and the probability of a reputational risk event following equation (3), with a logistic cumulative distribution function \( F(z) \).

\[ P\left(R_{ERi} = 1 \mid X'_{it}\right) = F(X'_{it} \beta') = F(z) \]
Finally, after the model is defined and the statistical tests are obtained, the reputational value at risk. $VaR_{Reputational}$ can be determined, and must obtain the outstanding shares $N_t$, the stock price $X_t$, and the market value is $Y_t = N_t \times X_t$. After that, calculate $\delta$ considering equation (2), and the $VaR_{Reputational}$, considering time horizon equals to one day, is:

$$VaR_{Reputational} = Y_t \times \beta^*_t \times \delta_t$$  \hspace{1cm} (4)

where $\beta^*_t = t \alpha \sigma(\hat{\beta}RR)$ is the parameter of severity of the reputational risk.

To a longer time horizon $\Delta$, considering the reputational events are iid, the value at risk will be:

$$VaR_{Reputational_\Delta} = VaR_{Reputational} \times \sqrt{\Delta}$$  \hspace{1cm} (5)

It is similar to the delta-normal method that is the simplest and usual method to measure market risk. However, to measure only reputational risk value, the volatility $\beta^*_t$ must be multiplied by the probability of reputational event $\delta$.

4. RESULTS AND DISCUSSION

4.1. Data

The empirical analysis uses database contains daily data of the period from January 2015 to December 2015 (246 observations) with commercial banks, universal bank holding, a commercial bank portfolio, and savings and loan banks listed on the Brazilian Stock Exchange, named BMF & Bovespa. These banks correspond to almost 70% of the Brazilian banking sector.

In the sequence is described the variables and the form of calculation.
The stock price return of banks is obtained by the difference of the share price logarithm over two business days.

$R_{SR}$ – The systemic risk factor corresponds to the Bovespa Index return, which is designed to gauge the stock market’s average performance tracking changes in the prices of the more actively traded and better representative stocks of the Brazilian stock market.

$R_{LF}$ – The liquidity factor corresponds to the logarithm of trading quantity. The liquidity variable is potentially important because traders must buy at asked prices and sell at bid prices, indicating that the bid-asked spread serves as part of the cost of trading.

$R_{PL}$ – The price level factor is measured by the current dividend to the price of the previous business day that corresponds to the most recently available dividend for the current stock price. This factor indicates whether the selling stock price is cheap or expensive.

$R_{ER}$ – The excess return factor is relative to the Bovespa Index in the previous month, measured by the mean of the difference between the return of the stock price and the return of the Bovespa index in the last 20 business days.

$R_{RR}$ – The reputational risk factor typifies a dummy variable that assumes one when a reputational event occurs at time $t$ and equals zero otherwise. Bad news represents a reputational event solely when the stock price falls on the same day of its occurrence.

4.2. Estimation and Analysis:

Before estimation, it was identified that the data series is stationary stochastic processes. The unit root trial was assessed by Elliot et al. (1996) and Levin et al. (2002).

It was performed Hausman test’s and Breusch-Pagan test’s, who indicating that the GLS estimates are consistent and discard pooled and fixed effects.
After choosing the random effect estimator, was estimated the stock prices return following equation (1). Table 1 confirms that the risk factors’ coefficients are statistically significant and so there is reputation effect on the stock price.

### Table 1: Estimating stock share return of the Brazilian banking system.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Std.Error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const</td>
<td>0.0086</td>
<td>0.0050</td>
<td>1.72</td>
<td>0.0849*</td>
</tr>
<tr>
<td>Systemic Risk</td>
<td>0.8321</td>
<td>0.0313</td>
<td>26.56</td>
<td>4.65E-133***</td>
</tr>
<tr>
<td>Reputation</td>
<td>-0.0226</td>
<td>0.0027</td>
<td>-8.87</td>
<td>2.54E-16***</td>
</tr>
<tr>
<td>Liquidity</td>
<td>-0.0014</td>
<td>0.0006</td>
<td>-2.38</td>
<td>0.0174**</td>
</tr>
<tr>
<td>Price level</td>
<td>0.0242</td>
<td>0.0124</td>
<td>1.95</td>
<td>0.052*</td>
</tr>
<tr>
<td>Excess Return</td>
<td>-0.1810</td>
<td>0.0983</td>
<td>-0.84</td>
<td>0.0658*</td>
</tr>
<tr>
<td>Sum Squared Resid</td>
<td>0.809577</td>
<td>S.E of regression</td>
<td>0.020308</td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>4878.809</td>
<td>Akaike criterion</td>
<td>-9745.618</td>
<td></td>
</tr>
<tr>
<td>Schwarz Criterion</td>
<td>-9712.109</td>
<td>Hannan-Quinn</td>
<td>-9733.304</td>
<td></td>
</tr>
</tbody>
</table>

Random-effects (GLS) estimation with 1968 observations, using Nerlove's transformation and including 8 cross-sectional units and time-series length equal to 246.

After obtaining the standard error of the reputational factor’s coefficient, equal to 0.0027, is identified the variance interval or $\beta_+$, searching the t-student distribution with $df = \infty$ and $\alpha = 1\%$. Thus, $\beta_+ = 2.576 \times 0.0027 = 0.0070$.

The Table 2 shows the probability of reputational risk estimated using the Logit model.
Table 2: Estimating probability of reputational risk event – Logit model.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Std.Error</th>
<th>z-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const</td>
<td>-7.0710</td>
<td>0.8914</td>
<td>-7.933</td>
<td>2.14E-15***</td>
</tr>
<tr>
<td>Systemic Risk</td>
<td>-45.4604</td>
<td>10.0547</td>
<td>-4.521</td>
<td>6.15E-06***</td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.3958</td>
<td>0.0949</td>
<td>4.170</td>
<td>3.05E-05***</td>
</tr>
<tr>
<td>Price level</td>
<td>-2.8693</td>
<td>3.2298</td>
<td>-0.888</td>
<td>0.3743</td>
</tr>
<tr>
<td>Excess Return</td>
<td>-62.3940</td>
<td>19.3019</td>
<td>-3.233</td>
<td>0.0012***</td>
</tr>
<tr>
<td>Mean Dependent var</td>
<td>0.029980</td>
<td>S.D Dependent var</td>
<td>0.170575</td>
<td></td>
</tr>
<tr>
<td>Sum Squared Resid</td>
<td>0.102006</td>
<td>S.E of regression</td>
<td>0.083140</td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-237.9986</td>
<td>Akaike criterion</td>
<td>485.9972</td>
<td></td>
</tr>
<tr>
<td>Schwarz Criterion</td>
<td>513.9211</td>
<td>Hannan-Quinn</td>
<td>496.2587</td>
<td></td>
</tr>
</tbody>
</table>

Number of cases correctly predicted = 1909 (97%)

f(beta’x) at mean of independent vars = 0.018

Likelihood ratio test – Chi-square(4) = 54.0698 [0.0000]

Logit estimation using 1968 observations, with standard errors based on Hessian.

Lastly, the annual Reputational Value at Risk of Brazilian Banking System in 31/12/2015 can be summarized in Table 3.

Table 3: Reputational VaR of Brazilian Banking System and BTG Pactual – 31/12/2015.

<table>
<thead>
<tr>
<th>Bank</th>
<th>Beta+</th>
<th>Delta</th>
<th>Market Value</th>
<th>Daily VaR</th>
<th>Annual VaR*</th>
</tr>
</thead>
<tbody>
<tr>
<td>BTG Pactual</td>
<td>0.022</td>
<td>0.009</td>
<td>82,101,600,000</td>
<td>16,077,378</td>
<td>255,220,469</td>
</tr>
<tr>
<td>Banking System</td>
<td>0.007</td>
<td>0.018</td>
<td>503,631,651,049</td>
<td>63,758,103</td>
<td>1,012,128,505</td>
</tr>
</tbody>
</table>

Obs.: With exchange rate USD 1.00 = BRL 3.9048, BTG Reputational VaR = 65,360,702 USD.

*Annual VaR = daily VaR $\sqrt{252}$
In addition, it calculated the reputational risk to the bank BTG Pactual, whose Chief Executive Officer was arrested in 2015 amid allegations of corruption in relation to Petrobrás scandal.

Note that the market value of BTG Pactual represents 16.3% of the Brazilian banking system’s market value, but the Value at Reputational Risk corresponds to 24%. This indicates that the investment bank faces huge exposure, where $\beta_+$ equal to 0.022 and delta is 0.009. BTG Pactual’s $\beta_+$ is much larger than the system, showing a huge reputational risk variance. The smaller delta is because the BTG’s negative news is almost all concentrated in the period of its reputation crisis; in the remaining business days between November and December of 2015, BTG’s performance had some positive reports.

The annual Reputational VaR of the Brazilian Banking System is not representative, representing almost 0.2% of the market value of the system, but rumors must be followed like liquidity risk because of deposit withdrawal, as shown by Diamond and Dybvig (1983).

Therefore, considering the reputational risk, our results confirm the BCB analysis, in which the large Brazilian banks had the ability to absorb the effects from the perfect macroeconomic storm in 2015.

5. CONCLUSION

This paper models and measures the reputational risk level of Brazilian banks, evaluating each bank’s stock price reaction against the announcement of bad news about the bank.

Our results indicate a robust way to quantify reputational risk that contributes to risk management, banking regulation and financial stability. Additionally, the variance of reputational risk in BTG Pactual represents more than twice the variance of reputational risk of the Brazilian banking system, showing a huge reputational risk during November and December 2015.

However, the annual Reputational VaR of the banking system was not representative in 2015, representing 0.2% of the market value. Finally, considering the reputational risk, our results confirm the BCB’s analysis, in which the large Brazilian banks had the ability to absorb the effects from the perfect macroeconomic storm of 2015.
Future research could examine a case where a Brazilian bank announces a loss because of internal fraud, and how its competitors’ stock prices react. The cross-bank reaction may be important if the bank’s lost customers favor its competitors. Future studies might test other measures, such as profit margin trend, capital turnover or earnings growths, compare their results and use these models to better understand Brazilian banks during macroeconomic crises and determine if negative rumors can affect the system as a whole.

Finally, Brazilian regulators must monitor the movements in reputational risk of the banking system and analyze their information to guide their supervisory actions.

REFERENCES


