**Backtesting Basel III:**

**Evaluating the Market Risk of Past Crises in Brazil through the Current Regulation**

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**Abstract**

Are the Basel III recommendations, from the Bank for International Settlement’s (BIS) Basel agreement, effective to a broad set of financial crises? We analyzed two of the main Basel III agreement’s recommendations to a back test: the capital requirements and the Value at Risk (VaR) methodology adapted to incorporate the BIS’s Stressed VaR. We tested the currency exchange and the currency exchange swaps contracts through tests of volatility-based VaR methodologies in the 2002.2 Brazilian confidence crisis scenario.

The main results: (a) They confirm the general consensus among economist that there is no methodology able to forecast crises with a high degree of accuracy; (b) To circumvent either the lack of historical information or the lack optimal window for stress patterns, the Stressed VaR can be calibrated with a historical VIX (Volatility Index, Chicago Board Options Exchange), working as a volatility scale; (c) Other densities, apart from the standard normal curve, shall be considered and (d) Daily oscillation limits may have a significant role on crisis mitigation.

**Resumo**

As recomendações do acordo de Basileia III, do Bank for International Settlements (BIS), são eficazes para amplo conjunto de crises financeiras? Submetemos duas das principais recomendações do acordo a um teste retroativo: os requisitos de capital e o Valor em Risco (VaR) Estressado. Testamos o câmbio e os contratos de swaps de câmbio via metodologias VaR para o cenário da crise de confiança brasileira de 2002.2, véspera das eleições presidenciais do mesmo ano.

Os principais resultados: (A) Eles confirmam o consenso geral entre economistas que não existe uma metodologia capaz de prever as crises com um elevado grau de precisão; (B) Para contornar quer a falta de informação histórica ou janela ideal a falta de padrões de estresse, o VaR Estressado pode ser calibrado com o VIX histórico (Índice de Volatilidade, Chicago Board Options Exchange), funcionando como uma escala de volatilidade;(C) Outras densidades, para além da curva padrão normal, devem ser consideradas e (D) Os limites diários de oscilação devem ter um papel importante na mitigação de crise.

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# Introduction

Would the Basel III agreement, proposed by the Bank for International Settlements (BIS), be effective, if applied to past financial crises? Would those crises be mitigated if the Basel III recommendations were already implemented? Caruana (2010) stated that Basel III generated significant progress in prudential financial regulation since the beginning of the global financial crisis that is the landmark of a new global economic context which imposes major challenges. This text turns the statement “*Basel III: Towards a Safer Financial System”* **–**title of the technical document from Caruana (ibid.) **–** to a question and submits two key Basel III agreement’s recommendations, minimum Capital Requirements and Stressed VaR to a back test, by emulating their existence at the time of a selected past crisis.

The Basel III agreement has some items considered a radical revision of Basel II, such as new parcels of capital requirements, like the counter-cyclical capital, that takes into account macroeconomic risks. Nevertheless, in another perspective, Basel III is not a new agreement, but rather a set of proposed amendments to the previous agreement, changing the latter measures that were deemed insufficient, either in conception, or in the used metric. Basel III either increases the requirements of Basel II or creates new demands, where the crisis has highlighted the procedures to be either insufficient to control the instability of the financial markets or to avoid the occurrence of more serious crises.

In order to establish a link between Basel III recommendations and the early warning approach (IMF), developed to face a recent past of crises, we refer to the vulnerability concept: according to Blejer and Schumacher (1998), the 1990’s currency crises revitalized the search for antecedent indicators of financial vulnerability. The evaluation of the solvency and vulnerability of the financial sector (banks and Central Banks) implies to evaluate the vulnerability and credibility of a country. Their proposed VaR implementation intended to be a general-purpose market risk analysis tool.

There are other five initial guidelines. First, Abiad (2003) stated that there is a general consensus among economist that there is no methodology able to forecast crises with a high degree of accuracy. Second, many authors enunciate but not empirically broadly test their proposed methodology. Third, as Blejer and Schumacher (ibid.) stated, a vulnerability analysis should not only deal with traditional operations, but with all assets that compose its portfolio, including the derivatives. Fourth, to validate the capital requirements recommendations it is necessary to verify their effectiveness when applied to currency based assets (highly volatile) from bank’s portfolios. Fifth, there is a timeline guideline which is the transient characteristic of nowadays Basel III recommendations. From BIS (2011), two excerpts:

1. *“The Committee is introducing these changes in a manner that minimizes the disruption to capital instruments that are currently outstanding. It also continues to review the role that contingent capital should play in the regulatory capital framework.”*
2. “*The Committee will put in place rigorous reporting processes to monitor the ratios during the transition period and will continue to review the implications of these standards for financial markets, credit extension and economic growth, addressing unintended consequences as necessary.”*

Consequently, it is crucial to observe the chronogram of Basel III implementation and its emphasis on the risk weighted assets (RWAs). Table 1.1 shows the Brazilian road map: the implementation chronogram of the Basel III recommendations for minimum capital requirements, where a keyterm is the regulatory capital (RC).

Table 1.1: Brazilian’s BASEL III Chronogram (Minimum Capital Requirements)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Implementation**  **Date:** | **Jan, 1st /13** | **Jan, 1st**  **/14** | **Jan, 1st /15** | **Jan, 1st**  **/16** | **Jan, 1st /17** | **Jan, 1st /18** | **Jan, 1st /19** |
| Core Capital | 4.5% | 4.5% | 4.5% | 4.5% | 4.5% | 4.5% | 4.5% |
| Level I | 5.5% | 5.5% | 6.0% | 6.0% | 6.0% | 6.0% | 6.0% |
| **Regulatory Capital** | **11.0%** | **11.0%** | **11.0%** | **9.875%** | **9.875%** | **8.625%** | **8.0%** |
| Capital Conservation | - | - | - | 0,625% | 1.250% | 1.875% | 2.5% |
| RC + Capital Conservation | 11.0% | 11.0% | 11.0% | 10.5% | 10.5% | 10.5% | 10.5% |
| Counter-Cyclical Capital | - | To 0.625% | To 1.25% | To 1.875% | To 2.5% | To 2.5% | To 2.5% |

Source: Brazilian Central Bank (2015).

Three observations outstand: (a) since 2005, the aggregated and individual Basel index of Brazilian banks stayed above 15%, as seen in Figure 1.1; (b) no systemic bank crisis occurred in Brazil at least in the last 60 years (Laeven and Valencia, 2008); and (c) the Regulatory Capital percentage of 11% (monthly), is equivalent to 20 days of 0.52% daily variation (see Table 1.2), a rather small variation compared to the daily volatility of quite a lot finance time series, specially those found in emerging market economies (Bekaert and Harvey, 1997). As an example, for the 30-day term currency swaps (U.S. Dollars/Brazilian Reais), the average standard deviations ranged from 1.55% (from 1999 to 2003) to 1.40% (from 2004 to 2014). Only 29.40% of the daily variations were lower than .52%, from 1999 to 2003, while only 28.48% of the daily variations were lower than .52%, from 2004 to 2014.

Figure 1.1: Agregated Brazilian Basel Index (all Brazilian Banks)



Source: Brazilian Central Bank (2015).

Table 1.2: Daily Loss Limits based on the monthly Regulatory Capital Limits

|  |  |  |  |
| --- | --- | --- | --- |
| **Monthly ↔Daily level** | **Monthly ↔Daily level** | **Monthly ↔Daily level** | **Monthly ↔Daily level** |
| 8.00%↔ 0.39% | 11.00%↔0.52% | 15.00%↔0.70% | 17.00%↔0.79% |

The volatility-based risk methods, such as the Value at Risk (VaR), became very popular in the 1990’s, departing from the *Riskmetrics™* document (JP MORGAN, 1996). The financial time series variance is usually modeled with GARCH (*Generalized Autoregressive Conditional Heteroscedasticity*) in order to capture the heteroscedasticity of the conditional variance of financial series, a stylized fact known since Engle (1982) and Bollerslev (1986).

Additionally, financial time series can be also subject to sudden or structural breaks. Consequently, a two-step protocol for volatility modeling is used in this text:

(a) The unconditional variance levels can be previously determined, for instance, with the ICSS (Iterative Cumulative Sum of Squares) algorithm from Inclán and Tiao (1994).

(b) The regime-switching feature, either a switching-regime GARCH model (SWGARCH) or a Levy process (with jumps) is incorporated into the volatility-based risk methods.

We developed a retrospective view of some Basel III recommendations as if they were already effective in the recent past. We choose a VaR methodology to evaluate the Brazilian pre-election period of 2002, known as a “*confidence crisis”.* The high volatiles currency exchange rate and mark-to-market currency exchange swaps are examined through empirical tests of a volatility-based methodology. The events of the second semester of 2002 were especially important, as the currency exchange swaps contracts debts exceeded 40% of the Brazilian internal debt in the end of this year. We evaluate the effect of two of the main BIS Basel III recommendations, minimum capital requirements and Stressed VaR, over currency exchange based assets.

A main concern is the absence of relevant historical data before June 2002 for currency exchange based assets, since the Brazilian currency floating regime started in 1999.02 and currency swaps contracts grew relevance only from June, 2002. We choose a key counterexample in which the insights can be extrapolated for other possible crisis that may happen in the very beginning either of a new currency (example: the Euro in January 2002) or a new financial factor (our own example: the U.S. Dollars/Brazilian Reais currency exchange coupon, created in August 1999) or even a new financial asset. Consequently, this text intends to contribute to improve the evaluation of the global regulatory recommendations that are part of the Basel III agreement.

The next section is a review of the Basel regulation and financial time series econometrics. The third section comprises the methodology and a brief description of both Brazilian currency exchange based financial series and of the VIX, a candidate for Global Volatility available since January, 1990. The results section comprises the validation of stressed VaR approaches for the chosen scenario, the evaluation of the VIX and the S&P 500 volatility as volatility alternatives (proxies) for the stressed volatility when lacking historical data. The fifth section discusses the results.

# Theoretical Review

This section presents a brief review of the BIS regulation and financial time series econometrics.

**Basel Regulation**

The Basel Committee on Banking Supervision was established in 1974 to advise national financial regulators on common capital requirements for internationally active banks, whose membership included representatives from the central banks and prudential regulators of more than 25 nations.

In 1988, the Basel Committee devised the initial Basel Capital Accord, which was a coordinated response to some of the perceived failings of deregulation as banks, in the rush to compete for larger market shares and had rapidly increased their domestic and foreign exposures. At some institutions these exposures were not matched by increases in the institutions’ capital bases, leading the minimum capital levels within the global financial system to erode.

Deregulation also allowed internationally active banks to take advantage of differences in national treatment of similar assets for capital purposes. These inconsistencies were exploited across jurisdictions in a manner that was producing unhealthy competition and regulatory arbitrage. In short, national standards did not always link capital requirements to actual risk levels and did not always account for exposures beyond those reflected within the balance sheet.

Consequently, a regulatory consensus started to build around a set of global standards that would provide guidance on the proper capital levels for internationally active banks, known as Basel II. In 2004,the Basel Committee offered a more comprehensive and risk-sensitive approach to capital regulation adopting the new framework Basel II, which developed a three “pillars” approach: (1) minimum capital requirements, (2) supervisory review process, and (3) market discipline.

The first pillar, already existent since Basel I, is reported to be the most important — and the most controversial — part of Basel II. Operational risk was added as a third factor for RWAs calculus, followed by a whole revision of Basel I recommendations concerning to RWAs. For accuracy reasons, targeting to match bank’s capital requirements with its risky assets, Basel II provided three methods of assessing credit risk: a basic “standardized” approach and two variants of an “internal ratings-based” approach — foundational and advanced. Under the standardized approach, banks calculate RWAs not only by reference to Basel’s elementary buckets, but also by the external credit ratings from firms like Standard & Poor’s, Moody’s Investor Service, and Fitch Ratings. The two internal ratings-based approaches permit banks to be more sophisticated and rely in varying degrees on their own risk.

The Basel IIIagreement is oftenconsidered an amendment of Basel II. Concerning RWAs, the new agreement recommends a temporary increase for its main item, the regulatory capital; meaning a raise from 8 to 11 percent relative to risky assets from bank’s asset books and defining a permanent increase of capital requirements in charge of two new items: Capital Conservation and Counter-Cyclical Capital, this last concerning to macroeconomic risks.

Williamson (2000) shows that there is a time frame for contracts and a time frame for day-to-day negotiation. This explains why agreements such as Basel I, II and III can be time frame inconsistent with daily economic agents´ activities. This could be a strong and clear reason why the BIS will constantly review its agreements, as explicitly declared in the BIS (2011) document – see the two excerpts exhibited in the introduction section of this text.

Minsky’s (2008) theories are invoked every time a new financial crisis occurs. His approach relates economic theory to political, economic, cultural and institutional environments and the need for financial regulations is a way to mitigate the financial instability of a capitalist economy. The main propositions of the financial instability hypothesis create a financial cycle.

While Caruana (2010) stated that Basel III would bring a safer financial system; BIS (2011) indicated the unpredictable nature of future crises. The unpredictable nature (and timing) of crisis can be seen as a plausible link to Minsky´s thought. On the other hand, authors like Cynamon and Fazarri (2008) alleged that the American credit crisis was predictable, as well as Abiad (2003) and Morales and Schumacher (2003) focused on early warning crisis detection.

**Financial Time Series Econometrics Review**

There are two recurrent stylized facts for financial time series found in the academic literature: volatility clustering and autoregressive conditional heteroskedasticity (ARCH) effects. The theory and modeling with ARCH and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) started with Engle (1982) and Bollerslev (1986). The existence of volatility clusters suggests either an approach under the viewpoint of changes in volatility regimes or an approach under the standpoint of volatility leaps.

For a long time it was thought that the stochastic processes associated with the financial series could be modeled through linear processes, almost always by random walk models. According to Brock *et al*. (1992), the most common reasons for deviations from the random walk model, as far as it affects the return of shares, are the volatility clustering and the calendar anomalies (for example, the weekend effect). The volatility clustering has been known for a long time, at least since Mandelbrot (1963).

The ARCH model, developed by Engle (1982), has an autoregressive structure in the conditional variances of the returns. This allows shocks of volatility to continue in time. The conditional variance is a linear function of the square of past innovations. Bollerslev(1986)proposed the GARCH models, in which the volatility of returns depends on the squares of precedent errors and precedent variances. The inclusion of information regarding past variances allows sensibility to the volatility clusters and allows that shocks in returns extend indefinitely in the future. The ARCH and GARCH models were conceived to deal with a single variance regime. By regime is understood that a constant or unconditional level of measure – e.g., average or variance– remains unchanged, so that a change in regime implies a change in level.

However, these models only reflect one series of coefficients for one equation of returns and one equation of volatility. For Diebold (1986 and 1996), and Lamoureux and Lastrapes (1990), the use of GARCH models is subject to error when sudden changes in variance occur, suggesting the introduction either of dummyvariables for each change of variance identified ex-post, or procedures to visualize the detection of outliers or levels of unconditional variance, as in Tiao and Inclán(1994).

The introduction of time series subject to changes in regimedeparts from Hamilton (1988 and 1990), who applied the EM (Estimation Maximation) algorithm for parameter estimation through maximum likelihood estimation (MLE). Hamilton and Susmel (1994), as well as Cai (1994), introduced the SWARCH (Switching ARCH) models, a generalization of the ARCH model of Engle (1982), which allows discrete changes in its level parameters through a Markov process.

In the first specifications found in the literature, the ARCH or GARCH variance was dependent to the entire history of regimes, as seen in Gray (1996). The SWGARCH models combine GARCH with regime switching. Bauwens *et al* (2010) still pointed the dependence on the entire history of regimes. Nevertheless, Haas *et al*. (2004, p. 497) developed a model were variances only depend on past shocks and their own lagged values: the path-dependency restriction was removed. This specification is analytically treatable, allows a separation of the process of conditional variance and offers direct parameter estimation through maximum likelihood. Next, we describe the conditional variance equation for the SWGARCH models in equation 2.1:

Equation 2.1: Conditional Variance in the SWGARCH Model

The conditional variance equation for the SWGARCH models (k, p, q) is:



Residuals: ; Either or .

Where stands for the k-regime variance at period t,  are constants.

A way to deal with diffusion problems is the use of semi martingales, but the procedural structure is very complex. The alternative is the use of Lévy process, additive processes (non homogeneous processes) or the use of models of stochastic volatility with leaps (ORNSTEIN-UHLENBECK). Kim *et al* (2011) tested a distribution based on Lévy’s processes, which allows the modeling without resorting to much abstraction.

Mandelbrot (1963) was pioneer on the use of stable (or alpha-stable) distributions to model skewness distributions and fat tails. The alpha-stable family is a class that includes several distributions subclasses such as the following: the Gaussian, Cauchy’s and Lévy’s distribution (also known as inverse Gaussian or Pearson V). The Lévy’s continuous stochastic procedure has stationary and independent increments. The Alpha-stable distributions can model the negative skewness and the excess of kurtosis that characterize financial returns. They earned some popularity in the 1960’s; nevertheless the interest has decreased, due both to mathematical complexity and huge computing power necessary to implement practical models.

Broda *et al.*, (2013) proposed the Stable mixture GARCH models, incorporating GARCH modeling with stable densities, with a possible incorporation of a Markov switching structure, as done in Haas *et al*. (2004) and prescribed in Bauwens *et al* (2010).

Different specifications for market risk models can be found in the literature, yet the well known Value at Risk (VaR) approach prevails. The VaR can be defined as the possible loss that could occur on a horizon of n days with a small probability. For parametric distributions, according to Jorion (1998, p. 87), “*VaR is simply a multiple of standard-deviation of a distribution, multiplied by a factor of adjustment that is directly related to the level of confidence*”. The simplest and most used procedure to calculate the VaR of a portfolio is the delta-normal method or standard variance-covariance model. The asset price changes are conditionally normally distributed, and the VaR of a portfolio is a linear combination of normal variables and is also normally distributed. Dornbusch (1998) and Blejer and Schumacher (1998) suggested the applicability of VaR to macroeconomic questions. Zangari (1997) stated that VaR applies only to stable environments.

Blejer and Schumacher (ibid.) suggested, in complement to VaR, the use of stress tests based on the extreme value theory (EVT). However, the use of stress-testing as a capital adequacy rule has two related shortcomings: (1) only a finite number of scenarios can be examined, yet there are an infinite number of possibilities; and (2) the stress-testing approach usually does not explicitly use the likelihood of the scenarios. Analogous to VaR, these two shortcomings generate the incentive for a firm to increase its catastrophic failure risk without changing its maximum loss.

The Stressed VaR approach was proposed by Kupiec (1998), incorporating stressed scenarios into the VaR methodology, in order to measure the tail risk. The author shows how assuming multivariate normal distributions for all risk factors leads to automatic consideration of value changes due to the non-stressed factors which are commonly ignored in stress testing or, in other words, using data from the 1997 Asian crisis, his conditional Gaussian Stress VaR (95%) approach to stress testing leads to historically accurate estimated value changes for a global portfolio with instruments in the U.S., European and Asian time zones.

BIS (2009) introduced its version of Stressed Value-at-Risk (SVaR): capital requirements based on a continuous 12-month period of significant financial stress, but keep working with the standard 99% confidence interval (one-tailed), 10-day holding period and the normal density. There is little academic literature on Kupiek’s (1998) Stressed VaR, like Colletaz *et al*. (2013) and even less on the BIS’s SVaR version, as pointed in BIS (2012). Instead, Kim *et al*. (2011) recommend the Average Value at Risk (AVaR) with stable innovations. On the other hand, as an operational example, the Brazilian Central Bank (2014 and 2015) utilizes, in Financial Stability Reports the traditional stress testing.

A candidate to substitute VaR and Stressed VaR is the Expected Shortfall (ES), as proposed in BIS (2012) and reiterated in BIS (2014). Unlike VaR, ES is a coherent risk measure, prescribed in Artzner *et al* (1999).

When utilizing the RiskMetrics™ VaR (TSAY, 2010), there is a simple conversion from VaR to ES. For a given upper tail probability p, the expected shortfall, with log returns, normal conditional distribution with mean zero and variance σ2t is described as a VaR function, approximately a 19% increase for p=2.5% and 14% for p=1%.

Equation 2.21: Expected Short Fall related to VaR under RiskMetrics™



Nevertheless, the time frame for institutional changes is bigger than a few years (as seen in Williamson, 2010) so that, until 2015, the VaR prevailed as the risk methodology in almost all documents and recommendations from BIS.

Many stock and futures exchanges, including BM&FBOVESPA, require that all operations must be registered and establish some daily limits of oscillation for financial assets. In this case, stressed values can be directly deduced from the daily limits of oscillation, dispensing the search for historical stressed values inputs for stressed VaR. Moreover, when an asset has pre-established oscillation limits, it is possible to use a probability distribution with barrier formula, from Dixit and Pindyck (1994), nevertheless this was not the case for the currency based assets of our sample.

# Data and Methodology

Our sample comprises daily data on currency exchange rate (PTAX), Brazilian currency swaps (U.S. Dollars/Brazilian Reais), the S&P500 stock exchange index and the VIX index. The PTAX represents the currency exchange rate between U.S. dollars and Brazilian Reais. The VIX is a volatility index, calculated by the Chicago Board Options Exchange as a weighted blend of prices for a range of options on the S&P 500. The VIX is quoted in percentage points and translates, roughly, to the expected movement (with the assumption of one standard deviation) in the S&P 500 over the next 30-day period, which is then annualized.

In 2002,the internal Brazilian debt comprehended two types of currency-indexed contracts: the currency exchange swaps, negotiated in the BM&FBOVESPA, and the NTN-D (National Treasury Notes, D series). The mark-to-market currency exchange swaps series began in August 1999. The Central Bank currency exchange swaps contracts began to be negotiated in April 2002 with a monthly adjustment of positions. In July 2002, three types of swap contracts were established - SCC, SC2, and SC3 – and two of them (SCC and SC3) were daily adjusted. The number of contracts exceeded 200 on July, 2002 and the total financial volume surpassed US$ 30 billions. The underlying asset is the spread between the interest rate and the currency exchange rate variation, defined as follows:

a) The interest rate of interbank deposits (DI), defined as the capitalized daily average of one-day DI rates, calculated by the Central of Custody and Financial Settlement of Securities (CETIP) and verified in the period between the trading day and the day preceding the expiration date;

b) The exchange rate variation, measured by the offered exchange rate of Brazilian reais per U.S. dollar for cash delivery traded in the foreign exchange market.

The daily adjustment of a contract is the difference between the position “carried over” from the previous day and the market quotation. It is credited to the holder of a long position (buyer), and debited to the holder of a short position (seller).

After collecting the data, our first step was to use the Iterative Cumulative Sum of Squares (ICCS) algorithm to identify the changes in the unconditional variances of the daily returns of the series of PTAX and currency swaps. Then, the daily returns were modeled with regime switching and heteroscedasticity, with the use of the SWGARCH code from Haas *et al*. (2004). Finally, the series were simulated with alpha-stable densities.

The sudden changes in the unconditional variance were evaluated with the ICCS algorithm developed by Inclán and Tiao (1994). Once estimated the change points, the next step was to identify political and/or economical events that could be responsible for changes in the level of unconditional volatility. The temporal series presents a stationary variance over the initial period. A sudden change in variance occurs some time later, possibly caused by some political and/or economic shock. The variance becomes stationary again, at another level, until another sudden change occurs. This process is repeated creating a temporal series of observations with an unknown number of sudden changes in variance.

Equation 3.1: Equation of Returns



Equation 3.2: Sudden Changes, Unconditional Volatility (AR/GARCH)

; 

WhereA0 is constant in the average equation; C is constant in the conditional variance equation; Q is the residuals coefficient; P is the conditional variance coefficient; Lev is the leverage coefficient, and D is the degree of freedom of the t-student distribution that models the return series. After running the GARCH model, the program runs the ICSS algorithm.

With regard to regime switching, the Hamilton’s (1990) model was adapted to estimate a 2-state Markov model, with average and variance being variables of a 1-dimension vector. Each series was tested individually. The duration of each regime can be easily derived from the Markov chain properties. Defining *D* as the duration of a specific regime, *St* the state variable at time *t*, *j* a index that stands for the regime *j*, *pjj* the probability of staying in the same regime *j* from time *t* to *t* + 1.

Equation 3.3: Expected Regime Duration (calculated by induction)



The probability pjj is the permanence in same regime j in consecutive time.

The SWARCH (switching ARCH) models from Hamilton and Susmel (1994) were utilized in preliminary tests, yet discarded on behalf of the parsimony of the SWGARCH models, which were based on Haas *et al*. (2004). Each series was modeled with SWGARCH, nesting a GARCH (1, 1), as seen in equation 3.4:

Equation 3.4: Variance Equation for SWGARCH (HAAS et al., 2004)



Where stands for the *k*-regime variance at period *t*,  are constants.

BIS (2009) recommends a stressed value-at-risk (SVaR), a methodology initially proposed by Kupiec (1998), exhibited in equation 3.5.

Equation 3.5: Required Capital calculated through Stressed VaR (BIS)

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Where: Max, RC, VaR, SVar and k stand for Maximum, Required Capital, Value at Risk, Stressed Value at Risk and a constant defined by the country financial regulator (usually a Central Bank). The original formula from Kupiec (1998) specifies only the last term, without the multiplier (3+k) and an arbitrary number N in place of the fixed 60.

The normal innovations densities are the one of a kind prescribed in the BISs’s recommendations. While there is a risk of double counting the VaR, for instance, when the present scenario is a stressed scenario (BIS, 2014), during non-turbulent periods, the first term (the volatility parcel already present in the VaR methodology) contributes marginally to the SVaR term, meaning a clear separation between volatility risk and tail risk.

The chosen method to optimize modeling is the MLE (Maximum Likelihood Estimation) with normal and alpha-stable innovations, based on Haas *et al*. (2004) and Broda *et al*. (2013), shown in equation 3.6 as the negative of the sum of innovations Xt. Alternatively, from Hall and Yao (2003), it is possible to apply a MLE generalization with a GARCH-like approach.

Equation 3.6: The Normal Log Likelihood and the Stable Log Likelihood

**;** simplifies to ****

The stable densities are defined according to Nolan (1997 and 2015). A random variable X is stable (α, β, γ, δ) if it has the following characteristic function (than can generate the second moment through a Fourier transform), described in equation 3.7:

Equation 3.7: Stable (α, β, γ, δ) Characteristic Function (to Fourier Transform)

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Where α, β, δ and γ stand for the characteristic parameter (tail), skewness, scale (equivalent to variance) and location (equivalent to mean). For a normal distribution, the tail value is 2, the skewness is zero, the scale is 1 and the mean is zero.

# Results

**Currency exchange rate and currency swaps contracts: daily volatility.**

In the first step of our test protocol, various changes in the unconditional volatility were detected in all daily returns series. When modeling the volatility with heteroskedasticity and regime switching - either with SWARCH or SWGARCH models — the number of levels implied a non-parsimonious number of parameters. The existence of various regimes of variance, with non-zero transition probabilities between these regimes, is not rejected. However, it is also appropriate to consider the hypothesis of the occurrence of various structural breaks, especially for the case of the huge jumps in the unconditional volatility of the daily returns series in the second semester of 2002, when the so-called confidence crisis occurred.

The high volatility levels of the Brazilian financial series in the second semester of 2002 were mainly determined by the uncertainty related to the Presidential election campaign. Razin & Sadka(2004) identified the presidential elections and the expected change of political and economical regime as being the two triggers of the Brazilian confidence crisis, known as such in spite of the economic fundamentals of the Brazilian were solid. Those triggers are a clear example of the unpredictable nature of future crises, as proclaimed in BIS (2011). According to Meirelles (2004), the Brazilian Central Bank offered currency exchange swaps contracts at the height of the confidence crisis through which the country suffered in the second semester of 2002.

The risk models based on either normal or t-student innovations, using data collected from 1999 to the first semester of 2002, were not able to forecast the jump of the volatility levels since June 2002, when the leftist candidate Lula, willing to calm down the market, launched the manifesto *Letter to the Brazilians*. The mark-to-market currency exchange swaps prices exhibited high unconditional volatility levels from July 26th, 2002. However, those high levels are possibly related not only due to the confidence crisis, but also to the increase in the number of currency swap contracts and to the large volume of conversions from contracts without daily adjustment (SC2) to contracts with daily adjustment (SC3) - an operational issue, rather linked to the operational risk of new terms of contracts than to market risk. The volatility decreased by August 13th, 2002, possibly as a result of the stand-by loan’s announcement from the IMF (International Monetary Fund), nevertheless higher than the former levels before June 2002.

While the exchange rate (U.S. Dollars/ Brazilian Reais) rose to almost 4 by October 22nd, 2002, the eve of the second round of the presidential elections; its unconditional volatility levels were the greatest since the beginning of the currency floating regime, started by 1999.2.

Table 2.4 shows the sudden changes in the unconditional volatility of the daily returns of both currency exchange and currency swaps price units (PU, the unit of negotiation of currency swaps contracts) in the BM&FBOVESPA stock exchange. The daily returns of swap prices presented 11 change points in the unconditional volatility. The table shows some political and/or economical events that could be responsible for the changes in the unconditional volatility of the daily series.

Table 4.1: Sudden Changes, Unconditional Volatility of Currency Swap Prices

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Period** | **From** | **To** | **Standard deviation** | **Possibilities** |
| 1 | August, 25th ,1999 | October 7th, 1999 | 1.20% | Initial phase of currency floating regime in Brazil |
| 2 | October 8th , 1999 | May 12th ,2000 | 0.73% | COPOM’s meeting kept basic interest rate at 19% per year |
| 3 | May 15th ,2000 | October 20th, 2000 | 0.47% | “Quiet” period |
| 4 | October 23rd, 2000 | December 1st, 2000 | 1.22% | “Quiet” period |
| 5 | December 4th, 2000 | March 13th ,2001 | 0.53% | “Quiet” period |
| 6 | March 14th ,2001 | December 17th, 2001 | 1.59% | Argentine’s default, energy crisis, Sep 11 |
| 7 | December 18th, 2001 | June 3rd, 2002 | 0.88% | “Quiet” period |
| 8 | June 4th , 2002 | July 25th, 2002 | 2.06% | Beginning of Presidential campaign in Brazil |
| 9 | July 26th, 2002 | August 6th, 2002 | 8.49% | Confidence crisis, swap auctions and conversions (SC2 for SC3) |
| 10 | August 7th, 2002 | November 13th, 2002 | 2.54% | Election’s eve and IMF stand-by Loan |
| 11 | November 14th, 2002 | February 4th , 2003 | 1.50% | Political transition; beginning of Lula’s government |

Figure 4.1 shows that the peak unconditional volatility of the currency swaps prices was almost the same (near 8% on August 8th, 2002) to all currency swaps series. At that time, some currency based assets were set to a maximum daily fluctuation of 7.5%, meaning that the peak volatilities were coherent with some pre-established daily oscillation limits. The currency exchange rate (PTAX) exhibited unconditional volatility levels lower than those of the currency swaps contracts, which are subject to, at least, other two risk factors: interest rates and currency exchange coupon.

Figure 4.1: Currency Swaps Prices - Daily Volatility (DTM= Days to Maturity)

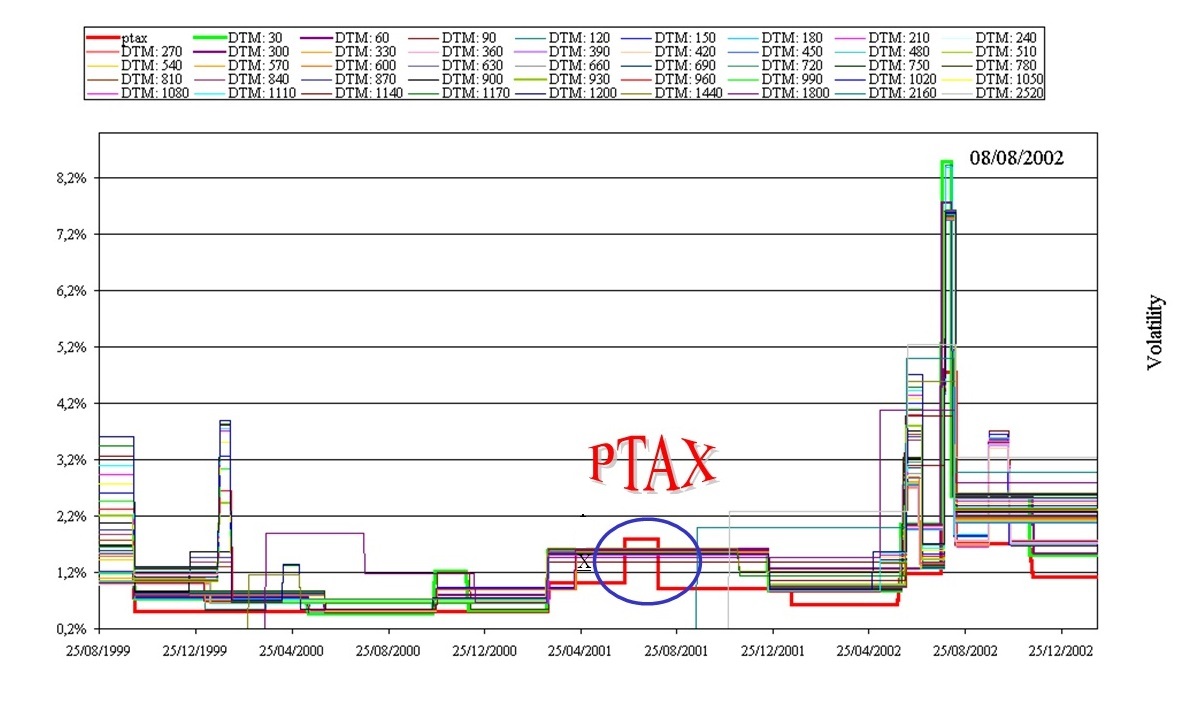


Table 4.2 exhibits the transition probabilities (P1 and P2), unconditional volatilities, regime durations (in days), and expected losses of the daily returns of currency swap prices and currency with two-regime volatility. The daily loss possibilities follow equation 4.1, which describes a VaR with one-day holding period divided by the mark-to-market asset value:

Equation 4.1: Expected Daily Loss, from Currency Exchange Swaps Prices



where is the volatility of regime s at day t; SF is the sensibility factor (2.33 for a 1% significance level);  is the mark-to-market value of the contracted currency exchange swaps at day t. The main component of a Principal Component Analysis (PCA, based on Litterman and Scheinkman, 1991) is possibly a currency exchange factor, responsible for 96.05 % of the variance over other factors that influence the currency swaps contracts.

The results confirm the effectiveness of the Stressed VaR approach from Kupiec (1998) adapted for a two-volatility regime switching model, however they do not shed a light for the BIS stressed VaR, in which the simultaneous use of high and (not very) low volatility parcels can be faced as an over specification.

Table 4.2: Daily losses for PTAX and Currency Exchange Swaps

Note: Transition probabilities (P1 and P2), volatility, duration (days), and expected losses (VaR/portfolio ratio).

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Expiring Days/asset** | **P1** | **P2** | **Low volatility** | **High volatility** | **Low volatility duration** | **High volatility duration** | **Low volatility daily loss** | **High volatility daily loss** |
| 270 | 0.9725 | 0.9644 | 0.91% | 2.83% | 36.37 | 28.10 | 2.12% | 6.59% |
| 300 | 0.9734 | 0.9661 | 0.82% | 2.57% | 37.54 | 29.51 | 1.92% | 5.99% |
| 330 | 0.9734 | 0.9661 | 0.75% | 2.37% | 37.60 | 29.50 | 1.76% | 5.51% |
| 360 | 0.9735 | 0.9661 | 0.69% | 2.19% | 37.71 | 29.52 | 1.61% | 5.11% |
| 390 | 0.9744 | 0.9678 | 0.65% | 2.04% | 38.99 | 31.04 | 1.51% | 4.76% |
| 420 | 0.9758 | 0.9700 | 0.61% | 1.92% | 41.32 | 33.31 | 1.41% | 4.47% |
| 450 | 0.9762 | 0.9707 | 0.57% | 1.81% | 42.00 | 34.16 | 1.32% | 4.21% |
| 480 | 0.9772 | 0.9714 | 0.54% | 1.74% | 43.84 | 34.91 | 1.27% | 4.06% |
| 510 | 0.9785 | 0.9728 | 0.52% | 1.67% | 46.60 | 36.76 | 1.22% | 3.89% |
| PCA | 0.12 | 0.04 | 0.030% | 3.163% | 1.14 | 1.05 | 0.070% | 7.369% |
| PTAX | 0.80 | 0.46 | 0.007% | 3.162% | 4.90 | 1.86 | 0.017% | 7.368% |

**Evaluating the VIX index as a volatility Proxy**

Table 4.3 shows the alpha-stable distributions for currency swaps, VIX, and S&P 500 series. The daily returns series were submitted to the STBLFIT and STBLPDF functions from Veillete (2010) and to the STABLEFIT function from Nolan (2015), with similar results which exhibit the non negligible probability of occurring the Black Monday volatility (October 19th, 1987), even in the S&P 500 series that ends in September 18th, 1987. The Kolmogorov-Smirnov test rejected the null hypothesis of normality at the 1% significance level for all series.

Table 4.3: Stable Distributions- VIX, Currency Exchange Swaps and S&P 500

Note: α, β, δ and γ stand for the characteristic parameter (tail), skewness, scale (equivalent to variance) and location (equivalent to mean), respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Series** | **α** | **β** | **δ** | **Γ** | **Black Monday**  **Probability (-23%)** |
| VIX (Since January 2nd ,1990) | 1.609991 | 1.00 | 0.002524 | 0.013149 | 0.187% |
| Currency Swaps 1999-2003 | 1.393691 | 0.2464 | 0.006498 | 0.001661 | 0.733% |
| Currency Swaps 2004-2014 | 1.612221 | -0.0708 | 0.006871 | 9.39E-05 | 0.432% |
| S&P (Jan, 4th, 1950 – Aug. 8th ,2015) | 1.617643 | -0.1213 | 0.004959 | 0.000183 | 0.258% |
| S&P (Jan, 4th, 1950 – Sep.18th,1987) | 1.716187 | -0.0949 | 0.004569 | 0.000238 | 0.123% |

**Next**, we calculate the VaR and Expected Shortfall for currency swaps positions based on the VIX index, according to equation 4.2.

Equation 4.2: VaR / ES for Currency Swaps, Based on Overall maximum VIX



Where: SF is the sensibility factor (SF=2.33 for a 1% significance level), is the volatility at day t, and the overall maximum historical daily VIX volatility (until August, 2015) is 5.09%.

The next tables (4.4 and 4.5) show that few violations occurred when using a maximum historical daily volatility VIX in the VaR for currency swaps: either only two days, when referring to overall maximum VIX, or only 9 days, when referring to maximum VIX until the analyzed period. Moreover, there is no violation when referring to the maximum Expected Shortfall of 13.60% (equation 2.13) at a 1% significance level.

Table 4.4: Only two Violations referring to the Overall Maximum VIX volatility

|  |  |
| --- | --- |
| Day | Loss |
| October 9th, 2008 | -12.881% |
| October 23rd, 2008 | -12.648% |

Table 4.5: Only Nine Violations referring to Maximum Historical VIX until Date

|  |  |  |  |
| --- | --- | --- | --- |
| Day | Loss | Day | Loss |
| July 30th ,2002 | -9.59% | September 30th 2008 | -8.54% |
| October 9th , 2002 | -6.74% | October 9th, 2008 | -12.88% |
| May 25th , 2006 | -9.47% | October 13th 2008 | -10.91% |
| August 17th 2007 | -8.72% | October 23rd, 2008 | -12.65% |
| September 19th 2008 | -8.48% |  |  |

The VIX is calculated from S&P500´s derivatives. We generated an alternate volatility index based on S&P500 volatility parameterizations. First, we fit the daily returns of the S&P500 index to an ARMA (1, 1)-GARCH (1, 1) model. The results are shown in Table 4.6. The log likelihood value for normal innovations is +56,296.80. The variance level, 8.0625E-07, compared to the GARCH coefficient (0.91), indicate a dependence on historical values. Nevertheless, the persistence - sum of GARCH + ARCH coefficients - is high (99.37%), suggesting changes in the unconditional variance that can be modeled with regime switch models (see DIEBOLD, 1986 and 1996). The log likelihood value for stable innovations is slightly superior to the result for the normal innovations (+55,071.00), while the log likelihood value for GARCH with stable innovations is negative: -16,507.60.

Table 4.6: S&P 500 Daily Return’s GARCH Fit (January, 1950 to August, 2015)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Parameter** | **C** | **AR (1)** | **MA (1)** | **K** | **GARCH (1)** | **ARCH (1)** |
| Value | 0.00054663 | -0.15823 | 0.25515 | 8.0625E-07 | 0.91022 | 0.083508 |
| Std Error | 7.30E-01 | 0.080562 | 0.07882 | 6.61E-05 | 0.0022535 | 0.0017177 |
| T Statistic | 74.879 | -19.641 | 32.371 | 122.030 | 4.039.206 | 486.150 |
| Value (Stable) | 0.000291 |  |  | 9.42E-06 | 0.85 | 0.05 |
| SE (Stable) | 0 |  |  | 0 | 0 | 0 |
| T (Stable) | Inf |  |  | Inf | Inf | Inf |

Next, we model the S&P500 index with SWGARCH. The results from tables 4.7 and 4.8 show that MLE fitting for alpha-stable densities is very sensible to the volatility levels and, at first, they do not favor regime switching, as some of the single volatility regime GARCH (1, 1) models, with stable innovations, exhibited better results than the switching regime models. Table 4.7 shows the results for the maximum likelihood estimation for the S&P 500 index - from January 4th, 1950 to August 20th, 2015 - with alpha-stable and normal innovations. The columns L1 and L2 are the unconditional volatility levels, ARCH and GARCH stand for the ARCH/GARCH coefficients, MLE\_STBL, MLE\_NORM and MLE\_GARCH mean, respectively, ARMA (1,1)-SWGARCH (1,1) with stable innovations/two volatility levels, ARMA (1,1)-SWGARCH (1,1) with normal innovations/two volatility levels and ARMA (1,1)-GARCH (1,1) with stable innovations/one high volatility level. All transition probabilities are equal to 50%.

Table 4.7: S&P 500 return’s MLE Fitting (Stable and Normal Innovations

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| L1 (%) | L2 (%) | ARCH1 | ARCH2 | GARCH1 | GARCH2 | MLE\_STBL | MLE\_NORM | MLE\_GARCH |
| 0.83 | 2.07 | 0.10 | 0.28 | 0.55 | 0.96 | 63,791 | 29,340 | 58.812 |
| 0.83 | 1.87 | 0.10 | 0.28 | 0.55 | 0.96 | 63,660 | 29,292 | 58.619 |
| 0.83 | 1.67 | 0.10 | 0.28 | 0.55 | 0.96 | 63,527 | 29,243 | 58.424 |
| 0.50 | 1.00 | 0.28 | 0.05 | 0.10 | 0.82 | 54,053 | 8,510 | 45.700 |
| 0.50 | 1.10 | 0.28 | 0.05 | 0.10 | 0.82 | 52,088 | 8,425 | 43.358 |
| 0.50 | 1.20 | 0.28 | 0.05 | 0.10 | 0.82 | 50,234 | 8,367 | 41.193 |
| 0.50 | 1.30 | 0.28 | 0.05 | 0.10 | 0.82 | 48,499 | 8,331 | 39.203 |
| 0.50 | 1.40 | 0.28 | 0.05 | 0.10 | 0.82 | 46,892 | 8,314 | 37.384 |
| 0.757 | 1.298 | 0.77 | 0.57 | 0.99 | 0.99 | 42,433 | 18,417 | 42.682 |
| 0.806 | 2.393 | 0.76 | 0.94 | 0.65 | 1.00 | 21,541 | 25,082 | **65,258** |
| E-7 | 0.81 | 0.99997 | 0.80268 | 0.99997 | 0.99997 | 176,700 | 93,256 | **159,060** |

Table 4.8 shows comparative results for the maximum likelihood estimation for the S&P 500 index, daily returns of Brazilian currency swaps (CS, with 30 days to maturity), and the main factor from currency swaps daily return’s Principal Component Analysis (PCA, possibly the daily exchange rate between U.S. Dollars and Brazilian Reais); with alpha-stable and normal innovations allowing different transition probabilities. L1 and L2 are the unconditional volatility levels; G1 and G2 stand for the GARCH coefficients of IGARCH modeling; P11 and P22 are probabilities to stay in the same regime in consecutive times; STBL, NRM and GARCH mean, respectively, ARMA (1,1)-SWGARCH (1,1) with stable innovations/two volatility levels, ARMA (1,1)-SWGARCH (1,1) with normal innovations/two volatility levels, and ARMA (1,1)-GARCH (1,1) with stable innovations/one high volatility level.

Table 4.8: MLE returns fitting (S&P 500 and Currency Swaps).

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Series** | **L1**  **(%)** | **L2**  **(%)** | **G1** | **G2** | **P11** | **P22** | **STBL** | **NRM** | **GARCH** |
| S&P500 | E-06 | 2 | 99.86 | 99.136 | 0.26 | 0.29 | 102,286 | 70,321 | 169,723 |
| S&P500 | E-06 | 2 | 83.08 | 99.90 | 0.02 | 0.88 | 468,027 | 12,600 | 512,243 |
| CS (1999-2003) | E-07 | 0.1 | 98.80 | 99.51 | 0.81 | 0.75 | 25,377 | 13,008 | NaN |
| CS (2004-2014) | 8E-07 | 1 | 96.59 | 98.15 | 0.20 | 0.14 | 22,213 | 9,175 | NaN |
| PCA | E-3 | 3.523 | 99.105% | 99.396% | 0,20 | 0,11 | 26,388 | -685 | NaN |

# Conclusion

This text evaluated the adequacy of two main Basel’s recommendations for market risk – minimum capital requirements and Stressed VaR - analysing a past financial vulnerability through the market risk exposure originated from currency exchange based assets. Would the effects of past crises be mitigated if those Basel III recommendations were already implemented? The chosen country and time were Brazil in the eve of the 2002´s presidential election. After applying the standard delta normal VaR methodology to the quite high daily return’s volatilities; both of the exchange rate (U.S. Dollars/Brazilian Reais) and of the currency swaps prices (from August, 1999 to February, 2003); it is possible to answer upon the effects of the two chosen recommendations.

First, is Stressed VaR effective for crisis periods? The answer is nowhen there is no recent turbulence to be referenced. In the specific case of the 2002´s Brazilian scenario, the number and volume of currency swaps only grew a couple of months before the crisis peak, so that the past does not work as a stress reference. Moreover, the high volatility levels did not sustain for a long period (from the end of July, 2002 to early August, 2012), and might not be eligible for future references. Also, the currency exchange volatility did not follow the currency swaps volatility, since they depend on different factors. Consequently, currency based assets cannot proxy the new asset (currency swaps), which is a strong reason to avoid much exposure from new financial instruments.

The BIS SVaR works like a sum of historical VaR and historical tail risk, therefore it is feasible with a necessarily pre-existent historical background, meanwhile capital requirements is a general approach. The stress reference usually works in a window approach, with the moving averages replaced by the window of stress. In the absence of historical data, we suggest that VIX volatilities can be used as an alternative volatility for the Stressed VaR. Besides that, while we follow BIS (2012) and BIS (2014) which recommend the substitution of VaR and Stressed VaR by the Expected Shortfall methodology, we also suggest that SWGARCH models can be a good alternative to describe the volatility of the financial series, competing with alpha-stable innovations models. In future tests, the transition probabilities between states may vary with time.

On the other hand, there is a key advantage for stable-based models, since they do not separate volatility from tail risk, what forcibly occurs when using models based on the standard normal distributions, as usually prescribed in BIS’s documents.

Second, concerning Basel III capital requirements: would have been effective in past crises?The answer is a conditional yes, once there is a previous point not much discussed in literature: the daily oscillation limits that, in the Brazilian case, exceeded 8.5% a day in the year 2002 – not to mention the key role of margins calls. Our simulations showed that assets with long term maturity exhibited a 6.59% daily loss (with a duration of 28.10 days), meaning a 13.18% loss in two days. The oscillation limits can play a stop loss role, mitigating crisis effects. In other words, a control over price oscillations should be more effective compared to a **macro** control over minimum capital requirements.

In this view, while the global Basel index rose from 8% to 11% due to the emergent need to quick respond to the financial crisis, the Brazilian banks have operated with a Capital Requirements index above 11% since 1998. So far, the increase of the Regulatory Capital requirements will be transferred to new Requirements items, such as the counter cyclical capital buffer. However, readers shall take into account the risk of disclosing information in crisis times, when transparency becomes a very sensitive issue, as observed in Eichengreen (2003).

Last but not least, three considerations: (a) market risk deals with daily information, apparently an evaluation advantage over credit risk that usually, deals with monthly disclosed data; (b) other risk experiences are scarce in the recent Brazilian history, as no systemic bank crisis occurred in the recent past (50 years, according to Laeven and Valencia, 2008) and (c) the use of past crises deals with just one similarity: high volatility, from different sources.

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2. IAG/PUC/RJ and National Bank for Economic and Social Development (BNDES). The views expressed in the paper are those of the author and do not necessarily reflect those of the BNDES. [↑](#footnote-ref-2)