

Applying Stress-Testing On Value at Risk (VaR) Methodologies

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Abstract

In recent years, *Value at Risk* (VaR) methodologies, i. e., Parametric VaR, Historical Simulation and the Monte Carlo Simulation have experienced spectacular growth within the new regulatory framework which is Basle II. Moreover, complementary analyses such a *Stress-testing* and *Back-testing* have also demonstrated their usefulness for financial risk managers.

In this paper, we develop an empirical Stress-Testing exercise by using two historical scenarios of crisis. In particular, we analyze the impact of the 11-S attacks (2001) and the Latin America crisis (2002) on the level of risk, previously calculated by different statistical methods. Consequently, we have selected a Spanish stock portfolio in order to focus on market risk.

Key words: Stress-Testing, Value at Risk, Market Risk Management.

I. Introduction

From a conceptual point of view, Value at Risk (VaR) needs to be defined previously in terms of certain parameters (time horizon, level of confidence and currency in reference), as well as some theoretical hypotheses. One of them has to do with stability which supposes that the VaR estimate is obtained for normal market conditions. This principle implies the exclusion of extreme scenarios characterized by high volatility levels that are defined by Jorion (1997) as Event Risk. Stress-Testing is a useful tool for financial risk managers because it gives us a clear idea of the vulnerability of a defined portfolio. By applying Stress-testing techniques we measure the potential loss we could suffer in a hypothetical scenario of crisis.

In the words of William McDonough, the president of the New York Federal Commission Bank,

“One of the most important functions of Stress-testing is to identify hidden vulnerabilities, often the result of hidden assumptions, and make clear to trading managers and senior management the consequences of being wrong in their assumptions”.

II. Scenario Analysis

Broadly speaking, there are different ways to develop the Stress-Testing exercise. Dowd (1998) distinguishes three main approaches:

- *Historical Scenarios of Crisis:* Scenarios are chosen from historical disasters such as the US stock market crash of October 1987, the bond price falls of 1994, the Mexican crisis of 1994, the Asian crisis of 1997, the Argentinean crisis of 2001, etc.
- *Stylized Scenarios:* Simulations of the effects of some market movements in interest rates, exchange rates, stock prices and commodity prices on the portfolio. These movements are expressed in terms of both absolute and relative changes. As the Derivatives Policy Group (1995) suggests:
 - Parallel yield curve in ± 100 basis points.
 - Yield curve shifts of ± 25 basis points.
 - Stock index changes of $\pm 10\%$.
 - Currency changes of $\pm 6\%$.
 - Volatility changes of $\pm 20\%$.

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- Hypothetical Events: A reflection process in which we have to think about the potential consequences of certain hypothetical situations such as an earthquake, an international war, a terrorist attack, etc.

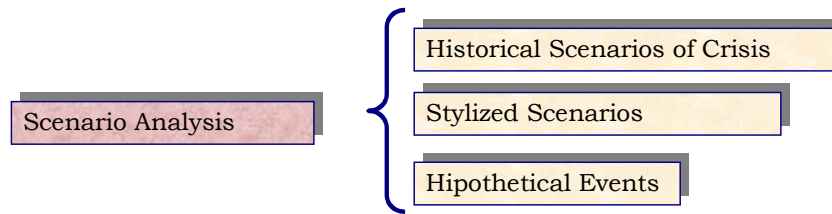


Fig. 1. Types of Scenario Analysis (Dowd, 1998)

III. Methodological Issues

Main Assumptions

In this paper, we want to evaluate the response of Value at Risk methodologies to the Stress-testing exercise based on historical scenarios of crisis. The first step is to calculate VaR estimates by three alternative methods: Parametric VaR, Historical Simulation and the Monte Carlo Simulation. In a second part, we put press on those estimates by introducing both the stressed volatility and the correlation observed in two scenarios of crisis; in particular, the impact of the 11-S attack in New York (2001) and the Latin American Crisis of July 2002.

Portfolio

The selected portfolio consists of five common Spanish stocks, such as: TELEFÓNICA (TEF), BBVA (BBVA), BSCH (SAN), ENDESA (ELE), REPSOL (REP). Those shares are the blue chips of the Spanish Market and they represent more than 50% of the IBEX-35.

It is also important to define the initial value of the position (portfolio), as well as the particular weights of each stock. In that sense, we are going to invest 100.000 € equally divided among the shares (Table 1). Moreover, the date used to calculate VaR has been set on 30 August 2002. If we want to assess the global position, we only have to multiply respective prices and number of shares. In that particular case, we have chosen the same weight for each stock, i. e., 20%.

Table 1

Initial position (euros)

Fecha VeR	TEF	ELE	BBVA	SAN	REP	TOTAL
30/08/2002						
Nº de títulos	2.182	1.653	1.998	2.937	1.504	10.273
Cotización	9.17 €	12.10 €	10.01 €	6.81 €	13.30 €	
Valor	20.000 €	20.000 €	20.000 €	20.000 €	20.000 €	100.000 €
Peso	20%	20%	20%	20%	20%	100%

Time Horizon

In this paper, we have selected a time window from 28 January 2000 to 30 August 2002 and it consists of 651 days of trading. For this period, we have transformed daily price series into logarithmic return series by using the following formula:

$$R_t = \ln \left[\frac{P_t}{P_{t-1}} \right]. \quad (1)$$

In other words, our sample data is composed of 650 historical daily returns. Secondly, we have calculated the historical volatility for each return series as the following equation illustrates:

$$\sigma = \sqrt{\frac{\sum_{i=1}^T (R_i - \mu)^2}{T-1}} \quad i=1,2,\dots,650, \quad (2)$$

where

- σ – sample standard deviation,
- T – total number of observations,
- μ – medium return of the series,
- R_i – return of individual asset.

Finally, in order to build up the stress-testing exercise, we have chosen two historical scenarios which are characterized for their respective high level of volatility:

- 11-S terrorist attacks in New York (2001)
- Brazilian crisis (July 2002).

The daily volatilities for each particular common stock in our portfolio have been calculated by using a mobile monthly window (20 days of market trading) as Figure 1 illustrates. We also plot (Figure 3) the daily volatility observed for the Spanish Stock Market Index (IBEX-35). Both charts reflect how risk, in terms of volatility, increases after these international events occur.

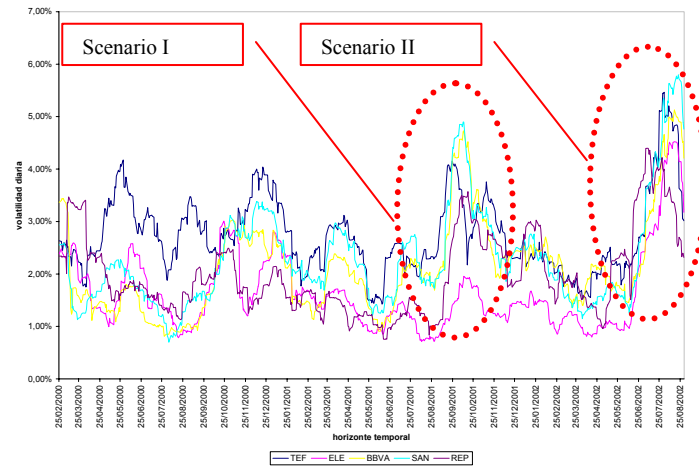


Fig. 2. Daily volatility for individual stocks

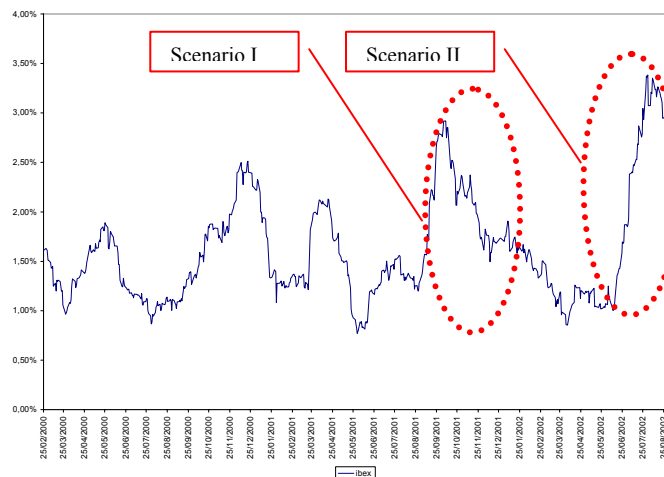


Fig. 3. Daily volatility for IBEX-35

VaR Parameters

Value at Risk (VaR) indicates the maximum loss which we can incur on a particular time horizon with a defined level of confidence. In other words, VaR, as a statistical estimate, requires the following parameters:

- The time horizon will be one day, i.e., we will estimate daily VaR, or DeaR (Daily Earnings at Risk).
- The level of confidence has been set at 95%.
- The currency used for reporting VaR figures is the Euro.

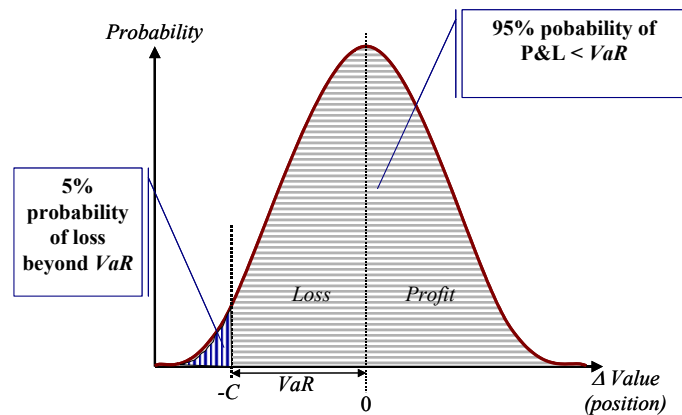


Fig. 4. VaR Concept

IV. Stress-Testing On VaR Methodologies

In general, the basis of the Stress-Testing exercise is to recalculate the Value at Risk estimate by using a higher volatility than the observed one for the historical window selected, i.e., 651 trading days. For this purpose, we have computed the daily volatilities for each scenario of crisis. These are presented in Table 2.

Table 2

Daily volatility for both scenario of crisis

	Fecha VeR	TEF	ELE	BBVA	SAN	REP
	30/08/2002	2.82%	1.81%	2.35%	2.52%	2.13%
Escenario I	Fecha	TEF	ELE	BBVA	SAN	REP
	11/10/2001	3.31%	1.96%	4.73%	4.90%	3.48%
Escenario II	Fecha	TEF	ELE	BBVA	SAN	REP
	09/08/2002	5.11%	4.51%	4.99%	5.63%	3.66%

From an operational point of view, the main problem with Stress-Testing appears when incorporating correlation. Empirical evidence¹ demonstrates that correlation is not constant over time; moreover, it fluctuates in periods of crisis. As *Aragonés and Blanco (2000)* point out, if we put pressure on correlation coefficients in an arbitrary way, probably, the newly calculated correlation matrix will not be positive defined and, as a consequence, its elements will not have internal consistency.

For this reason, it is strongly recommended not only pressing volatilities up, but also the correlation matrix $\bar{\rho}$.

In practice, once we have calculated the correlation coefficients between pairs of stocks using a monthly mobile window, we can select the correlation observed for those days of maximum volatility levels, which corresponds to 11/10/2001 and 09/08/2002, respectively. From here, we have designed both stressed correlation matrices (Tables 3 and 4) whose determinants are positive:

$$|\bar{\rho}| > 0. \quad (3)$$

Table 3

Correlation matrix scenario I

	Matriz de correlación: Escenario I				
	TEF	ELE	BBVA	SAN	REP
TEF	100%	56.82%	66.24%	74.49%	45.88%
ELE	56.82%	100%	74.07%	73.49%	65.36%
BBVA	66.24%	74.07%	100%	93.68%	80.05%
SAN	74.49%	73.49%	93.68%	100%	76.14%
REP	45.88%	65.36%	80.05%	76.14%	100%

Table 4

Correlation matrix scenario II

	Matriz de correlación: Escenario I				
	TEF	ELE	BBVA	SAN	REP
TEF	100%	74.87%	74.39%	76.97%	54.05%
ELE	74.87%	100%	85.19%	84.50%	69.38%
BBVA	74.39%	85.19%	100%	89.75%	76.99%
SAN	76.97%	84.50%	89.75%	100%	59.24%
REP	54.05%	69.38%	76.99%	59.24%	100%

¹ Jackson (1996) and Mori, Ohsawa and Shimizu (1996) analysed such phenomena.

According to *Alexander y Leigh* (1997), to ensure that the correlation matrix is positive defined, it must comply with the Cholesky mathematical property, that is:

$$A \cdot A^T = \overline{\rho}, \quad (4)$$

where,

$\overline{\rho}$ – Correlation matrix,

A – Cholesky matrix,

A^T – Transposed Cholesky matrix.

We have also verified that stressed correlation matrices can be decomposed into Cholesky factors as Tables 5 and 6 illustrate.

Table 5

Cholesky matrix scenario I

	Matriz de Cholesky: Escenario I				
	TEF	ELE	BBVA	SAN	REP
TEF	100%	0.00%	0.00%	0.00%	0.00%
ELE	56.82%	82.29%	0.00%	0.00%	0.00%
BBVA	66.24%	44.27%	60.43%	0.00%	0.00%
SAN	74.49%	37.87%	45.63%	30.57%	0.00%
REP	45.88%	47.75%	47.19%	7.67%	57.70%

Table 6

Cholesky matrix scenario II

	Matriz de Cholesky: Escenario II				
	TEF	ELE	BBVA	SAN	REP
TEF	100%	0.00%	0.00%	0.00%	0.00%
ELE	74.87%	66.29%	0.00%	0.00%	0.00%
BBVA	74.39%	44.50%	49.86%	0.00%	0.00%
SAN	76.97%	40.54%	28.98%	39.90%	0.00%
REP	54.05%	43.61%	34.85%	-25.41%	57.58%

Stress-Testing and Parametric VaR

Stress-Testing is very easy to apply when dealing with the parametric methodology because we only have to estimate on 30/08/2002 the stressed VaR for each scenario of crisis as formula 5 indicates:

$$VaR(stressed) = \omega_i \cdot \underbrace{1,6449}_{Z^*} \cdot \sigma_{i,daily}^* \quad (5)$$

where

ω_i – initial value of the position maintained in stock_i (20.000 Euros),

$\sigma_{i,daily}^*$ – daily volatility of the stock_i associated to a stressed scenario,

Z^* – depends on the level of confidence; at 95% confidence its value is equal to -1,6449.

In Tables 7 and 8 we present the individual VaR estimates associated with both scenarios of crisis. We can define a new magnitude which is raw VaR, with the aggregation of individual VaR's, so it give us a global measure of risk without standing diversification benefits. If we want to have a more realistic idea of the risk exposure, it is necessary to introduce another estimate, which is diversified VaR or net VaR. For incorporating diversification effects, we apply the following formula:

$$VaR_{portfolio,t} = \sqrt{V^T \cdot \rho^* \cdot V} \quad (6)$$

$V = \begin{bmatrix} VaR_{1,t} \\ VaR_{2,t} \\ \vdots \\ VaR_{n,t} \end{bmatrix}$: Column vector of dimension $(n \times 1)$ which represents non diversified indi-

vidual VaR's. It is calculated from the product of $V = \overline{\sigma^*} \cdot Z^* \cdot \overline{\omega}$

$V^T = [VaR_{1,t} \quad VaR_{2,t} \quad \dots \quad VaR_{n,t}]$: The transposed vector of V is calculated as $V^T = \overline{\omega^T} \cdot Z^* \cdot \overline{\sigma^*}$.

Table 7

Individual VaR scenario I

Escenario I	TEF	ELE	BBVA	SAN	REP
Valor inicial	20.000 €	20.000 €	20.000 €	20.000 €	20.000 €
Volatilidad diaria	3,31%	1,96%	4,73%	4,90%	3,48%
Z (95%)	1,6449	1,6449	1,6449	1,6449	1,6449
VeR individual	1.090,37 €	643.24 €	1.555,58 €	1.611,27 €	1.145,17 €

Table 8

Individual VaR scenario II

Escenario II	TEF	ELE	BBVA	SAN	REP
Valor inicial	20.000 €	20.000 €	20.000 €	20.000 €	20.000 €
Volatilidad diaria	5.11%	4.51%	4.99%	5.63%	3.66%
Z (95%)	1,6449	1,6449	1,6449	1,6449	1,6449
VeR individual	1.681,16 €	1.484,15 €	1.641,65 €	1.853,01 €	1.204,43 €

In Tables 9 and 10 we have computed the diversified VaR for our portfolio in both stressed scenarios. Moreover, we have also calculated another interesting estimate, which is EaR (Earning at Risk). It is the maximum gain we can expect with a certain confidence level within a selected time period. In particular, we have estimated a 95% percentile. We notice that both figures, VaR and EaR, coincide because of the underlying assumption of normal distribution.

Table 9

Correlated VaR scenario I

Escenario I		Nivel de confianza	Horizonte temporal
VeR correlacionado	5.391,11 €	95%	1 dia
EaR correlacionado	5.391,11 €		
Ratio VeR/EaR	100%		
Ratio VeR/Valor de la cartera	5.39%		

Table 10

Correlated VaR scenario II

Escenario II		Nivel de confianza	Horizonte temporal
VeR correlacionado	7.061,43 €	95%	1 dia
EaR correlacionado	7.061,43 €		
Ratio VeR/EaR	100%		
Ratio VeR/Valor de la cartera	7.06 %		

Stress-Testing and the Monte Carlo Simulation

The Monte Carlo Simulation is based on the generation of random prices as follows:

$$P_t = P_{t-1} \cdot e^{\sigma \cdot \varepsilon \cdot \sqrt{t}}, \quad (7)$$

where

P_t is the simulated price,

P_{t-1} is the current price of the stock,

ε is a random variable which is distributed as a normal standardized, i.e., with $\mu=0$ and $\sigma=1$,

σ is the daily volatility of the stock,

\sqrt{t} is an adjusted factor which transforms daily volatility into wider time horizons. In this paper, as VaR is estimated one day hence, its value is equal to one.

In the case of a portfolio, composed by multiple assets, the previous formula cannot be applied because it is only valid for a single asset. Therefore, the process of generating random numbers is more complex; in other words, the historical correlation between shares should be incorporated in such a process. For this reason, and from a methodological point of view, the normal random numbers, ε , should be transformed into correlated random numbers, Z , by using the Cholesky Matrix:

$$\underbrace{\begin{bmatrix} Z_{TEF} \\ Z_{ELE} \\ Z_{BBVA} \\ Z_{SAN} \\ Z_{REP} \end{bmatrix}}_{\substack{\text{Correlated} \\ \text{random} \\ \text{numbers}}}_{5 \times 1} = \underbrace{\begin{bmatrix} A^* \end{bmatrix}}_{\substack{\text{Cholesky-matrix} \\ 5 \times 5}} \cdot \underbrace{\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix}}_{\substack{\text{random} \\ \text{numbers}}}_{5 \times 1}, \quad (8)$$

where

Z is a vector of transformed normal variables which embodies the historical correlation,

ε is a vector of normal standardized variables,

A^* is the stressed Cholesky Matrix for each scenario of crisis as Tables 5 and 6 show, respectively.

For simulating 1.000 correlated and stressed prices from current prices (see Table 1) we should generate 1.000 Z vectors, as the sub-index i indicates in the following equation:

$$\begin{aligned} P_{TEF,i}^i &= 9,17 \cdot e^{\sigma_{TEF}^* \cdot Z_{TEF}^i} \\ P_{ELE,i}^i &= 12,10 \cdot e^{\sigma_{ELE}^* \cdot Z_{ELE}^i} \\ P_{BBVA,i}^i &= 10,01 \cdot e^{\sigma_{BBVA}^* \cdot Z_{BBVA}^i} \\ P_{SAN,i}^i &= 6,81 \cdot e^{\sigma_{SAN}^* \cdot Z_{SAN}^i} \\ P_{REP,i}^i &= 13,30 \cdot e^{\sigma_{REP}^* \cdot Z_{REP}^i} \end{aligned} \quad i=1,2,\dots,1.000. \quad (9)$$

Once we have computed the random paths for individual stock prices, we can obtain the simulated value for the portfolio by multiplying number of shares and simulated prices. We can also calculate the simulated profit and loss distribution as:

$$P_s \text{ \& } L_s = W_i - W_t, \quad (10)$$

where

W_i is the simulated value for the scenario i ,

W_t is the current portfolio value on 30 August 2002, which is 100.000 Euros.

If we put in order each simulated result for the portfolio from low to high, we can directly infer both VaR and EaR estimates as 5% and 95% percentiles of that distribution as well as other parameters such as standard deviation and media (Tables 11 and 12).

Table 11

Monte Carlo Simulation scenario I

Pérdida máxima	-9.315,52 €		
Ganancia máxima	12.602,29 €		
Promedio	118,62 €		
Desviación estándar	3.330,85 €	Nivel de confianza	Horizonte temporal
VeR	5.179,94 €	95%	1 día
EaR	5.623,93 €		
Ratio VeR/EaR	92,11%		
Ratio VeR/Valor posición	5.18%		

Table 12

Monte Carlo Simulation scenario II

Pérdida máxima	-14.476,87 €		
Ganancia máxima	14.905,28 €		
Promedio	-28,46 €		
Desviación estándar	4.340,78 €	Nivel de confianza	Horizonte temporal
VeR	7.032,16 €	95%	1 día
EaR	7.261,98 €		
Ratio VeR/EaR	96,84%		
Ratio VeR/Valor posición	7,03%		

Stress-Testing and Historical Simulation

To some extent, Stress-Testing appears to be a mechanical process based on increasing the volatility and correlation following a certain mathematical formulation. In contrast, when applying Stress-Testing on a Historical Simulation, this exercise presents a clear difference. In that sense, correlation can not be stressed directly because it is incorporated in the historical simulated price series. So, the practical implementation goes through the following steps:

- Selection of two historical windows associated to both scenarios of crisis. In particular, we have computed the previous 20 days of trading from 11/10/2001 for the first scenario, and 20 days of trading from 9/08/2002 for the second one.
- Computation of historical stock returns for each time window.
- Generation of historical simulated prices by using the following formula:

$$P_i = P_t \cdot e^{R_i}, \quad (11)$$

where

P_i is the simulated price for the scenario i ,

P_t is the current price of the stock,

R_i is the historical return $i = 1, 2, \dots, 19$.

From this point, the process is identical to that described for the Monte Carlo Simulation. In Tables 13 and 14 we sum up all the calculations for each scenario analyzed.

Table 13

Historical Simulation scenario I

VeR correlacionado	4.456,76 €	Nivel de confianza	Horizonte temporal
EaR correlacionado	4.540,95 €	95%	1 dia
Ratio VeR/EaR	98,15%		
Ratio VeR/Valor posición	4,46%	Escenario I	

Table 14

Historical Simulation scenario II

VeR correlacionado	5.769,37 €	Nivel de confianza	Horizonte temporal
EaR correlacionado	6.858,42 €	95%	1 dia
Ratio VeR/EaR	84,12%		
Ratio VeR/Valor posición	5,77%	Escenario II	

Finally, we conclude with a comparison among the results of the Stress-Testing as Table 15 illustrates.

Table 15

Summary

Paramétrico	Normal	Escenario I	Escenario II
VeR	2.978,38 €	5.397,11 €	7.061,43 €
EaR	2.978,38 €	5.397,11 €	7.061,43 €
Ratio VeR/EaR	100,00%	100,00%	100,00%
Ratio VeR/Valor posición	2,98%	5,39%	7,06%
Monte Carlo	Normal	Escenario I	Escenario II
VeR	2.810,13 €	5.179,94 €	7.032,16 €
EaR	3.155,87 €	5.623,93 €	7.261,98 €
Ratio VeR/EaR	89,04%	92,11%	96,84%
Ratio VeR/Valor posición	2,81%	5,18%	7,03%
Simulación Histórica	Normal	Escenario I	Escenario II
VeR	2.817,33 €	4.456,76 €	5.769,37 €
EaR	2.727,47 €	4.540,95 €	6.858,42 €
Ratio VeR/EaR	103,29%	98,15%	84,12%
Ratio VeR/Valor posición	2,82%	4,46%	5,77%

V. Conclusions

After applying Stress-testing on VaR methodologies, the main conclusions obtained from Table 15 are as follows:

1. In general, the Stress-Testing exercise always implies a higher level of risk measured in terms of VaR. As Table 15 reflects, VaR figures increase for both stressed scenarios.
2. The impact of Brazilian crisis (scenario II) in our portfolio is greater than that of the 11-S terrorist attacks. That is due to the narrow relationship between the Spanish firms (BSCH, REPSOL, TELEFÓNICA, BBVA AND ENDESA, whose shares are included in the portfolio) and the Latin American countries such as Argentina, Brazil, etc.
3. The response of VaR methodologies to the Stress-Testing exercise is not the same. For both scenarios of crisis, Parametric VaR is the most reactive. In contrast, in terms of EaR, the Monte Carlo Simulation demonstrates more sensitivity.
4. From the methodological point of view, we should ensure the internal consistency of the Stress-testing exercise. For that reason, we must verify that the Correlation matrix is positive defined and, thus can be decomposed into its Cholesky factors.

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