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Value at Risk In Dominican Banking: Evaluating the Regulatory Method

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VALUE AT RISK IN DOMINICAN BANKING: EVALUATING THE REGULATORY METHOD

by

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ABSTRACT

Value at Risk In Dominican Banking: Evaluating the Regulatory Method

BY

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Financial institutions in the Dominican Republic, since 2004, have used the regulatory Value at Risk to measure market risk. This method is subject to criticism. The purpose of this study is to compare the regulatory VaR method against the Historic Simulation, Generalized Autoregressive Conditional Heteroskedasticity, and Monte Carlo approaches. The latter is more conservative and its assumptions are more realistic.

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INTRODUCTION

During the last three decades, risk management has become part of the daily operations of financial, non-financial, and regulatory institutions. Its increasing popularity comes from the need to keep track of the risks which firms incur when doing daily business; for these reasons, “Value-at-Risk (VaR) has become the industry standard by choice or by regulation” (Basak and Shapiro, 2001).

“The Value-at-Risk is a measure of market risk that tries to combine the sensitivity of the portfolio to market changes and the probability of a given market change” (Marrison, 2002). It is defined as the maximum possible loss during a determined period with a given confidence level, usually 99 percent.

The use of VaR traces back to the late 80’s, when financial institutions in need of measuring portfolio risk created the concept. But it wasn’t until the mid-90’s when it peaked with J.P. Morgan’s attempt to establish a market standard with its RiskMetrics[tm] system (Linsmeier and Pearson, 2000). Around the same time, the Basel Committee for Banking Supervision (BCBS) proposed the use of VaR models as a means to calculate capital requirements to hedge against market risk. The discussion intensified when the U. S. Securities and Exchange Commission started discussing the use of “VaR as one of the measures of corporate risk” (Alonso and Arcos, 2005).

Latin America is not a stranger to VaR methods, since this is the measure of risk used by regulatory agencies, both private and governmental. Taking into account Basel I[1] amendments made in the mid 90's, and Basel II capital and risk quantifications, regulatory agencies have developed the means to estimate the VaR and allocate capital accordingly. They also use it to prevent possible liquidity problems due to portfolio deterioration. These efforts are ongoing. Recently, the BCBS said in Basel III that it "is raising the resilience of the banking sector by strengthening the regulatory capital framework, building on the three pillars of the Basel II" (BCBS, 2010). At the same time, "the European Banking Authority is collecting new information from lenders to help them revise their assessments of the bloc's financial institutions and their exposures to the eurozone debt crisis" (Walker, 2011).

The purpose of this study is to test whether the current regulatory framework of Latin American banks regarding capital allocation through market risk measurement by VaR is adequate. We compare regulatory VaR with other methods. We show that the current regulatory method underestimates VaR in some cases.

The Dominican Republic regulatory method, which measures the exchange rate[2] effects over the net position[3] of banks, takes into consideration the Basel II standardized approaches for a VaR that are followed by many Latin American countries like Chile and Peru. The Dominican regulatory agency, the Superintendence of Banks (SIB), considers two different ways to measure VaR: 1)

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[1] Basel I, II, and III are regulatory frameworks that contain suggestions on what is banking best practices.

[2] Exchange rate, Dominican peso per dollar

[3] Net position, the difference between assets and liabilities in foreign currency, US dollars.

in the context of exchange rates and 2) in the context of interest rates. This paper will only focus on the exchange rate VaR, leaving for further research the revision of the interest rate VaR method used by the regulatory agency.

LITERATURE REVIEW

VaR is a measure of the maximum possible loss of value of a portfolio due to market fluctuations, interest rates changes or exchange rate movements, given a specific amount of time and a confidence level. It "namely is the best single measure to asses market risk because it combines information on the sensitivity of the value of the asset or assets, to changes in market-risk factors[4] with information on the probable amount of change in those factors" (Marrison, 2002).

Methods to capture the effects of the exchange rate VaR have been of great interest to risk managers inside financial and non-financial institutions. Linsmeier and Pearson (1999), from the University of Illinois, describe the details of the most common and practiced approaches: 1) historical simulation, 2) parametric VaR, and 3) a Monte Carlo simulation. Marrison (2002) and Zambrano (2003) address the same methods, and, after describing them, they highlight the drawbacks of each method.

A more recent study done by Vergara and Ochoa (2009) measures VaR on a hypothetical Colombian stock portfolio and shows that structured[5] Monte Carlo models are more robust than parametric VaR or historic simulation. Alonso and Arcos (2005) evaluated different methods to estimate exchange rate VaR on a representative stock portfolio of seven Latin American countries. They showed

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[4] The risk factors are market rates and prices that affect the value of a bank's assets and liabilities.

[5] Structured meaning the use of models to explain the behavior of the exchange rate.

that the General Autoregressive Conditional Heteroskedasticity (GARCH) models performed well in countries like Argentina and Brasil.

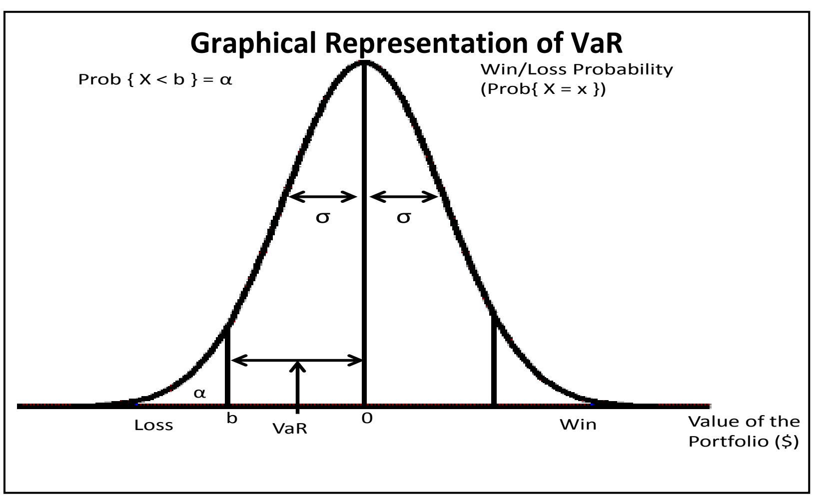
In this paper, we will estimate the VaR of a net position of a hypothetical Dominican bank worth US$26,291,566 by the method required by regulation and compare these results to the ones obtained through historic simulation, the GARCH(1,1) model, and the Monte Carlo approach.

THEORETHICAL FRAMEWORK

Although the concept underlying VaR is simple, its calculation may not be so. VaR shows how much is expected to be lost under adverse market fluctuations[6]. If we wanted an adverse movement whose probability of occurrence is less than 1%, that value would be obtained by multiplying the standard deviation by 2.33. Under normal distribution, the VaR would be defined as:

$$VaR_t = 2.33\sigma_t$$

where σ_t is the standard deviation of the variable or market factor in question, and subscript *t* is the index of time. As an example, imagine a stock portfolio of US$1,000 with a daily price standard deviation of σ_t = 0.08, given a confidence level of 99%. The VaR is US$186.4. This value can be read as follows: for every 100 days, there will be one day in which the portfolio will lose US$186.4 or more in value.



Source: Own Creation

[6] Market fluctuations refer to changes in market factors, interest rates or exchange rates.

The most commonly used VaR methods assume that the behavior of the returns is normal, even though "there is significant evidence on the non-normality of financial assets" (Vergara and Maya, 2009). Other than normal, some methods assume the variance to be invariant or deterministic, while others allow for it to change every period, becoming stochastic.

The most common approaches to calculate the VaR can be classified as parametric, which are those in need of parameters (mean, standard deviation, etc) to be estimated, and non-parametric. Included in the parametric approach are the regulatory method and the GARCH approach used in this paper. The non-parametric approach is through historic simulation.

DATA

Exchange Rate

The exchange rate in the Dominican Republic during the observed period responded to a set of strategies traced by the monetary and public policymakers that aimed to keep the economy growing. The efforts are visible through the gross domestic product (GDP) growth, which remained positive, despite the concurrent global economic crisis.

To avert a deterioration of the exchange rate due to an overheating economy and the international crisis, monetary policy turned restrictive via an increase in open market operations in 2007 and 2008. Monetary authorities also raised overnight[7] interest rates, which, in turn, increased the overall interest rates of the economy. Other factors, including the direct foreign investment (DFI), also helped keep a stabilized exchange rate. The DFI was US$1,667M in 2007 and US$2,870M in 2008. The latter is the greatest foreign investment number ever registered.

The data used are the exchange rate, Dominican Peso/US Dollar, which is the one demanded by regulation. More specifically, “the historic series will be constructed in reference to the exchange rate, by which, following section m) of the Article 4 of the Regulation of Market Risk, it corresponds to the average buy

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[7] The rate that the Central Bank gives the Banks for their deposits

value of US dollars from banks of multiple services[8]" (SIB, 2006). These observations were obtained from the data base of the Central Bank of the Dominican Republic under its economics statistics section.

One of the methods I analyze, the GARCH model, needs the exchange rate to be stationary, meaning that the mean and variance do not change over time. Because of this, we test whether the time series is stationary through various methods: first, by looking at a graph, and second, by using unit root[9] tests, namely, the Augmented Dickey-Fuller (ADF) test and KPSS tests.

The graph below shows the evolution of the exchange rate from January 1 of 2006 to December 31 of 2006. This the period from which the observations of this paper were taken. The reasons for choosing this period are: 1) because the data is available; and 2) the data avoids inclusion of the financial crisis era that may create “noise.”

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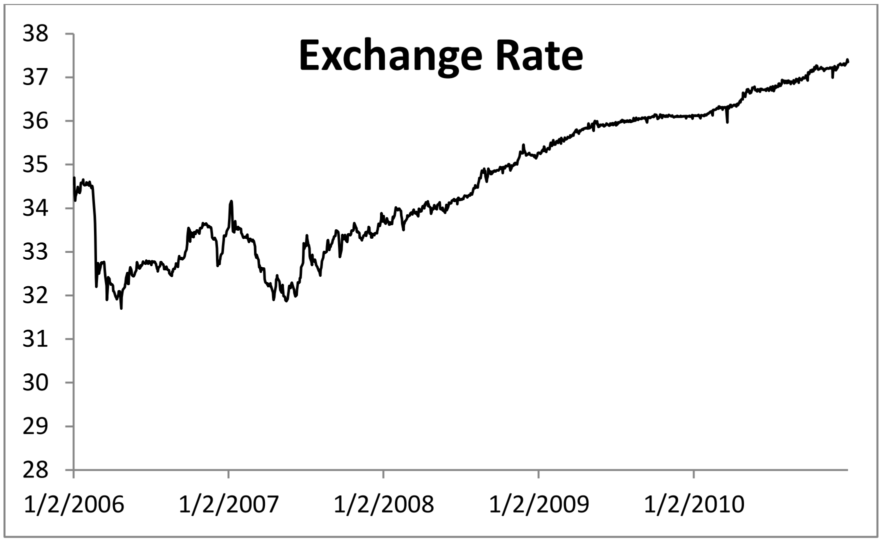
[8] Banks of multiple services are those which offer a variety of services, loans for every purpose (such as buying a car or a house), investments, and others aside from offering the services of a remittance office like western union. The next section, Banking and Net Position, has more information on the matter.

[9] “The terms non-stationary, random walk, and unit root are considered synonyms”(Gujarati, 2003)



Source: Own Creation

By looking at the graph of the exchange rate it is obvious that the series is non-stationary. There is an increasing trend and level of volatility that is not maintained through time.

The ADF test has three types: 1) drift, 2) random walk and 3) trend. Most of the time, despite the type used, the results are the same. For simplicity we will be testing using random walk approach. The test involves the following model:

$$\Delta y_t = \beta y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \cdots + e_t$$

where Δy is the differenced exchange rate, y is the exchange rate in levels, t is the time index (t for today's observation and $t-1$ for yesterday's observation), e stands for the error term, β is the coefficient of yesterday's exchange rate in levels, and δ is the coefficient of past differenced exchange rate observations. We are in the presence of a unit root if we fail to reject the null hypothesis β=1.

This means that the exchange rate follows a non-stationary process. The t-statistic is determined by

$$DF = \frac{\beta}{SE(\beta)}$$

where SE(β) is the standard error of the coefficient β and the critical values are obtained from the Dickey Fuller Table.

The KPSS test, developed by Kwiatkowski, Phillips, Schmidt and Shin (1992), is:

$$y_t = \varepsilon t + r_t + e_t$$

$$r_t = r_{t-1} + u_t$$

where *y* is the exchange rate, *εt* contains a predictable value, *r* is a random walk term, *e* is the stationary error term, *t* the time index, and *u* is the error term with variance σ^2_t. If we fail to reject the null hypothesis of σ_t = 0; then the exchange rate follows a stationary process. In other words, the null hypothesis of the test is that the series is stationary. The t-statistic is determined

$$LM = \frac{{}_{t=1}^{T} e_t^{\,2}}{\sigma_e^2}$$

where σ_e^2 is the estimated variance of the error term. The critical values are found in “testing the null hypothesis of stationary against the alternative of a unit root” (Kwiatkowski et al, 1992).

The unit root tests are made using the R software. Within the R software, the functions *ur.df()* and *ur.kpss,* from the *urca* package, were used to run the ADF test, and KPSS test, respectively.

Unit Root Test on Exchange Rate			
Unit Root Test	t-statistic	Critical Value 1%	Critical Value 5%
ADF	0.917	-3.43	-2.86
KPSS	14.478	0.739	0.463

Source: Own Creation

The ADF test shows that there is a unit root. It is evident by observing that the test fails to reject the null hypothesis of a unit root as shown, in the table above, with a T-statistic of 0.917, which is lower than the critical values measured at significance levels of 1% and 5%. The KPSS test, as well, reveals the same results as the ADF, by rejecting the null hypothesis of stationarity with a t-statistic of 14.478 and critical values of 0.739 and 0.463 for significance levels of 1%, and 5%, respectively

To eliminate non-stationary, the most common approach is to transform the data by differencing. I follow Hyndman ((2001). The differenced exchange rate can be seen as the returns on the exchange rate, in other words, how much it changes marginally from one day to another. However, since the regulatory VaR, and the historic simulation approach, work with the percentage change of the exchange rate, a further transformation will be made to the differenced data in order to obtain the percentage change of the exchange rate. The series under this transformation holds the same properties as if it were just differenced. The percentage change on the exchange rate will be called "returns on exchange rate." The returns on exchange rate will be determined through the following formula:

$$returns\ on\ exchange\ rate = \frac{X_t - X_{t-1}}{X_{t-1}}$$

where *X* stands for an observation and *t* is the index of time. As an example, let X_t be today's exchange rate and X_{t-1} be yesterday's exchange rate. If X_t=38.5 RD$/US$ and X_{t-1}=38.1 RD$/US$, today's return on exchange rate is $\frac{38.5-38.1}{38.1} = 0.010$.

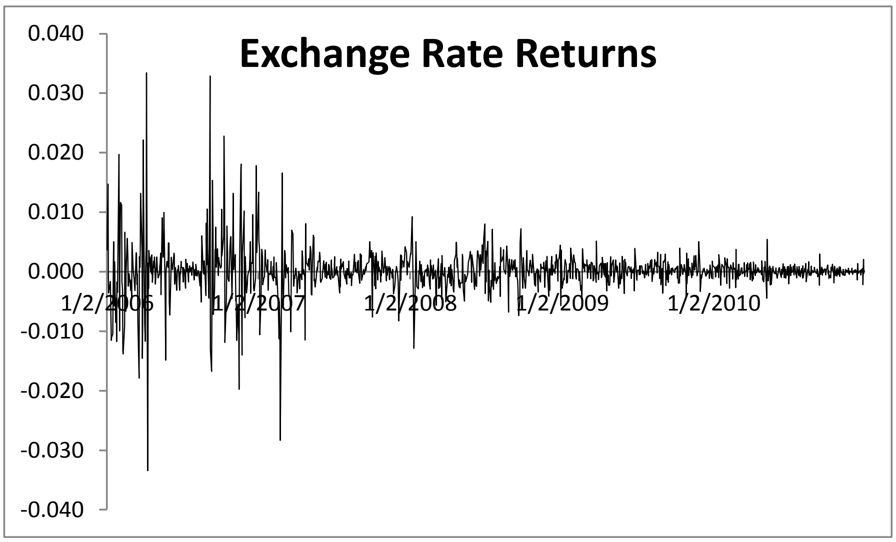
The ADF test and KPSS test results on the returns on exchange rate stationarity are shown in the following table:

Unit Root test on Returns on Exchange Rate			
Unit Root Test	t-statistic	Critical Value 1%	Critical Value 5%
ADF	-20.833	-3.43	-2.86
KPSS	0.1737	0.739	0.463

Source: Own Creation

The results show that by working with the returns on exchange rate, the non-stationary problem is solved. The ADF test with a t-statistic of negative 20.833 and critical values of -3.43 and -2.86 reject the null hypothesis of unit root. At the same time, the KPSS test with a t-statistic of 0.1737 and critical values of 0.739 and 0.463, fails to reject the null-hypothesis of stationarity. It is important to know that we are working with the returns on the exchange rate because: 1) it follows a stationary process and 2) it is the transformation used by the regulatory VaR.

Even though the ADF test and the KPSS test have shown that the returns on the exchange rate are stationary, by looking at the exchange rate returns graph, it looks like the volatility is clustered. Volatility clustering means that periods of high volatility are followed by periods of high volatility and that periods of low volatility are followed by periods of low volatility. “This implies that the volatility is not constant, hence it will depend on time” (Alonzo y Arcos, 2005), thereby violating one of the main assumptions of the regulatory VaR used in the Dominican Republic.



Source: Own Creation

The graph shows volatility is high before 2008 and low after. In the presence of such clustered volatilities, the regulatory VaR may underestimate the VaR.

Detecting that the distribution of the series is normal is of vital importance since it is one of the assumptions of the parametric method used by regulation. When a probability distribution[10] is said to be normal it means that the random observations that compose it are gathered around its mean. In the case of the returns of the exchange rate, it means that the majority of the

[10] A probability distribution is the function that holds the function that expresses the probability of a random variable taking some value. The most common probability distribution is normal, related to Gaussian Bell. Other probability distributions are T-Student, Chi-squared, and others.

observed returns are gathered around the mean of the observed returns. To define the distribution of a random variable, descriptive statistics[11] are often used, especially the mean, standard deviation, skew and kurtosis. Marrison ((2002) says that in the presence of a normal distribution the skew and kurtosis are 0 and 3, respectively.

Evaluating the returns on exchange rate, we see that the probability distribution does not resemble one of a normal distribution, as it has a skew of negative 1.893 and a kurtosis of 27.673. The negatively skewed probability distribution reveals that the probability of returns being positive is greater than negative. Furthermore, the high kurtosis of 27.673 tells us that the occurrence of extreme events is higher than that predicted by the normal distribution. The descriptive statistics of the returns are in the next table:

Descriptive Statistics Returns on Exchange Rate RD/US	
Mean	6.58209E-05
Standard Error	6.25538E-05
Median	0.000129726
Standard Deviation	0.002216913
Sample Variance	4.9147E-06
Kurtosis	27.67378979
Skewness	-1.893580835
Range	0.044967075
Minimum	-0.028358053
Maximum	0.016609022
Sum	0.08267102
Count	1256

Source: Own Creation

[11] Standard deviation measures de dispersion, skew measures the asymmetry of a distribution, and kurtosis is related to the width of the tails.

To corroborate the results a test developed by Jarque and Bera (1980) was used. This test evaluates whether the returns on exchange rates have a skewness and kurtosis matching that of a normal distribution. The null hypothesis of the test is that the returns on the exchange rate are distributed normally. This test will be done using the *jarque.bera.test()* function from the *tseries* package. The JB test statistic is defined

$$JB = \frac{n}{6}\left(s^2 + \frac{1}{4}(k-3)^2\right)$$

where *n* is the number of observations, *s* is the skewness and *k* the kurtosis of the returns on exchange rate. The critical values of the test come from the Chi-squared table. The results show that, with a test statistic of 32610.9 and a p-value of 2.2e^{-16}, the null hypothesis of normality is rejected with a 99% confidence interval.

Banks and their Net Positions

The Dominican Republic's banking system, as well as the system in other Latin American countries, serves as an engine of growth, channeling resources to the productive activities of the nation. It is regulated by the SIB which has been around since 1947. However it wasn't until 2002 when it got the legal framework to supervise the Dominican banking system as it does now with total independence.

Since the 2003 financial crisis, this sector's contribution to the country's gross domestic product (GDP) has been increasing, growing from 3.3% in 2003 of the GDP in 2003 to 4% in 2010, according to the Central Bank's numbers. Currently, it is composed of 68 financial institutions, of which 15 are banks of multiple services, 24 are banks of savings and credit, 18 are credit corporations and 11 are associations of savings and credit. One of the main features that distinguish these institutions is that only two of them, banks of multiple services and associations of savings and credit, can accept all forms of deposit (savings accounts, checking account and certificate of deposits).

The banking sector's total assets rose to US$20,759.5 million in 2010, which represents 41% of the GDP. On the other hand, the total amount of liabilities rose to US$18,388.5 million, representing 36% of the GDP. From these numbers we can infer that the capital held by these institutions is US$2,370.9 million, meaning that the system is divided between 11% capital and 89% liabilities or debt. The importance of VaR arises from this leverage, as is characteristic of the banking business. By keeping track of the probable loss that the bank's assets face, capital can be allocated, thereby avoiding insolvency by not being able to comply with the banks debt.

Financial institutions in the Dominican Republic are required by regulation to measure the exchange rate risk exposures through the market risk report on their net positions. The net position of a bank is measured by the difference between the book value all the assets and liabilities it holds in foreign currency. Currently all Dominican banks must prepare a monthly report on their current position. These values are gathered in the accounting department on the last working day of the month.

Information on bank’s financial statements are in the public domain and are published through the SIB’s web page (http://www.sb.gob.do). However, the information contained in the market risk report on the net position report is not public. Because of this, one of the top banks of multiple service’s market risk report on net position will be slightly altered to create a hypothetical bank, for which the market risk will be calculated in this paper. This hypothetical bank will maintain the essence of the real bank since the structure, meaning the composition of assets and liabilities, will be held. The values of the accounts that comprise both assets and liabilities used in this paper are approximations of the real values that are held by a bank. For this paper, the choice of a bank of multiple services responds to the fact that this type of bank in the Dominican Republic resembles the majority of banks in Latin America in the services it provides.

The next table shows the accounts and the net position to be used in this paper (in dollars).

Net Position Accounts	
ASSETS AND CONTINGECIES	
AVAILABILITY	55,246,173
CREDIT PORTFOLIO	**176,393,472**
INTERBANK GIVEN	-
REPOS	-
PORTFOLIO WITH CLASIFICATION A y B	146,413,426
PORTFOLIO WITH CLASIFICATION C	15,211,169

PORTFOLIO WITH CLASIFICATION D y E	14,768,878
INVESTMENTS	**21,586,124**
INSTRUMENTS TO NEGOTIATE	-
INSTRUMENTS AVAILABLE TO SELL	-
INSTRUMENTS HELD TO MATURITY	-
OTHER INSTRUMENTS OF DEBT	21,586,124
INSTRUMENTS WITH RESTRICTED AVAILABILITY	-
ACCOUNTS RECEIVABLES	559,721
FIXED ASSETS	-
PERMANENT STOCK INVESTMENT	-
OTHER ASSETS	509,278
CONTINGENCIES	7,718,709
PROVISIONS FOR ASSETS AND CONTINGENCIES	(7,544,884)
TOTAL ASSETS AND CONTINGECIES IN FOREIGN CURRENCY	**254,468,594**
LIABILITIES, EQUITY AND CONTINGENCIES	
INTERBANK RECEIVED	-
VOLAITLE PORTION OF PUBLICS DEPOSITS	34,326,045
PERMANENT PORTION OF PUBLICS DEPOSITS	163,251,278
RESTRICTED PUBLIC DEPOSITS AND INSTRUMENTS	3,234,037
ACCOUNT PAYABLES	90,046
OBTAINED FINANCING	5,426,207
OBLIGATIONS	382,806
MICELLANEOUS CREDITORS AND PROVISIONS	1,190,657
OTHER LIABILITIES	91,104
FUNDS IN ADMINISTRATION	-
SUBORDINATED DEBT	11,878,487
SUBORDINATED DEBT CONVERTIBLES IN CAPITAL	-
EQUITY	-
CONTINGENCIES	8,177,596
PROVISIONS FOR CONTINGENCIES	128,765
TOTAL LIABILITIES AND CONTINGENCIES IN FOREIGN CURRENCY	**228,177,028**
NET POSITION IN FOREIGN CURRENCY	**26,291,566**

Source: Own Creation

The previous table shows all the accounts taken into consideration by the net position report sent to the Dominican regulator. These accounts hold those items commonly seen in financial statements. For example, “availability” holds cash, deposits in other banks, reserves in the central bank, etc. The “credit portfolio” holds all the loans, “investments” holds all the bonds bought by the bank, and so on. The net position of the Dominican banks in risk is US$26,291,566.

METHODS AND RESULTS

In this section, the methods and models to be tested are described, highlighting the pros and cons and results of each method. The first method presented is the parametric method required by the banking regulators of the Dominican Republic. After this, we proceed to determine the VaR through the historic simulation approach. Then we model the volatility of the risk factor using a GARCH(1,1) model. Finally, a Monte Carlo simulation is performed with the support of the GARCH model.

The number of observations varies depending on the method. There are 260 observations from December 21 of 2009 to December 31 of 2010 to determine the standard deviation of the returns of the exchange rate as is required by the regulatory method of the SIB. The same 260 observations are used to determine the maximum loss through historic simulation approach so it can be compared to the regulatory VaR. A different 1,257 observations will be used from January 2 of 2006 to December 31 of 2010 to model GARCH. The sample of 1257 observations was selected to avoid the financial crisis of 2003.

Regulatory VaR as demanded by SIB

The regulatory VaR assumes that the probability distribution is normal and the volatility constant. It also assumes that "changes in the instrument[12]

[12] An instrument is an asset of any kind that can be traded. Example: stocks or bonds.

values are assumed to be linear[13] with respect to the changes in the risk factor" (Marrison, 2002). These implications, together, are reflected on the VaR. For a linear relationship, a bond with a value of US$100, and a hypothetical exchange rate standard deviation of 0.02, the maximum loss derived from an appreciation[14] of the exchange rate given a 99% confidence level would be US$100*(2.33*0.02*38)= RD$177. For a quadratic relationship, a bond with a value of US$100, and a hypothetical exchange rate standard deviation of 0.02, the maximum loss derived from an appreciation of the exchange rate given a 99% confidence level would be US$100*$(2.33*0.02*38)^2$ =RD$313.57.

Among the benefits of the regulatory method are that it is simple and fast to calculate, therefore making it easy to implement in countries like the Dominican republic where VaR is a new concept. However, it does not consider the effects of "fat tail"[15] events, because of the normality assumptions, or clustered volatilities.

According to the regulatory method of the SIB (on page 9 of the guide for the application of the regulation, for market risk) "the value at risk for variations in the exchange rate will be made through:

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[13]Linear changes when there exists a linear relationship between two variables, example y = 5x. this relationship is of first degree meaning that the maximum power to which this variable, x, is raised is 1. An increase in *X* by 2 increases *Y* by 10, so the relationship is linear.

[14] The value of the Dominican peso rises with respect to the dollar. Example: if we have an exchange rate of 38RD$/US$ an appreciation of 3%, 37RD$/US$, would mean that the Dominican peso's value has risen with respect to the dollar.

[15] Fat tail "is a property of probability distributions exhibiting extremely large kurtosis" (Cook Pine Capital, 2008)

Value at Risk = Net Position in Foreign Currency * Exchange Rate Expected Volatility * Root Squared of the time needed to dispose the position

Source: SIB

where Exchange Rate Expected Volatility is the standard deviation[16] of one year of daily observations of the exchange rate, or 260, which is multiplied by 2.33, which corresponds to 99% level of confidence, and the squared root of the time needed to dispose the position to avoid further loss[17], which is defined to be $\sqrt{5}$ by the SIB. This is less than the number of days suggested by Basel II, which is $\sqrt{10}$. The SIB's decision on defining that the number of days needed to dispose of the net position to be 5 days results in a smaller VaR by 29%.

The result of the VaR on a net position of US $26,291,566 is:

$$VaR = US\$26{,}291{,}566 * 2.33 * 0.001433 * \sqrt{5} = US\$196{,}293.3$$

The resulting VaR on the net position is US$196,293.3 meaning that there is a 1% probability that the banks net position will suffer a loss of US$196,293.3 or higher based on regulatory measurements.

Historic Simulation

The historic simulation approach does not make any assumptions on the distribution of returns that are different from the parametric approach. This approach is simpler in its calculation and interpretation. It consists in "taking at

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[16] Standard deviation of the sample $sd = \sqrt{\frac{1}{N}\sum_{1}^{n}(x_i - m)^2}$ where *m* is the mean of the sample *x* is the observation, *i* s the index of the particular observation and *N* the total number of samples.

[17] Disposing the position is the result of various operations that take the value of the net position to cero. For example: selling bonds or stocks.

least 250 observations" (Marrison, 2002) and calculating the percentage change of the exchange rate. The number of observations is arbitrary; however, for the purpose of this paper, we will be considering 260 observations, which is the same amount of observations required by the regulatory method. After we obtain the daily returns of the exchange rate, it is used to estimate the variation in value of the net position. Basically, it takes the exchange rate returns, and measures how the value of the portfolio would change in the face of these returns. The VaR is determined by the following formula:

$$VaR = Net\ position * Returns * \ \overline{5}$$

This approximation uses historic returns to derive the VaR through the percentile of the sampling distribution. In other words, after taking the exchange rate 260 observations, estimating its returns, and calculating how the value of the portfolio changes, by multiplying the net position by the returns of the exchange rate, and arranging the values of the VaR from higher to lower, the 99% VaR would be the loss corresponding to the third worst value.

Historic Simulation 260 observations

Net Position	26,291,566

	Date	Buy	Returns	VaR (US$)
1	3/22/2010	35.9652	-0.0097313930	-572,106
2	11/25/2010	36.9926	-0.0062761180	-368,971
3	9/27/2010	36.9229	-0.0032042510	-188,377
4	2/15/2010	36.1268	-0.0024936500	-146,601
5	8/26/2010	36.8513	-0.0022172720	-130,353
6	9/6/2010	36.8743	-0.0021969490	-129,158
7	12/30/2009	36.0511	-0.0021557230	-126,734

8	7/5/2010	36.6954	-0.0021532640	-126,590
9	7/9/2010	36.6807	-0.0020153770	-118,483
10	12/3/2010	37.1604	-0.0019893870	-116,956
11	6/28/2010	36.6865	-0.0017239430	-101,350
12	12/31/2010	37.3478	-0.0016480020	-96,886
13	5/14/2010	36.6292	-0.0016339720	-96,061
14	5/11/2010	36.6687	-0.0015968180	-93,876
15	7/23/2010	36.7994	-0.0015314600	-90,034

Source: Own Creation

Through estimation of the VaR by historic simulation, there is a 1% probability that the loss in value will be equal to or greater than US$188,377[18].

The one percentile VaR will be given by the third value (VaR US$) arranged from low to high. To determine that is the third value from low to high will be done though the following formula:

$$n = \frac{P}{100} * N + \frac{1}{2}$$

where *n* is the number of the observation from low to high under VaR US$ and *P* is the percentile (0 ≤ P ≤ 100). In this case, since we are looking for the 1 percentile, P is equal to 1 and *N,* the number of observations, is 260:

$$n = \frac{1}{100} * 260 + \frac{1}{2} = 3$$

Although the limitations of non-normality that affect the regulatory VaR are not present in the historic simulation approach, it holds other disadvantages: the VaR comes as a result of a single recent event, making it sensitive to past events. In other words, it assumes that the risky event that happened in the

[18] See Appendix B for the results on 1000, 1257, and 2011 observations.

past, and made the value of the instrument drop, and will occur again in the future. Another disadvantage is that the VaR will depend on the amount of observations taken into consideration; this is called the "window effect" by Marrison (2002). For example, if we have data that includes crisis observations, when the data gets updated and "the crisis observations drops out of our window of historical data" (Marrison, 2002), the VaR will drop immediately and drastically.

GARCH

The exchange rate returns in the Dominican Republic, just as stock returns from Argentina, Brazil, Chile, Mexico (Ojah y Karemera, 1999), and Colombia (Alonzo and Arcos, 2005), have excess kurtosis and clustered volatilities, as demonstrated in the data section. This means that the assumption of static volatilities required by the SIB may underestimate the VaR.

GARCH is not subject to this allowing the VaR to be estimated using the following equation

$$VaR_t = Net\ position * 2.33\sigma_t$$

where σ_t represents the conditional volatility or conditional standard deviation of the returns of the exchange rate available at time t.

Given the probability distribution, and the existence of clustered volatility, there exists "the potential to model volatility" (Alonzo y Arcos, 2005). The conditional standard deviation can be modeled using the GARCH model introduced by Bollerslev (1986).

"The most widely used GARCH specification asserts that the best predictor of the variance in the next period is the weighted average of the long-run average variance, the variance predicted for this period, and the new information that is captured by the most recent squared residuals" (Engle, 2001). The GARCH model representation of variance is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 e_{t-1}^2$$

$$\alpha_0 > 0, \alpha_1 > 0, \alpha_2 \geq 0, \text{ and } \alpha_1 + \alpha_2 < 1$$

where σ^2 is the variance, t is the index of time, α_0 is the long term mean of the variance, e^2 is the error term or innovation term squared, and α_1 and α_2 are the weights of the explanatory variables of yesterday's variance σ_{t-1}^2 and yesterday's error term squared e_{t-1}^2 respectively. Being more explicit in the use of the time index, t refers to today's observation and the $t-1$ index refers to yesterday's observation.

For the estimation of the parameters the R software will be used, specifically the *garchFit*() function from the fGarch package which estimates the parameters through maximum likelihood[19]. The GARCH(1,1) results are given in the next table for a sample of 1257 observations of returns on exchange rate:

GARCH Output

	Estimate	Std. Error	t value	Pr(>|t|)
α_0	9.321e-07	1.569e-07	5.941	2.83e-09
α_1	5.224e-01	8.385e-02	6.230	4.67e-10
α_2	3.200e-01	8.212e-02	3.897	9.74e-05

Source: Own Creation

[19] It is a method for estimating parameters. This methods intuition is that given a data set, the maximum likelihood will give a set of parameters that will help replicate the data.

As can be seen through the p-value (Pr(>|t|)), with a 95% level of confidence, the past variance of the returns and past disturbances are statistically significant in explaining today's volatility. This output gives us the parameters needed to estimate the conditional volatility. With it, next period's volatility can be forecasted, henceforth the VaR. To forecast the January 1, 2011 variance, we will be using the parameters from the GARCH output α_0, α_1, α_2, which is the estimated conditional variance for December 31 of 2010, 0.00000189641, and a randomly generated error term, or innovation, 0.00091853, using the *rnorm()* function. The randomly generated error term may have various implications. Since its randomly generated, in some cases it may cause the standard deviation to be really low, making the VaR less than the regulatory VaR. In the same way, the randomly generated error term may generate a high standard deviation making the VaR be greater that the regulatory. The randomly generated error term, in this case, resulted in a higher VaR. The estimated conditional variance for today σ_t^2 it is a value that is stored, when the *garchFit()* function is executed, and can be extracted using *garchFit()@h.*t function. The forecasted conditional variance representation is:

$$\sigma_{t+1}^2 = \alpha_0 + \alpha_1\sigma_t^2 + \alpha_2 e_t^2$$

and the forecasted number is a result from the following process:

$$\sigma_{t+1}^2 = 9.321\mathrm{e}^{-07} + 5.224\mathrm{e}^{-01} * 1.896410\mathrm{e}^{-06} + 3.200\mathrm{e}^{-01} * (9.1853\mathrm{e}^{-04})^2$$

$$\sigma_{t+1}^2 = 2.19277\mathrm{e}^{-06}$$

$$\sigma_{t+1} = 0.0014808$$

$$VaR = US\$26{,}291{,}566\ * 2.33 * 0.0014808 * \sqrt{5} = US\$\ 202{,}840.3$$

The forecasted standard deviation, 0.0014808, resulted in a VaR of US$202,840.3.

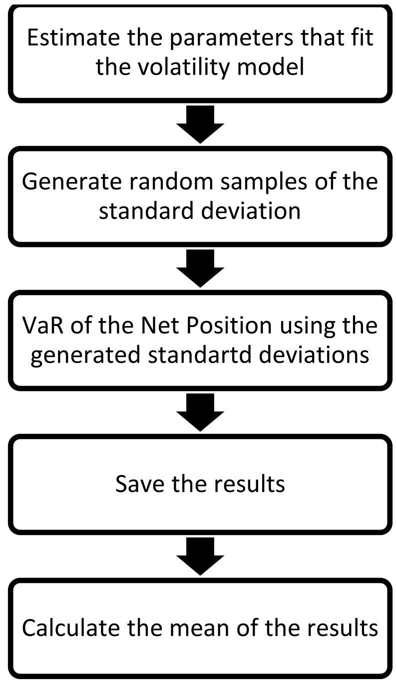
Even though this method overcomes the clustered volatility problem, present in the regulatory method, it assumes that the probability distribution of the exchange rate returns is normal.

Monte Carlo

With the help of the parameters determined through GARCH model, a Monte Carlo[20] (MC) study can be used to generate random scenarios. This method has an advantage in that it can use a full volatility model, like the GARCH(1,1) of the exchange rate conditional volatility, to generate an infinite number of scenarios. However, despite the MC advantage of infinite sample generation, it depends on the normality behavior of the risk factors just like the regulatory method. The following tree shows how to carry out The Monte Carlo process.

[20] Monte Carlo is the exercise that allows generate random scenarios for future volatilities and the estimating the VaR for each of the generated scenarios.

Monte Carlo Tree



Source: Own Creation

The first step, estimating the parameters that fit the volatility model, refers to the parameters that fit the conditional variance σ_t^2, from the GARCH Output table. With these parameters α_0, α_1, α_2, and the conditional variance at time *t,* December 31 of 2010, which is 0.00000189641, the only element missing to obtain the conditional variance at t+1 is the error term, which is generated using the *rnorm()* function. The number of generated error terms its random. For the purpose of this paper we arbitrarily chose 1,000,000. Numbers much higher than that would take a considerable amount of time to generate. Numbers much lower than that would create an inferior approximation to the expected VaR. After generating 1,000,000 error terms and with it various scenarios for the variance, we proceed to calculate a VaR for each scenario with the following formula.

$$VaR = US\$26{,}291{,}566 \ * 2.33 * \sqrt{conditional\ variance} * \sqrt{5}$$

After estimating 1,000,000 VaR, the mean of these results is calculated to get an expected VaR for the next period. The result of the Monte Carlo Process has given an expected VaR of US$229,368.8, 17%, which is higher than the regulatory result.

Results

The results of the different methods used in this paper to calculate VaR are in the following table

Results		
Method	VaR	Difference
Regulatory	196,293	
HS	188,377	-4%
GARCH	202,840	3%
MC	229,369	17%

Source: Own Creation

We show that the regulatory method, which is parametric, effectively underestimates the VaR by 3% when compared with the results of the GARCH approach, and 17% with the Monte Carlo simulation. On the other hand, the regulatory method's VaR is greater than the VaR calculated with historic simulation by 4%, defying the theory; perhaps this is due to probability distribution of the returns on exchange rate or the number of observations. Further research on the impact of skewed returns on VaR needs to be made alongside evaluating the returns on exchange rate on other countries.

CONCLUSION AND SHORTCOMING

VaR is a measure of loss in the value of the portfolio in a given period under a given probability. The increasing popularity of it began when JP Morgan, through Riskmetrics, various regulators in the United States (FED and SEC) and the BCBS endorsed its use. As a result, many Latin American regulatory agencies made financial institutions calculate VaR as a mean to assess risk. However, the main assumptions of the SIB regulatory VaR, normality and the presence of clustered volatility, tend to underestimate VaR.

After looking at this study’s results and acknowledging the pros and cons of each method, which method to implement to assess risk is lies at the discretion of the risk manager. However, I believe that the Monte Carlo approach is the best since it overcomes the clustered volatility problem inherent in the regulatory VaR; at the same time, it allows us to get a more accurate value of the expected VaR than the GARCH approach through the generation of multiple scenarios. When compared to the historic simulation approach, it may be a better method, considering the negatively skewed probability distribution which gives a lesser VaR than the regulatory method and the drawback of considering past risky events as common future risky events.

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APPENDICES

Appendix A

Market Risk Report

MARKET RISK REPORT 03
NET POSITION REPORT IN FOREIGN CURRENCY
MONTHLY FREQUENCY
(US$)

		TERM_1	TERM_2	TERM_3	TERM_4	TERM_5	TERM_6	TERM_7	TERM_8	TERM_9	TERM_10	TERM_11	TERM_12	
		0-15 DAYS	16-30 DAYS	31-60 DAYS	61-90 DAYS	91-180 DAYS	181-360 DAYS	1-2 YEARS	2-3 YEARS	3-4 YEARS	4-5 YEARS	MÁS 5 YEARS	INDETERMINED MATURITY	TOTAL
	ASSETS AND CONTINGECIES													
1	DISPONIBILITIES	55,246,173												55,246,173
2	CREDIT PORTFOLIO	**15,789,932**	**9,751,160**	**2,746,583**	**8,904,064**	**3,621,954**	**27,750,734**	**15,674,173**	**16,372,534**	**11,740,449**	**13,725,027**	**35,547,984**	**14,768,878**	**176,393,472**
3	INTERBANK GIVEN	-												-
4	REPOS													-
5	PORTFOLIO WITH CLASIFICATION A y B	15,545,786	9,597,795	2,744,174	8,901,637	3,614,453	27,735,274	15,600,057	14,384,911	9,771,228	11,755,451	26,762,660		146,413,426
6	PORTFOLIO WITH CLASIFICATION C	244,146	153,365	2,409	2,427	7,500	15,460	74,117	1,987,623	1,969,221	1,969,576	8,785,324		15,211,169
7	PORTFOLIO WITH CLASIFICATION D y E	-	-	-	-	-	-	-	-	-	-	-	14,768,878	14,768,878
8	INVESTMENTS	**2,510,000**	**5,905,866**	**-**	**-**	**-**	**8,065,603**	**-**	**1,426,909**	**-**	**1,705,431**	**1,972,316**		**21,586,124**
9	INSTRUMENTS TO NEGOTIATE	-	-	-	-	-	-	-	-	-	-	-		-
10	INSTRUMENTS AVAILABLE TO SELL	-	-	-	-	-	-	-	-	-	-	-		-
11	INSTRUMENTS HELD TO MATURITY	-	-	-	-	-	-	-	-	-	-	-		-
39	OTHER INSTRUMENTS OF DEBT	2,510,000	5,905,866	-	-	-	8,065,603	-	1,426,909	-	1,705,431	1,972,316		21,586,124
12	INSTRUMENTS WITH RESTRICTED AVAILABILITY	-	-	-	-	-	-	-	-	-	-	-		-
13	ACCOUNTS RECEIVABLES		559,721											559,721
14	FIXED ASSETS													-
15	INVERSIONES PERMANENTES EN ACCIONES													-
16	OTHER ASSETS	480,238	29,040	-	-	-	-	-	-	-	-	-	-	509,278
17	CONTINGENCIES	43,762	668,336	350,540	713,410	2,492,078	2,540,491	739,100	-	-	-	-	170,993	7,718,709
18	PROVISIONS FOR ASSETS AND CONTINGENCIES	(692,026)	(607,159)	(108,932)	(345,260)	(181,488)	(1,382,661)	(598,142)	(663,599)	(437,707)	(575,278)	(1,398,831)	(553,801)	(7,544,884)
	TOTAL ASSETS AND CONTINGECIES IN FOREIGN CURRENCY	73,378,079.42	16,306,963.72	2,988,190.55	9,272,214.12	5,932,543.19	36,974,166.08	15,815,131.39	17,135,844.85	11,302,741.77	14,855,180.08	36,121,468.91	14,386,069.63	254,468,593.70
	LIABILITIES, EQUITY AND CONTINGENCIES													
19	INTERBANK RECEIVED	-												-
20	VOLAITLE PORTION OF PUBLICS DEPOSITS	13,795,379.0	6,258,991.0	8,075,288.1	6,196,386.5									34,326,044.6
21	PERMANENT PORTION OF PUBLICS DEPOSITS												163,251,278.2	163,251,278.2
22	RESTRICTED PUBLIC DEPOSITS AND INSTRUMENTS	-	-	-	-	-	-	-	-	-	-	-	3,234,037.2	3,234,037.2
23	ACCOUNT PAYABLES	-	90,045.7	-	-	-	-	-	-	-	-	-	-	90,045.7
24	OBTAINED FINANCING	5,048,834.3	377,372.7	-	-	-	-	-	-	-	-	-	-	5,426,206.9
25	OBLIGATIONS	382,806.3	-	-	-	-	-	-	-	-	-	-	-	382,806.3
26	MICELLANEOUS CREDITORS AND PROVISIONS	-	-	-	-	-	-	-	-	-	-	-	1,190,657.2	1,190,657.2
27	OTHER LIABILITIES	45,427.6	45,676.0	-	-	-	-	-	-	-	-	-	-	91,103.6
28	FUNDS IN ADMINISTRATION													-
29	SUBORDINATED DEBT	-	597,418.3	-	-	1,772,316.0	-	7,058,624.9	2,450,128.0	-	-	-		11,878,487.2
30	SUBORDINATED DEBT CONVERTIBLES IN CAPITAL	-	-	-	-	-	-	-	-	-	-	-	-	-
31	EQUITY													-
32	CONTINGENCIES	83,037.6	1,186,741.7	350,539.6	723,410.0	2,492,078.0	2,540,491.0	771,882.0	-	-	-	-	29,416.1	8,177,596.0
33	PROVISIONS FOR CONTINGENCIES	-	-	-	-	-	-	-	-	-	-	-	128,765.5	128,765.5
	TOTAL LIABILITIES AND CONTINGENCIES IN FOREIGN CURRENCY	19,355,484.84	8,556,245.19	8,425,827.71	6,919,796.48	4,264,394.00	2,540,491.00	7,830,506.85	2,450,128.00	-	-	-	167,834,154.13	228,177,028.19
	NET POSITION IN FOREIGN CURRENCY	54,022,594.58	7,750,718.53	(5,437,637.15)	2,352,417.64	1,668,149.19	34,433,675.08	7,984,624.54	14,685,716.85	11,302,741.77	14,855,180.08	36,121,468.91	(153,448,084.50)	26,291,565.51

Appendix B

Historic simulation 1000 observations

Net Position	26,291,566

	Date	Buy	Returns	VaR (US$)
1	1/11/2007	33.5903	-0.0128846650	-757,486
2	3/22/2010	35.9652	-0.0097313930	-572,106
3	9/20/2007	33.0437	-0.0073870720	-434,284
4	8/27/2007	33.0434	-0.0067921600	-399,309
5	11/25/2010	36.9926	-0.0062761180	-368,971
6	12/31/2007	33.696	-0.0056936370	-334,727
7	3/6/2007	32.9372	-0.0056523580	-332,301
8	7/12/2007	32.9064	-0.0051286830	-301,514
9	3/28/2007	32.3777	-0.0050677940	-297,934
10	5/11/2007	31.9853	-0.0049400530	-290,424
11	9/21/2007	32.881	-0.0049359450	-290,183
12	7/9/2007	33.1436	-0.0049029370	-288,242
13	3/19/2007	32.5408	-0.0046112420	-271,094
14	5/11/2009	35.7733	-0.0044348070	-260,721
15	2/18/2008	33.4998	-0.0042625700	-250,595

Source: Own Creation

Historic simulation on 1257 observations

Net Position	26,291,566

	Date	Buy	Returns	VaR(US$)
1	2/23/2006	32.4086	-0.0284	-1,667,162
2	1/11/2007	33.5903	-0.0129	-757,486
3	4/24/2006	31.6991	-0.0115	-675,268
4	2/20/2006	33.8219	-0.0113	-663,886
5	1/4/2006	34.3323	-0.0106	-623,581
6	3/21/2006	31.8983	-0.0101	-594,314
7	3/22/2010	35.9652	-0.0097	-572,106
8	2/22/2006	33.3408	-0.0092	-540,078
9	12/6/2006	32.804	-0.0083	-485,633
10	10/3/2006	33.2359	-0.0076	-447,056
11	9/20/2007	33.0437	-0.0074	-434,284

12	3/20/2006	32.2224	-0.0068	-400,751
13	8/27/2007	33.0434	-0.0068	-399,309
14	2/17/2006	34.206	-0.0066	-385,782
15	2/24/2006	32.2014	-0.0064	-377,071

Source: Own Creation

Historic simulation 2011 observations (2003 Crisis observations)

Net Position	26,291,566

	Date	Buy	Returns	VaR(US$)
1	9/30/2003	31.49	-0.0901291960	-5,298,671
2	9/30/2004	31.49	-0.0901291960	-5,298,671
3	1/27/2003	51.18	-0.0701645180	-4,124,953
4	1/27/2004	51.18	-0.0701645180	-4,124,953
5	2/13/2003	44.56	-0.0569215020	-3,346,400
6	2/13/2004	44.56	-0.0569215020	-3,346,400
7	2/16/2003	42.25	-0.0532322420	-3,129,509
8	2/16/2004	42.25	-0.0532322420	-3,129,509
9	8/23/2003	37.51	-0.0494120270	-2,904,920
10	8/23/2004	37.51	-0.0494120270	-2,904,920
11	5/11/2003	46.54	-0.0488515530	-2,871,970
12	5/11/2004	46.54	-0.0488515530	-2,871,970
13	9/29/2003	34.46	-0.0439974470	-2,586,598
14	9/29/2004	34.46	-0.0439974470	-2,586,598
15	5/12/2003	44.86	-0.0367656290	-2,161,441
16	5/12/2004	44.86	-0.0367656290	-2,161,441
17	2/12/2003	47.17	-0.0356102180	-2,093,515
18	2/12/2004	47.17	-0.0356102180	-2,093,515
19	9/23/2003	36.51	-0.0347229070	-2,041,350
20	9/23/2004	36.51	-0.0347229070	-2,041,350
21	11/10/2003	27.73	-0.0340337700	-2,000,836
22	11/10/2004	27.73	-0.0340337700	-2,000,836
23	4/12/2005	28.22	-0.0334525970	-1,966,669
24	3/18/2003	43.84	-0.0332017940	-1,951,924
25	3/18/2004	43.84	-0.0332017940	-1,951,924

Source: Own Creation