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A REVIEW OF RECENT APPROACHES TO EVALUATING VALUE AT RISK IN FINANCIAL MARKETS

ALI OU-YASSINE[1,*], ABDELMONSIF HICHMANI[2], MOHAMED SALAH EDDINE ARROUCH[3]

[1]Department of Mathematics and Management, LISTI Laboratory, ENSA Agadir, University Ibn Zohr, Morocco

[2]Department of Mathematics, ENSA Kenitra, Ibn Tofail University, Morocco

[3]Department of Mathematics, FS El Jadida, Chouaib Doukkali University, Morocco

[*]Corresponding author: a.ouyassine@yahoo.com

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Abstract. By reviewing the works published in [12] and [21], this paper explores semi-parametric methods to enhance the quantification of improbable financial risks and assess the impact of Covid-19 on the Moroccan stock market. First, we conducted a comparative analysis of two distinct Value at Risk (VaR) methods: Cornish-Fisher VaR (CF-VaR) and historical VaR (H-VaR). Our studies indicate that the Cornish-Fisher VaR method is more efficient than the historical VaR method in estimating unlikely financial risks. Furthermore, CF-VaR provides an excessive estimate of actual losses, necessitating new efforts to refine these estimates using Extreme Value Theory (EVT). To this end, we employed EVT to assess the VaR of the Moroccan stock market during the Covid-19 pandemic. The quantitative findings demonstrate that the EVT approach is more effective than historical VaR and variance-covariance VaR methods.

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Key words and phrases. value at risk; historical VaR; variance-covariance; Cornish-Fisher VaR; extreme value theory; unlikely financial risks; COVID-19; semi-parametric approaches.

1. Introduction

The coronavirus outbreak has unequivocally highlighted a critical issue in risk management in recent years. This concern is specifically related to estimating improbable risks in the realm of financial engineering. A global pandemic was officially declared after initial cases of Covid-19 were reported in China and South Korea. A state of emergency worldwide was declared in January 2020 as a result of this.

In order to regain control over the escalating situation, governments had no choice but to implement measures of isolation and social distancing. These essential actions, however, caused significant economic repercussions and triggered severe crises across various sectors.

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Morocco was not spared from the enormous impact of the outbreak. The death toll in the country reached 15,617 people, with an estimated 1,000,000 cases reported. In 2020 alone, the Moroccan economy suffered significantly, deteriorating by almost 7%.

The purpose of this study is to evaluate the methodologies recommended in financial engineering and risk management when faced with unexpected risks.

Over half a century of dedicated research has resulted in significant evolution of the field of risk measurement. Due to its numerous applications in engineering, economics, and science, it has firmly established itself as a successful field in engineering sciences and beyond. This is especially evident in the area of financial engineering [8].

In 1994, JP. Morgan Morgan introduced the Value at Risk (VaR) methodology, a prominent approach for dealing with financial risk measurement challenges and their extensions. The industry is utilizing this method extensively, and it also provides a simpler way to interpret risk measures.

Rigorous scientific research has been undertaken to find a multifaceted and less restrictive theory to make this method suitable and more practical. In principle, there are three approaches for estimating the "VaR" Risk Value:

- Non-parametric approach: hybrid method, historical simulation....
- Semi-parametric approach: extreme values, CAViaR ...
- Parametric approach: univariate or multivariate GARCH models, RiskMetrics ...

Lately, the majority of scientific research using these last three approaches has been restricted to focused only on the measurement of highly probable financial risks, i.e., risks whose probability of occurrence is high but their severity is low and risks whose probability is low and gravity are high).

These are operational risks that are generally overseen by risk managers. In this paper, we are interested in semi-parametric approaches to develop our studies on the measurement of unlikely financial risks, i.e., risks whose probability is low, but their severity is high. These are the unlikely risks often overlooked by risk managers. They are difficult to predict and anticipate.

For this reason, the main content of this work includes two new in-depth studies for the estimation of unlikely financial risks in the Moroccan financial market. We started with a comparison between the historical VaR approximation recently published in [12] and [21], and the Cornish-Fisher VaR approximation that we suggested.

The main goal that motivated us to focus on the Cornish-Fisher VaR approximation is that it makes use of several interesting properties that are not provided by the historical VaR approximation. Thus, the choice of the Cornish-Fisher VaR approach is mainly justified by its ability to solve problems of measuring unlikely financial risks; ones which arise in the case of catastrophic events. Since CF VaR provides an imprecise estimate of actual losses, additional research is needed to better estimate them.

In this regard, we adopted the EVT in the evaluation of the VaR on the Moroccan stock market during the Covid-19 pandemic. This specific choice allowed us to improve the Cornish-Fisher VaR approximation and make it remarkably efficient and more practical while showing simple expectations. The estimate was applied to the MASI index (Moroccan All Shares Index).

2. Literature Review

2.1. **The basis of value-at-risk (VaR).**

Value at Risk is a synthetic indicator, which reflects the minimum loss for a given level of risk and time horizon.
The bases of the VaR are:

- The probability that the loss will not be higher than expected.
- The forecast horizon.
- Return volatility.

Let $w_1, w_2, ..., w_n$ a random variables expressing the data of a given financial asset.
and $T(w) = Pr(w_t < w/\Omega_{i-1})$ the cumulative distribution function of the set of information Ω_{i-1} available at time $i-1$.

Let w_i follows stochastic process:

$$w_i = \theta_i + \epsilon_i = \theta_i + \sigma_i z_i \tag{1}$$

With $\theta_i = E(\epsilon_i/\Omega_{i-1}$, $\sigma_i^2 = E(\epsilon_i^2/\Omega_{i-1})$ et $z_i = \frac{\epsilon_i}{\sigma_i}$ admits a conditional distribution function $H(t)$,

$$H(z) = Pr(t_i < t_i/\Omega_{i-1}).$$

The $VaR(\lambda)$ is written as the quantile of the probability distribution of financial data:

$$T(VaR(\lambda)) = Pr(w_i < VaR(\lambda)) = \lambda \tag{2}$$

This quantile can be evaluated by: Inverting the distribution function of financial data $T(w)$. Inverting the distribution function of financial data standardized $H(t)$.
If the last case is chosen, it will be necessary to evaluate θ_i and σ_i^2.

$$VaR(\lambda) = T^{-1}(\lambda) = \theta_i + \sigma_i H^{-1}(\theta) \tag{3}$$

herefore, the evaluation of VaR involves the specification of $T(w)$, $H(t)$ and θ_i and σ_i^2, [5].

2.2. **The basis of Cornish-Fisher approximation and the theory of extreme values.**

2.2.1. *Cornish-Fisher approximation concept.* The Cornish Fisher approximation is the transformation from the Gaussian case into a non-Gaussian one, (resp from random variable w into random variable M).

$$t \approx N(1,0), \quad E(t)=0, E(t^2)=1, E(t^3)=0, E(t^4)=3$$

$$M = t + (t^2-1)\frac{R}{6} + (t^3-3t)\frac{L}{24} - (2t^3-5t)\frac{R^2}{36}$$

The CF transformation is:

$$b = \frac{L}{24} \quad c = \frac{R}{6}$$

$$M = a_0 + a_1 t + a_2 t^2 + a_3 t^3$$

$$a_0 = -c \quad a_1 = 1 - 3b + 5c^2 \quad a_2 = c \quad a_3 = b - 2c^2$$

L is a kurtosis parameter and R is a skewness parameter.

2.2.2. *Extreme Value Theory concept.* The theory of extreme values makes it possible to know the asymptotic behavior of the maxima of values taken by the values of identically distributed and independent random variables. It includes parameters that can be estimated based on the extreme values taken by the distribution of data above a certain level (excess method).

Consider X as a random variable whose distribution function $T()$ is unknown:

$$T(x) = Pr(X \leq x) \tag{4}$$

Let θ as a value of X located in the right tail of the distribution. It can be considered as an extreme value. We would like to have information on the probability that X exceeds θ, (see [13]). The probability that the difference between X and θ does not exceed an amount y, in the case where X exceeds the value θ, is to make a donation by:

$$T_\theta(y) = Pr(X - \theta \leq y/X > \theta) = \frac{T(y+\theta) - T(\theta)}{1 - T(\theta)} \tag{5}$$

$T(y+\theta) - T(\theta)$ is the probability that X is between θ and $\theta + y$ and $1 - T(\theta)$ is the probability that X exceeds θ, [13].
Conversely, the probability of the difference between X and θ exceeds y, knowing that X already exceeds θ, is given by $1 - T_\theta(y)$. Knowing that $X > \theta$, [13].

The Balkema-de Haan-Pickands theorem [1974 and 1975] If the distribution of X is a priori unknown, we have the possibility to approximate this unknown distribution validly, but only in its tail of distribution, by a generalized Pareto law whose parameters (η, τ) must be evaluated. This means that the distribution function of excess returns y over $\theta, T_\theta(y)$, can be approximated by $H_{\eta,\tau}(y)$ the distribution function of the generalized Pareto distribution with parameters η and τ defined as

$$T_\theta(y) = H_{\eta,\tau}(y) = 1 - \left(1 + \eta \frac{y}{\tau}\right)^{-1/\eta}, \quad if \quad \eta \neq 0 \tag{6}$$

η is the form parameter: It gives information about the more or less thick character of the tail distribution. The more η is high, the more the tail of the distribution is thicker. Therefore, the probability of having extreme returns is high. In contrast, when η tends to zero, the tail of the distribution tends to have the same properties as those of a normal distribution and the probability of extreme returns is low. The τ parameter is only a leveling parameter.

The parameters η and τ can be estimated for a pre-chosen θ value. The level θ should not be too high or too low. We can estimate the values of η and τ by the likelihood method, [3].

3. Application of Cornish-Fisher Approximation and Extreme Value Theory for VaR Calculation

3.1. **The Cornish-Fisher approximation VaR.**

The Cornish-Fisher transformation provides a simple way to express value-at-risk measures based on skewness and kurtosis parameters. Given the target values for (actual) skewness and kurtosis, it is therefore appropriate to calculate the parameters L and R and use them as input to the following formulas. For a Gaussian distribution, the value at risk (centered and reduced) at confidence level $1 - \lambda$ is:

$$VaR_{1-\lambda} = \nu_\lambda = -x_\lambda = -N^{-1}(\lambda)$$

For transformed distribution

$$\begin{aligned} VaR_{1-\lambda} &= -M_\lambda = -a_0 - a_1 t_\lambda - a_2 t_\lambda^2 - a_3 t_\lambda^3 \\ &= \nu_\lambda + (1 - \nu_\lambda^2)\frac{R}{6} + (5\nu_\lambda - 2\nu_\lambda^3)\frac{R^2}{36} \\ &+ (\nu_\lambda^3 - 3\nu_\lambda)\frac{L}{24} \end{aligned}$$

That is a simple expression involving the skewness and kurtosis parameters and the VaR value at the same threshold for a Gaussian distribution.

3.2. **Extreme value theory VaR.**

The objective is to approximate $T(x)$ for values of X that are high enough. we can write:

$$\begin{aligned} T(x) &= T(\theta + y) = T_\theta(y).(1 + T(\theta)) + T(\theta) \\ &= H_{\eta,\tau}(x - \theta).(1 - T(\theta)) + T(\theta)) \end{aligned} \tag{7}$$

we can approximate $T_\theta(y)$ par $H_{\hat{\eta},\hat{\tau}}(x - \theta)$. Consider n as the total number of observations, [3].

In the portfolio returns data, n_θ is the number of observations where $X > \theta$. The estimator of $T(\theta)$

is $\hat{T}(\theta) = (n - n_\theta).n^{-1}$, It is the proportion of X that is greater than θ among the n observations that precede the date at which the VaR is estimated. The estimate of $1 - T(\theta)$ is therefore equal to $\frac{n_\theta}{n}$. By substituting the different parameters of the generalized Pareto distribution by their estimates, we find for $X > \theta$ that [3],

$$\begin{aligned}\hat{T}(x) &= \hat{T}(\theta + y) \\ &= \frac{n - n_\theta}{n} + H_{\hat{\eta},\hat{\tau}}(x - \theta).(\frac{n_\theta}{n}) \end{aligned} \tag{8}$$

Therefore:

$$\hat{T}(x) = \hat{T}(\theta + y) = 1 - \frac{n_\theta}{n}.(1 + \hat{\eta}.\frac{x - \theta}{\hat{\tau}})^{-\frac{1}{\hat{\eta}}} \tag{9}$$

So:

$$\begin{aligned}P(x > \theta) &= 1 - \hat{T}(\theta + y) = \frac{n_\theta}{n}(1 - H_{\hat{\eta},\hat{\tau}}(x - \theta)) \\ &= \frac{n_\theta}{n}.(1 + \eta.\frac{x - \theta}{\tau})^{-\frac{1}{\eta}} \end{aligned} \tag{10}$$

The VaR at the level λ (avec $\lambda > T(\theta)$) is calculated as the particular value of $x = \theta + y$ for which we verify that:

$$\hat{T}(\theta + y) = \lambda \tag{11}$$

The estimated VaR of level x is therefore such that:

$$\widehat{VaR}_\lambda = \theta + \frac{\hat{\tau}}{\hat{\eta}}\left[\left(\frac{n}{n_\theta}(1 - \lambda)\right)^{-\eta} - 1\right], \tag{12}$$

With $\lambda > 1 - \frac{n_\theta}{n}$.

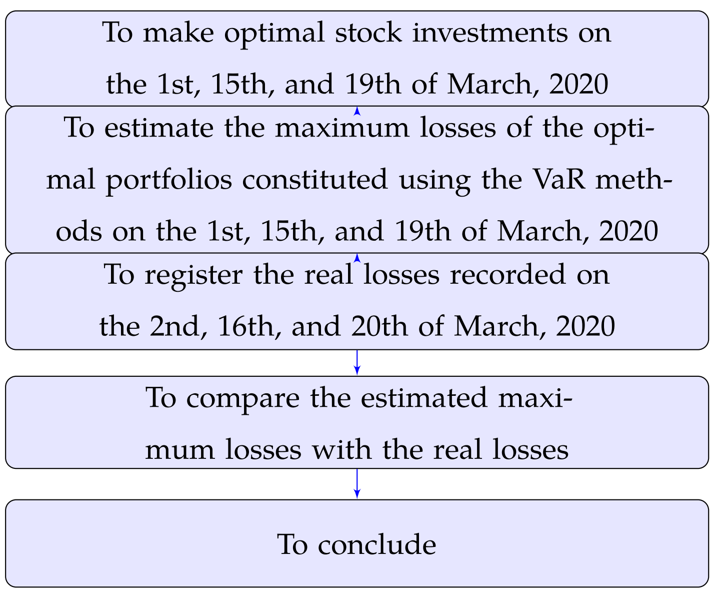
4. Materials and Methods

Inspired and motivated by results in [12] and [21]. We discovered that the research conducted in these two recent works validates the variance-covariance VaR, classifying it as a robust and efficient approach in contrast to the historical VaR. This observation prompted us to clarify and provide a global critical analysis of these contemporary results.

It is well understood that in the majority of real-world risk measurement scenarios, we must analyze data that follows a non-normal distribution. This deviation from normal levels can be attributed to the high frequency of fluctuations in financial markets and the influence of many factors, including rare events.

Subsequently, the variance-covariance VaR approach is not applicable in this case. Since its application requires normality for the distributions of the samples studied, see [19,20], while historical VaR is valid for non-normal distributions. In addition, the studies proposed in the paper [12] are based on market data during the period of the Covid 19 pandemic crisis. This raises many questions about this study

because it is very difficult to build a data portfolio that respects normality in the crisis period.
To this effect, historical simulation is recommended against variance-covariance to properly respond to the problem of non-normality, but historical VaR still remains insufficient to tackle the major challenges of the unlikely risks of financial market fluctuations.
Rigorous research has been done to overcome the deficiencies of the historical VaR approach. In this first contribution, we proposed an improved version of the variance-covariance VaR by adding the two extensions of skewness and kurtosis (Called Cornish-Fisher approximation).
Our first Objective is to evaluate the effect of the crash caused by an unlikely risk (Covid-19) on the Moroccan stock market (AUTOHALL stocks). Thus, to test whether the VaR calculation correctly estimated the losses from this disaster. Considering an optimal portfolio, we have suggested a time period extending from 07/19/2016 (date of introduction of the company SODEP as a new investor in the Casablanca market) to 03/19/2020.
Then, we calculated the maximum loss not to be exceeded by investors with a confidence level of 99% by proposing the VaR model with the two approaches: historical and Cornish Fisher. Finally, this study compared the estimated maximum loss with the actual loss recorded for the different dates 02^{nd}, 16^{th}, and 20^{th} in the month of March 2020.
The first approach can be summarized as follows:



The data studied brings together 24 sectors listed on the Casablanca Stock Exchange (see figure 1).

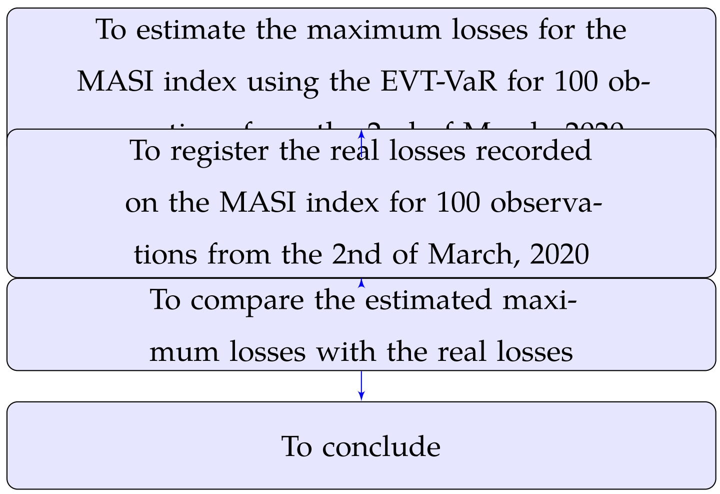
After comparing the Cornish-Fisher VaR (CF VaR) approximation and historical VaR, we found the effectiveness of CF VaR in most of the cases studied. But Cornish Fisher VaR overestimates losses and more research is needed to better estimate them.

For this reason, our second contribution adopts the extreme value theory approach in estimating value at risk. The process allowed us to improve CF VaR and make it very efficient and more practical by giving a precise estimate of losses which must not be exceeded while keeping simple hypotheses.

The second objective of this work is to apply the theory of extreme values to the evaluation of value at risk in the case of the Covid-19 epidemic in Morocco.

This event is an example of an unlikely risk, we will calculate the maximum loss which must not be exceeded for 100 observations from the date of appearance of a first contamination with Covid-19 for a confidence level of 99% by the VaR model with application of extreme value theory.

The second approach can be summarized as follows:



4.1. **Descriptive Statistics.**

4.1.1. *Descriptive Statistics of the first approach.* Normality and stationarity test.

FIGURE 1. Fluctuations of stock market returns from 07/19/2016 to 03/2020

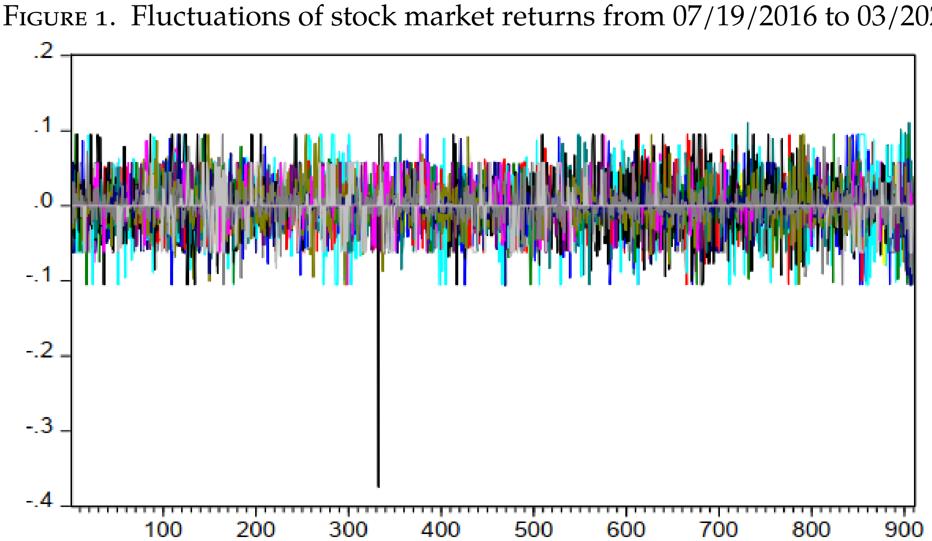
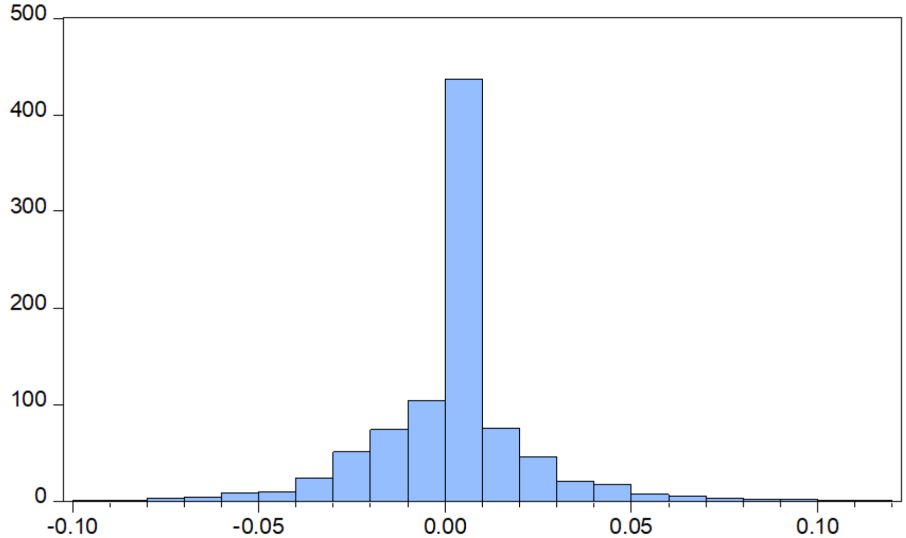


Figure 2. Results of the normality test from 19/07/2016 to 01/03/2020



- Figure 2 shows that the distribution of the studied data is not normall.
- Table 1 shows that the distribution of the studied data is stationary.

Table 1. Results of the stationarity test from 19/07/2016 to 01/03/2020.

Series: AUTOHALL				
Sample: 1897			Jarque-Bera: 868.4360	
Observations: 897			Probability: 0.000000	
Mean	Median	Maximum	Minimum	Std. Dev.
0.000561	0.000000	0.110957	-0.090796	0.020795
Skewness: 0.471585			Kurtosis: 7.727174	

Null Hypothesis: AUTOHALL has a unit root Exogenous:None None Lag Length: 3 (Automatic - based on SIC, maxlag=20)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-19.38853	0.0000
Test critical values	Level	1 %	-2.567554	
		5 %	-1.941178	
		10 %	-1.616461	

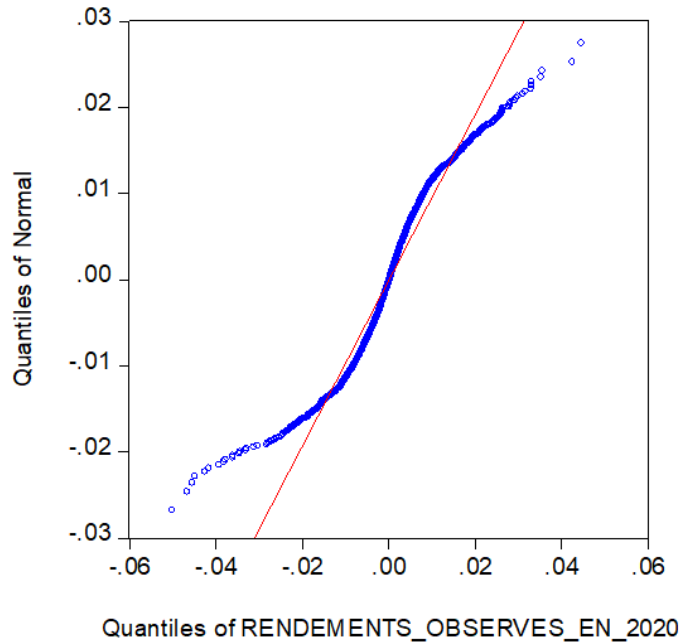
4.1.2. *Descriptive Statistics of the second approach.* Starting with the visualization of parameter θ, we can apply the maximum likelihood method to evaluate η and τ. that is to say, we will look for η and τ for a maximization of the following expression:

$$\sum_{j=1}^{n_\theta}[log\frac{1}{\tau}(1+\frac{\eta(w_j-\theta)}{\tau})^{\frac{-1}{\eta-1}}]$$

By optimizing the relative relationship between bias and effectiveness. Theoretically, we can take the value θ (the estimators will be biased for a low value θ) and if the number of extreme observations considered in the study is reduced (the value θ is high), hence the overestimation of the variance.

To estimate the value θ: we use the Quantile-Quantile (Q-Q) plot.

Figure 3. The Q-Q representation of the data on Mars 02, 2020.



4.2. **Numerical Results and Discussion.**

4.2.1. *Numerical results and discussion of the first approach.* Numerical Results and discussion of the first approach

TABLE 2. Numerical Results of CF- VaR approach.

Date	Losses	Expected returns					
		0.01 %	0.02 %	0.03 %	0.03 %	0.05 %	MAX
02/03/2020	H-VaR	5.92 %	5.82 %	5.66 %	5.39 %	5.33 %	4.06 %
	CF-VaR	25.64 %	25.64 %	20.29 %	18.40 %	14.06 %	9.18 %
	Real	0.75 %	0.84 %	1.05 %	1.13 %	1.12 %	1.12 %
16/03/2020	H-VaR	5.54 %	5.45 %	5.30 %	5.17 %	5.02 %	5.45 %
	CF-VaR	25.29 %	23.65 %	19.60 %	19.60 %	19.60 %	9.77 %
	Real	7.95 %	8.15 %	8.11 %	8.10 %	7.59 %	5.88 %
20/03/2020	H-VaR	7.19 %	7.12 %	7.06 %	6.98 %	6.64 %	6.11 %
	CF-VaR	18.71 %	18.71 %	18.71 %	16.71 %	16.71 %	9.74 %
	Real	0 %	0 %	0 %	0 %	0 %	0 %

Source: Author treatment methods.

FIGURE 4. Recorded losses and estimated losses on 02/03/2020

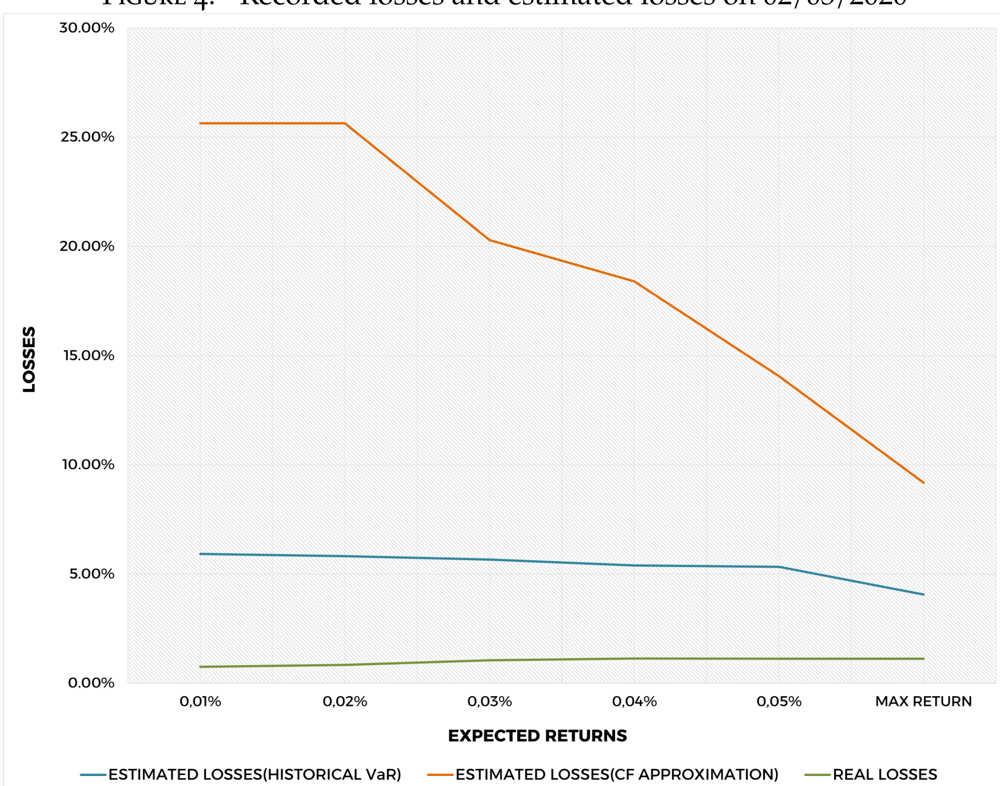


FIGURE 5. Recorded losses and estimated losses on 16/03/2020

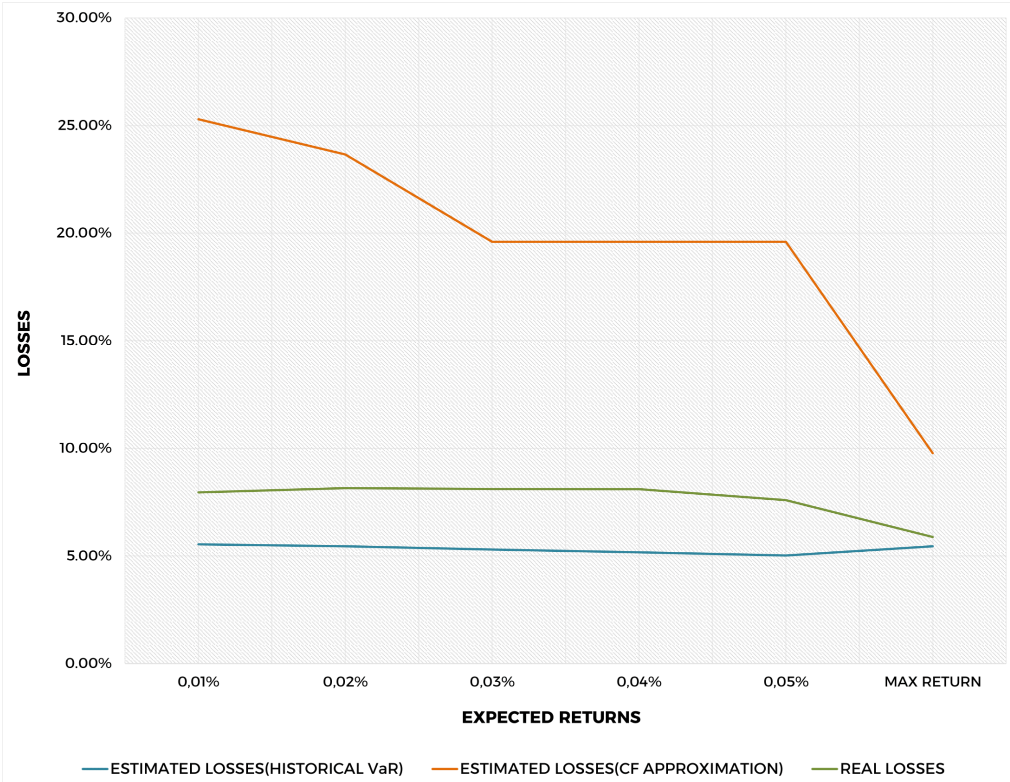
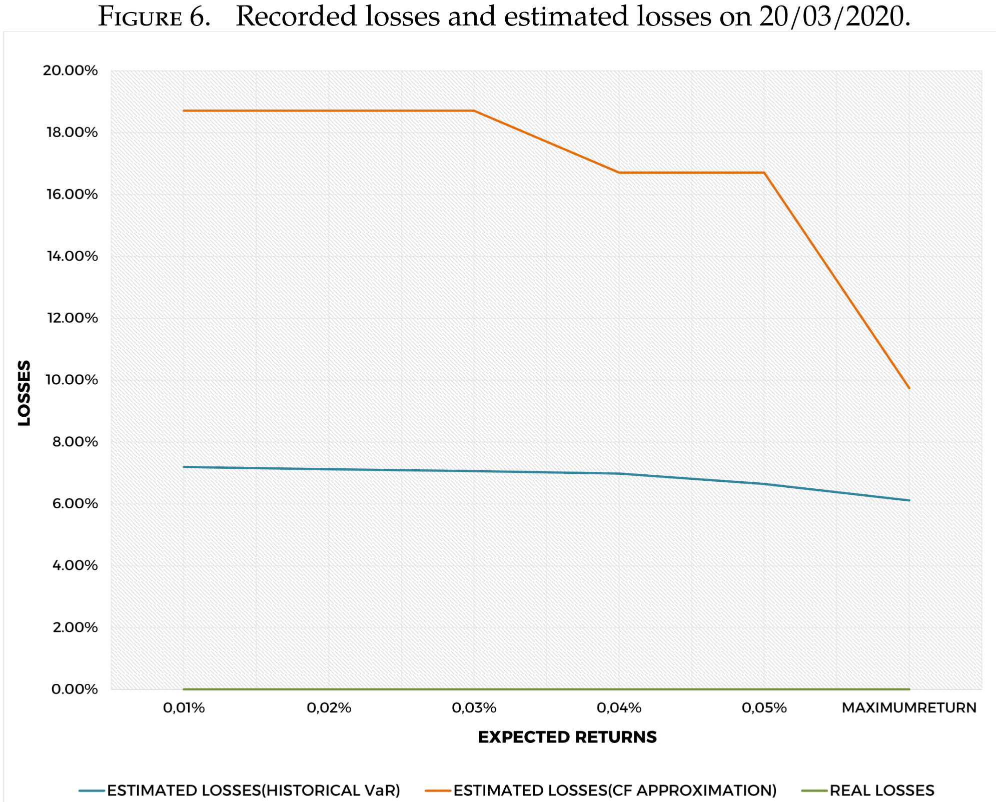


FIGURE 6. Recorded losses and estimated losses on 20/03/2020.



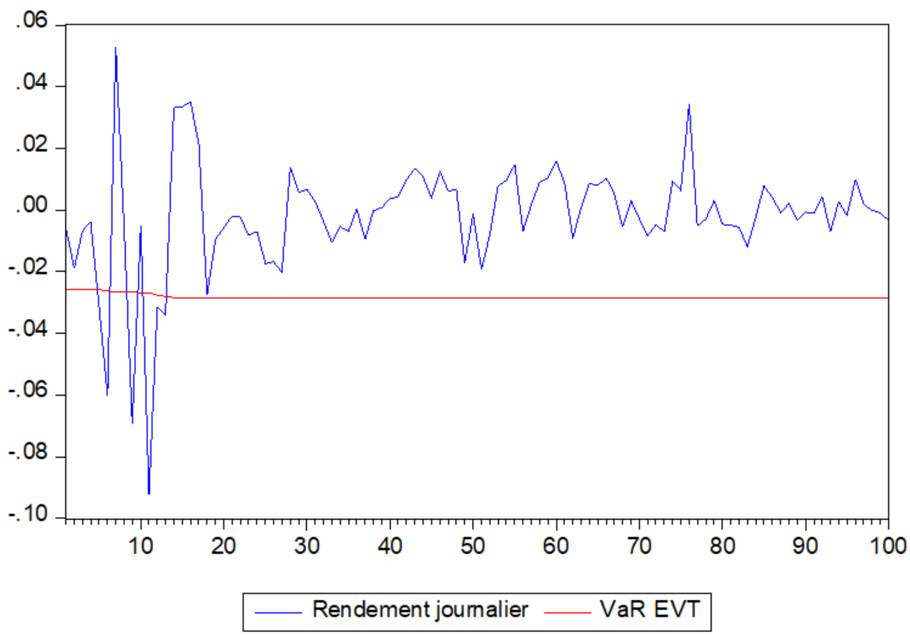
4.2.2. *Numerical Results and discussion of the second approach.* For Mars 02, 2020 the results of the optimization are as follows

Table 3. Results of the optimization for Mars 02, 2020.

$\lvert\mu\rvert$	0.02542 V_P
β	0.0000001
ξ	0.09 V_P
N	4254
n_μ	26
Confidence level	99 %

Source: our treatment methods.

Figure 7. Real losses and estimated losses for the 100 observations after Mars 02, 2020.



With the choice of a confidence level of 99% and a data of 4768 observations, the maximum losses evaluated by the Value at risk EVT were exceeded four times by the actual losses evoked by COVID 19.

5. Discussion

We opted for extreme value theory (EVT), in hopes of responding to the major drawback of numerous applications which required non-normality and stationarity of the sample studied. The EVT is applicable to samples collected from this type of distribution. This methodology provided us with a reliable estimate of losses and provided a powerful solution to numerous issues related to measuring improbable financial risks.

Then, the evaluation was applied to the MASI index which is the main stock index of the Moroccan Stock Exchange. It is made up of all the values listed on the Casablanca Stock Exchange.

The numerical results of our second contribution show that the extreme value theory is more efficient than the historical VaR and variance-covariance VaR approaches published recently in [12] and [21].

At this point in our research, we cannot yet determine whether our approaches are completely relevant for solving the various financial risk problems in reality. Consequently, we are encouraged to increase our efforts to establish new, more general methods.

We summarize our perspectives in three points as follows:

1. The first disadvantage is the sensitivity of EVT to the choice of the level. EVT requires a level above which extreme events are taken into account. The choice of this threshold can have a significant impact on the results. Our first perspective is to reduce and control the sensitivity of the EVT to the threshold choice.
2. EVT offers important advantages in the analysis of data that is not of a normal distribution. It is also important to know its disadvantages. One of the main limitations of EVT is the need to construct a very large sample of data to have reliable evaluations. Estimation accuracy can only be achieved when a sufficient number of extreme events are observed. In cases where extreme events are rare, it can be very difficult to obtain reliable estimates using EVT.
   In this sense, our second perspective is to make EVT more practical even if the sample studied in periods of crisis is not sufficiently large.
3. Progress remains to be made to deal with more complex cases. The evolution of the assets making up a financial portfolio, and more generally risk aggregation requires a multivariate approach. Our third perspective is that the extension of the extreme value theory in the multivariate case makes it possible to study the correlation of markets in crisis periods.

6. Conclusion

In this paper, we have mainly focused on the applications of the value at risk (VaR) method by adopting the Cornish Fisher VaR (CF VaR) approach and more generally the extreme value theory (EVT) for the estimation of unlikely financial risks of the Moroccan financial market (Casablanca

Stock Exchange). The numerical results showed considerable improvement in most cases compared to previously used approaches.

Initially, we put forth a comparison between the recently published historical VaR approximation in [12] and [21], and the Cornish-Fisher (CF) VaR approximation that we proposed. Our primary focus is on evaluating the impact of Covid-19 on the Moroccan stock market. The numerical findings show that the CF VaR is superior to both the historical VaR and the variance-covariance VaR in estimating improbable financial risks.

Our decision to focus on the comparison between the Cornish-Fisher (CF) value-at-risk (VaR) approximation and the historical VaR approximation is primarily motivated by the unique advantages that CF VaR method yields. The CF VaR approximation has some interesting features that are not present in the historical VaR approximation. The choice of the CF VaR approach is primarily justified by its ability to address the challenges associated with quantifying improbable financial risks, especially those that emerge during catastrophic events. Unfortunately, CF VaR provides an estimate of losses that is too loose compared to actual losses. Therefore, additional research is needed to better estimate them.

Accordingly, the EVT approach adopted in the measurement of the value at risk in the Moroccan stock market during the period of Covid-19 pandemic. Allowed us to improve the CF VaR approximation and make it very efficient and more practical while keeping simple hypotheses.

Eventually, extreme value theory received much attention both theoretically and practically. The areas of application are indeed very varied. Today risk management has become fundamental in all these areas. However, the estimate made by the EVT is strongly unstable (even if some authors claim the opposite). The theory of extremes is therefore not a miracle method for measuring the risk of these rare events. It becomes necessary to develop other, more suitable approaches to tackle the risk of catastrophic events.

Authors' Contributions. All authors have read and approved the final version of the manuscript. The authors contributed equally to this work.

Conflicts of Interest. The authors declare that there are no conflicts of interest regarding the publication of this paper.

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