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Article

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National University of Political Studies and Public Administration
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Market Risk Management - Modeling the Distribution of Losses Using Romanian Securities

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Abstract: Market risk with its major components, such as the risk of interest rate instruments, currency risk, and risk related to stock and commodity investigations, represents the risk of losses in balance sheet and off-balance sheet positions, resulting from negative market price movements. Portfolios of instruments traded for short-term profits, called trading portfolios, are exposed to market risk or risk of loss, resulting from changes in the prices of instruments, such as stocks, bonds, and currencies. This paper, through theoretical and empirical methods, assesses risk by using the probability distribution of daily variations in government bond yields. Long-term government securities in most cases have a higher return due to the higher level of risk assumed regarding changes in risk factors such as interest rates, which, when raised above a certain threshold, cause a price decrease, which illustrates the price sensitivity to long-term bonds. Using Value at Risk as the main element for determining the maximum possible loss on investment in a trading book, as well as statistical tests to measure the similarity between two or more distributions such as the Kolmogorov-Smirnov test, Anderson -Darling or Chi-squared, we identified the most representative theoretical probabilistic distribution both for the value of losses and for the frequency of risk events. At the same time, the most used distributions to manage the market risk by advanced methods and, of course, the distributions used in this paper, were Weibull and Pareto (including the generalized form), as well as other distributions, because they better capture the asymmetry in queues and the presence of thick tails. Modeling the distribution of losses requires choosing from a set of probable distributions, the one with the highest log-likelihood.

Keywords: market risk management; value at risk; distribution of losses.

Introduction

Market risk is the ability of banks to incur losses due to a negative impact on the market value of assets or gains as a result of market changes. This type of risk is caused by fluctuations in various market parameters, such as exchange rates, interest rates, and different commodity and stock prices, taking into account that banks may be concerned with stocks and securities, as well as off-balance sheet items, such as forward contracts in the case of foreign exchange contracts or futures contracts in the case of commodities. Market risk can also be seen as price risk, as banks can make either a profit or a loss due to the movement of the market price of the instruments used. The market risk factors include several components, such as interest rates, exchange rates, stock and commodity prices, including their volatility (a factor with a strong influence on the value of derivative options) and the correlations between them. Market risk is made up of several types of risk, including currency risk, interest rate risk, price risk, specific risk, liquidity risk, and equity risk.

The purpose of measuring market risk is that the market risk measurement system should illustrate the sensitivity of end-of-day exposure to potential adverse changes in the factors that influence the value of the company's positions and therefore most of the time it can be said that it generally reflects exposure to normal market conditions. From the perspective of the banking system, exposure to market risk by investing in government securities is centered on opportunity costs and interest rate fluctuations through significant positive changes in prices. Interbank interest rates are indicators to anticipate developments, fixed income

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instruments. In the case of bonds, they have a fixed rate called a coupon, except that investment decisions are not based solely on their value but rather on their return to maturity.

The exchange rate is relevant for the foreign exchange position, which has become an indirect risk factor for the loan portfolio of uncovered borrowers, and the expectations related to the appreciation or depreciation of the exchange rate are directly related to the confidence of foreign investors in holding instruments denominated in local currency.

Literature review and model development

Value at Risk (VaR) is a statistical procedure by which the financial risk of an investment can be measured and which usually indicates the 1% or 5% probability of incurring a loss in a certain period (1 day, 1 week, or even 1 month). In other simplified words, VaR, also known as "value at risk", represents the maximum loss that an investment can bear in a time horizon.

This value is most commonly used by commercial and investment banks to determine the magnitude and ratio of potential losses in their institutional portfolios. This method has statistical assumptions that are often not relevant for financial data because in specialized studies it is mentioned that the evolution of asset prices is considered to follow a normal distribution and the past price information is sufficient to quantify future risk.

Knowing the probability distribution of daily changes in government bond yields becomes a factor of significant importance in risk assessment. Therefore, the loss distribution approach is similar to the risk value method, representing a direct method of risk assessment by which different probability distributions are simulated.

The most well-known statistical tests that have the role of measuring the similarity between two or more distributions and which we will use in this paper are the Kolmogorov-Smirnov, Anderson-Darling, and Chi-squared test and, as distributions through which the market risk is managed, we will use the following: Weibull, Log-Logistic, Pareto, and Gamma. One of the important aspects to start the analysis on the loss assessment is choosing the database. Long-term government securities offer a higher return, given the additional level of risk assumed regarding changes in risk factors, but the longer the waiting period to maturity, the more the price will decrease as interest rates increase, as shown by the price sensitivity for long-term bonds. Therefore, we chose a long period that captures the various phenomena and possible structural changes that do not have clarity for the portfolio instruments.

There are several ways to calculate the value at risk, such as the parametric VaR method, which is characterized using estimated profitability data and involves a normal distribution of profitability, the historical VaR method, which is characterized by the use of historical data and the Monte Carlo method, which is characterized by the use of computer software which generates hundreds, or thousands of possible results based on the initial data entered by the user.

According to Hayn's (1995) study, from the point of view of risk management, the hypothesis is that all shareholders who have a liquidation option do not expect losses to be perpetuated. The conclusions of the study show that the longer the response time, the more the response coefficient is given by the loss effect.

Kupiec, P. (1996) examines the informational content of trading volume in terms of forecasting the volatility of conditions and market risk of international stock markets, and the performance of parametric models Value at Risk (VaR) is investigated in times of crisis and post-crisis. The findings indicate that the inclusion of trading volume in the volatility specification greatly improves the performance of the proposed VaR models, especially in times of crisis.

Darryll Hendricks (1996) shows the importance of using value-at-risk models and emphasizes the importance of market participants finding and using credible risk measurement models. On the other hand, McNeil and Fre (2000) analyze a process for calculating the value of risk and the value of the associated risk and using the backtesting method applied to the historical daily return series, it is shown that the procedure

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uses better estimates than other procedures that neglect the heavy tail of innovations or the stochastic nature of volatility.

Acerbi and Tasche (2002) reported that expected deficit (ES) is a measure of risk rather than a remedy for value-at-risk (VaR) deficiencies. The authors compared some of the definitions of expected deficit (ES) illustrating that there is a definition that is robust in providing a consistent measure of risk, regardless of the underlying distributions. Simone Manganelli and Robert F. Engle (2003) studied and analyzed the performance of the best-known univariate VaR methodologies, and the results they reached were as a historical simulation method can be considered as exceptional circumstances of the CAViaR framework, of course taking account of the basic assumptions and shortcomings of the model. Campbell (2005) analyzes a variety of backtests, which highlight the behavior of Value-at-Risk (VaR) measures based on the unconditional hedging properties of a VaR model and their relevance from a risk management perspective. The conclusion reached was that tests examining several types of Quantiles can determine inaccurate VaR models.

Csaba Balogh-Gergely Kóczán (2009) shows the importance of market risk and government securities returns, methodologies, and technical calculations. It shows that transparency in financial markets is extremely important and the Hungarian government security market is less transparent than usual in Western Europe due to the lack of electronic interbank trading platforms. He uses the information at risk (Value at Risk) as a standard tool for the maximum possible loss from the investigation of a trading book over a certain time horizon.

Sandip Mukherji (2011) investigates the market and inflation risks of treasury securities with different maturities at different times. The results showed that securities, real returns, volatility, market, and inflation risks are increasing based on the time to maturity. Also, Nihan Sölpük Turhan (2020) shows that statistical tests are frequently used to analyze whether statistical tests are used in accordance with research and chi-square tests are frequently used in the paper. The method used by the author was a qualitative one and was developed based on the vast specialized literature in the field. In Nihan Sölpük Turhan's study, a delimitation was made between the fit of the model on the database, homogeneity, and the independence of chi-square tests. The author, using three different tests, performed several studies that differ depending on the population hypothesis and statistical formulas.

Treapăt and Anghel (2013) analyzed and highlighted the features of management and especially financial management. The conclusions highlighted that in the business field a strong point that is part of the management objectives is to gain new clients, to increase the market share that leads to maximizing the profits obtained in the long term.

As a series of data used, as mentioned above, in calculating the value at risk and modeling the distribution of losses to quantify the market risk we've used yields on 5-year government bonds in Romania, calculated based on the midpoint between bid and ask daily quotations for approximately 10 years: 10/01/2011 – 06/09/2021, at which calculation methods were applied for the daily yields and the returns over one day, five days and ten days respectively (in percentages). The analysis was performed using EViews 10 software, Distribution Fitting package, Excel, and EasyFit to calculate losses.

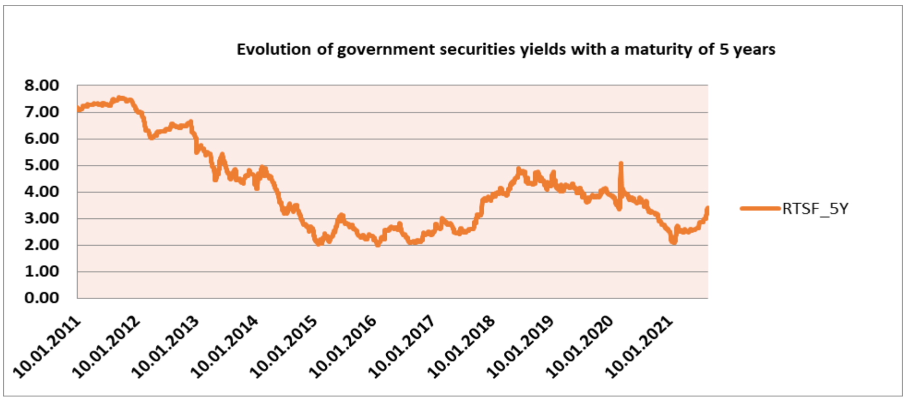
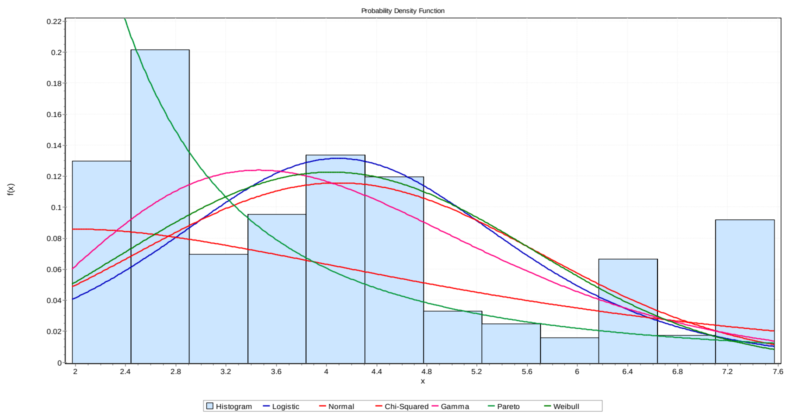


Figure 1. Evolution of government securities yields with a maturity of 5 years (Own representation)

Distribution fitting modeling

Modeling the distribution of losses requires choosing from a set of probable distributions the one with the highest log-likelihood. The normal distribution, considered implicit most of the time in the loss analysis, is not explanatory for the evolution of the data, the non-parametric or even bimodal or trimodal distributions being present most often. In the following we will present several types of distributions tested using the EasyFit software and, later, we will choose the one that has the highest log-likelihood.

Very often there are several non-parametric distributions, such as the bimodal or trimodal ones, as is the case of the data series collected and analyzed in this paper.



RTSF 5Y	
Probabilistic function	**Log-likelihood**
Normal	**-5,088.75**
Weibull	**-4,997.92**
Logistic	**-5,138.48**
Pareto	**-8,907.07**
Gamma	**-4,859.94**
Chi-Square	**-5,525.95**
Maximum	**-4,859.94**

Figure 2. RTSF (5Y) probability density function
(Own representation)

Comparing the results obtained from the table above, it can be seen that the most appropriate distribution on the analyzed data series and which has the highest log-likelihood is the Gamma distribution. Another way in which the veracity of the results obtained in Fig. 3 can be observed is by performing QQ-Plot and PP-Plot.

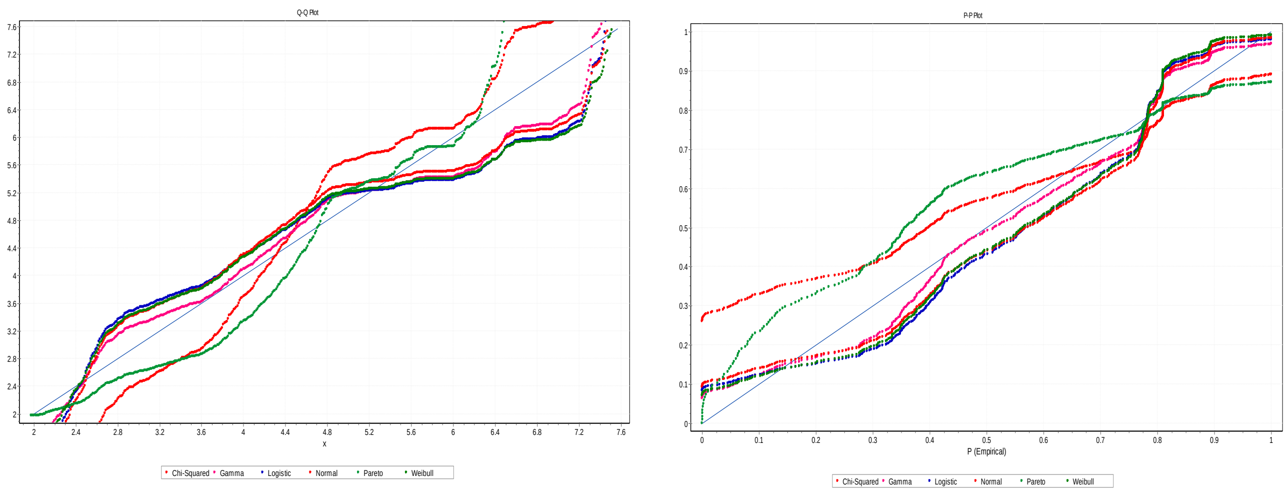


Figure 3. RTSF (5Y)- QQ-Plot, PP-Plot
(Own representation)

Next, we've applied methods to calculate yields and change yields to one day, five days, and ten days (as a percentage). In the following, we will also illustrate the results obtained.

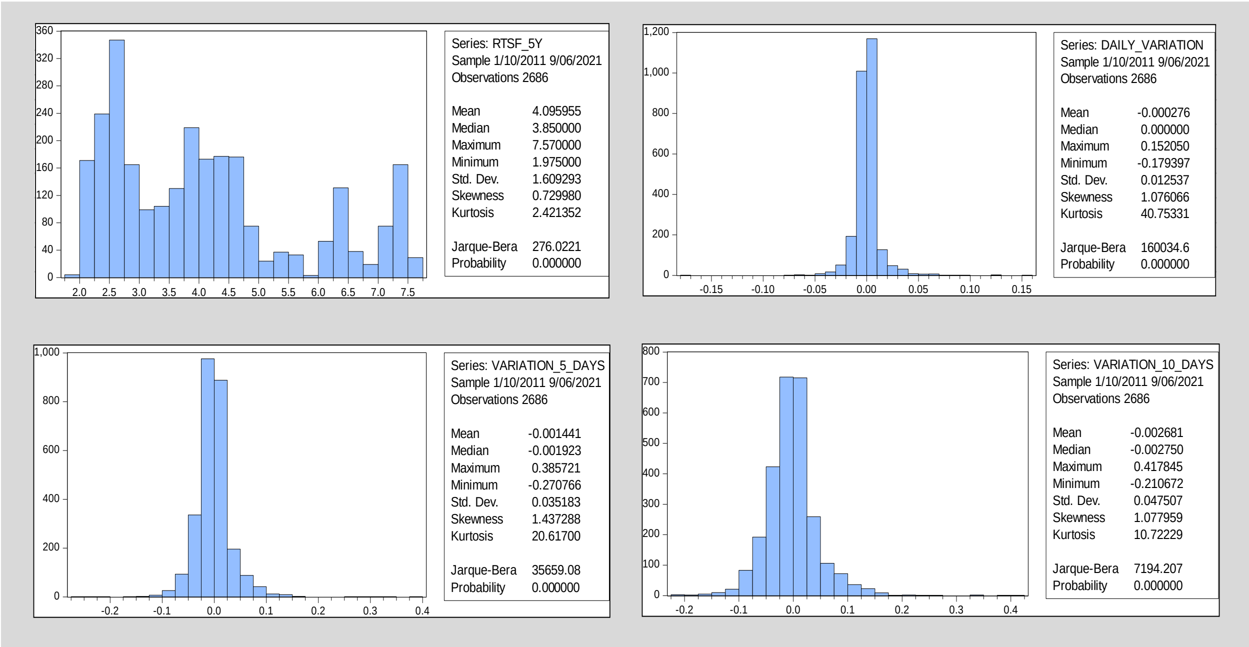


Figure 4. Histogram and descriptive statistics of the residual series and the variation of the series (Own representation)

The four figures above show the results obtained on the data series, namely the RTSF series and the change of RTSF at one day, five days, and ten days respectively, having a probability of 0.0000, which is lower than the allowable threshold of 0.05, which indicates that the series does not come from a normal distribution. For the RTSF_5Y series, the Kurtosis coefficient, having a value of 2.42, which is not exceeding the threshold value of 3, shows that the RTSF series comes from a platikurtic distribution and the asymmetry is to the right, due to the positive value of the Skewness coefficient (0.72) with a value different than 0.

The rest of the obtained results show that the RTSF series, with the returns after one day, five days, and ten days, show an asymmetry to the right, with positive values exceeding the value of 0, the distribution being a leptokurtic one. Below we will test which distribution is best suited for the initial series and the three series created, namely the series of yields after one day, five days, and ten days.

The goodness of Fit- Summary RTSF 5Y

The Goodness of Fit-Summary of a statistical model describes how well it fits a set of observations. The goodness of Fit measures usually summarizes the discrepancy between the observed values and the expected values within the model in question. Such measures can be used in statistical testing of hypotheses, such as: testing the normality of the residues, testing whether two samples are taken from identical distributions (Kolmogorov - Smirnov test) or whether the resulting frequencies are following a specified distribution (Pearson's chi-square test). In the analysis of variance, one of the components in which the variance is partitioned may be a sum of squares that do not match.

Analyzing from a statistical point of view by using the Kolmogorov-Smirnov test for the series of yields of government securities with a maturity of 5 years, we will illustrate in the table below the most suitable distributions to be used in explaining the distribution of the data series and the returns after one day, five days and ten days.

Tabel 1. Goodness of Fit- Summary RTSF_5Y, RTSF 5Y_1d, RTSF 5Y_5d, RTSF5Y_10d

Goodness of Fit - Summary-RTSF							Goodness of Fit - Summary-RTSF- 1 day variation						
RTSF	Kolmogorov-Smirnov		Anderson Darling		Chi-Squared		RTSF_1d	Kolmogorov-Smirnov		Anderson Darling		Chi-Squared	
Distribution							Distribution						
	Statistic	Rank	Statistic	Rank	Statistic	Rank		Rank	Statistic	Rank	Statistic	Rank	Statistic
Gen. Pareto	0.0555	1	31.524	10	N/A	N/A	Johnson SU	0.10006	1	42.103	2	530.5	2
Johnson SB	0.06503	2	301.43	52	N/A	N/A	Dagum (4P)	0.11788	2	65.186	5	799.43	7
Pearson 6 (4P)	0.06506	3	21.329	3	401.22	3	Log-Logistic (3P)	0.12056	3	63.384	3	745.14	4
Gamma (3P)	0.06517	4	21.422	5	408.02	4	Cauchy	0.1236	4	23.487	1	456.87	1
Pert	0.06842	5	21.141	1	523.16	15	Burr (4P)	0.12756	5	63.835	4	722.11	3
Gen. Gamma (4P)	0.06896	6	27.101	7	N/A	N/A	Gen. Extreme Value	0.13532	6	182.7	16	N/A	N/A
Burr (4P)	0.06983	7	21.165	2	444.76	9	Laplace	0.13962	7	80.62	6	769.22	6
Weibull (3P)	0.07075	8	21.389	4	443.69	8	Error	0.13962	8	80.62	7	769.22	5
Dagum (4P)	0.07524	9	31.176	9	N/A	N/A	Gen. Pareto	0.16271	9	706.91	28	N/A	N/A
Triangular	0.07892	10	31.926	13	410.64	5	Hypersecant	0.16513	10	118.69	8	1264.1	8
Pearson 5 (3P)	0.08418	11	34.478	16	452.06	10	Pearson 5 (3P)	0.16657	11	150.2	11	1484	9
Lognormal (3P)	0.0846	12	31.92	12	398.15	2	Pearson 6 (4P)	0.16658	12	148.25	10	1484	10
Frechet (3P)	0.08679	13	35.559	20	504.32	13	Lognormal (3P)	0.16914	13	153.61	12	1524.2	11
Burr	0.08726	14	37.287	24	537.5	16	Fatigue Life (3P)	0.16978	14	154.67	13	1525.3	12
Inv. Gaussian (3P)	0.08745	15	31.698	11	410.77	6	Logistic	0.17431	15	140.43	9	1603.3	13
Log-Logistic (3P)	0.08755	16	36.671	22	415.73	7	Inv. Gaussian (3P)	0.1819	16	157.46	14	1848.5	14
Gamma	0.08842	17	41.366	27	687.51	30	Gamma (3P)	0.1843	17	185.37	18	1931.7	15
Gen. Extreme Value	0.0902	18	35.098	19	658.84	24	Gen. Gamma (4P)	0.18622	18	180.19	15	1962	16
Frechet	0.09034	19	45.121	29	500.69	12	Normal	0.18818	19	183.17	17	2103.8	17
Pearson 6	0.09097	20	35.094	18	615.65	21	Erlang (3P)	0.18949	20	185.76	20	2112.8	18
Log-Gamma	0.09121	21	34.874	17	546.75	17	Beta	0.19241	21	185.8	21	2207	19
Log-Pearson 3	0.09148	22	34.27	14	664.26	25	Gumbel Max	0.19284	22	187.86	22	N/A	N/A
Pearson 5	0.09187	23	34.288	15	603.92	20	Error Function	0.19651	23	185.68	19	2213.9	20
Fatigue Life (3P)	0.09307	24	29.954	8	389.49	1	Uniform	0.22418	24	647.72	27	N/A	N/A
Inv. Gaussian	0.09362	25	36.476	21	679.16	29	Weibull (3P)	0.22699	25	297.79	25	N/A	N/A
Fatigue Life	0.09467	26	37.264	23	665.64	26	Frechet (3P)	0.23348	26	291.21	23	N/A	N/A
Lognormal	0.09489	27	37.849	25	672.44	28	Gumbel Min	0.24785	27	293.45	24	N/A	N/A
Reciprocal	0.09816	28	26.471	6	549.09	18	Kumaraswamy	0.26071	28	435.88	26	4807.5	21
Gen. Gamma	0.09816	29	46.235	31	739.07	33	Pert	0.36941	29	759.83	29	10202	22
Gumbel Max	0.09925	30	40.797	26	727.38	32	Triangular	0.4024	30	770.63	30	14799	23
Nakagami	0.10055	31	50.553	34	789.4	37	Rayleigh (2P)	0.5193	31	1001.1	31	16704	25
Normal	0.103	32	83.135	40	781.71	36	Power Function	0.52223	32	1036.6	32	20801	26
Log-Logistic	0.10575	33	43.832	28	670.83	27	Exponential (2P)	0.56071	33	1111.4	33	15683	24
Exponential (2P)	0.10587	34	45.819	30	452.59	11	Levy (2P)	0.61951	34	1311.1	34	48607	27
Goodness of Fit - Summary-RTSF- 5 days variation							Goodness of Fit - Summary-RTSF- 10 days variation						
RTSF_5d	Kolmogorov-Smirnov		Anderson Darling		Chi-Squared		RTSF_10d	Kolmogorov-Smirnov		Anderson Darling		Chi-Squared	
Distribution							Distribution						
	Rank	Statistic	Rank	Statistic	Rank	Statistic		Rank	Statistic	Rank	Statistic	Rank	Statistic
Cauchy	0.04145	1	10.666	1	122.03	1	Laplace	0.03517	1	5.2701	1	54.53	2
Dagum (4P)	0.06956	2	22.34	6	350.74	7	Error	0.03517	2	5.2701	2	54.53	1
Log-Logistic (3P)	0.06984	3	20.984	5	348.9	6	Dagum (4P)	0.04311	3	8.5008	4	149.61	5
Johnson SU	0.07131	4	13.137	2	228.09	4	Log-Logistic (3P)	0.04402	4	8.8907	6	155.62	6
Laplace	0.07181	5	17.998	3	140.92	3	Burr (4P)	0.04421	5	8.6102	5	158.89	7
Error	0.07181	6	17.998	4	140.92	2	Cauchy	0.05362	6	16.13	8	177.45	8
Gen. Extreme Value	0.08605	7	67.257	9	N/A	N/A	Hypersecant	0.06288	7	12.953	7	130.02	3
Hypersecant	0.09934	8	36.698	7	341.34	5	Johnson SU	0.06339	8	7.9539	3	137.43	4
Burr (4P)	0.10418	9	74.686	16	707.2	16	Gen. Extreme Value	0.06598	9	48.152	21	N/A	N/A
Pearson 5 (3P)	0.106	10	74.044	13	732.13	18	Pearson 6 (4P)	0.07346	10	37.687	18	370.91	20
Logistic	0.11037	11	50.194	8	479.06	8	Logistic	0.07594	11	21.056	9	197.83	9
Lognormal (3P)	0.11785	12	73.618	12	701.37	15	Pearson 5 (3P)	0.07939	12	30.792	10	342.21	17
Fatigue Life (3P)	0.11867	13	74.143	14	689.16	11	Lognormal (3P)	0.08043	13	31.207	11	340.71	16
Gen. Pareto	0.11908	14	638.23	28	N/A	N/A	Fatigue Life (3P)	0.08153	14	31.645	12	338.7	13
Gen. Gamma (4P)	0.11962	15	73.204	11	691.57	13	Gen. Gamma (4P)	0.08185	15	32.455	14	343.62	18
Gamma (3P)	0.11971	16	72.918	10	691.57	12	Gamma (3P)	0.08286	16	32.213	13	338.93	14
Frechet (3P)	0.12268	17	105	22	N/A	N/A	Beta	0.08336	17	33.855	15	354.91	19
Beta	0.12489	18	82.92	18	719.02	17	Erlang (3P)	0.09537	18	34.678	16	308.48	10
Erlang (3P)	0.12697	19	74.488	15	670.53	10	Normal	0.09541	19	46.669	20	332.11	12
Inv. Gaussian (3P)	0.12702	20	75.904	17	668.84	9	Inv. Gaussian (3P)	0.09632	20	34.867	17	309.97	11
Normal	0.1279	21	84.529	19	694.12	14	Gumbel Max	0.09916	21	45.72	19	340.59	15
Gumbel Max	0.12803	22	87.334	20	N/A	N/A	Gen. Pareto	0.10304	22	578.16	29	N/A	N/A
Error Function	0.14319	23	90.286	21	765.86	19	Error Function	0.11544	23	55.608	22	375.76	21
Uniform	0.16794	24	584.84	26	N/A		Weibull (3P)	0.11955	24	101.52	23	812.57	22
Weibull (3P)	0.17404	25	165.54	23	N/A	N/A	Kumaraswamy	0.12099	25	102.53	24	840.7	23
Gumbel Min	0.18259	26	186.97	24	N/A	N/A	Frechet (3P)	0.13828	26	164.33	26	N/A	N/A
Kumaraswamy	0.18686	27	236.78	25	2084.7	20	Uniform	0.14322	27	588.68	30	N/A	N/A
Pert	0.31103	28	605.14	27	6957	22	Gumbel Min	0.14587	28	148.49	25	N/A	N/A
Pearson 6 (4P)	0.34938	29	655.7	29	8086.1	23	Pert	0.25868	29	411.44	27	3602.1	25
Triangular	0.38521	30	676.18	30	6752.7	21	Rayleigh (2P)	0.31654	30	452.42	28	3295.7	24
Rayleigh (2P)	0.43558	31	770.03	31	8530.6	24	Triangular	0.39568	31	642.21	31	4213	26
Power Function	0.49238	32	950.61	32	14925	25	Exponential (2P)	0.44041	32	786.18	32	7461.3	27
Exponential (2P)	0.51603	33	982.89	33	15333	26	Power Function	0.44162	33	803.02	33	N/A	N/A
Levy (2P)	0.58786	34	1213.6	34	28259	27	Levy (2P)	0.53817	34	1044.5	34	13425	28

Source: Made by the authors using EasyFit Software and data collected from the NBR website

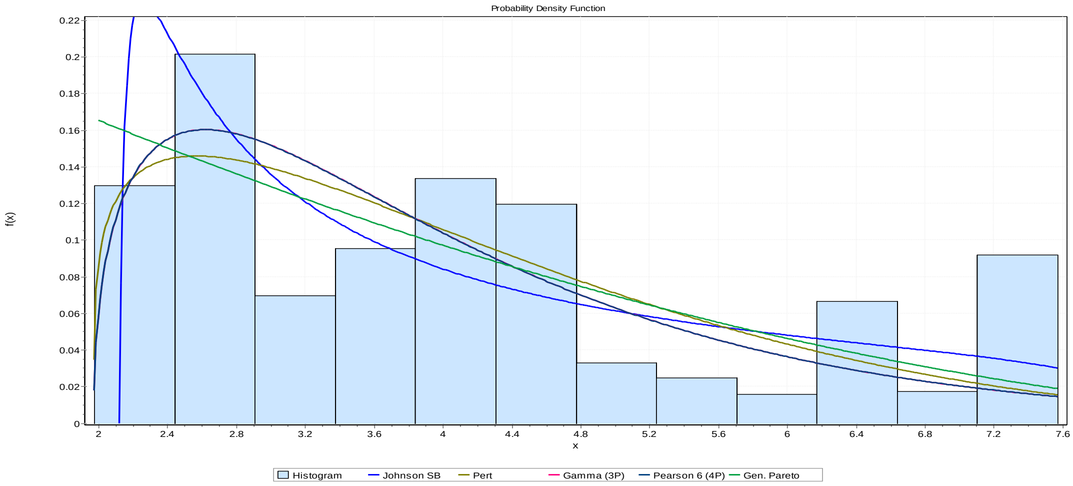


Figure 5. Probability Density Function for the most illustrative 6 distributions for RTSF (Own representation)

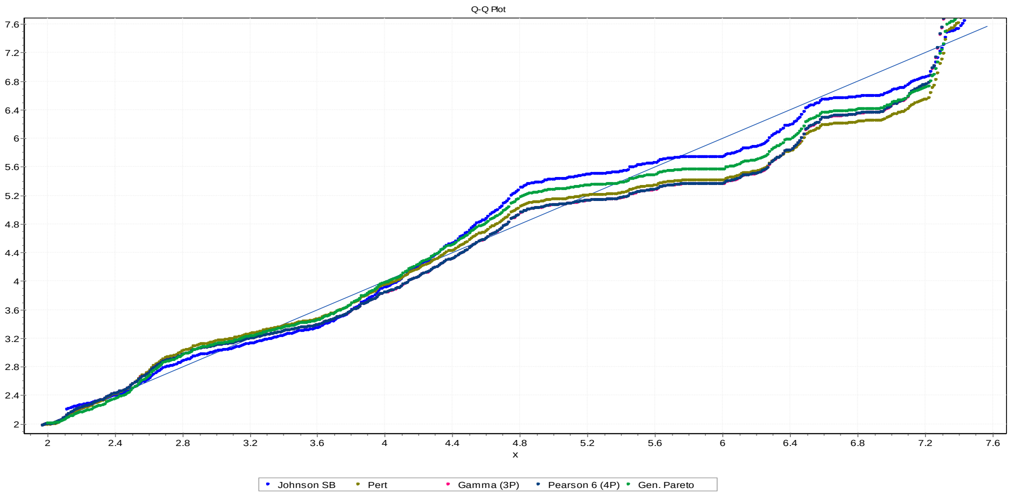


Figure 6. QQ-Plot for the most illustrative 6 distributions for RTSF (Own representation)

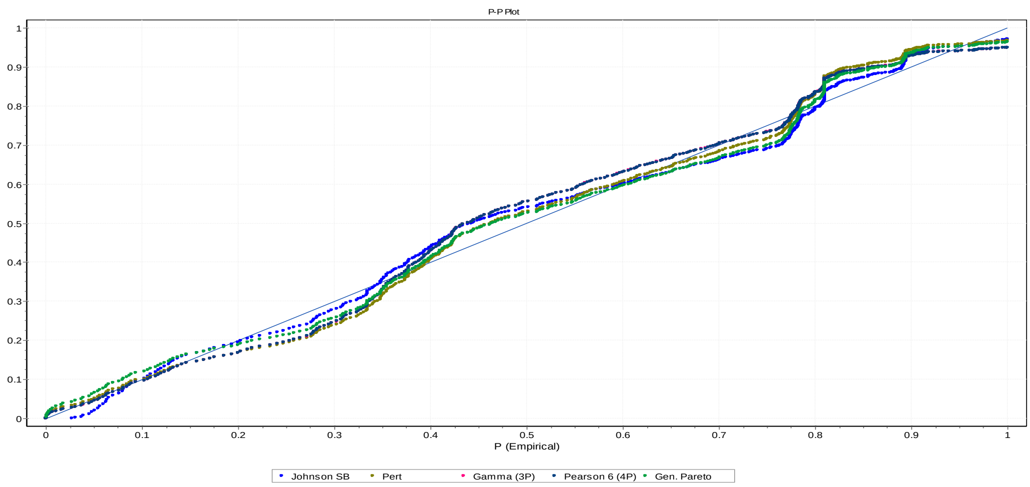


Figure 7. PP-Plot for the most illustrative 6 distributions for RTSF (Own representation)

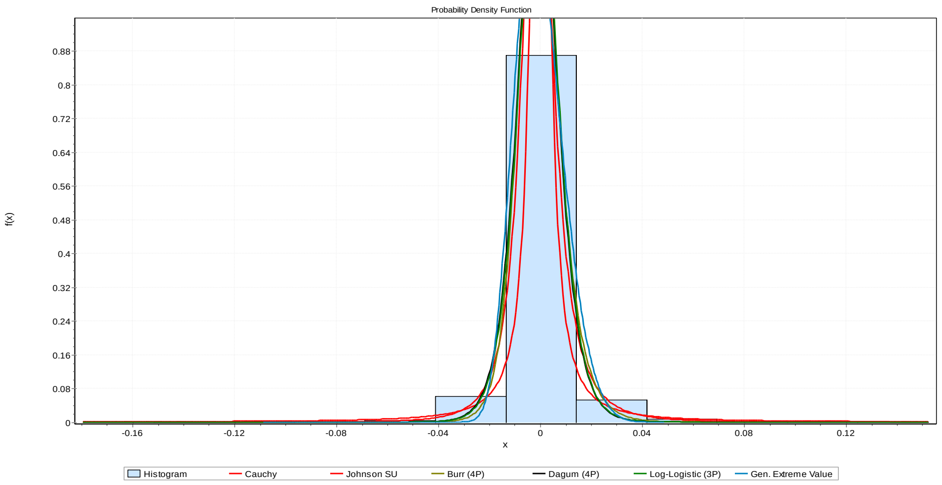


Figure 8. Probability Density Function- for the most illustrative 6 distributions for RTSF_1d (Own representation)

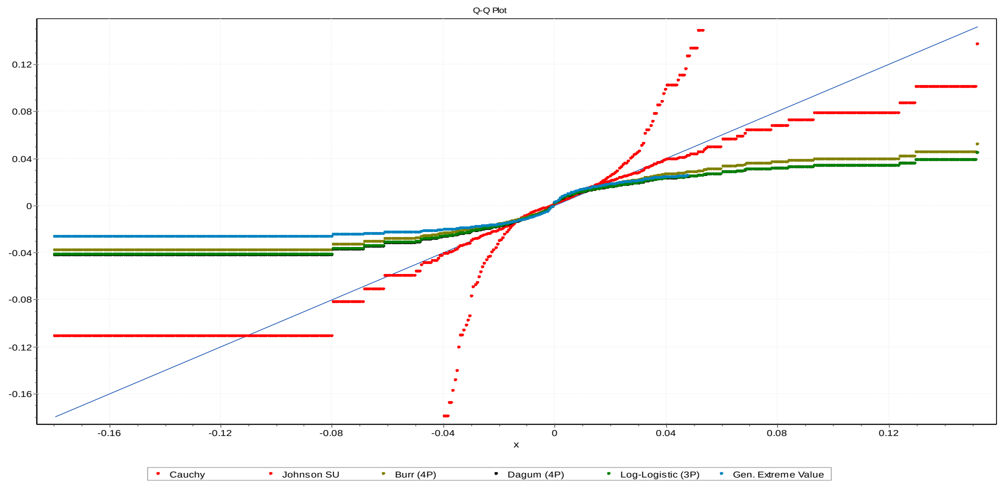


Figure 9. QQ-Plot- for the most illustrative 6 distributions for RTSF_1d (Own representation)

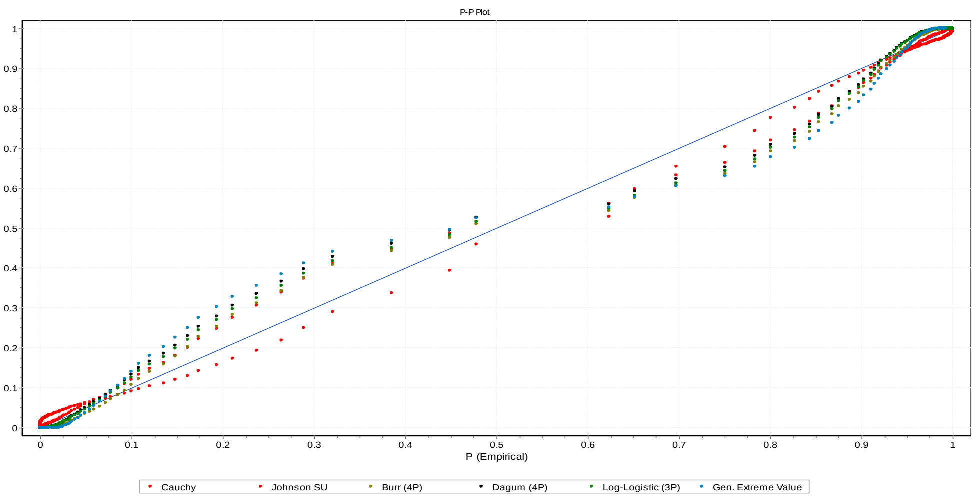


Figure 10. PP-Plot- for the most illustrative 6 distributions for RTSF_1d (Own representation)

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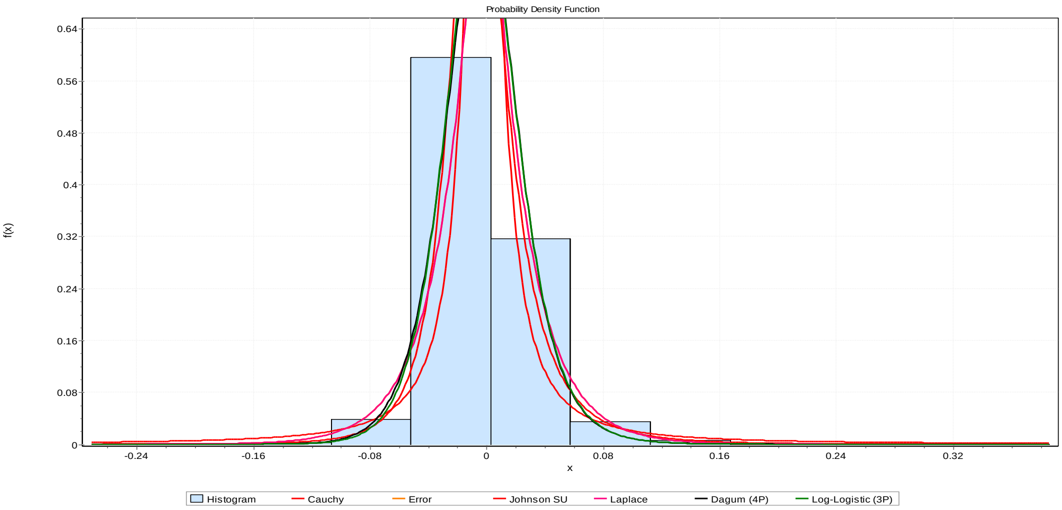

Figure 11. Probability Density Function - for the most illustrative 6 distributions for RTSF_5d (Own representation)

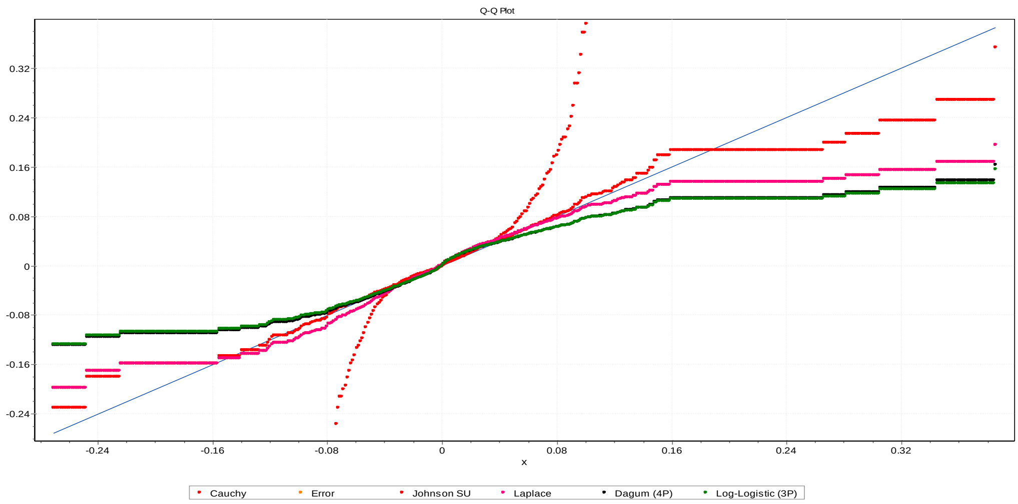

Figure 12. QQ-Plot - for the most illustrative 6 distributions for RTSF_5d (Own representation)

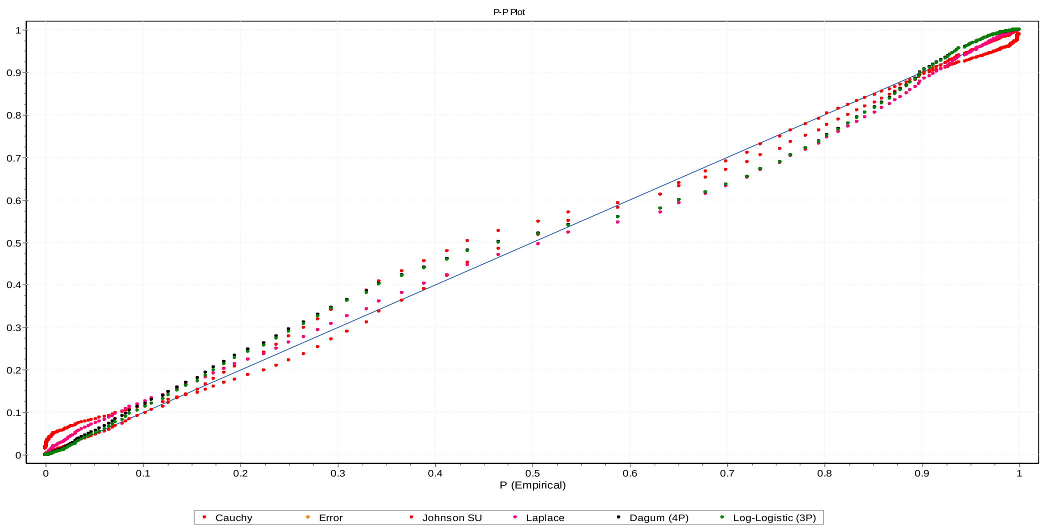

Figure 13. PP-Plot - for the most illustrative 6 distributions for RTSF_5d (Own representation)

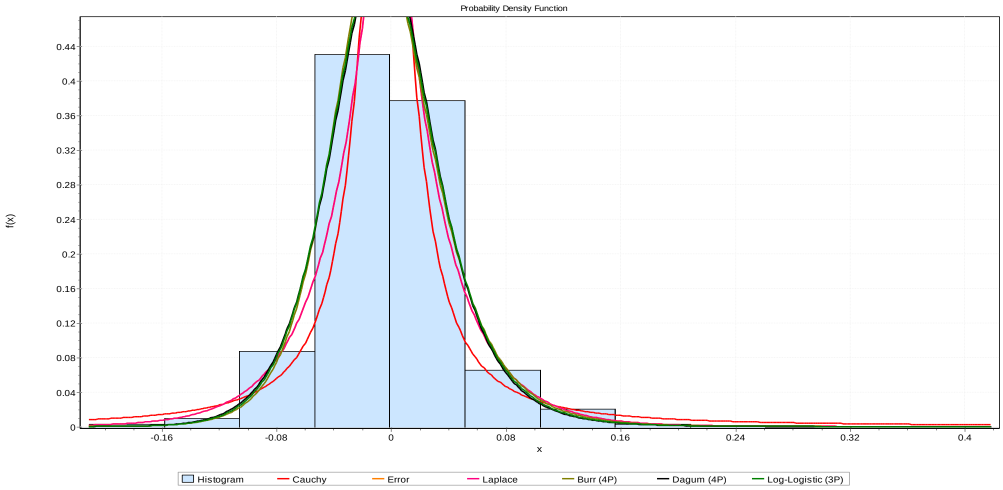

Figure 14. Probability Density Function- for the most illustrative 6 distributions for RTSF_10d (Own representation)

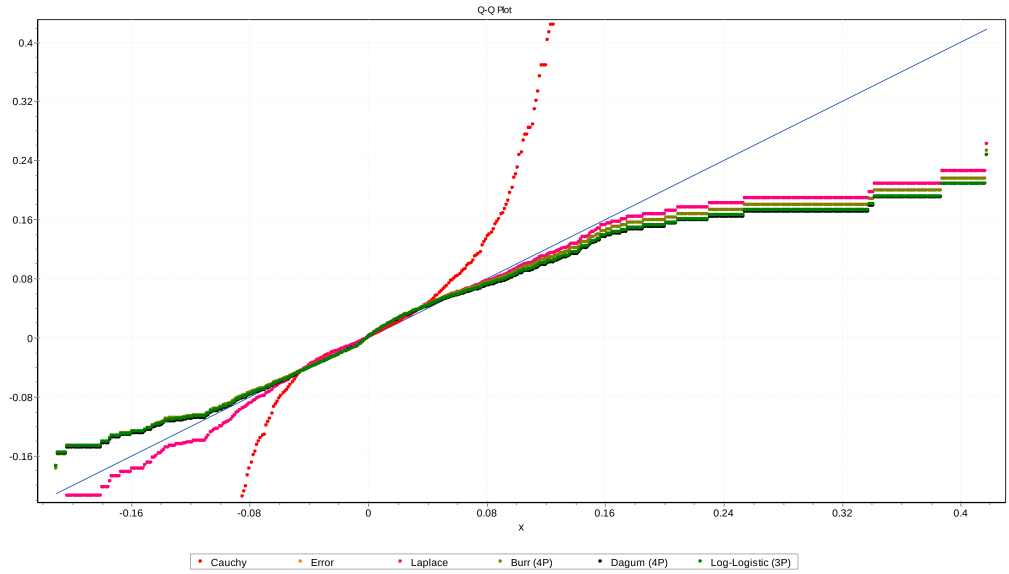

Figure 15. QQ-Plot - for the most illustrative 6 distributions for RTSF_10d (Own representation)

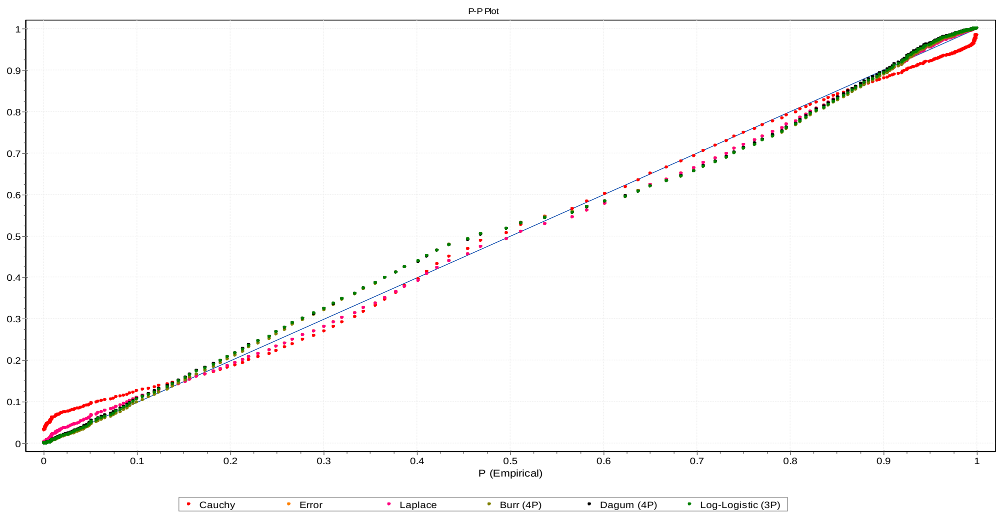

Figure 16. PP-Plot - for the most illustrative 6 distributions for RTSF_10d (Own representation)

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Considering the results obtained with the help of EasyFit, it can be observed that, in the case of the RTSF returns series, the most appropriate distribution for the analyzed data series is General Pareto, with a statistic of 0.0555. In the case of RTSF series changes at one day, the most suitable distribution for the analyzed data series is Johnson SU, with a statistic of 0.10006. In regards to the next case, of RTSF series changes at five days, the most suitable distribution for this data is Cauchy, with a statistic of 0.04145 and, in the case of the RTSF series changes at ten days, the most suitable distribution for the data series is Laplace, with a statistic of 0.03517. It can be said that the Cauchy distribution, which, for the 5-day RTSF changes series case, was more suitable, is conservative, in the sense that it leads to an overestimation of the risk, as it can be seen in Fig .11, Fig. 12 and Fig.13. On the other hand, Log-Logistic distribution (3P) seems among the most suitable distributions for the analyzed series (considering the rank provided by the Kolmogorov Smirnov test), which underestimates the risk, therefore it's more favorable.

In conclusion, for the 5-day RTSF-5Y return series, the most suitable distribution that our analysis showed was Log-Logistic (3P).

Following the results obtained, we will calculate the value at risk for a 99% confidence level for each of the six most illustrative distributions, according to the tables below:

Tabel 2. Results obtained - The most illustrative six distributions for RTSF

RTSF_1 day				RTSF_5 days				RTSF_10 days			
	p=0.001	p=0.01	p=0.99		p=0.001	p=0.01	p=0.99		p=0.001	p=0.01	p=0.99
Johnson SU	-0.07	-0.03	0.04	Cauchy	-4.03	-0.40	0.40	Laplace	-0.21	-0.13	0.12
Dagum (4P)	-0.03	-0.02	0.01	Dagum (4P)	-0.11	-0.08	0.08	Error	-0.21	-0.13	0.12
Log-Logistic (3P)	-0.03	-0.02	0.02	Log-Logistic (3P)	-0.10	-0.07	0.08	Dagum (4P)	-0.15	-0.10	0.12
Cauchy	-0.96	-0.10	0.10	Johnson SU	-0.15	-0.08	0.11	Log-Logistic (3P)	-0.14	-0.10	0.11
Burr (4P)	-0.03	-0.02	0.03	Error	-0.16	-0.09	0.10	Burr (4P)	-0.14	-0.10	0.13
Gen. Extreme Value	-0.02	-0.01	0.02	Laplace	-0.16	-0.10	0.10	Cauchy	-6.60	-0.66	0.65

Source: Made by the authors using EasyFit Software and data collected from the NBR website

Therefore, taking into account the results obtained in the table above, it can be seen that for the 1-day modified RTSF series in the case of the Johnson SU distribution, a VaR level of approximately 0.04 was found and, with a probability of 1%, the maximum possible loss for a day is 0.03 currency units.

As in the case of the data series RTSF_1 day, we calculated the value at risk for the other two series, thus obtaining, as for the RTSF series with returns after five days, in the case of Logistic distribution (3P), the resulting VaR level is about 0.08. It can be seen that, with a probability of 1%, the maximum possible loss recorded for five days is 0.07 units.

In the case of the RTSF series with change at ten days, the VaR level turned out to be 0.12 and, with a probability of 1%, the maximum possible loss that is recorded for ten days is 0.13 units.

Backtesting

Tabel 3. VaR results

	1d	5d	10d
Analytical VaR	-2.92%	-8.32%	-11.47%
Historical VaR	-3.01%	-7.96%	-10.47%
Standard deviation	1.24%	3.49%	4.65%
Mean	-0.04%	-0.20%	-0.65%
Expected Shortfall	-4.3%	-11.8%	-11.8%
Deviation (test)	1.45%	3.87%	5.94%
Mean (test)	0.16%	0.67%	1.04%

Source: Made by the authors using Excel and data collected from the NBR website

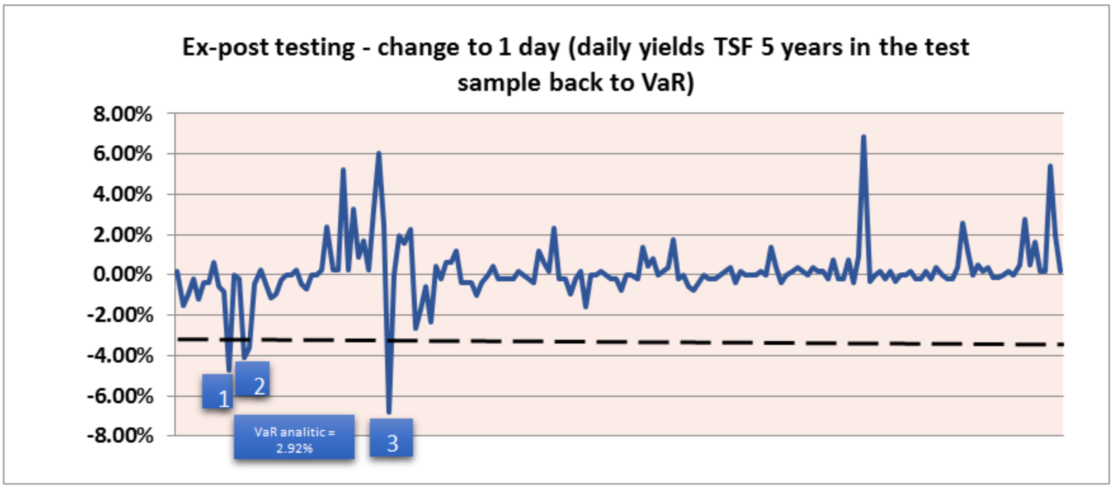

Figure 17. Ex-post testing_1d (daily yields TSF 5 years in the test sample back to VaR) (Own representation)

According to Figure 17, there is an analytical VaR level of 2.92% and we can note that there are three negative peaks. The first peak illustrates the value of -0.0476 related to the day of 18.01.2021, a day with a rather high impact on the bond market.

The long-term financing costs of the Romanian state increased gradually between the 11th and 15th of January 2021 and, Romania's 10-year interest rate increased by 0.2%. From the public information of the period, it appears that investors are reporting an increasingly speculative bond market, with a predominance of long-term bonds. In other words, to achieve a positive real return, it is necessary to reduce yields in the context of increasing public debt.

The second peak in Figure 17 from 21.01.2021 shows the decrease caused by the yield curve of government securities in RON, after the reduction of the monetary policy interest rate by the NBR when the short-term yields decreased and led to a certain extent and segmentally, the yields on government securities, and, thus, the difference in yield between 10-year and 3-year RON bonds increased.

The third peak, noticed on 02.03.2021, shows, according to NBR, that the net interest margins applied in the domestic banking sector evolved divergently in January by increasing RON over EUR. The decline in EUR, as well as the external macro-financial climate and domestic news, were felt in the financial market and the yield curve shifted upwards over the short and medium-term.

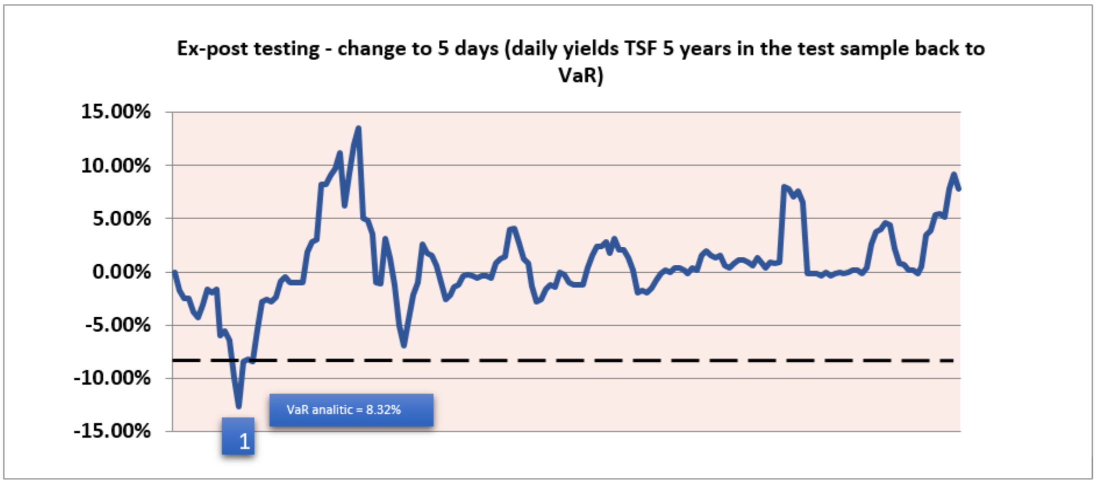

Figure 18. Ex-post testing_5d (daily yields TSF 5 years in the test sample back to VaR) (Own representation)

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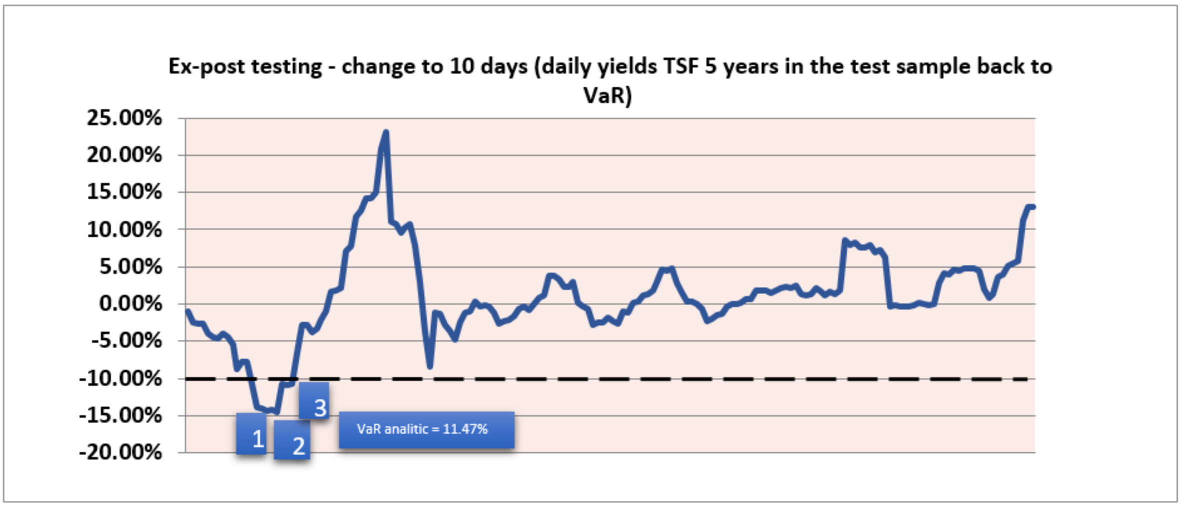

Figure 19. Ex-post testing_10d (daily yields TSF 5 years in the test sample back to VaR)
(Own representation)

Figures 18 and 19 highlight the dates: 22.01.2021, when the effects of the day 21.01.2021, whose events were mentioned above, are still present in the financial market, the date of 28.01.2021, when the evolutions in the international markets and the internal factors had an impact on the financial market and from our country and, at the level of the money market, the interest rates recorded marginal fluctuations and the date of 02.02.2021, when a decrease of the chart was observed as a result of the increase of GBP, EUR, and USD over RON.

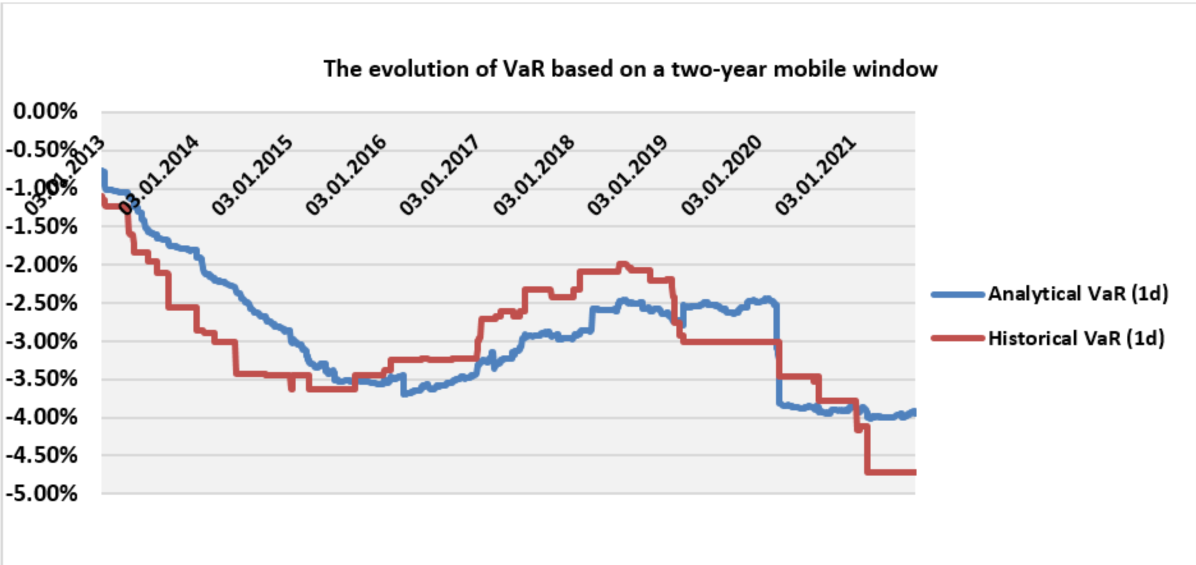

Figure 20. The evolution of VaR based on a two-year mobile window
(Own representation)

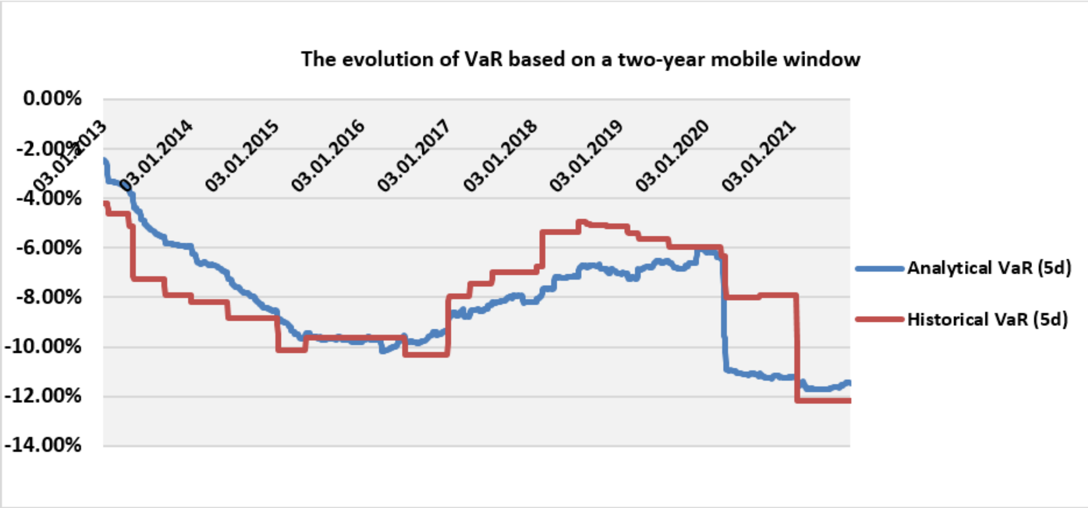

Figure 21. The evolution of VaR based on a two-year mobile window (Own representation)

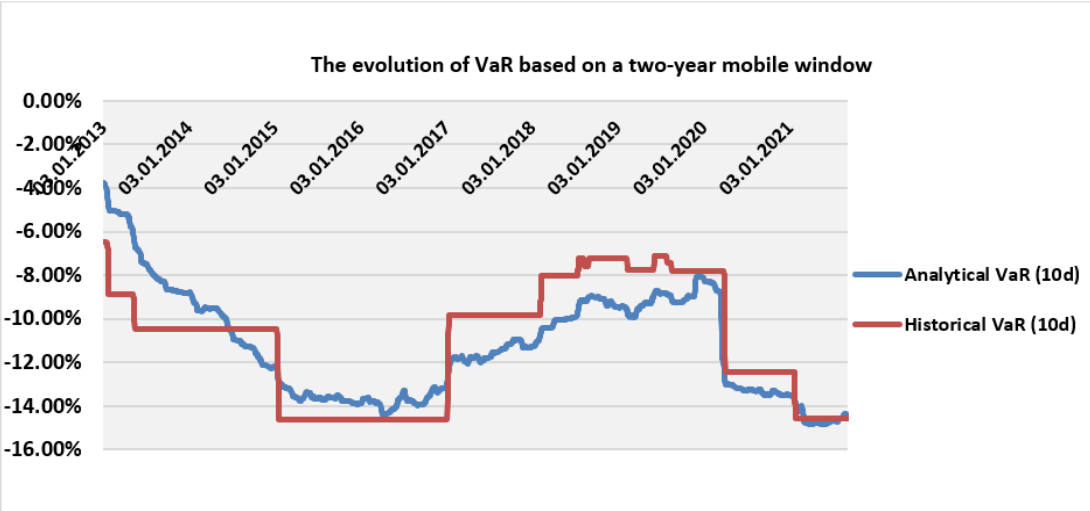

Figure 22. The evolution of VaR based on a two-year mobile window (Own representation)

Conclusion

Government bond yields (RTSF_5 y) are one of the representative factors in quantifying market risk.

According to the analysis done in this paper, it can be stated that the time series comes from a Gamma distribution, and the determination of the maximum possible loss when investing in these instruments by classical methods, such as risk value or expected shortfall, is not conclusive and, therefore, the technique called Distribution fitting has the role of reducing these problems.

The Kolmogorov-Smirnov test statistic, based on the best distribution hierarchies, suggests that:

- RTSF_5y returns are better fitted by the General Pareto distribution (which is more advanced than the Gamma distribution)
- RTSF_5y with change to one day is better fitted by the Johnson-Su distribution
- RTSF_5y with change to five days is better fitted by the Cauchy distribution
- RTSF_5y with change to ten days is better fitted by the Laplace distribution

The analysis confirms the fact that during the pandemic period the market volatility increased, which led to increased volatility of government securities, taking into consideration, the estimation of risk through the value at risk (VaR) method.

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